Improved GrabCut Algorithm for Classify Mycobacterium Tuberculosis

Nia Saurina[1,2], Nur Chamidah[1], Riries Rulaningtyas[3], Aryati Aryati[4]

[1]*Department of Mathematics, Faculty of Science and Technology, Universitas Airlangga*
Jl. Dr. Ir. H. Soekarno, Mulyorejo, Kec. Mulyorejo, Surabaya, Jawa Timur 60115

[2]*Department of Informatics, Faculty of Technic, Universitas Wijaya Kusuma Surabaya*
Jl. Dukuh Kupang XXV/54 Surabaya, Jawa Timur 60225

[3]*Department of Physic, Faculty of Science and Technology, Universitas Airlangga*
Jl. Dr. Ir. H. Soekarno, Mulyorejo, Kec. Mulyorejo, Surabaya, Jawa Timur 60115

[4]*Department of Clinical Pathology, Faculty of Medicine, Universitas Airlangga*
Jl. Airlangga No.4 - 6, Kec. Gubeng, Surabaya, Jawa Timur 60115

[1]nia.saurina-2022@fst.unair.ac.id
[2]nur-c@fst.unair.ac.id
[3]rulaningtyas@gmail.com
[4]aryati@fk.unair.ac.id

Abstract— **Feature extraction is a stage in the image processing process. There are many feature extraction methods used for image processing, one of which is foreground extraction. Foreground extraction, which is image segmentation, is needed to separate the main object in the image that will be processed in image processing. It is needed to select the main object from the background so that the image processing process can focus on the main object. There are several algorithms that can be applied to perform foreground extraction, one of the most popular is the GrabCut algorithm. In this article, we propose a method for classifying Mycobacterium Tuberculosis as the main object by adding the yolov8 architecture to perform foreground extraction and classification of microscopic images of tuberculosis. In this article, foreground extraction is carried out using the GrabCut algorithm and adding the yolov8 architecture using bounding boxes. The Mycobacterium Tuberculosis data used was 1265 images. The proposed method can classify and calculate the number of Mycobacterium Tuberculosis. The best results on the validation dataset are method using Yolov8, with a data partition of 90:10 which produces an accuracy value of 82%, a precision value of 99%, a Recall value of 82.9%, an mAP value of 80% and a MAPE value of 6.1% which has a very accurate interpretation of forecasting results.**

Keywords— image classification, foreground extraction, GrabCut, yolov8, Mycobacterium Tuberculosis

I. Introduction

Tuberculosis is a chronic infectious disease caused by the bacterium Mycobacterium tuberculosis [1]. A person will become infected by simply breathing air that has been contaminated by these bacteria, but it depends on the person's immune system, air circulation/ventilation conditions, frequency of contact with TB people [2]. Early diagnosis and successful treatment of TB is crucial to prevent further spread of the bacteria and development of resistant strains [3].

In recent years, researchers have turned to machine learning as a potential solution to enhance TB diagnosis from pulmonary chest X-rays. Machine learning algorithms can learn patterns from vast datasets, and when applied to medical imaging, they have the potential to aid radiologists in detecting subtle features indicative of TB with high accuracy [4-7].

TB can be combated or eradicated through early detection, based on testing methods such as culture tests, chest radiography, sputum smear microscopy, and nucleic acid amplification. Chest computed tomography, histopathological examination of biopsy samples, and new molecular diagnostic tests can also improve diagnoses [8].

Identifying active TB cases is crucial for reducing disease transmission and strengthening disease control. Screening for Acid-Fast Bacilli (AFB) by conventional sputum smear microscopy of direct smears of sputum (DS) is the first line test used for TB laboratory diagnosis. Analysis of DS is easy to perform, quick, and inexpensive, but has limited sensitivity, with a detection threshold of 5000 to 10,000 AFB/mL of sputum [9]. Bacterial culture is the gold standard for diagnosis; it is highly sensitive and detects as low as 10 AFB/mL of sputum. However, it is laborious and time-consuming, requiring up to 12 weeks to provide results. Complex laboratory facilities are also required because handling of TB organisms requires conditions of biosafety containment level 3 (BSL3) [10]. The manual microscopic method is strenuous and time consuming, gives various sensitivity and high false negative rate detection [11-12]. Computer application for disease detection or classification is one of the areas that has received the most attention. Numerous studies have proposed methods for classifying medical images to help diagnose a disease [13].

