

## ABO-Vision: Automatic Blood Type Detection with YOLOv4-Tiny and Morphological Image Processing

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| Article Information                                                                                                                 | ABSTRACT                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 |
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| <b>Article History</b><br><br><b>Received</b> : June 22, 2025<br><b>Revised</b> : July 07, 2025<br><b>Published</b> : July 18, 2025 | <p>Blood is a red-colored fluid in the human body that plays a crucial role in maintaining the immune system. According to the ABO system, blood is classified into four main types: A, AB, B, and O. This classification is essential for facilitating blood transfusions. Currently, blood type determination is still performed manually by healthcare professionals, who observe the presence or absence of clumping (agglutination) in the blood when it reacts with specific antigens. Numerous studies have been conducted to support and enhance healthcare services, particularly as technological advancements continue to grow rapidly across various fields. In the medical field, these advancements have led to the development of increasingly sophisticated medical devices, including blood type detection tools. These devices typically use manual optical sensors to read blood agglutination by detecting changes in light intensity. However, such devices are not fully automated and still require human intervention, making them prone to human error. Today, automated blood type detection systems utilizing cameras and smartphones—integrated with various image processing methods and Artificial Intelligence (AI) are being increasingly developed. Therefore, this study focuses on the development of a blood type detection model that combines image processing and Deep Learning (DL) to support an intelligent, fast, and efficient healthcare system, achieving a detection accuracy of 98%.</p> |
| <b>Keywords:</b><br><br><i>Blood Type;<br/>Thresholding;<br/>Morphological Segmentation;<br/>Yolov4-Tiny.</i>                       |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          |

## INTRODUCTION

The human body is composed of approximately 70% fluid, and one of the most vital fluids involved in nearly all physiological processes is blood. Blood is a red-colored fluid whose primary function is to transport oxygen to cells throughout the body. It also plays a crucial role in supplying the body with nutrients, removing metabolic waste products, and serving as a key component of the immune system to defend the body against diseases (Arviananta et al., 2020).

Blood consists of four main components: red blood cells, white blood cells, platelets, and plasma. The surface of blood cells is covered with numerous proteins, one of which is antigen. These antigens, genetically inherited and referred to as agglutinogens, form the basis for blood type classification depending on their presence or absence on the surface of red blood cells (Madani, 2023).

Human blood type determination is typically carried out using two systems: the ABO system and the Rhesus (Rh) system. In the ABO system, blood types are classified based on the

presence of two glycolipid antigens on the membrane of red blood cells, namely antigen A and antigen B. Blood that contains only antigen A is classified as type A, while blood that has only antigen B is type B. Blood containing both antigens is classified as type AB, and blood with neither antigen A nor B is classified as type O, this is the most common blood type worldwide (Tortora & Derrickson, 2017).

Blood typing is essential to ensure compatibility in blood transfusion processes. Blood transfusion is the procedure of transferring blood from one individual to another (Komaretno & Riawati, 2021). The transfused component may include whole blood or specific parts such as red blood cells, plasma, or platelets (Wenah et al., 2021). This procedure is commonly performed in cases of significant blood loss due to accidents or severe anemia (Ojeka et al., 2021). One of the critical steps prior to transfusion is checking for blood type compatibility to prevent dangerous immune reactions. Incompatible blood transfusion can cause agglutination (clumping) and hemolysis (destruction of red blood cells), potentially leading to kidney damage (Magar et al., 2022).

However, to this day, blood typing is still commonly performed manually, relying on the visual observation skills of medical personnel (Rosita & Arfira, 2019). This makes the accuracy dependent on the examiner's vision. Errors in determining blood type can occur, especially when testing large numbers of samples. Loss of concentration and fatigue are key factors contributing to such mistakes (Hendrawati & Hasanudin, 2022).

