Diagnosis Model in Smear-Negative Pulmonary Tuberculosis Using Faster R-CNN

Nur Azizah[*1], Benny Mutiara[2], Prihandoko[3], Po Abas Sunarya[4]
[1] Faculty of Science and Technology, University of Raharja, Indonesia
[2,3] Faculty of Computer Science and Information Technology, Gunadarma University, Indonesia
[4] Faculty of Economics and Business, University of Raharja, Indonesia
E-mail: [*1]**nur.azizah@raharja.info**, [2]amutiara@gmail.com, [3]prihandoko@gmail.com,
[4]abas@raharja.info

Abstract

Background: One of the most important human organs in the respiratory system is the lung. The main function of the lung is the respiration process, which is responsible for pumping air into the body. The health of the lung organs is very important, because if this organ is disturbed it will affect the health of the rest of the body. One of the diseases that attacks the lungs is Tuberculosis (TB). TB disease can be cured, but if it is delayed in getting treatment it can increase the risk of death. Method: This research developed a Smear Negative Pulmonary Tuberculosis diagnosis model using the Deep Learning method using the Faster R-CNN algorithm. The data used in this research are x-ray images of the lungs at the Jakarta Repository Center - Indonesian Tuberculosis Eradication Center (JRC-PPTI) clinic, totaling 220 datasets. At the preprocessing stage, the images used for training and testing were used with a size of 1280 x 1280 to see the effect on the accuracy of the prediction results of the Faster RCNN model. The test results are in the form of accuracy values that reflect the performance of the Faster RCNN model in classifying normal (without TB) and abnormal (with TB) test data. Results: The research implementation carried out the training process and testing process for 75% of training images, and 25% for testing images. Training images are labeled using the Img label. In the testing stage of the faster RCNN model, the accuracy value was 62.04%, precision was 40.00%, recall was 64.52% and F1-score was 49.38%. Conclusion: From the results of this research it is concluded that the Faster RCNN model test results using the ResNet 50 model have an accuracy value of 62.04%, Precision of 40.00%, Recall of 64.52% and F1-score of 49.38%.

Keywords — *Smear Negative Pulmonary Tuberculosis (SNPT), Deep Learning, Faster RCNN*

1. INTRODUCTION

One of the most important human organs in the respiratory system is the lungs. The main function of the lungs is the respiration process, which is responsible for pumping air into the body. The health of the lung organs is very important, because if this organ is disturbed it will affect the health of the rest of the body. One type of disease that attacks the lungs is Tuberculosis (TB). TB is the most common disease experienced by society and is one of the highest causes of death in the world (World Health Organization, 2020). TB disease is caused by the bacteria Mycobacterium tuberculosis which is classified as an infectious bacteria. From World Health Organization data (2020), Indonesia is the country that ranks third in the number of TB cases with 842,000 or 46 percent of the total cases. In Indonesia's National Tuberculosis

Control Guidelines, it is reported that one of the causes of the increasing TB burden is the failure of the TB program. One of the causes of this failure is non-standard TB case discovery or diagnosis and inadequate diagnostic management (PNPT, 2014).

TB diagnosis is difficult for several reasons (Imianvan and Obi, 2012; Alvarez-Uria et al., 2012). The explanation is as follows: 1) TB symptoms, such as fever, cough, cough with phlegm, coughing up blood and weight loss, are similar to the symptoms of lung cancer (Bhatt et al., 2012), pneumonia (Uzoka et al., 2011), and also infection Acute Respiratory Tract (ARI), asthma and Chronic Obstructive Pulmonary Disease (COPD) (TB CARE I, 2014), 2) In pediatric patients, the clinical picture of TB is non-specific, lung photographs are difficult to interpret (Kusuma, 2007) and sputum is difficult to obtain (WHO, 2012), 3) In cases of a small number of germs (paucibacillary TB) (Kusuma, 2007; Nesredin, 2012), 4) In cases of extra pulmonary TB (extrapulmonary TB) because patients often do not show TB symptoms (Radzi et al., 2011; Jain, 2011; Bahadori and Azizi, 2012), 5) In HIV positive patients, chestradiography results may be atypical due to other infections (Saranchuk et al., 2007; Swai et al., 2011), 6) In cases of BTA pulmonary TB negative (Smear-Negative Pulmonary Tuberculosis, abbreviated as SNPT) (Mello et al., 2006; Muvunyi and Masaisa, 2006; Benfu et al., 2009; Santiago-Mozos et al., 2013).

