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AUTOMATIC DETECTION OF TUBERCULOSIS BACTERIA USING MICROSCOPE IMAGING SYSTEM BASED ON MOTORIZED SERVO AND DEEP LEARNING TECHNIQUES

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Abstract. *This research presents an automated system for detecting tuberculosis bacteria in sputum samples using deep learning. The study primarily focuses on developing a detection algorithm based on the YOLOv8 architecture to accurately identify tuberculosis bacteria. The system integrates a computer, camera, and microcontroller to automate the movement of preparation and focus servos for enhanced scanning efficiency. Performance testing of the microscope-robot system reveals a precision rate of 81.28% and a recall of 90.71%, demonstrating a balanced performance. The precision-confidence curve shows high confidence in classifying positive samples, while the recall-confidence analysis indicates the model's strong ability to identify true positives. Despite the 75.1% overall accuracy, there are some false positives and false negatives. The system holds promise for accelerating and improving tuberculosis detection. Future work will focus on refining the model to enhance accuracy and overcome existing limitations. This research contributes to the development of faster, more reliable diagnostic technology for tuberculosis detection in medical settings.*

Keywords: Tuberculosis detection, Deep learning, Automated system, YOLOv8 model

1. **Introduction.** Tuberculosis remains a significant global health challenge, with millions of new cases emerging annually [1]. According to the World Health Organization (WHO), tuberculosis continues to pose a major public health threat worldwide, resulting in over 10.6 million new cases and 1.4 million deaths in 2022 alone [2]. The Global Tuberculosis Report of 2022 estimated the global burden at 10.5 million cases, with Southeast Asia contributing 4.8 million, making it the region with the highest tuberculosis incidence [3]. Indonesia ranks as the second largest contributor to the global tuberculosis burden, following India, with 969,000 reported cases, equivalent to 354 cases per 100,000 population. The estimated tuberculosis-related deaths in Indonesia are projected to reach

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144,000, or 52 deaths per 100,000 population [4]. Despite significant efforts to control the disease, early detection and effective treatment remain the primary challenges. Additionally, a considerable proportion of the population with weakened immune systems due to malnutrition, other infectious diseases, and low socioeconomic status further contribute to the elevated tuberculosis incidence in Indonesia [5].

Managing tuberculosis in Indonesia involves a multifaceted approach coordinated by the Ministry of Health and its partners. The strategy for the Tuberculosis Control program in Indonesia for the 2020-2024, as outlined in [6] encompasses six key strategies. These include bolstering government commitment and leadership, enhancing access to healthcare services for tuberculosis patients, optimizing promotion and prevention efforts, leveraging research and technological advancements, fostering community involvement and collaboration with other stakeholders, and reinforcing program management within the healthcare system. This strategy is structured around three primary functions: case identification, treatment and prevention, as well as three enablers aimed at optimizing contextual factors to support the achievement of functional strategies. Aligned with the three pillars of the End TB Strategy, it underscores the integration of treatment and prevention, establishing a robust support infrastructure, and promoting innovation and extensive research to realize the goal of tuberculosis elimination by 2030.

One of the primary approaches to treating and preventing tuberculosis involves regular examinations, encompassing sputum analysis and radiological imaging, such as chest X-rays. These examinations aid in early case detection and monitoring treatment response [7]. Consistently screening individuals exhibiting symptoms or those at elevated risk, such as contacts of tuberculosis patients, facilitates the identification of new cases and curtails disease transmission while also mitigating the risk of drug resistance. Hence, thorough and routine examinations represent a crucial endeavor in tuberculosis treatment and prevention. Although the introduction highlighted the global impact of tuberculosis, it did not clearly address the shortcomings of current detection methods. The existing diagnostic techniques, such as sputum smear microscopy and chest X-rays, often suffer from limitations in sensitivity, accuracy, and timely detection, particularly in resource-limited settings. These methods may lead to delayed diagnoses, missed cases, and an increased risk of transmission and drug resistance. This gap in efficient, accurate, and rapid detection underscores the necessity of this research, aiming to advance diagnostic technology and improve tuberculosis detection capabilities.

An effective method for diagnosing tuberculosis in patients involves microscopic examination. This examination typically employs the Ziehl-Neelsen staining or auramine methods [8]. The process entails obtaining a sputum sample from the patient using a specialized container, followed by staining the sample with a specific dye, such as carbol fuchsin for the Ziehl-Neelsen method or auramine for the auramine method. Mycobacterium tuberculosis bacteria present in the sample will appear as pink rods [9]. This procedure necessitates technical proficiency to ensure accurate results and is typically performed by trained laboratory personnel. It represents a relatively swift and efficient means of detecting tuberculosis bacteria in sputum samples.

Operating a microscope to detect tuberculosis bacteria necessitates technical proficiency from trained laboratory personnel. Presently, several researchers have developed systems that utilize microscope images to detect tuberculosis bacteria, reducing reliance on the technical expertise of laboratory personnel. This system employs advanced digital imaging and data processing technologies to accurately identify tuberculosis bacteria in sputum samples. This approach enables faster and more precise detection and enhances the overall diagnostic process efficiency. Pangestu et al.'s research [10] employed image processing to detect and quantify mycobacterium tuberculosis in digital sputum examinations using a microscope. The system achieves semi-automatic detection through several stages, including preprocessing, segmentation, feature extraction, fuzzy logic classification, and bacteria counting.