Among other methods, sputum smear microscopy is the most used method, especially in developing countries, because it is simple, low cost, and easy to maintenance [14]. Much research regarding TB bacilli detection has been reported. Rulaningtyas, et al. [15] developed an automatic classification of TB bacilli using a neural network. Panicker [16] proposed an automatic detection of TB bacilli based on two one-class classifiers. Most of the recently advanced object detection lies on fine-tuned of pre-trained CNNs in ImageNet [17]. This process can generate the final model quickly and requires way fewer instance-level annotated training data than the classification task [18].

Feature extraction is a method used to extract the characteristics of objects in an image with the aim of recognizing the object [19]. One of the stages in feature extraction is acquisition, which is a process of getting image data from analog to digital form [20]. Separating the background from the foreground is important in processing computer vision-based applications [21]. Retrieving foreground features can be done using the GraphCut algorithm approach. An algorithm that efficiently separates the background from the foreground. However, the GrabCut algorithm then emerged as a replacement for the GraphCut algorithm with the advantages provided by GrabCut [22]. So the next approach is the GrabCut method, a foreground extraction algorithm where the user provides input in the form of an image accompanied by a selected foreground area using a bounding box indicating the exact location of the foreground or with a mask indicating the foreground and background and then the algorithm will separate the foreground from the background [23].

GrabCut is the one of the most powerful techniques to segment single or multiple image to the particular foreground and background region. Graph cut is the effective techniques for segmenting the monochrome image only. Grabcut is an extension of the graph cut algorithm to segment the color image and it need the help of user interaction for the high quality of the segmentation [24].

There are so many researches improved GrabCut algorithm. In [25] Shengcho Zhang, Yuelong Zhao,Pengcheng Bai has proposed the object localization improved GrabCut for lung parenchyma segmentation.In their paper,object localization improved GrabCut is used as algorithm. In [26] Feilong Kang,Chunguang Wang,Jia Li and Zheying Zong proposed the multiobject piglet image segmentation method based on an improved noninteractive GrabCut algorithm. In [27] Haijian Ye,Chengqi Liu,Peiyun Niu has proposed the cucumber appreance quality detection under complex background based on image processing.

In this paper, we develop the GrabCut algorithm by adding the Yolov5 architecture to perform Mycobacterium Tuberculosis classification. Section 2 provides a methodology on object detection using YOLO and GrabCut. Section 3 explains the results of the trial analysis. Section 4 provides conclusions and future work.

II. METHODOLOGY

GrabCut, is initialized with some manual interaction: the user drags a rectangle over a region of the image where the foreground is. Then, the algorithm considers everything outside the rectangle as known background, and, from the information of these pixels and the relation between neighbours inside the rectangle, the probable contour of the foreground is found [28].

GrabCut is an improved algorithm for Graph Cuts through iterative methods, mainly for color images [29]. Figure 1 shows two examples of GrabCut segmentation.

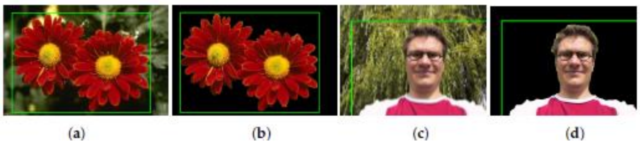

Fig. 1. Two examples of GrabCut. (a) Original image, (b) Segmentation result, (c) Original image, (d) Segmentation result [29].