The diagnosis of pulmonary TB with negative BTA and positive culture can be confirmed by sputum culture, but it takes 6 to 8 weeks. In addition, equipment for culture is rarely found in developing countries (WHO, 2015; Mello et al, 2006; Muvunyi, 2006), so the use of culture is limited and rarely recommended. Methods such as nucleid acid amplication tests, can provide faster results, but are expensive and the equipment is not often found in developing countries. So in conditions of limited equipment, the diagnosis of SNPT is confirmed by symptoms, physical examination results and supporting examination results (at least by chest radiography examination, abbreviated as CXR). However, the results of CXR examination between active and inactive tuberculosis are difficult to differentiate. For this reason, an accurate final diagnosis is very necessary to reduce costs and the possibility of cases of underdiagnosis and overtreatment (Bhatt et al, 2012; Muvunyi, 2006).

TB disease can be cured, but if treatment is delayed it can increase the risk of death. Early detection of TB disease is very important so that TB sufferers can be treated immediately and minimize the risk of complications. TB disease can generally be diagnosed through a chest x-ray examination. Therefore, we need a system that is able to differentiate between normal (without TB) and abnormal (with TB) x-rays accurately and quickly.

Previous research using the Convolutional Neural Network (CNN) method to detect TB disease through chest X-rays was carried out by Ovy et al (2021). This research aims to determine the CNN model that is able to produce the best performance in detecting TB disease by producing the highest accuracy value in detecting TB disease, namely 91.57%.

In previous research related to computer-based classification, TB diagnosis has been carried out using several types of input. These inputs include digital images of tissue samples (Osman et al., 2010, 2011), images of TB germs (Santiago-Mozos et al., 2013; Siena et al., 2012), sputum aroma with an electronic nose (Kodogiannis, 2013), cough sounds (Tracey et al., 2011), lung sound waves (Becker et al., 2013; Lestari et al., 2012), medical record data (Uçar and Karahoca, 2011; Uçar et al., 2013; Nesredin, 2012) and blood (Lauria, 2015).

Computer Vision (CV) and Machine Learning (ML) technology is currently very developed and has been used in various fields, including the health sector. The combination of these two methods is often used in various studies to detect and classify several diseases such as: pneumothorax (Chan, Zeng, Wu, Wu, & Sun, 2018), breast cancer (Kaushal, Bhat, Koundal, & Singla, 2019), brain tumors (Rajan & Sundar, 2019), kidney stones (Nithya, Appathurai, Venkatadri, Ramji, & Anna, 2020), pneumonia (Biswas, Ghosh, Bhattacharyya, Platos, Snasel, & Chakrabarti, 2020) and skin cancer (Savera, Suryawan, & Setiawan, 2020). In previous research, TB could be detected using several CV and ML methods. Graph cut segmentation methods (Jaeger, Karargyris, Candemir, Folio, Siegelman, Callaghan, Mcdonald, 2013) and pyramid histograms of oriented gradients (Santosh, Vajda, Antani, & Thoma, 2016) are used to extract shape and texture features in images. . Meanwhile, image classification uses several methods such as support vector machine (SVM), alternating decision tree and neural network. The accuracy results produced in both studies were still not optimal, where the highest accuracy value obtained was 86.3%. Development still needs to be done to get better performance with high accuracy values.

According to the Indonesian National Tuberculosis Control Guidelines (2014), as well as the International Standard for Tuberculosis Care (ISTC) (2014), the TB diagnosis process begins with finding suspected TB using the main symptoms, physical and laboratory examination, determining the diagnosis and determining the classification of the type of TB patient. Patients with symptoms of coughing up phlegm for more than two weeks are considered suspected of having TB. In fact, these symptoms are also found in other lung diseases. The final diagnosis is made based on the results of a sputum examination. If the results of the microscopic examination are positive, then the patient is diagnosed with BTA positive pulmonary TB. If the results of the microscopic examination are negative, then additional supporting examinations are carried out, at least with a chest X-ray examination to determine whether the patient is diagnosed with smear negative pulmonary TB (P2PL, 2014). The final diagnosis is made by a TB-trained doctor.