The Deep Gaussian Multivariate Hosmer-Lemeshow Feature Learning method via partial differential equation enhances face recognition by combining efficient feature learning and robust classification, achieving superior accuracy and speed compared to existing techniques [11]. Other research utilizes deep learning methods to detect tuberculosis bacteria and control their spread, thereby enhancing accuracy through medical imaging analysis. Deep learning algorithms significantly enhance the clarity and diagnostic precision of MRI images for tuberculosis identification, leading to increased Signal-to-Noise Ratio (SNR) and Carrier-to-Noise Ratio (CNR), which result in improved differentiation between tuberculosis and pneumonia [12]. Utilizing deep learning alongside a multi-stage method for fluorescence microscopic imaging enables automatic detection and quantification of Mycobacterium tuberculosis in sputum samples with an error rate of less than 5%, providing a rapid and precise alternative [13]. Application of the YOLOv5 algorithm has demonstrated strong performance in automatically detecting and enumerating Mycobacterium tuberculosis from sputum smear images, achieving an overall accuracy of 87.6% [14]. Methods like YOLOv5 and Attention-Based Multiscale CNN improve accuracy to 86.09% and 97.56%, addressing the limitations of manual detection. These findings demonstrate the potential of deep learning to accelerate TB diagnosis, enhance accuracy, and support laboratory decisions [15,16]. Deep learning techniques have proven highly effective in tuberculosis detection and diagnosis across various medical image modalities. They enhance tuberculosis identification accuracy and offer a quicker and more dependable alternative to traditional manual examination methods.

Recent studies highlight YOLOv8's significant advantages over earlier architectures like YOLOv5, Faster R-CNN, and other deep learning models in diverse object detection applications. Brighty et al. [17] reported that YOLOv8 achieved 90% accuracy and a mean Average Precision (mAP) of 90% on benchmark datasets such as KITTI and LASIESTA, processing at 30 Frames per Second (FPS), demonstrating high sensitivity to object movement. In the medical field, Özbilge et al. [18] showed that YOLOv8 outperformed CenterNet, EfficientDet, and Faster R-CNN in detecting malaria parasites in thin blood smear images, excelling in both speed and accuracy. Khriss et al. [19] emphasized YOLOv8's flexibility in detecting underwater plastic debris, showcasing its ability to handle various object shapes and sizes under challenging conditions. Additionally, Niu et al. [20] integrated YOLOv8 with Context Guided Reasoning Network (CGRNet) using Res2Net architecture, significantly improving detection accuracy by leveraging advanced feature learning capabilities. Collectively, these innovations in YOLOv8's architecture enable superior performance across multiple domains, establishing it as a reliable solution for high-precision and efficient object detection tasks.

Despite prior investigations, there remains a gap in research regarding automatically searches for tuberculosis bacteria by utilizing a motor movement mechanism as a component of a microscope-rotating robot. In this context, a robot was designed with a deep learning system capable of automatically detecting, calculating, and storing the location of tuberculosis bacteria in samples. The deep learning used uses the YOLOv8 architecture because of its high inference speed, good detection accuracy, adaptability to various types of data, broad support from the community, and scalability in training on large datasets. This makes YOLOv8 a potential choice for tuberculosis detection from sputum microscopic images based on its efficiency, accuracy, and adaptability. In addition, this robot can display detection result information to users, providing a potential solution to increase efficiency and accuracy in tuberculosis diagnosis through the use of more sophisticated technology.

2. **Material and Method.** This section outlines the workflow of the automated microscope rotating robot system utilized for tuberculosis bacteria detection employing the deep learning method with the YOLOv8 architecture. Initially, the user inputs commands via a desktop application developed using a minicomputer. This application is equipped with control buttons facilitating the movement of the servo motor mounted on the microscope, along with an option for automatic servo movement based on tracking results. This functionality enables focus adjustment, allowing users to modify the microscope's focus or depth of view on the observed object. The microcontroller computes and transmits instructions to the servo, facilitating focus adjustment by moving the servo motor to search for bacteria through the microscope. Concurrently, the system captures image input from a camera integrated into the microscope. Following this, the input image is processed by the mini PC. Consequently, the system identifies the position of tuberculosis bacteria and relays the results back to the microcontroller. The microcontroller then computes servo movements to resume bacteria search based on the position results and dispatches instructions to the servo.