Let the binary vector A = {A1, A2, A3, …, A_p, …, An, where Ap is the assignment of pixel p in set P, with 0 for the background and 1 for the foreground. As shown in Figure 2, an undirected graph G = (v,e) is created from the input image. The node v of the graph corresponds to the pixel p ϵ P of the image, and there are two additional nodes: the foreground terminal (a source S) and the background terminal (a sink T). Their relationship is as follows.

$$v = P \cup \{S, T\}$$

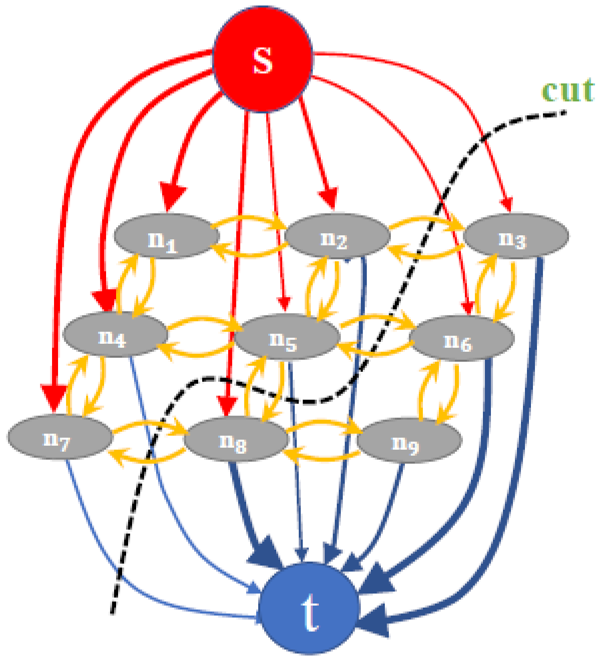

Fig. 2. S-T diagram of the GrabCut segmentation process [29]

The procedures of GrabCut are given as follows.

Step 1: Input the image. The user selects the label region U' with a rectangular region to initialize the foreground. The region inside U' is all the foreground objects F0, and the region outside U' is all the background region B'.

Step 2: For each pixel p, p ϵ F' assign a label A_p = 1 to the pixel p. p ϵ B'; assign a label A_p = 0 to pixel *p*.

Step 3: Using the K-means clustering algorithm, the foreground object region F' and the background region B' are respectively clustered into K kinds of pixel.

Step 4: The GMMs of the foreground and the background are initialized with the two sets of labels A_p = 0 and A_p = 1, respectively (the GMM of the foreground and the background, respectively, have K Gaussian components), and the parameters (л, μ, σ) of the two GMMs are obtained.

Step 5: Substituting each pixel *p* in the foreground object region F' into the two obtained GMMs, the probability that the pixel belongs to the foreground object region and belongs to the background region, respectively, are obtained (the one with the highest probability is most likely to generate the pixel *p*, that is, the Gaussian component k_p of the pixel p). The probability takes the form of a negative logarithm to obtain the regional term F.

Step 6: The Euclidean distance (i.e., the two norms) between every two neighbouring pixels in the foreground region F' is calculated and the boundary term V is obtained.

Step 7: the minimum value of energy min E (A, k, θ, P) is obtained using the maximum flow minimum cut algorithm. The calculated result is again assigned to the set of pixels $A_p = 0$ and $A_p = 1$ in the foreground object region F'.

Step 8: Repeat steps 4 through 7 until the convergence and output image.

