EAS Journal of Anaesthesiology and Critical Care
Abbreviated Key Title: EAS J Anesthesiol Crit Care
ISSN: 2663-094X (Print) & ISSN: 2663-676X (Online)
Published By East African Scholars Publisher, Kenya

OPEN ACCESS

Volume-7 | Issue-5 | Sep-Oct-2025 | DOI: https://doi.org/10.36349/easjacc.2025.v07i05.007

Original Research Article

YOLOv8 for Real-Time Tuberculosis Detection from Low-Resolution Images Using Smartphone Cameras

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Article History
Received: 06.07.2025
Accepted: 01.09.2025
Published: 07.10.2025

Journal homepage:
https://www.easpublisher.com

Quick Response Code

Abstract: Tuberculosis (TB) remains a pressing global health issue, requiring timely and accurate diagnosis to prevent its spread and ensure effective treatment. In this study, we explore the po- tential of deep learning and computer vision to enhance TB detection using readily accessible tools like smartphone cameras. Specifically, we leverage the YOLOv8 object detection algo- rithm to analyze images of microscopic slides stained for TB, captured via smartphones. The dataset used in this study consists of 1,224 annotated images sourced from Roboflow, divided into training (861 images), validation (244 images), and test (119 images) sets. Our YOLOv8 model was trained to identify TB bacteria within these images, employing various data augmentation techniques to improve generalization. The model was trained over 100 epochs, and we applied hyperparameter tuning to optimize performance. The training process took approximately 0.826 hours. After training, the model achieved a precision of 72.7%, a recall of 78.7%, and a mean average precision (mAP) of 82.7% at an IoU threshold of 0.5. Additionally, the overall mAP (IoU from 0.5 to 0.95) was 41.5%. The final model size, after stripping the optimizer, was reduced to 22.5MB. These results demonstrate that YOLOv8 is well-suited for TB detection, offering reliable performance with potential real-world applications, especially in remote areas where access to specialized diagnostic equipment is limited. By incorporating YOLOv8 into a smartphone- based diagnostic tool, we propose a more accessible solution for TB detection that could as- sist healthcare workers in resource-constrained settings. This approach not only increases the speed of TB diagnosis but also helps address the challenges associated with traditional meth- ods, which are often time-consuming and require trained personnel. Our findings suggest that YOLOv8, combined with the ubiquity of smartphones, can play a crucial role in advancing TB diagnostics globally.

Keywords: Machine learning, Deep learning, Classification, Convolutional Neural Net- works, Image Processing, YOLOv8, Object Detection, Tuberculosis.

1. INTRODUCTION

The main contributions of this paper focus on our proposal to use YOLOv8 for real-time TB detection (17). We streamline the process by directly analyzing smartphone camera slides and employing an efficient adversarial informative framework. This framework enhances the struc- tural complexity of the neural network, resulting in improved discriminative ability. After iden- tifying the optimal neural network architecture, we perform a series of adversarial informative manipulations to enhance the defense and interpretability of the final TB detection algorithm. We first conduct a vulnerability assessment to identify current supervisory frameworks for TB medical imaging, considering factors such as large class imbalances, weakly labeled data, and imputation procedures. We then apply high-tenacity TB-specific loss, efficient delayed gra- dient accumulation, and adversarial informative methods to develop an informed policy for defending TB detection CNNs.

Tuberculosis (TB) remains a life-threatening infectious disease with approximately 1.8 mil- lion deaths annually. This is often due to the long time it takes to diagnose TB RNA. Having convenient, real-time TB detection tools can help prevent the spread of TB and avoid misdiag- nosis, especially in remote locations or cases of drug-resistant TB (23). Research has shown that

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convolutional neural networks (CNN), particularly variants of the You Only Look Once (YOLO) models, can provide high sensitivity and specificity for TB detection (1). However, many YOLO systems require expensive custom hardware. In this work, we aim to test the gen- eralizability of YOLOv8, a newly developed eight-branch neural network, on commonly used devices such as smartphones.