2.1. **Mechanical and hardware design.** Figures 1 and 2 illustrate the working mechanism and hardware design of the robot. This robot is equipped with an Olympus CX23 microscope and Dynamixel AX-12A servo, alongside an NUC mini-computer and OpenRB-150 microcontroller. In this configuration, the computer is fitted with a camera positioned to capture images through the microscope lens to relay instructions to the OpenRB-150 microcontroller. The microcontroller is tasked with driving the servo motor responsible for both microscope preparation and focusing. The preparation servo enables horizontal movement to scan the entire area of the sputum sample while the focus servo adjusts the microscope's focus. Through this technology integration, the system can efficiently capture images, scan sputum samples, and detect tuberculosis bacteria using deep learning methods. The computer and microcontroller interact synergistically in this setup to govern the microscope's movement and functionality. The computer leverages the camera to identify relevant areas and directs the microcontroller to maneuver the preparation and focus servos as necessary.

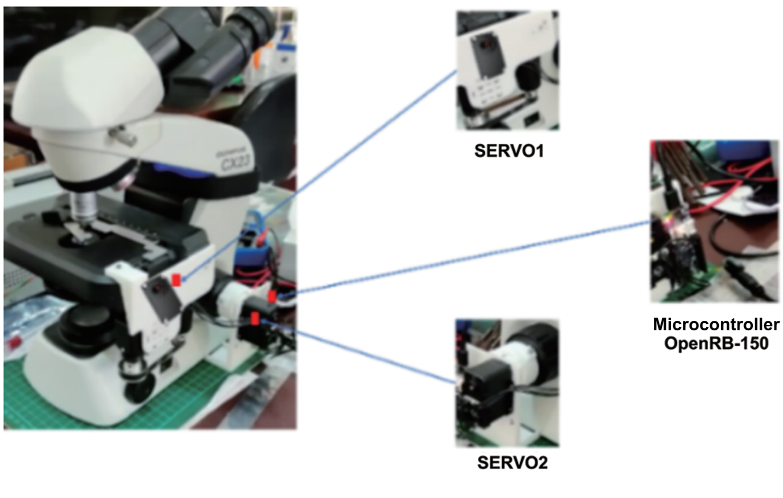


Figure 1. Robot mechanics

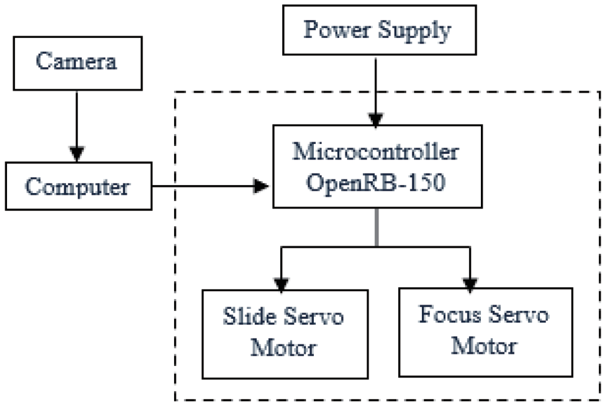


FIGURE 2. Hardware design

2.2. **Tuberculosis detection.** Dr. Soetomo Hospital in Surabaya provided videos from which 120 key frames were extracted. From these videos, 120 key frames were extracted, which were then processed to generate a total of 1200 samples through data augmentation techniques. The augmentation process included transformations such as rotation, scaling, and flipping to enhance the dataset's diversity and robustness, ensuring the model's generalizability across varying conditions. Each sample underwent an annotation process where labels indicating normal or abnormal heart conditions were assigned based on expert analysis. This annotation was crucial for enabling the deep learning model to accurately learn and differentiate cardiac conditions. The prepared dataset was subsequently used for training and validating the model using the YOLOv8 architecture. Figure 3 provides a visual representation of the dataset distribution and characteristics, which highlights the effectiveness of the data augmentation process in improving model performance.