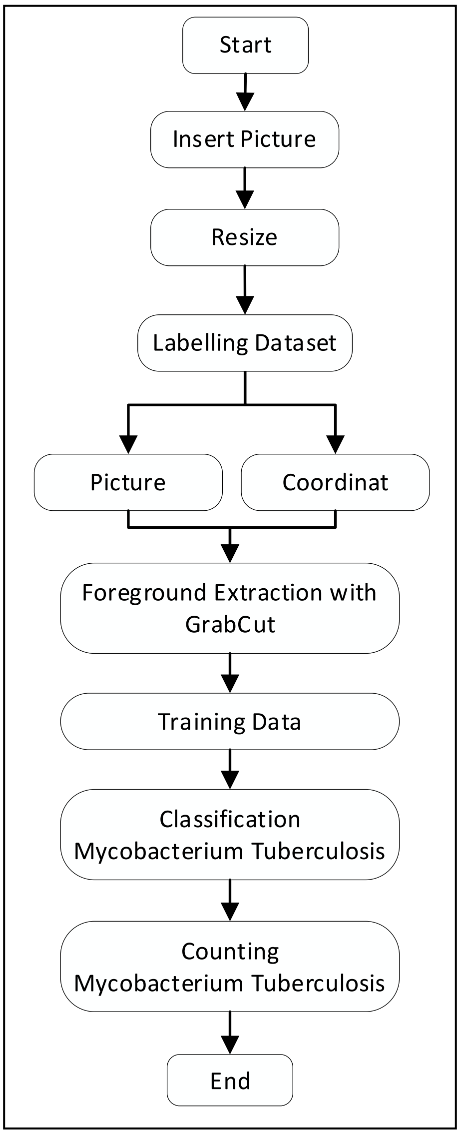

Fig. 3. Metodologi Penelitian

The system model in this research can be seen in Figure 3. Mycobacterium Tuberculosis as a Data Image was entered into the algorithm, then resized from 1632x1442 to 640x480, then labelled the dataset using yolov8 with a bounding box, so that the dataset produces an image that has the location of Mycobacterium Tuberculosis along with location coordinates in the form of text. After obtaining the two datasets, foreground extraction was carried out using GrabCut. After that, run the data training process.

A. Data Description and Pre-processing

Data collection used in this research included microscopic images of tuberculosis from GDC Dr. Soetomo Airlangga University. Building a model using the YOLO method requires a dataset for training. The dataset used in this research is to include microscopic images of tuberculosis 1265 images taken by staining Acid Fast Bacteria using the Zheil Neelsen method to help with the initial microscopic diagnosis of tuberculosis. The fixation process carried out in this staining can make the bacterial wall layer open so that it can absorb coloring agent used.

B. Labelling Dataset

Dataset labelling or what can be called annotation is the process of providing information on various human movements. The obtained image dataset is labelled one by one to obtain the coordinates of the ground-truth bounding box which can be compared with the prediction bounding box.

Figure 4 shows an image of Mycobacterium Tuberculosis in one field of view, then using Yolov8 to label data using a Bounding Box to mark the position of Mycobacterium Tuberculosis.

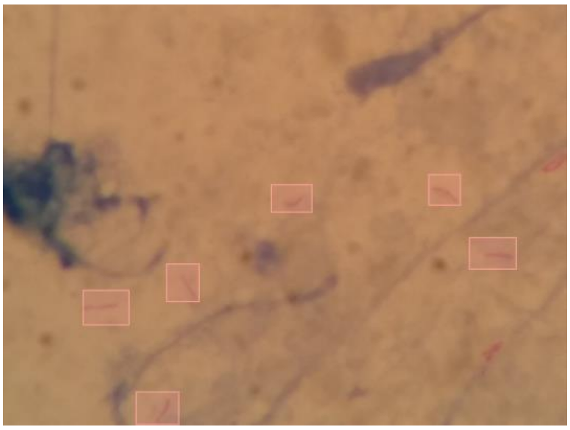

Fig. 4. Labelling Data With Bounding Box

C. Proposed Method with YOLO

The dataset that has been labelled in the previous stage will be trained to form a pattern whose results are in the form of weights. These weights will be used to detect objects in the image. Training will be carried out using You Only Look Once (YOLO) version 8. The software used in the training data retrieval process is Pycharm, and the programming language uses Python.

Research about GrabCut dan Yolo has been done by [30] to created model uses ant lion fitness to forecast paddy leaf diseases correctly. By achieving improved performance metrics, the experimental findings demonstrate the effectiveness of the designed model, and the obtained results are validated with other traditional models. Then there are another research by [31] used yolo dan GrabCut for Contour Extraction of Individual Cattle from an Image Using Enhanced Mask R-CNN Instance Segmentation Method. GrabCut provides the avenue for cutting edge segmentation method which helps in removing heterogeneous objects from an image while the homogenous objects are retained. Yolov2 used for build an architecture Enhanced Mask R-CNN to made Contour Extraction of Individual Cattle. Another research by [32] used yolov3 dan GrabCut for improved fused features using Deep Convolutional Neural Network (DCNN), which classifies the different types of skin cancer.

