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Blood Cell Detection using YOLOv5s with Enhanced Feature Fusion and Attention Mechanisms

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ABSTRACT
Automatic detection and classification of blood cells (BCs) are essential for clinical medical diagnoses, but traditional methods, such as manual counting and hematology analyzers, are time-consuming and error-prone. This work introduces an advanced one-stage network based on an improved YOLOv5s model to enhance blood cell detection efficiency. Several models were explored, including YOLOv5 with hybrid architectures like BiFPN, Transformer, and CBAM attention modules. Additionally, combinations such as YOLOv5 + Trans + CBAM + BiFPN were analyzed to leverage multi-scale feature fusion and attention mechanisms for improved accuracy. For further evaluation, more advanced versions like YOLOv5x6, YOLOv8, and the latest YOLOv9c were implemented to push the boundaries of detection precision and speed. These hybrid models demonstrated significant improvements in detecting blood cells with higher accuracy, scalability, and processing efficiency. A user-friendly interface was built using the Flask framework to allow for easy testing and authentication. This approach offers a robust and reliable solution for automating blood cell detection, reducing manual intervention in clinical diagnostics.

INTRODUCTION

Complete blood count (CBC) is known as full blood examination (FBE) or full blood count (FBC), which is a common medical diagnostic examination that provides the percentage of cells in the blood. The human blood is composed of plasma and cellular components that contain thrombocytes (platelets), erythrocytes (or red blood cells (RBCs)), and leukocytes (or white blood cells (WBCs)). The primary function of RBCs is delivering oxygen to and taking back CO2 away from the tissues via blood flow. WBCs are an important component of the immune system that defends against infection and diseases. The coagulation mechanism of platelets helps blood to clot and recover wounds. CBC reports the numbers and types of RBCs, WBCs, platelets, and hemoglobin. In general, an abnormal change in the count of BCs type may be related to a type of illness. So, doctors can infer and judge a person's health by analyzing various features of BCs as well as their counts. BCs detection and identification technology could help doctors effectively in disease diagnosis, including that of malaria, dengue, anemia, infections, leukemia, and so forth. For example, a low RBCs count means anemia. Thrombocytopenia characterized by abnormally low levels of platelets, is a feature of acute leukemia and aplastic anemia. For WBCs, an abnormally high WBC count often occurs in infections and inflammation. For patients undergoing chemotherapy or radiation therapy, monitoring of BCs counts is essential for them, because these treatments lead to a decrease of the BCs production in bone marrow.

LITERATURE SURVEY

3.1 AYOLOv5: Improved YOLOv5 based on attention mechanism for blood cell detection:

https://www.sciencedirect.com/science/article/abs/pii/S1746809423004676

ABSTRACT: A crucial component of biological study and clinical trials is the microscopic examination of cells and tissues. Although tremendous progress has been made in computer-assisted microscopy cell detection techniques, especially recently based on deep learning, it still needs to be determined to accurately identify cell targets in the presence of dense and complex cell distribution. In this research, an improved YOLOv5 (AYOLOv5) based on the attention mechanism is suggested to address the issue of the low recognition rate of cell detection caused by this circumstance. Based on YOLOv5, the attention mechanism is introduced to improve the convolutional neural network's features in areas of the picture with a high density of features. The convolutional block attention module (CBAM) and the transformer encoder block are used in this study to develop the attention mechanism. The YOLOv5 integrated convolutional block attention module increases the weight of cell-dense regions in blood cell pictures and aids the network's ability to resist information other than cells. Additionally, the transformer block is introduced to YOLOv5′s processing of upper and lower feature data to improve the network's capacity to gather details about various cell properties, enabling AYOLOv5 to recognize and distinguish blood cells in cell-dense areas. The experiment was done on the dataset BCCD, and the mAP results for cell detection reached 93.3%, better than previously discovered. Also, the validation set's average recognition accuracy increased from 89% to 98%. The experimental results demonstrated that the suggested AYOLOv5 could extract the cells' feature information more effectively, considerably improving the cell pictures and recognition performance.

3.2 Improved blood cell detection method based on YOLOv5 algorithm:

https://ieeexplore.ieee.org/abstract/document/10082206

ABSTRACT: The proposed blood cell target detection algorithm based on YOLOv5 addresses the issue of low average accuracy and serious miss detection due to small blood cells and serious cell adhesion in blood cell detection by target detection algorithms. By adding the CBAM (Convolutional Block Attention Module) to the YOLOv5 framework's backbone network and the BIFPN (bidirectional feature pyramid network) to the neck network, the algorithm improves the model's ability to extract features. The experimental results show that the average accuracy (mAP) of the improved YOLOv5 blood cell target detection algorithm is 89.9%, representing a increase over the native YOLOv5s type, and the recall rate and accuracy rate are also increased by 3.2% and 4.2%, respectively. This meets the requirements of the actual scene for blood cell detection.