Numerous studies have been conducted to reduce the risk of blood typing errors. Various blood type detection tools have been developed to support faster and more accurate classification. (Hermawan et al., 2020). Initial research included the development of devices using LEDs and optical sensors to detect blood types based on agglutination. This later evolved into the integration of microcontrollers and optical sensors for educational and prototyping purposes in blood typing research (Vinesh et al., 2021). Subsequent studies explored the use of cameras to automatically detect blood types from agglutination images (Setiawan & Rahmadewi, 2024). More recent research has incorporated image processing, machine learning (ML), deep learning (DL), and artificial intelligence (AI) for blood type classification and detection (Turakit et al., 2024; Praven et al., 2021; Mahmood et al., 2023; Paz-Soto et al., 2023; Sangeetha, 2023; Ridoy & Islam, 2020). The latest advancements involve the creation of smart blood type detection systems using AI, integrated with Internet of Things (IoT) for medical record management.

Thus, this study aims to develop a blood type detection method using image data. The proposed method implements image processing techniques, including thresholding and morphological segmentation, combined with the YOLOv4-Tiny deep learning model for automatic blood type detection.

A grayscale image is generated by converting a color image (RGB) into shades of gray using the average intensity of its red, green, and blue components. A binary image is a digital image consisting of only two pixel values 1 for the object and 0 for the background. Thresholding is used to convert grayscale images into binary images by comparing each pixel value against a certain threshold (Heryanto et al., 2020).

Morphological operations are image processing techniques that focus on the shape of objects or segments in an image, typically applied to binary images. Their goal is to differentiate objects from the background using binary representation (object vs. non-object). These operations can also be applied to grayscale or color images and are useful for analysis and decision-making based on small patterns, similar to the concept of masks in other processing techniques (Nuridinawati et al., 2021).

YOLOv4-Tiny is a lightweight version of YOLOv4, designed for mobile and embedded devices. Its network structure is simpler, consisting of 29 convolutional layers and 2 detection heads. Although its detection accuracy is approximately two-thirds of that of YOLOv4, it operates up to 8 times faster. With TensorRT optimization, it can reach speeds up to 1774 FPS, making

YOLOv4-Tiny highly suitable for real-time object detection applications, where speed is prioritized over precision (Jiang et al., 2021).

The development of this algorithm and method is expected to improve detection accuracy and facilitate the process of human blood type identification.

## RESEARCH METHODS

Basically, blood type is determined by the presence of antigens on the surface of red blood cells, not by the morphology (physical shape) of the red blood cells themselves. Across all blood types (A, B, AB, O), the morphology of red blood cells is relatively similar when observed with the naked eye or under a standard microscope. The external structure including shape and size does not significantly vary by blood type. The differences in blood types are defined by the specific antigens present on the membrane surface of red blood cells. These antigens are not visible through conventional morphological observation, but they can be detected using biochemical, serological, or immunological techniques.

In the context of computer vision, blood type classification can be achieved by observing the pattern of agglutination or the reaction of blood during typing tests using image data. Therefore, this study focuses on the automatic classification of human blood types based on the ABO system using image-based computer vision approaches. The algorithm implemented involves an image processing model that includes stages such as image preprocessing, morphological segmentation, and object detection model training using YOLOv4-Tiny. Blood image datasets, collected using a digital camera, are then systematically processed and trained following the workflow illustrated in Figure 1.