YOLOv8 [33]. capabilities and improvements in a computer vision model used for tasks such as object detection, classification, and segmentation. It mentions that YOLOv8 is easy to use and can be trained on large datasets. The architecture of YOLOv8 includes different scales of feature maps and utilizes structures like B1-B5, P3-P5, and N4-N5 in the backbone, FPN, and PAN [34].

The enhancements introduced in YOLOv8 compared to previous versions. These include the adoption of Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) as part of the neural network architecture, as well as the development of a new labelling tool to simplify the annotation process [35].

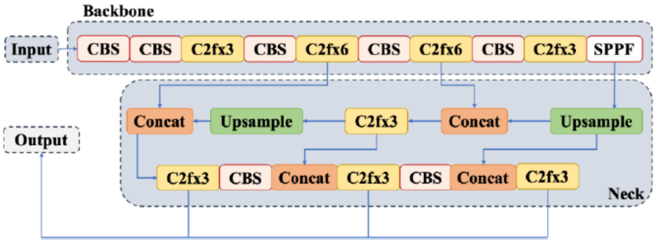

Fig. 5. Architecture Yolov8 [33]

III. RESULT

At this chapter, the test results of the design preparations that have previously been carried out are presented.

A. *Creation of a Mycobacterium Tuberculosis Classification System*

The method used to detect and classify Mycobacterium Tuberculosis using YOLO method. First, the dataset obtained is labelled in one class, namely image. After labelling is complete, we then enter the preprocessing stage to determine the angle, where this angle becomes a reference for the position of the Mycobacterium Tuberculosis object. If the object goes outside a predetermined angle the system will not detect the object. Apart from angles, there is also bounding boxes which is used to classify objects in the frame, so that deep learning can later make decisions to determine objects.

1) Dataset Creation: Dataset creation aims to prepare data that will be used for training. The data is in the form of image of Mycobacterium Tuberculosis which were obtained by taking data from GDC Dr. Soetomo Airlangga University. The data obtained amounted to 1265 which were used as image train and image test.

2) Foreground Extraction: The Grab Cut well extracted foreground with minimal user interaction via combining edge and appearance models. The appearance model is statistically described using the Gaussian Mixture Models (GMMs), in which one problem is that the number of Gaussians has a significant influence on accuracy of the segmentation; the other is that the GMMs is inefficient on the inhomogeneous sub-regions. The implementation effect is low for high-textured images [36].

3) Training Data: Training data aims to produce a weight that will be used in the Mycobacterium Tuberculosis detection process. The data training process was carried out using Deep Learning method using PyCharm. The training process lasts for 9 hours with training using 4000 max batches, with image size 640x480 and batch size 16 with 1 class. Figure 5 is a image of Mycobacterium Tuberculosis from the Deep Learning training results.

B. *Performance Testing*

Foreground extraction is a task of distinguishing between the specific object and background. The foreground extraction is formulated as a joint optimization for the foreground extraction and appearance parameters.

Figure 6 shows an image of Mycobacterium Tuberculosis in one field of view, then using Yolov8 to label data using a Bounding Box to mark the position of Mycobacterium Tuberculosis.

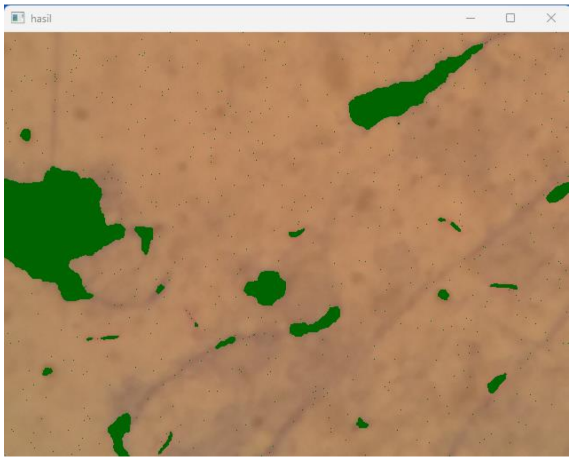

Fig. 6. Foreground Extraction with GrabCut

Figure 7 shows the classification results of the proposed method. With the addition of the yolov8 architecture, the GrabCut algorithm can be used to classify Mycobacterium Tuberculosis. The resulting method can even calculate the number of Mycobacterium Tuberculosis.