Previous research using computer-based classification methods and using medical record data as input to find TB suspects was carried out by Santos et al (2007b) and Asha et al. (2010, 2012, 2011a, 2011b). Santos et al (2007b) combined Bayesian Network and Artificial Neural Network (ANN) methods to become Bayesian Neural Network (BNN). His research shows that BNN accuracy increases by 6% when compared to ANN. In 2010, Asha et al carried out a comparison of ensemble methods and concluded that Random Forest had better performance compared to Bagging and Adaboost. In 2011, Asha et al compared the performance of Support Vector Machine (SVM) and ensemble methods and concluded that SVM had comparable performance to Random Forest and better than Bagging and Random Forest. In 2012, Asha et al used the associative classification method and produced accuracy that was comparable to their previous research.

In diagnosing this disease, generally the diagnostic tool or technique used is to carry out an x-ray on the patient's chest. The image data produced from this technique is called a chest x-ray (CXR) image. This technique was chosen because it is economical and easy to use. (C. Qin et al, 2018). On CXR, an image of the inside surface of the patient's chest can be seen which is used as consideration by an expert to determine whether a patient is infected with pneumonia or tuberculosis.

Along with the rapid progress of technology, especially in the field of deep learning which is part of the machine learning method, image problems such as classification continue to be developed to become more dynamic for various problems, where differentiating an object in an image can be done with the help of machine computing without human intervention. So the predictions produced by deep learning models in terms of detecting a disease can help an expert in diagnosing possible diseases suffered by a patient.

This research will use classification techniques using deep learning methods using the Faster Region Convolutional Neural Network (Faster R-CNN) model to produce early and late TB diagnosis models, especially in cases with negative BTA. Faster Region Convolutional Neural Network (R-CNN) is a method based on deep learning object detection which is commonly used to detect objects. Previous research that is relevant to the algorithm the author uses is Yilin Xieet.al(2020) in research entitled "Computer-Aided System for the Detection of Multicategory Pulmonary Tuberculosis in Radiographs". In this study, a system was designed to diagnose tuberculosis using the Faster R-CNN algorithm by detecting multicategories on chest radiographs.

In this research, we propose a deep learning approach using the Faster Region Convolutional Neural Network (Faster R-CNN) method to detect SNPT through chest X-Ray images. Evaluation was carried out to determine the performance of the proposed method in the form of precision, recall, F-1, and accuracy. With the method we propose, it is hoped that we can provide a more comprehensive picture in order to help and complete the diagnosis modelSmear-Negative Pulmonary Tuberculosis (SNPT)the beginning and end of the patient.

From several literatures used as references, no research has been found that carries out initial and final diagnosis using the Faster Region Convolutional Neural Network (Faster R-CNN) method in deep learning.

This research uses the Faster Region Convolutional Neural Network (Faster R-CNN) method in deep learning which is currently popular to increase the accuracy value in detecting TB disease.

2. METHODOLOGY

This research develops a Smear Negative Pulmonary Tuberculosis diagnosis model using the Deep Learning method using the Faster R-CNN algorithm. The data used in this research are x-ray images of the lungs at the Jakarta Repository Center - Indonesian Tuberculosis Eradication Center (JRC-PPTI) clinic, totaling 220 datasets. At the preprocessing stage, the images used for training and testing were used with a size of 1280 x 1280 to see the effect on the accuracy of the prediction results of the Faster RCNN model. The test results are in the form of accuracy values that reflect the performance of the Faster RCNN model in classifying normal (without TB) and abnormal (with TB) test data.