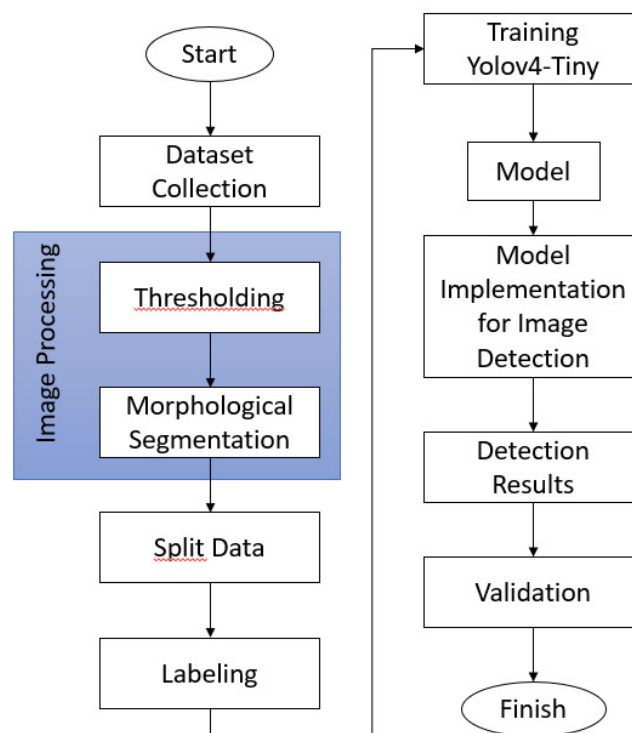


**Figure 1.** Workflow of the Blood Type Detection System

### Sequence of Resarch Stages

The stages in this study, starting from dataset acquisition to model validation, are described as follows::

## 1. Start

This is the initiation stage, which includes problem identification and determining the technological approach to be used. In this research, we applied a combination of image processing and deep learning methods.

## 2. Dataset Collection

In this study, we collected our own dataset by manually capturing images using a camera. The dataset consists of four blood types, with a total of 340 images: 85 images each for blood types A, B, AB, and O. The dataset was uploaded to Google Colab in a compressed ZIP file format. It was then extracted and organized for further processing.

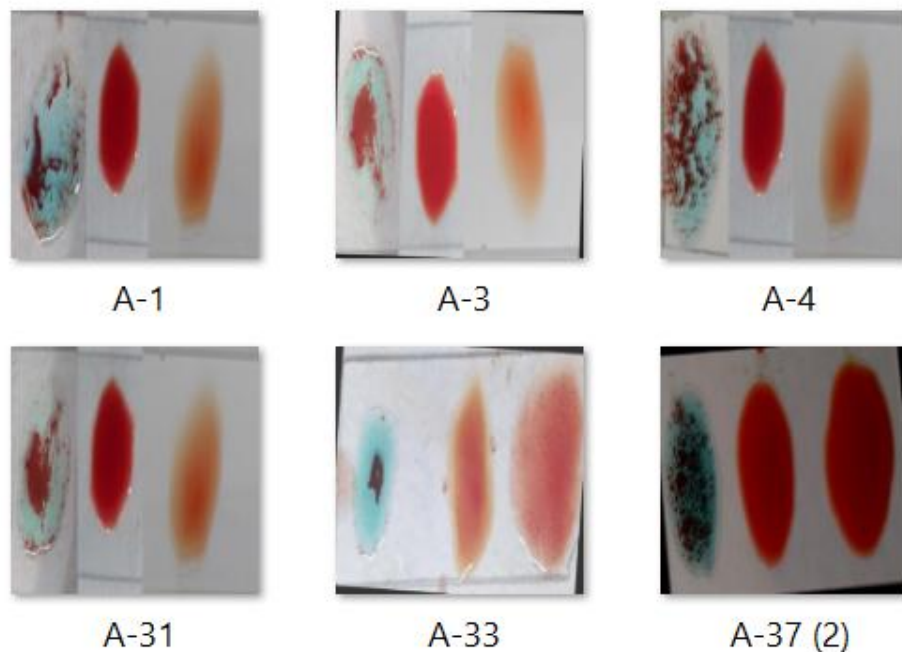


**Figure 2.** Sample of the Dataset

## 3. Thresholding

The dataset images were converted from BGR color space to HSV using OpenCV. Red color segmentation was then performed using two HSV ranges to account for red's dual spectral areas. The results of both ranges were combined into a binary mask that separates the red-colored objects (droplets or blood labels) from the background, effectively highlighting the key areas of interest.

## 4. Morphological Segmentation

This step involves morphological operations such as dilation, erosion, and closing to refine the thresholding results, eliminate noise, and improve object shape.