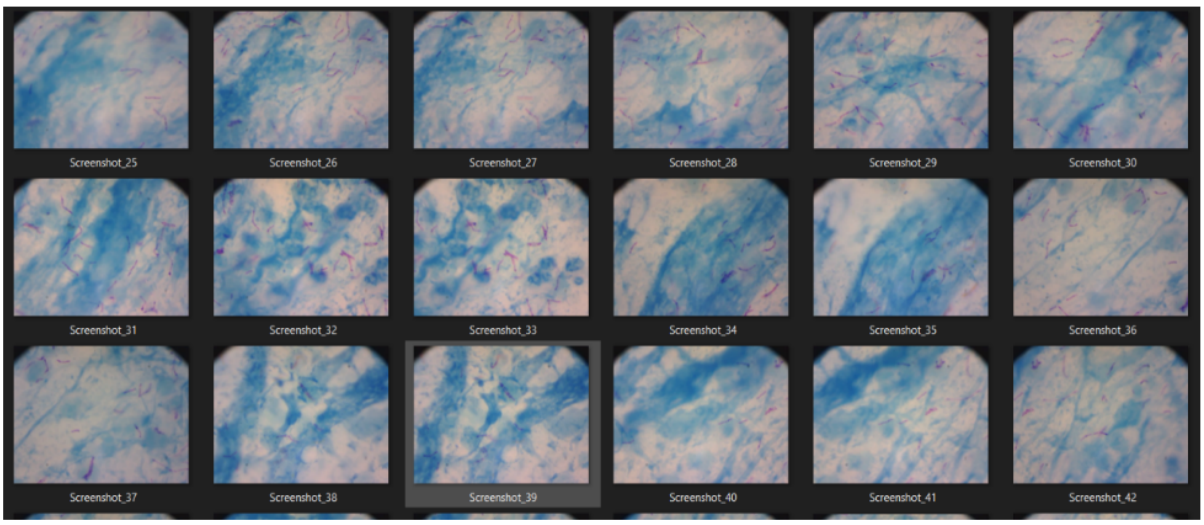


FIGURE 3. Training data

Figure 4 shows an illustration of the labeling process entails annotating the open mouth area of each image using the labelimg.py tool, resulting in an eXtensible Markup Language (XML) file corresponding to each annotated image. Subsequently, all data recorded in the XML file is converted into a Comma Separated Values (CSV) file format.

The model architecture proposed in this study is based on the YOLOv8 deep learning technique for tuberculosis bacteria detection. Additionally, for direct bacteria detection,