3. RESULTS AND DISCUSSION

1. Results

a. Research Implementation

In this study, the dataset was divided into training and testing data, with 75% training images and 25% testing images. The training image is labeled using the Img label, producing an img file for labeling training images. Images to be used in the training process which is useful as a ground truth box to produce anchors in the training process. System training to detect TB in images using the convolution neural network method with the Resnet50 architecture. The results of labeling using labelImg can be seen in Figure 1. and the Image Labeling process using LabelImg can be seen in Figure 2

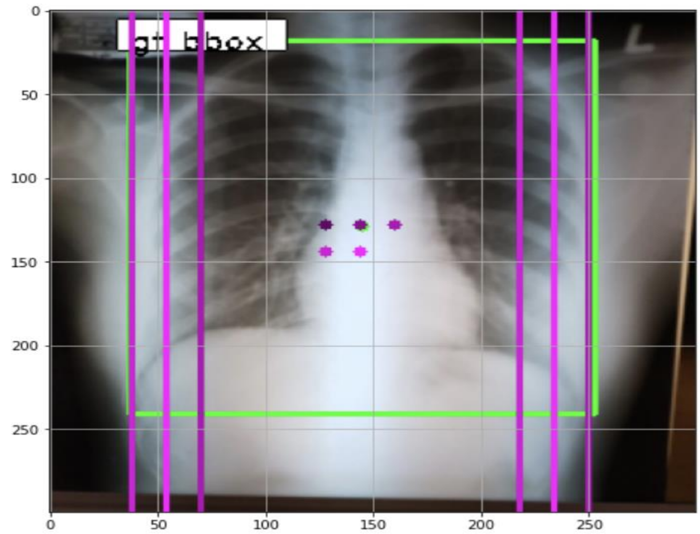


Figure 1. Image Labeling Process

```
    # Add text
    textLabel = 'gt bbox'
    (retval,baseLine) = cv2.getTextSize(textLabel,cv2.FONT_HERSHEY_COMPLEX,0.5,1)
    textOrg = (gt_x1, gt_y1+5)
    cv2.rectangle(img, (textOrg[0] - 5, textOrg[1]+baseLine - 5), (textOrg[0]+retval[0] + 5, textOrg[1]-retval[1] - 5), (0, 0, 0), 2)
    cv2.rectangle(img, (textOrg[0] - 5,textOrg[1]+baseLine - 5), (textOrg[0]+retval[0] + 5, textOrg[1]-retval[1] - 5), (255, 255, 255), -1)
    cv2.putText(img, textLabel, textOrg, cv2.FONT_HERSHEY_DUPLEX, 0.5, (0, 0, 0), 1)

    # Draw positive anchors according to the y_rpn_regr
    for i in range(debug_num_pos):

        color = (100+i*(155/4), 0, 100+i*(155/4))

        idx = pos_regr[2][i*4]/4
        anchor_size = C.anchor_box_scales[int(idx/3)]
        anchor_ratio = C.anchor_box_ratios[2-int((idx+1)%3)]

        center = (pos_regr[1][i*4]*C.rpn_stride, pos_regr[0][i*4]*C.rpn_stride)
        print('Center position of positive anchor: ', center)
        cv2.circle(img, center, 3, color, -1)
        anc_w, anc_h = anchor_size*anchor_ratio[0], anchor_size*anchor_ratio[1]
        cv2.rectangle(img, (center[0]-int(anc_w/2), center[1]-int(anc_h/2)), (center[0]+int(anc_w/2), center[1]+int(anc_h/2)), color, 2)
#         cv2.putText(img, 'pos anchor bbox '+str(i+1), (center[0]-int(anc_w/2), center[1]-int(anc_h/2)-5), cv2.FONT_HERSHEY_DUPLEX, 0.5, color, 1)

print('Green bboxes is ground-truth bbox. Others are positive anchors')
plt.figure(figsize=(8,8))
plt.grid()
plt.imshow(img)
plt.show()
```