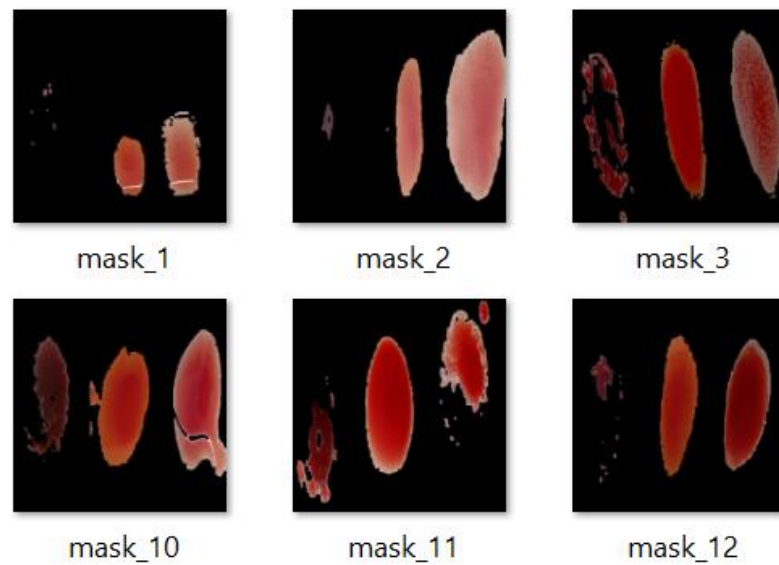


**Figure 3.** Sample of Image Processing Results

### 5. Data Splitting

The processed dataset was split into training data (80%) and test data (20%) using the hold-out split method. This step is essential to ensure that model evaluation is conducted objectively.

### 6. Image Labeling

After splitting, the next step was to label the objects in all training images. Manual labeling was performed using an annotation tool called LabelImg. Each object was labeled according to its class so that the model could learn to correctly detect and classify blood types.

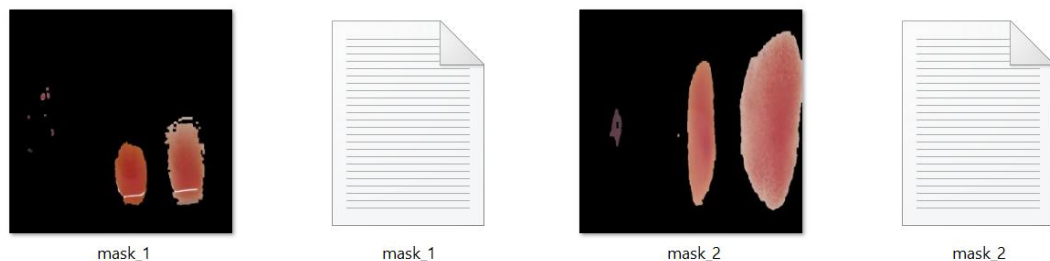


**Figure 4.** Sample of Image Labeling Output

### 7. YOLOv4-Tiny Training

The training process used YOLOv4-Tiny, a lightweight version of YOLOv4, suitable for deployment on resource-constrained devices. Training was conducted in the Google Colab environment with GPU enabled. Configuration files were adjusted to match the number of classes and the dataset directory structure.