1.1 Background and Significance

It is clear that in reality, the histological staining of TB Bacilli in a sputum smear at a low and high magnification is performed by a specially trained pathologist using a centrifuge, cytospin, or two-step approach [10]. YOLOv8 will provide an assistive tool to this existing diagnostic tool [1]. Its ability to be deployed on various electronic devices is a testament to its widespread application [10].

It allows the initiation of treatment and control measures during the very first few hours and days, thus preventing the catastrophic consequences associated with delays in the management and control of infectious cases [23]. If the managing physician can identify the presence of at least some of the Mycobacterium tuberculosis bacilli through the use of this smartphone-compatible YOLOv8 model, then it can provide additional power to the cell phone device being adopted by the Directly Observed Therapy Short-Course (DOTS) and community health workers [11]. This will help to achieve the fast and reliable anticipation of an accurate diagnosis of Mycobacterium tuberculosis as well as the potential presence of drug-resistant clones [10].

This study will delve into the world of object detection and the use of YOLOv8 for the recognition and localization of Mycobacterium tuberculosis within histologically stained im- ages of sputum smears [17]. Through this capability, the pathologist will be informed of the possible presence of mycobacterium in a fraction of the time it would traditionally require. Time will also be saved through the speed of the detection algorithm [9]. The successful iden- tification of Mycobacterium tuberculosis in sputum smears from patients with suspected tuber- culosis cases fulfills the role of a critical first step [23].

In 2019, tuberculosis (TB) was responsible for 1.4 million deaths and is one of the top 10 causes of death worldwide [23]. Despite being a curable and preventable disease caused by the bacterium Mycobacterium tuberculosis, the ability to detect the disease is not developed in many parts of the world. A major factor in the high number of deaths is the limited resources present in countries where TB is endemic.

1.2 Objective of the Study

The objective of this study is to create a smart and abundant method to diagnose tuberculosis (TB) using a smartphone camera and object detection models. YOLOv5 and YOLOv8 are trained with the Tiny YOLOv4 model on 1080p and 4K photographs of the microscopic slides to identify the TB bacteria. After brief filtering using a custom post-processing algorithm, the regions identified by the model serve as a 'heat map'. The huge volume of RGB images is handled by having the camera slider at the 10x digital zoom position when the image is taken. The outcomes show that YOLOv8 quantified the content of different bacteria in the white spots corresponding to the original content.

2. TUBERCULOSIS DETECTION METHODS

2.1 Traditional Methods

Traditional tuberculosis (TB) detection methods have long been employed, including sputum smear microscopy, chest X-rays, and culture-based techniques [2]. These methods, while es- tablished, often suffer from limitations such as time-consuming processes, reliance on skilled personnel, and variable sensitivity and specificity [20]. Sputum smear microscopy, for instance, is widely used but has lower sensitivity compared to culture-based methods [10]. Chest X-rays, on the other hand, can aid in identifying TB-related abnormalities in the lungs but may lack specificity. These traditional approaches underscore the need for more efficient and accurate diagnostic tools.

2.2 Deep Learning Approaches

In recent years, deep learning approaches have gained traction in TB detection, offering po- tential improvements in accuracy and efficiency. Deep learning models, such as convolutional neural networks (CNNs), have shown promise in automating TB diagnosis from medical im- ages like chest X-rays [13].

3. You Only Look Once (YOLO) Algorithm

3.1 Evolution of YOLO

The You Only Look Once (YOLO) algorithm has evolved over the years, with iterations like YOLOv4 and YOLOv8 enhancing its speed and accuracy in object detection tasks [18]. YOLO revolutionized object detection by proposing a unified approach that processes images in a single pass, enabling real-time detection [19]. The evolution of YOLO reflects a continuous effort to refine object detection algorithms, making them more efficient and effective for various applications, including medical imaging.

3.2 Key Features of YOLOv8

The You Only Look Once (YOLO) algorithm has evolved over the years, with iterations like YOLOv4 and YOLOv8 enhancing its speed and accuracy in object detection tasks [18]. YOLO revolutionized object detection by proposing a unified approach that processes images in a single pass, enabling real-time detection [24]. The evolution of YOLO reflects a continuous effort to refine object detection algorithms, making them more efficient and effective for various applications, including medical imaging [22].