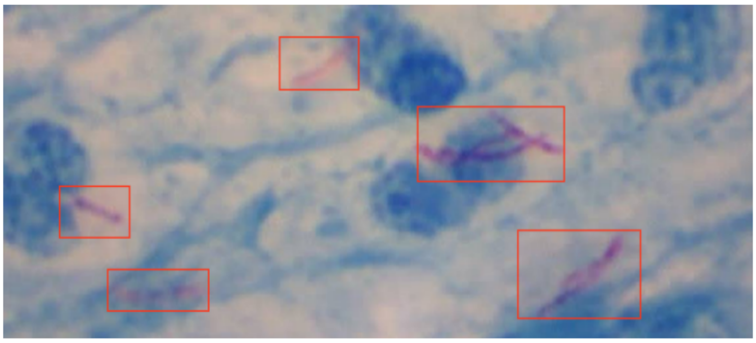


FIGURE 4. Labeling data

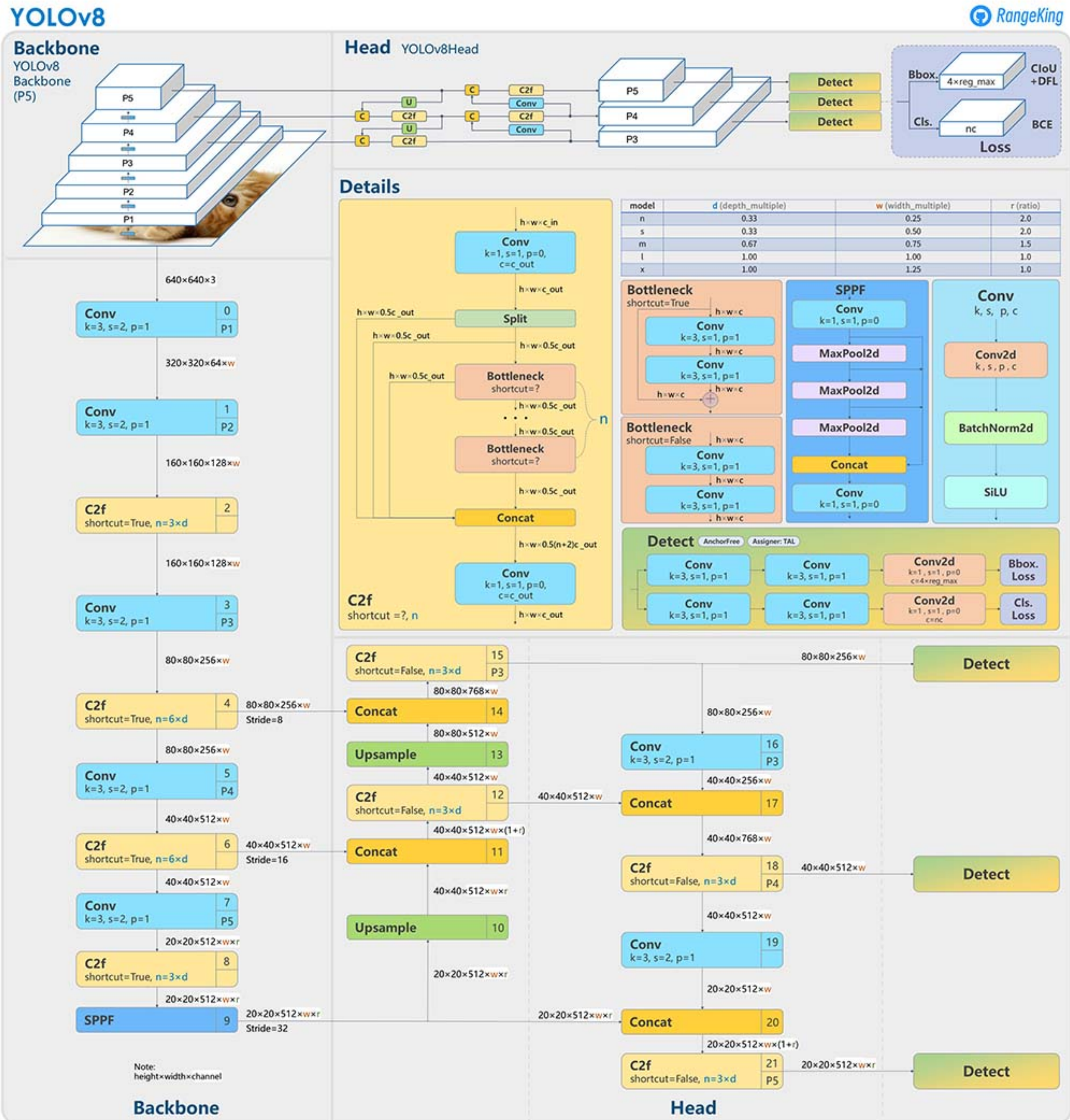


FIGURE 5. YOLOv8 model structure

the authors adopted the DeepSORT algorithm, recognized as one of the most efficient algorithms for multi-object tracking compared to ORB and Kalman filter algorithms [21]. YOLOv8 represents the latest advancement in YOLO model technology, serving for object detection, image classification, and instance segmentation tasks [22]. The detailed architecture of the YOLOv8 network is visualized in Figure 5, created by GitHub user RangeKing [23].

2.3. **Tuberculosis automatic search.** Figure 6 depicts a servo drive mechanism with convolution-based scanning which is an approach that leverages image processing to identify relevant areas or features within a sputum sample. This method operates on a principle akin to convolutional deep learning, albeit employing servo drive technology. Once these areas or features are identified, the coordinates or location information is utilized to maneuver the servo motor, allowing the camera or image sensor to adjust its position and capture images from various angles or positions. Employing this technique enhances the efficiency of ensuring comprehensive coverage of the sputum sample in the image capture process. Consequently, the servo drive mechanism with convolution-based scanning offers increased accuracy and effectiveness in capturing images.

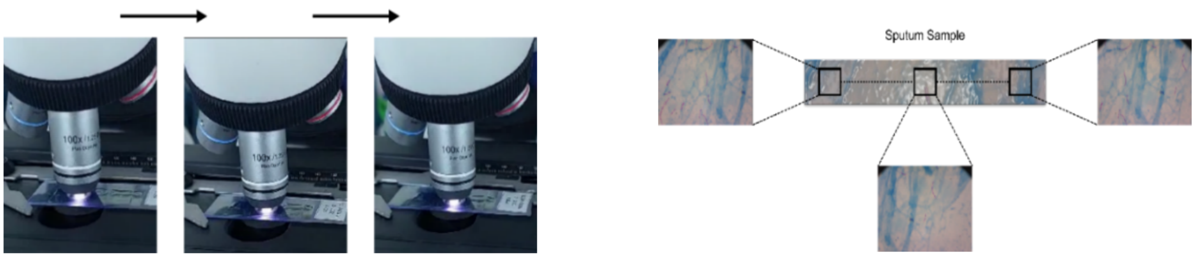


FIGURE 6. Servo drive mechanism & image sampling

The mathematical formula governing servo movement in the horizontal direction (θ_x), for horizontal coordinate of the area relevant to the sputum sample (x_c) considering the relevant area and the image size (n) is expressed as follows:

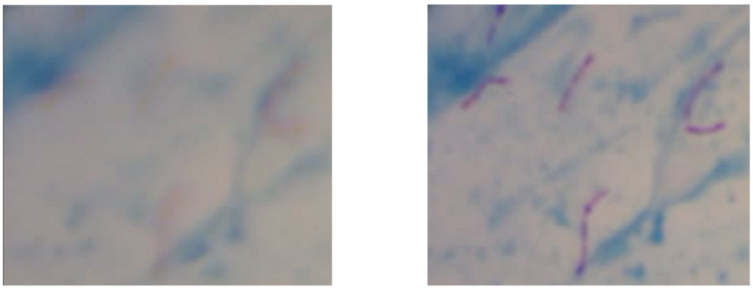
$$\theta_x = \frac{s}{n} x \left(x_c - \frac{n}{2} \right) \tag{1}$$

where θ_x represents the rotation angle required for the servo in the horizontal direction, s denotes the maximum angle of horizontal servo rotation, indicating the maximum limit of servo rotation in the horizontal direction, and n represents the image width (number of pixel columns). x_c denotes the central horizontal coordinate of the area relevant to the sputum sample. During the servo-driven process with convolution-based scanning of the phlegm sample, the system operates automatically by executing a series of integrated actions. Initially, the servo motor moves horizontally to scan the entire sample area while the camera or image sensor simultaneously captures images from each scanned position. A limit switch is integrated into the servo movement to ensure the servo returns to its initial position if it reaches a certain limit, facilitating position correction in case of slippage.