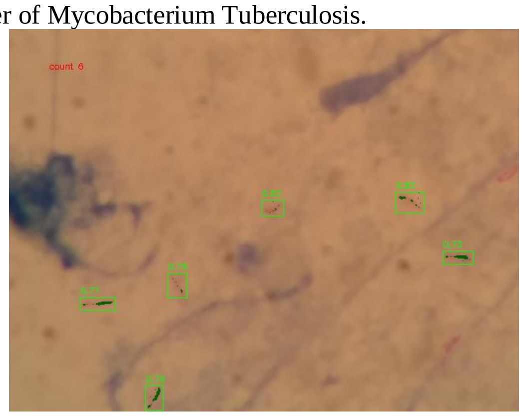

Fig. 7. Classification and calculate the amount of Mycrobacterium Tuberculosis with Proposed Method

Measuring the performance of the confusion matrix uses 4 terms that will show the results of the classification process, namely:

- True Positive (TP) = The total of data that is positive and classified by the system correctly.
- True Negative (TN) = The total of data that is positive and classified by the system incorrectly.
- False Positive (FP) = The total of data that is negative and classified by the system correctly.
- False Negative (FN) = The total of data that is negative and classified by the system incorrectly.

The data partition testing scenario is carried out using the holdout method, or generally known as data partition testing. For the test scenario, the dataset will be divided into two types and stored in the train and test folders. For the dataset that can be used, there are 1265 data consisting of two classes, namely, Mycobacterium Tuberculosis and Non Mycobacterium Tuberculosis, which will later be combined and then combined with portions that have been determined in the test and train folders, then the data training or training process is carried out, which is a the process of training data to be able to learn and detect a predetermined object. The data partition will be tested into four training scenarios with the following details:

1. Train 60% (759 data) and Test 40% (506 data).
2. Train 70% (885 data) and Test 30% (380 data).
3. Train 80% (1012 data) and Test 20% (253 data).
4. Train 90% (1138 data) and Test 10% (127 data).

The aim of this test is to find the best Mean Average Precision (mAP) value for each data partition scenario.

TABLE II
TABLE OF OVERALL RESULTS OF DATA PARTITION TESTING

No	*Data Partition (%)*	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*mAP (%)*	*MAPE (%)*
1	60 : 40	61,39%	75,6%	78%	72,6%	15,2%
2	70 : 30	68,81%	79,2%	78,2%	74,1%	12,6%
3	80 : 20	77,52%	80,3%	80%	78,5%	9,3%
4	90 : 10	82%	99%	82,9%	80%	6,1%

Table 2 explains that there are four test scenarios with a data partition of 60:40 which produce an accuracy value of 61.39%, a precision value of 75.6%, a Recall value of 78%, a mAP value of 72.6% and a MAPE value of 15.2%. For the second test scenario with a data partition of 70:30 which produces an accuracy value of 68.81%, a precision value of 79.2%, a Recall value of 78.2%, a mAP value of 74.1% and a MAPE value of 12.6 %. For the third test scenario with a data partition of 80:20, it produces an accuracy value of 77.52%, a precision value of 80.3%, a Recall value of 80%, a mAP value of 78.5% and a MAPE value of 9.3%. Then in the fourth test scenario with a 90:10 data partition which produces an accuracy value of 82%, a precision value of 99%, a Recall value of 82.9%, a mAP value of 80% and a MAPE value of 6.1%. Based on [35] a MAPE value of 6.1% has a very accurate interpretation of forecasting results. The MAPE value in this study was obtained by comparing the number of Mycobacterium Tuberculosis classifications produced by the proposed model with the number of Mycobacterium Tuberculosis calculated by GDC Laboratory Assistant Dr. Soetomo Airlangga University in 1265 images.