3.3 Automatic identifying and counting blood cells in smear images by using single shot detector and Taguchi method:

https://link.springer.com/article/10.1186/s12859-022-05074-2

ABSTRACT: Background: Researchers have tried to identify and count different blood cells in microscopic smear images by using deep learning methods of artificial intelligence to solve the highly time-consuming problem. Results: The three types of blood cells are platelets, red blood cells, and white blood cells. This study used the Resnet50 network as a backbone network of the single shot detector (SSD) for automatically identifying and counting different blood cells and, meanwhile, proposed a systematic method to find a better combination of algorithm hyperparameters of the Resnet50 network for promoting accuracy for identifying and counting blood cells.

The Resnet50 backbone network of the SSD with its optimized algorithm hyperparameters, which is called the Resnet50-SSD model, was developed to enhance the feature extraction ability for identifying and counting blood cells. Furthermore, the algorithm hyperparameters of Resnet50 backbone networks of the SSD were optimized by the Taguchi experimental method for promoting detection accuracy of the Resnet50-SSD model. The experimental result shows that the detection accuracy of the Resnet50-SSD model with $512 \times 512 \times 3$ input images was better than that of the Resnet50-SSD model with $300 \times 300 \times 3$ input images on the test set of blood cells images. Additionally, the detection accuracy of the Resnet50-SSD model using the combination of algorithm hyperparameters got by the Taguchi method was better than that of the Resnet50-SSD model using the combination of algorithm hyperparameters given by the Matlab example. Conclusion: In blood cell images acquired from the BCCD dataset, the proposed Resnet50-SSD model had higher accuracy in identifying and counting blood cells, especially white blood cells and red blood cells.

3.4 Complete Blood Cell Detection and Counting Based on Deep Neural Networks:

https://www.mdpi.com/2076-3417/12/16/8140

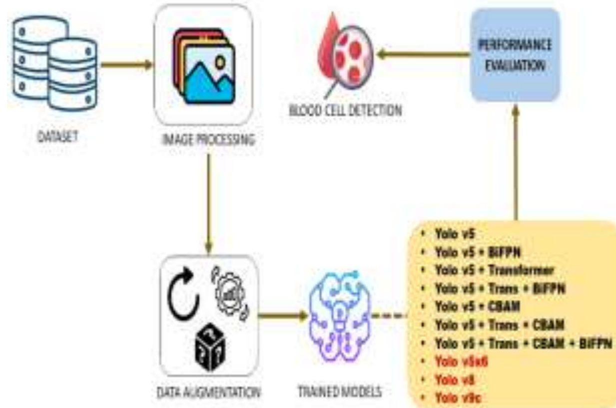
ABSTRACT: Complete blood cell (CBC) counting has played a vital role in general medical examination. Common approaches, such as traditional manual counting and automated analyzers, were heavily influenced by the operation of medical professionals. In recent years, computer-aided object detection using deep learning algorithms has been successfully applied in many different visual tasks. In this paper, we propose a deep neural network-based architecture to accurately detect and count blood cells on blood smear images. A public BCCD (Blood Cell Count and Detection) dataset is used for the performance evaluation of our architecture. It is not uncommon that blood smear images are in low resolution, and blood cells on them are blurry and overlapping. The original images were preprocessed, including image augmentation, enlargement, sharpening, and blurring. With different settings in the proposed architecture, five models are constructed herein. We compare their performance on red blood cells (RBC), white blood cells (WBC), and platelet detection and deeply investigate the factors related to their performance. The experiment results show that our models can recognize blood cells accurately when blood cells are not heavily overlapping.