Throughout the scanning process, the system conducts autofocus by automatically adjusting the servo to optimize camera focus, ensuring the resulting image is sharp and clear, as in Figure 7. Autofocus on the microscope camera is essential to ensure that the image of the sputum sample is well-focused before the tuberculosis bacteria detection process is performed using a deep learning algorithm. By maintaining optimal focus, the accuracy of detecting tuberculosis bacteria is enhanced as the resulting image exhibits clear details and is not blurry. Utilizing the entropy method, the autofocus process can be expedited and made more accurate [24], thereby enhancing the overall speed and accuracy of detecting tuberculosis bacteria in sputum samples. The following mathematical formula describes the entropy method in the context of autofocus on a microscope camera:

$$E = -\sum_{i=1}^{n} p_i \log(p_i) \tag{2}$$

where E represents entropy, and signifies the probability of each pixel intensity value in the image, and n denotes the number of pixels in the image. In the context of autofocus, the entropy method serves to gauge the level of uncertainty or "fuzziness" present in a microscope image. The objective is to attain the maximum entropy value, indicative of a well-focused image. Put differently, the autofocus process endeavors to identify the focus position wherein the image entropy reaches its zenith, signaling maximum detail within the image [25].



(a) (b)

FIGURE 7. Autofocus: (a) Blur image; (b) clear image

Once the entropy value reaches its peak, the process of detecting tuberculosis bacteria using a deep learning algorithm can commence on the image. Subsequently, each captured image undergoes analysis by a pre-trained deep learning model tailored for tuberculosis bacteria detection. This model processes the images and identifies the presence of bacteria along with their respective locations in the image, as depicted in Figure 8. Throughout the bacteria detection process, the system also computes the number of bacteria detected in the phlegm sample by tallying the number of areas or points identified as bacteria in

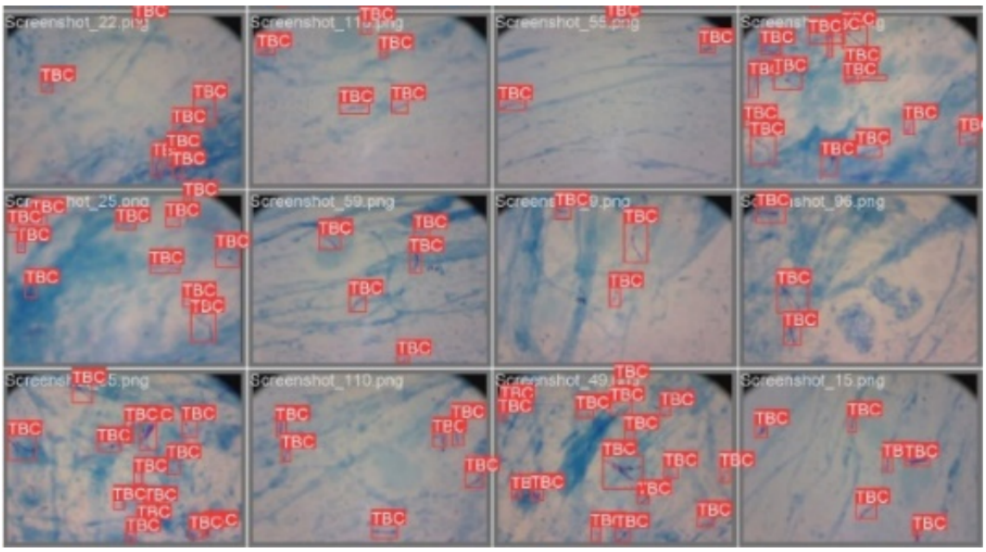


FIGURE 8. Detection result

each image. This integration enables the system to automatically capture images, detect the presence of tuberculosis bacteria, and efficiently enumerate the bacteria in sputum samples.

3. **Results and Discussion.** The system proposed in this research facilitates the automation of scanning sputum samples and detecting tuberculosis bacteria through the utilization of deep learning techniques. The primary focus of this study is the development of a detection algorithm capable of accurately recognizing the presence and location of tuberculosis bacteria in sputum samples. Additionally, this research encompasses the development of an integrated control system involving a computer, camera, and microcontroller to automatically adjust the preparation servo and focus servo based on instructions from the detection software. Consequently, the objective of this research is to contribute to the advancement of faster, more efficient, and more accurate diagnostic technology for detecting tuberculosis bacteria in sputum samples. In this section, the results of several conducted tests will be elucidated, commencing with black box testing for robots utilizing servo motor drive mechanics and components, namely the Olympus CX23 microscope, Dynamixel AX-12A servo, NUC minicomputer, and microcontroller OpenRB-150. Testing was conducted to assess various fundamental functions of the robot, including servo motor movement capabilities and integration between the computer and microcontroller. A table has been prepared to delineate the test results encompassing the test scenarios and their corresponding outcomes.