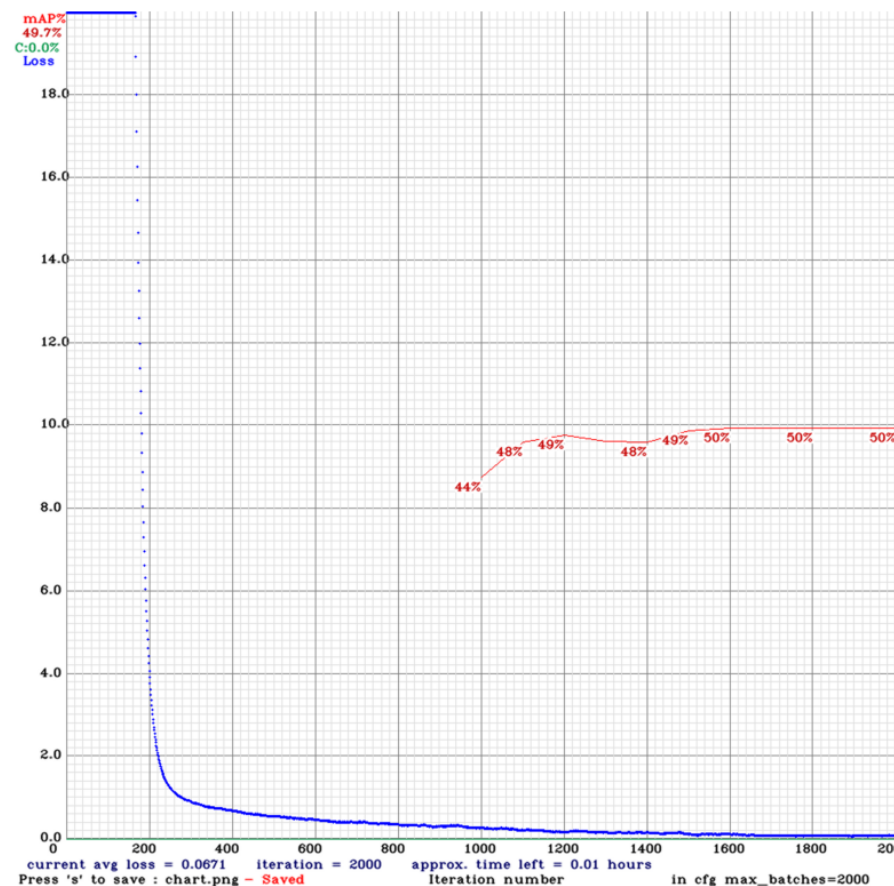


**Figure 5.** mAP Accuracy Graph from Training

## 8. Model Implementation for Detection

The trained model was then used to test and detect blood types from new images.

## 9. Detection Results

The model produced bounding boxes and classification labels on the input images. These results were either displayed or saved for evaluation documentation.

## 10. Validation

Model evaluation was performed using the confusion matrix method to assess performance metrics.

## 11. End

After the model was successfully validated, the research was completed, and the system can now function as an automated blood type classification tool.

## Tools and Materials

1. Software: Python, Google Colab, OpenCV, Darknet, LabelImg
2. Hardware: Laptop/PC with GPU access (via Colab), Camera/Smartphone
3. Dataset: Images of scanned blood type labels

## RESULTS AND DISCUSSION

The development of a human blood type detection algorithm using image processing and object detection based on deep learning has been successfully carried out. This method has proven effective in accurately detecting human blood types, as illustrated in Figure 6 below. In the figure, the proposed method successfully detects the blood type automatically. The bounding box clearly indicates that the detected blood type is Type A, along with its corresponding confidence score.

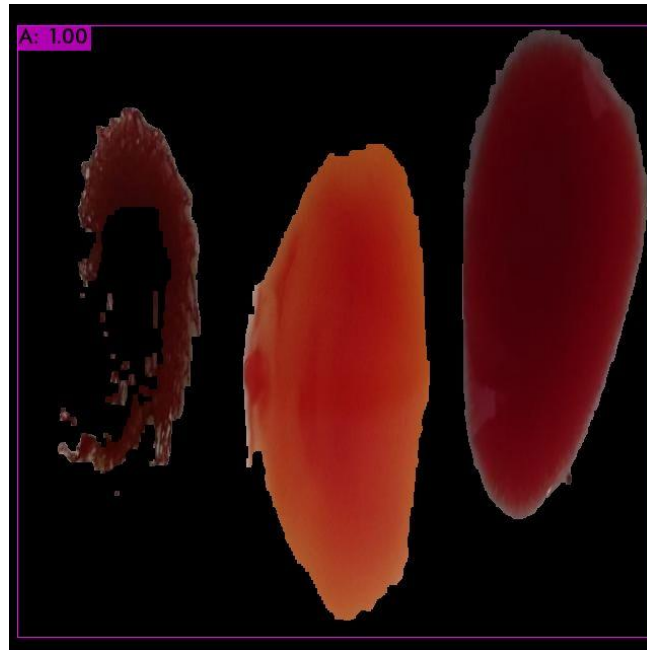


**Figure 6.** Sample of Detection Results

To validate the effectiveness of this method, a series of tests were conducted. The evaluation used a test dataset consisting of 64 blood sample images. Each image was tested both manually and automatically using the proposed method to determine how accurately the system could classify human blood types. The test results are presented in Figure 7.