3.5 An Improved EIoU-Yolov5 Algorithm for Blood Cell Detection and Counting:

https://ieeexplore.ieee.org/abstract/document/9904093

ABSTRACT: At present, detecting blood cells commonly depends on artificial count by observing microscope. Artificial observation takes a lot of manpower. In the object detection algorithm for real-time detection, the representative algorithm of the real-time object detection algorithm is Yolov5 algorithm. However, the accuracy of Yolov5 algorithm is low. In order to improve the accuracy of the algorithm, realize the automation of blood detection and reduce the workload of manual count, this paper proposes an improved algorithm EIoU-YOLOV5 based on Yolov5, which improves the Loss function of prediction box by replacing CIoU Loss with EIoU Loss. Experimental results on the common data set BCCD show that, compared with the original Yolov5 algorithm, the Recall of EIou-YOLOV5 algorithm increased from 0.855 to 0.917, which increased by 6.2 percentage points. Therefore, it reduced the missed rate effectively. The result of mAP@0.5 is increased from 0.899 to 0.922, which is raised by 2.3 percentage points. Among them, the detection of platelet increased the most. It increased from 0.858 to 0.92, which increased by 6.2 percentage points. Therefore, the improved EIoU-yolov5 algorithm can better assist clinical diagnosis.

SYSTEM ARCHITECTURE:



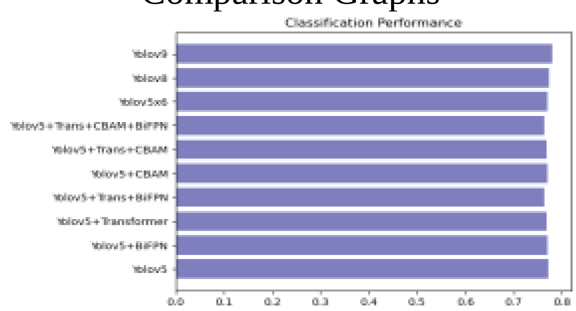
Tables:

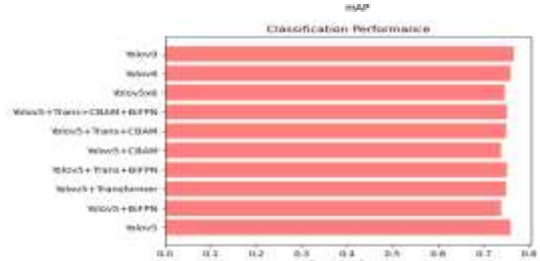
Performance Evaluation – Detection

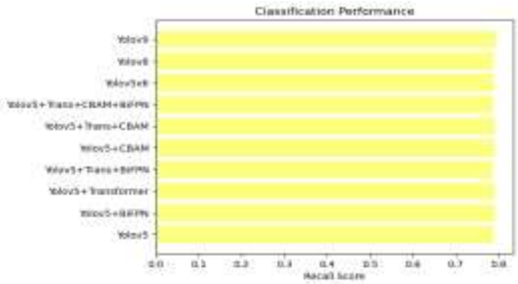
ML Model	Precision	Recall	mAP
Yolov5	0.760	0.788	0.771
Yolov5+BiFPN	0.740	0.792	0.770
Yolov5+Transformer	0.750	0.791	0.768
Yolov5+Trans+BiFPN	0.752	0.788	0.764
Yolov5+CBAM	0.740	0.792	0.770
Yolov5+Trans+CBAM	0.750	0.791	0.768
Yolov5+Trans+CBAM +BiFPN	0.752	0.788	0.764
Extension Yolov5x6	0.747	0.790	0.770
Extension Yolov8	0.760	0.788	0.773
Extension Yolov9	0.767	0.795	0.780

Graphs:

Comparison Graphs

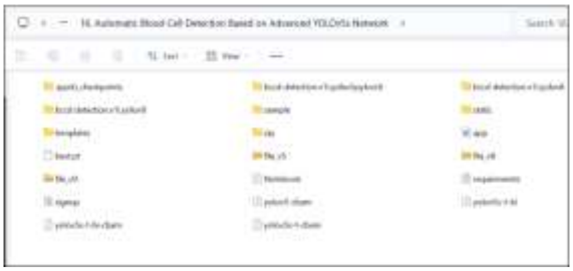






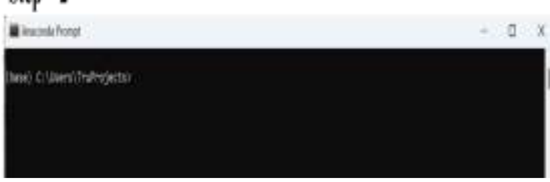
Screens:

Code Folder



Step - 1

Step – 2



Step - 3

Step - 4

Step - 5

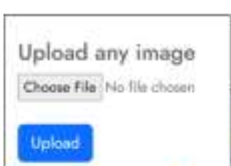
IMPLEMENTATION:

User Dashboard

Step - 6

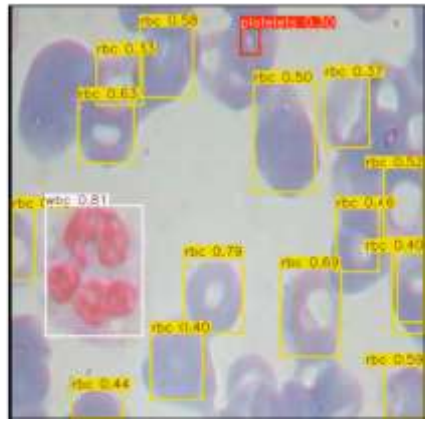
Step - 7

Step 8

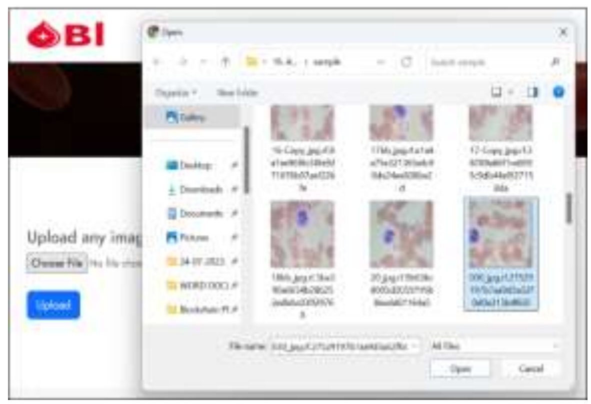


Step – 9
Test case 1

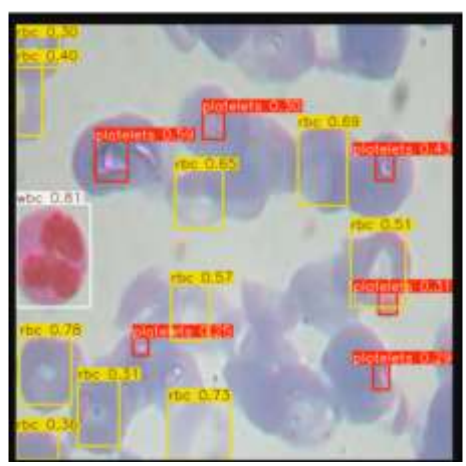
Result of Step – 9
Test case 1



Step – 9
test case 2

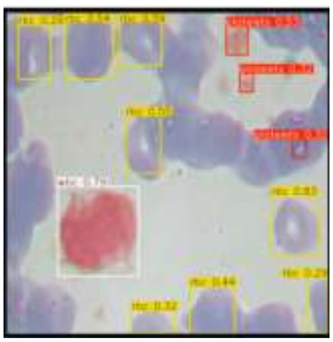


Result of Step – 9
Test case 2



Step – 9
test case 3

Result of Step – 9
Test case 3



CONCLUSION

In conclusion, the implementation of an advanced YOLOv5s model for the automatic detection and classification of blood cells significantly enhances clinical diagnostic processes. By integrating hybrid architectures such as BiFPN, Transformer, and CBAM, the proposed system leverages multi-scale feature fusion and attention mechanisms, resulting in improved accuracy and efficiency in blood cell detection. The exploration of more advanced versions, including YOLOv5x6, YOLOv8, and YOLOv9c, further pushes the boundaries of detection precision and speed, addressing the complexities inherent in blood cell images. The user-friendly interface developed using the Flask framework ensures that healthcare professionals can easily interact with the system, facilitating seamless testing and authentication. This innovative approach reduces the reliance on traditional methods, which are often time-consuming and prone to errors, thereby streamlining clinical workflows. The ability to achieve high accuracy and real-time processing in blood cell classification not only enhances diagnostic efficiency but also contributes to improved patient outcomes. Overall, this robust solution demonstrates the potential of deep learning technologies in transforming clinical diagnostics and supporting medical professionals in their decision-making processes.

Future Scope:

The future scope of this automated blood cell detection system includes expanding its application to detect and classify various hematological disorders, such as leukemia and anemia, by training the model on diverse datasets. Integrating advanced deep learning techniques, like transfer learning and generative adversarial networks (GANs), could further enhance detection accuracy. Additionally, incorporating real-time monitoring features for clinical settings could improve patient care. Future development may also focus on optimizing the system for deployment on mobile devices, making it accessible for remote diagnostics. Collaborating with medical professionals for continuous model refinement and validation will ensure the system's clinical relevance.

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