No	**Testing scenario**	**Testing steps**	**Test result**
1	Servo Horizontal Movement Test	1) The computer sends a horizontal movement command to the microcontroller. 2) The microcontroller processes commands and moves the servo horizontally. 3) Check whether the servo moves according to the command.	Succeed
2	Servo Focus Movement Test	1) The computer sends a focus movement command to the microcontroller. 2) The microcontroller processes commands and drives the servo to adjust the microscope's focus. 3) Check whether the servo moves according to the command.	Succeed
3	Computer Integration with Microcontroller	1) The computer sends control instructions to the microcontroller via the appropriate connection. 2) The microcontroller receives instructions and responds by moving the servo according to the instructions. 3) Check whether the communication and integration between the computer and the microcontroller runs smoothly.	Succeed
4	Servo Movement Stability & Consistency Test	1) Send a series of servo movement commands in a certain time interval. 2) Check whether the servo movement is consistent and stable in executing commands.	Succeed
5	Testing the Entire Robot System	1) Execute a series of movement and focus commands from the computer to the microcontroller. 2) Check the microcontroller's and servo's response in executing the command. 3) Double check the accuracy and consistency of the servo movement.	Succeed

This research also conducted tests on deep learning algorithms utilizing the YOLOv8 architecture. The study's findings demonstrate that implementing the YOLOv8 model in detecting tuberculosis bacteria in sputum samples yields satisfactory performance. Through meticulous training involving 100 epochs and relevant datasets, the test results indicate significant performance of the automatic microscope rotating robot in detecting tuberculosis bacteria using the deep learning method with the YOLOv8 architecture. The resulting confusion matrix reveals 1079 True Positives (TP), indicating the model's capability to accurately detect tuberculosis bacteria in sputum samples. However, there were 248 False Positives (FP), signifying an error in classifying negative samples as positive. Moreover, the model exhibits shortcomings in identifying positive samples as negative, with True Negatives (TN) at 0 and False Negatives (FN) at 110. With an overall accuracy rate of 75.1%, further evaluation is necessary to enhance model performance and ensure greater accuracy in detecting tuberculosis bacteria in sputum samples utilizing deep learning technology with the YOLOv8 architecture.

The analysis pertaining to research on automatic microscope rotating robots for detecting tuberculosis bacteria using deep learning methods with the YOLOv8 architecture yielded intriguing findings shown in Figure 9. Firstly, based on the F1 curve, it was observed that the model achieved an F1 score of 0.857. This score suggests that the model maintains a commendable balance between precision and recall in detecting tuberculosis bacteria. Another analysis, the precision-confidence curve, offers valuable insights into the model's performance in detecting tuberculosis bacteria. At a high confidence threshold level, precision achieves a value of 1.00, signifying flawless predictions with no false positives. This underscores the model's exceptionally high confidence in classifying samples as positive, which is crucial for ensuring accuracy in the tuberculosis bacteria detection process. However, at lower confidence threshold levels, precision decreases to 0.761. This indicates that while the model still exhibits good performance in classifying samples, there is some uncertainty or error in positive predictions.

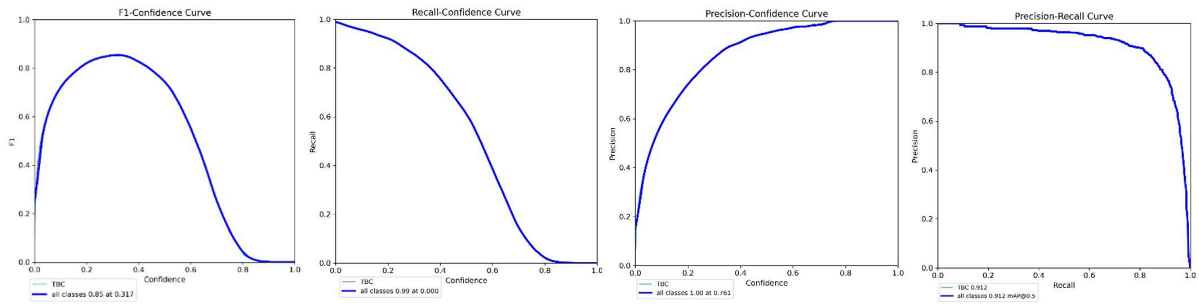


Figure 9. Analysis result

The recall confidence result for all classes is 0.99 at a confidence threshold level of 0.00, which shows that the model has a very high level of recall for all classes, even at a low confidence threshold level. This indicates that the model tends to correctly identify the majority of positive samples that are actually positive, although there is a slight possibility of False Negatives (FN). Although a value of 0.99 is a high level of recall, because the recall value is only based on True Positives (TP) and False Negatives (FN), it cannot be considered alone as a measure of overall model performance. The results of the analysis of the confusion matrix obtained showed a precision value of around 0.8128 or 81.28%, which indicates how many of the positive predictions are truly positive. In addition, the recall is around 0.9071 or around 90.71%, which shows how many of the entire positive class the model managed to predict correctly. These two values show quite good performance in detecting tuberculosis bacteria in sputum samples. Furthermore, the mAP@50 value is also around 0.8128, which is the average of precision at each recall point between 0 and 1 with an interval of 0.05. These results provide a strong picture of the model's ability to perform detection with a fairly good level of accuracy.

The training results for the refined YOLOv8 model are presented in Figure 10, showcasing the evolution of metrics such as training loss, validation loss, precision, recall, mAP@0.5, and mAP@0.5:0.95 as the number of epochs increases. It is evident that both training and validation losses decrease over time, indicating significant improvements in model learning. Furthermore, consistent improvements were observed in precision, recall, mAP@0.5, and mAP@0.5:0.95, signifying an enhancement in the overall detection performance of the model. Based on these findings, it can be concluded that the tuberculosis bacteria detection model has demonstrated effectiveness in accurately identifying tuberculosis bacteria, particularly across various scenarios.