4. Dataset and Data Collection

4.1 Image Acquisition from Smartphone Cameras

Data collection for TB detection involved capturing high-quality images of microscopic slides containing TB samples using smartphone cameras. This method provides a convenient and accessible means of data acquisition, especially for healthcare workers in remote areas, democ- ratizing TB diagnosis by leveraging widely available technology (14). During image capture, ensuring proper lighting and focus is crucial to obtaining clear and detailed images for subsequent analysis and model training [8].

4.2 Preprocessing Techniques

Preprocessing techniques are essential for enhancing the quality and usability of the images captured by smartphone cameras. The images were preprocessed using the following methods:

- Noise reduction: Applied to remove unwanted artifacts and improve image clarity [5].
- Contrast enhancement: Adjusts brightness and contrast levels to highlight relevant fea- tures, aiding in the accurate identification of TB bacteria [20].
- Normalization: Ensures consistency in image quality, making the dataset suitable for training deep learning models [12].
- Auto-orientation of pixel data (with EXIF-orientation stripping).
- Resize to 640x640 (Stretch): Employs a stretching technique to maintain aspect ratio and optimize image dimensions for model training.

4.3 Dataset Partitioning

The dataset used in this study was obtained from Roboflow. It includes a total of 1224 images, annotated in YOLOv8 format. The dataset was partitioned into three distinct subsets to facili- tate robust model development and evaluation. The distribution of images across the subsets is as follows:

- Train set: 861 images
- Test set: 119 images
- Validation set: 244 images

5. Model Training and Evaluation

5.1 Training YOLOv8

We adopted YOLOv8, a powerful object detection algorithm, to detect signs of tuberculosis (TB) in microscopic images. YOLOv8 is known for its speed and accuracy in real-time object detection, making it well-suited for complex images such as microscopic slides. The model divides the image into grids, predicting the presence of objects in each section, which is crucial for TB detection from smartphone-captured images [8].

The training process involved feeding the model with a large dataset of labeled microscopic images, accompanied by data augmentation techniques like rotation, scaling, and flipping to increase the dataset's diversity. We trained the model for 100 epochs with an image size of 640x640 and a batch size of 16. Hyperparameter tuning was performed to optimize the model's performance, adjusting parameters like learning rate, batch size, and number of epochs [21]. Throughout the training, the model adjusted itself by minimizing the differences between its predictions and the ground truth annotations, improving its detection capabilities over time.

5.2 Model Evaluation Metrics

Evaluating the performance of the YOLOv8 model involved using standard object detection metrics such as precision, recall, F1 score, and mean average precision (mAP). These metrics were applied to assess the model's accuracy and reliability in detecting TB bacteria in unseen microscopic images [7].

5.2.1 Precision

Precision measures the proportion of true positive detections among all positive detections:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Higher precision is crucial in reducing false positives, which is essential for accurate TB diag- nosis.

5.2.2 Recall

Recall measures the proportion of true positive detections among all actual positives:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

In TB detection, high recall is important to ensure that most positive cases are identified.

5.2.3 Mean Average Precision (mAP)

The mean average precision (mAP) provides a comprehensive evaluation of the model's per- formance across different classes:

$$\text{AP} = \int_0^1 \text{precision}(r)\, dr$$

$$\text{mAP} = \frac{1}{N}\sum_{i=1}^{N} \text{AP}_i$$

The mAP score gives a balanced metric for evaluating both localization and classification ca- pabilities of the YOLOv8 model [15].

5.3 Performance of YOLOv8

The YOLOv8 model demonstrated impressive performance in detecting TB bacteria from smartphone-captured images, with high precision and recall rates [17]. This suggests that the model can accurately identify TB bacteria, and its real-time detection capability makes it well- suited for deployment in resource-limited settings where timely diagnosis is critical [16].