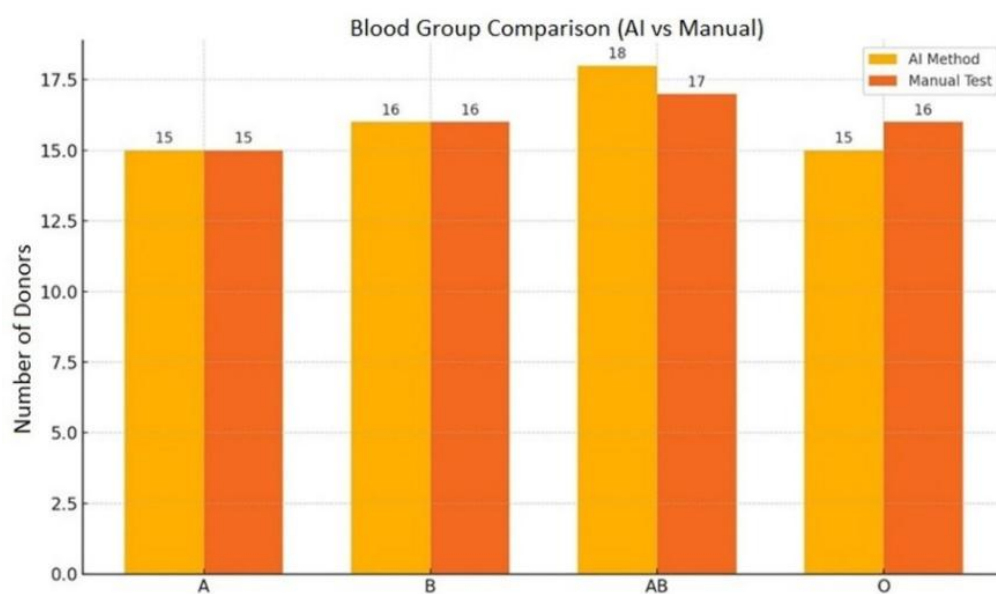


**Figure 7.** Method Testing Results

Based on the results, only 1 misclassification occurred out of 64 images. The actual blood type was Type O, but the method incorrectly predicted it as Type AB. This misclassification was due to an insufficient volume of blood in the sample, which made the agglutination reaction less visible.

From these results, the accuracy of the method in detecting blood types was calculated using the confusion matrix. A confusion matrix provides information about classification predictions versus actual values and is commonly used to evaluate classification models. From the confusion matrix, several performance metrics can be derived, such as accuracy, error rate, sensitivity, specificity, precision, and false positive rate (Yang & Berdine, 2024). The confusion matrix for this study is shown in Table 1.

**Table 1.** Confusion Matrix Calculation

|                 |       | Actual Value |         |
|-----------------|-------|--------------|---------|
| Predicted Value | True  | TP = 63      | FP = 0  |
|                 | False | FN = 1       | -TN = 0 |

To calculate the accuracy of the method, the following formula is used:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

By applying the values from Table 1:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Accuracy = \frac{63 + 0}{63 + 0 + 0 + 1}$$

$$Accuracy = \frac{63}{64}$$

$$Accuracy = 0.98 = 98\%$$

Thus, based on the above calculations, the accuracy of this detection method is 98%. This result shows that although the training accuracy was only 50%, the actual detection accuracy after testing is significantly high. For future development, improving training accuracy could be achieved by increasing the size of the dataset or applying data augmentation techniques in cases where collecting additional data is not feasible.

## CONCLUSION

Based on the results of this study, it can be concluded that the proposed system successfully implemented image processing algorithms, namely Thresholding and Morphological Segmentation, in combination with the YOLOv4-Tiny object detection algorithm to automatically detect human blood types based on image input. The proposed method offers an innovative and efficient solution to accelerate the blood type identification process, achieving a detection accuracy of 98%.

The developed model can be embedded into a smartphone application to enable mobile blood type detection, with additional features such as data storage. Furthermore, future studies could expand the method to detect other blood components and provide early indications of

specific diseases through blood sample analysis, thereby broadening the diagnostic capabilities of this approach in the medical field.

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