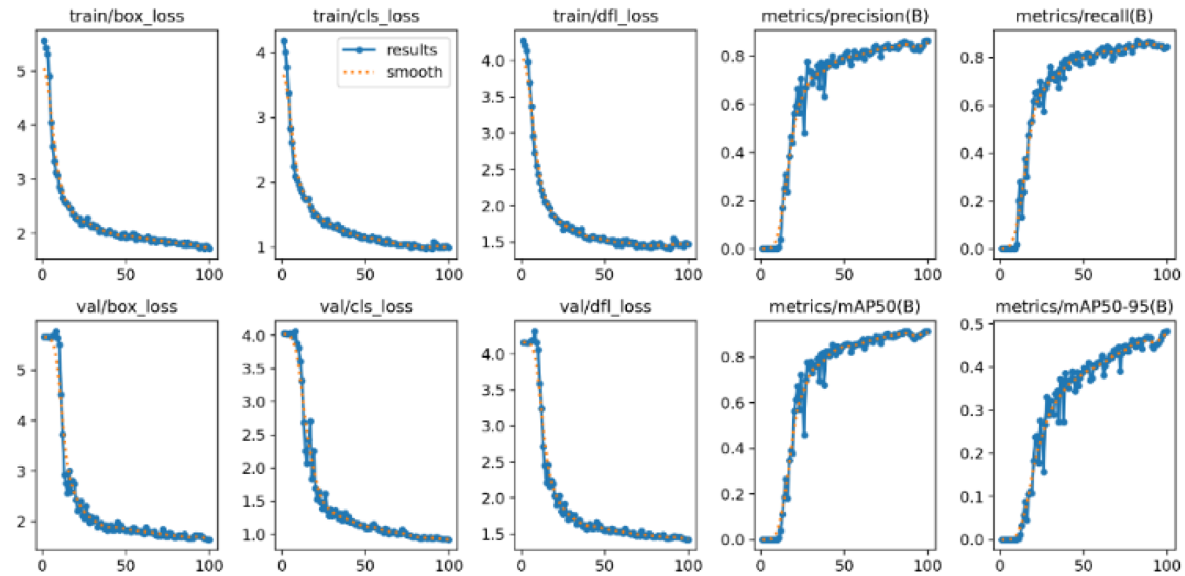


Figure 10. Result of YOLOv8

The findings of this research demonstrate the effectiveness of using the YOLOv8 architecture for tuberculosis bacteria detection, with notable results such as an F1 score of 0.857, precision of 81.28%, recall of 90.71%, and an mAP@50 value of 81.28%. Compared to existing methods that rely on manual examination or other machine learning models with limited feature extraction capabilities, the proposed YOLOv8-based approach offers significant advantages in terms of automation, accuracy, and efficiency. Manual detection methods often suffer from subjectivity and require expert analysis, leading to potential delays and variability in results. Furthermore, earlier automated detection systems typically exhibit lower precision and recall due to limited data processing or simpler architectures. In contrast, the integration of deep learning with the YOLOv8 framework enables this study to achieve a higher recall rate and better precision-confidence balance, ensuring reliable detection even at varying confidence thresholds. Additionally, the incorporation of an automated microscope rotating robot enhances the practicality of the system, outperforming conventional static systems by allowing dynamic, real-time adjustments. These advantages highlight the potential of this research in advancing tuberculosis diagnostic technology, paving the way for faster, more accurate, and more scalable solutions.

4. **Conclusions.** The research findings demonstrate that the proposed system effectively automates the process of scanning sputum samples and detecting tuberculosis bacteria through the utilization of deep learning techniques. The primary focus of this research lies in developing a detection algorithm capable of accurately recognizing the presence and location of tuberculosis bacteria in sputum samples. Additionally, the integration of the control system between the computer, camera, and microcontroller enables automatic movement of the preparation servo and focus servo in accordance with instructions from the detection software. The deep learning algorithm was tested using the YOLOv8 architecture, which exhibited satisfactory performance, with the model accurately detecting tuberculosis bacteria in sputum samples. Furthermore, evaluation of YOLOv8 model training results demonstrates significant enhancements in detection performance, characterized by reduced training and validation error rates and consistent improvements in precision, recall, and mean Average Precision (mAP). Based on these results, it can be inferred that the developed system holds promise for detecting tuberculosis bacteria in sputum samples with satisfactory accuracy. However, this study has several limitations that should be acknowledged. The dataset used for training and validation, while augmented to increase sample diversity, was sourced from a single institution, which may limit the generalizability of the model to other environments or populations. These limitations suggest the need for further research to incorporate more diverse and representative datasets and address the class imbalance. Future studies should also explore optimizing the YOLOv8 architecture for higher accuracy and computational efficiency, especially for implementation in resource-constrained settings. The integration of real-time feedback mechanisms and broader validation on independent datasets could further enhance the robustness and applicability of the proposed system.

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