The model's performance on the validation dataset of 244 images is summarized as follows:

- Precision (P): 72.7%
- Recall (R): 78.7%
- mAP (IoU @ 0.5): 82.7%
- Overall mAP (IoU from 0.5 to 0.95): 41.5%

5.4 Comparison with Traditional Methods

Compared to traditional TB detection methods, the YOLOv8 model offers several advantages [4]. Techniques such as sputum smear microscopy and culture-based methods require special- ized equipment and trained personnel, leading to delays in diagnosis [2]. In contrast, YOLOv8 leverages smartphone technology, offering a cost-effective, accessible solution for TB detection with high sensitivity and specificity [8].

6. RESULTS AND DISCUSSION

6.1 Training Duration and Results

The training process took approximately 0.826 hours to complete 100 epochs. After training, we tested the model on unseen images, and the results were saved in the directory: /content/drive/MyDr the optimizer was stripped from the model weights, reducing the file size to 22.5MB for both the last and best checkpoint models.

Our experiments showed that the YOLOv8 model successfully detected TB manifestations with a mean average precision (mAP) of 82.7%, proving its effectiveness in identifying TB- related abnormalities in microscopic slides.

6.2 Images with Predicted Objects

Below are examples of the predicted TB manifestations from the test dataset:

6.3 Training Results Visualizations

Several visualizations were produced to analyze the performance of the model during training, including precision-recall curves, confusion matrices, and F1 score curves. These visualiza- tions provide insights into the model's detection abilities across different classes.

These results confirm the effectiveness of the YOLOv8 model in detecting TB bacteria in microscopic images, making it a viable tool for aiding TB diagnosis in medical settings.