For the calculation of Accuracy, Precision, Recall, and F1 Score according to the results of the confusion matrix in Figure 8 in the best data training process.

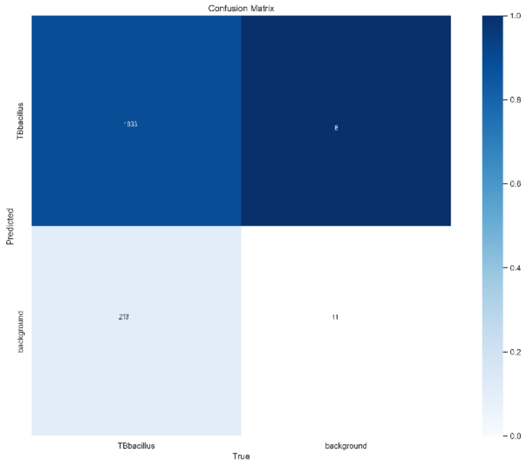

Fig. 8. Confusion Matrix with Yolov8

For the detailed calculation process in Table II, we explain the 90:10 data partition which produces the best value in the data testing process.

Accuracy is the result of accuracy to define the level of closeness of the actual value to the predicted value. The higher the accuracy level, the better the method performance. The formula for calculating accuracy is as in formula (1).

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

$$Accuracy = \frac{1033 + 11}{1265}$$

$$Accuracy = 0{,}8252$$

Precision is the level of accuracy of the requested data with the data provided by the model. Precision is the TP classification of all data that is predicted to be positive into a positive class value. The formula for carrying out precision calculations is as in formula (2).

$$Precision = \frac{TP}{TP+FP} \text{ ....(2)}$$

$$Precision = \frac{1033}{1033 + 8}$$

$$Precision = 0{,}992$$

Recall is the level of success of the system in obtaining information. The formula for calculating recall is as in formula (3).

$$Recall = \frac{TP}{TP+FN} \text{ ....(3)}$$

$$Recall = \frac{1033}{1033 + 213}$$

$$Recall = 0{,}8290$$

F1 Score which is a comparison of precision and recall. The formula for calculating the F1 Score is as in formula (4).

$$F1\ Score = 2x\frac{PrecisionxRecall}{Precision+Recall} \ldots\ldots\ldots\ldots\ldots\ldots..(4)$$

$$F1\ Score = 0{,}9033$$

The model was applied with GrabCut Algorithm and the training results are illustrated in Figure 9. The diagram depicts the values per epoch for box_loss, cls_loss, dfl_loss, precision, and recall (both train and validation). The box_loss represents the loss incurred in localizing the bounding boxes of the detected objects, while cls_loss reflects the loss associated with classifying the objects into different categories. The dfl_loss corresponds to the loss incurred in refining the predicted bounding boxes.

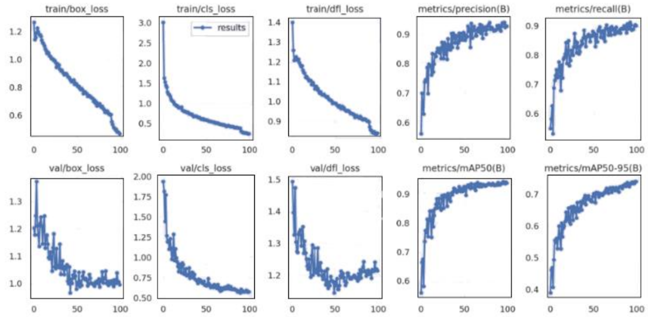

Fig. 9. Classification Mycrobacterium Tuberculosis with GrabCut Algorithm

IV. Conclusions

Retrieving foreground features can be done using the GrabCut algorithm approach. With the YOLO architecture, GrabCut can be improved to made classification and calculate the amount of Mycobacterium Tuberculosis. The best of results on the validation dataset are method using Yolov8, with a data partition of 90:10 which produces an accuracy value of 82%, a precision value of 99%, a Recall value of 82.9%, an mAP value of 80% and a MAPE value of 6.1% which has a very accurate interpretation of forecasting results.

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