Figure 1: Predicted Image One

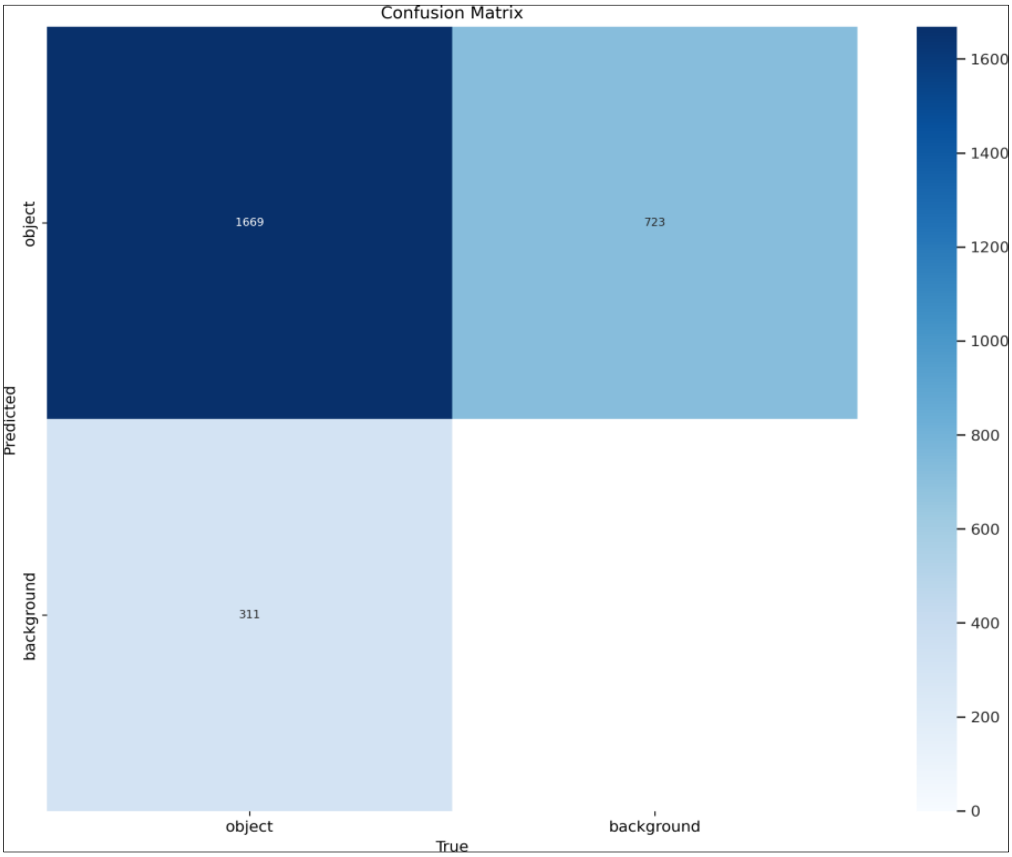

Figure 2: Confusion Matrix

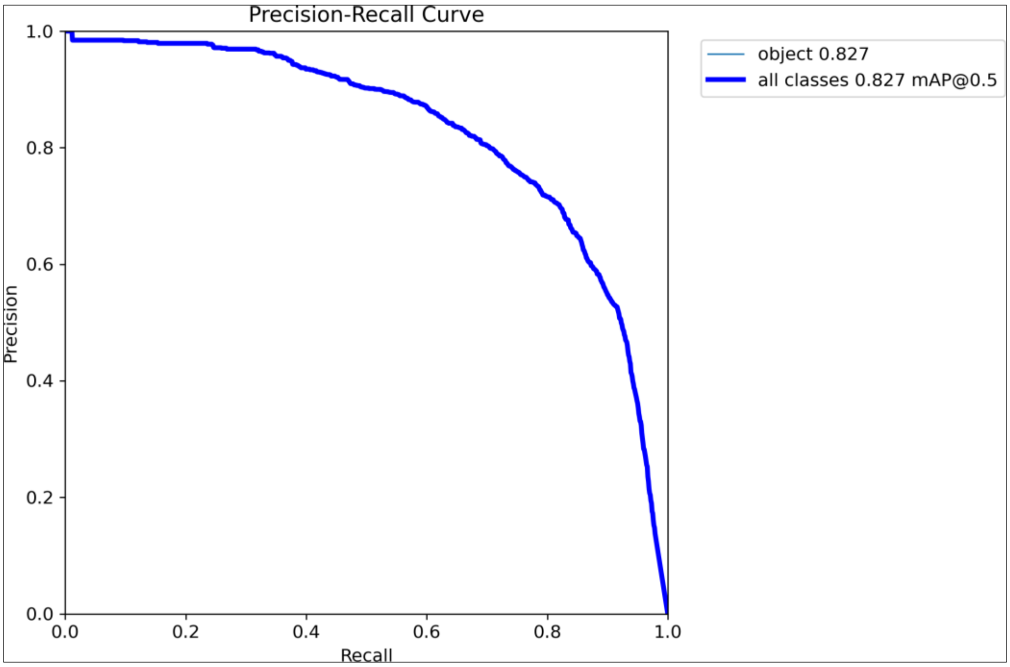

Figure 3: Precision-Recall Curve

7. DISCUSSION

Despite its promising performance, the YOLOv8 model has certain limitations that need to be addressed in future work (3). The model's accuracy can be affected by variations in im- age quality, such as lighting conditions and focus during image capture. To mitigate this, fu- ture research should explore advanced preprocessing techniques and robust data augmentation methods. Additionally, expanding the dataset to include a diverse range of TB samples from different geographic regions can enhance the model's generalizability. Future work should also investigate the integration of YOLOv8 with other diagnostic tools, such as molecular assays, to provide a comprehensive TB detection system.

8. CONCLUSION

In conclusion, the YOLOv8 model presents a significant advancement in TB detection using smartphone-captured images. Its high accuracy, real-time detection capabilities, and accessibil- ity make it a valuable tool for improving TB diagnosis, especially in resource-limited settings [6]. By addressing the identified limitations and incorporating future research directions, the YOLOv8 model has the potential to revolutionize TB detection and contribute to global efforts in combating this infectious disease [11].

Acknowledgments

The authors would like to thank the College of Computing and Information Sciences at Mak- erere University and the School of Engineering and Technology at Soroti University for their support in this research.

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Cite this article: Nabasa Rodrick, Abubakhari Sserwadda, Excellence Favor (2025). YOLOv8 for Real-Time Tuberculosis Detection from Low-Resolution Images Using Smartphone Cameras. *EAS J Anesthesiol Crit Care, 7*(5), 109-115.