Figure 2. Image Labeling Process using LabelImg

b. Training

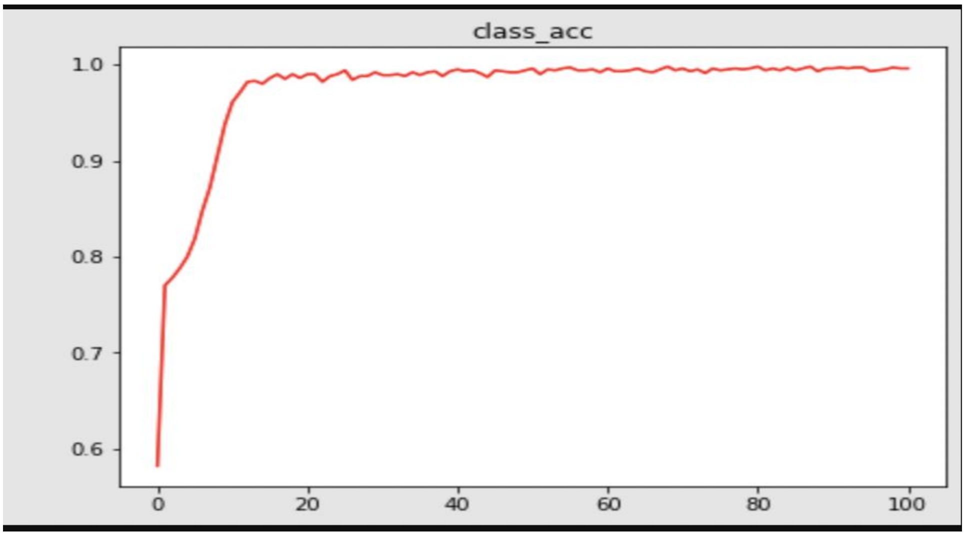


Figure 3. Accuracy Value Results

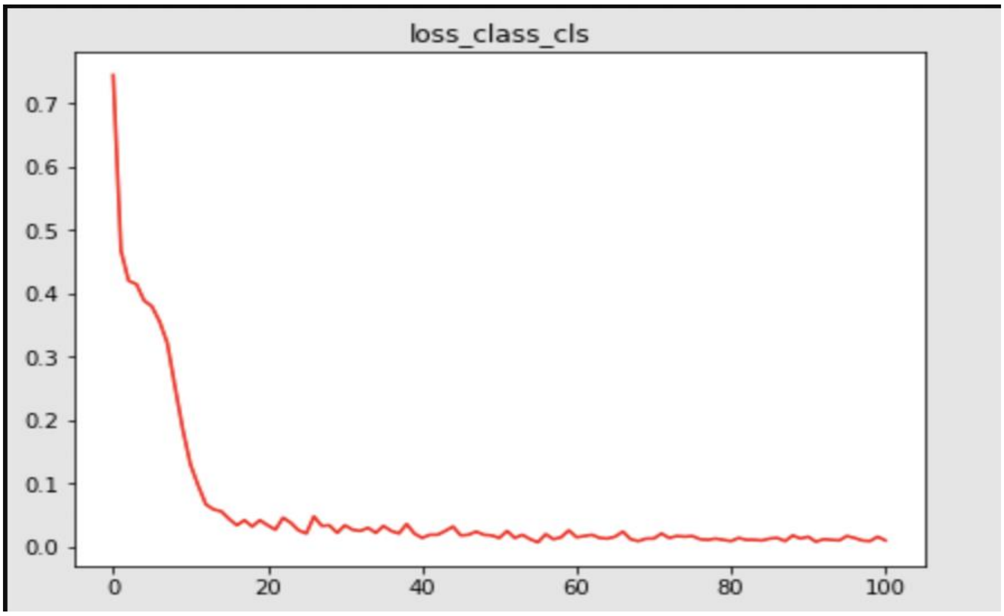
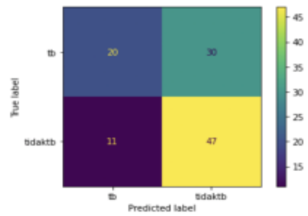


Figure 4. Loss Value Results

In the image 3 above, the training process was built using Google Collaboration with 100 epochs, Adam optimizer, learning rates 0.0001 and 220 batch sizes in training using the Resnet architectural process which obtained the "*.h5" model. Calling the training image then the image is divided by 220 from the batch size so that 1 epoch goes through a process of 220 images then it is completed up to 100 epochs where with the Resnet architecture we get the lowest value of total loss which is divided into loss in training 0.0001 and for the lowest value the total loss function is 0.3 can be seen in image 4 above. Training is carried out for 7 hours.

c. Faster RCNN Model Testing

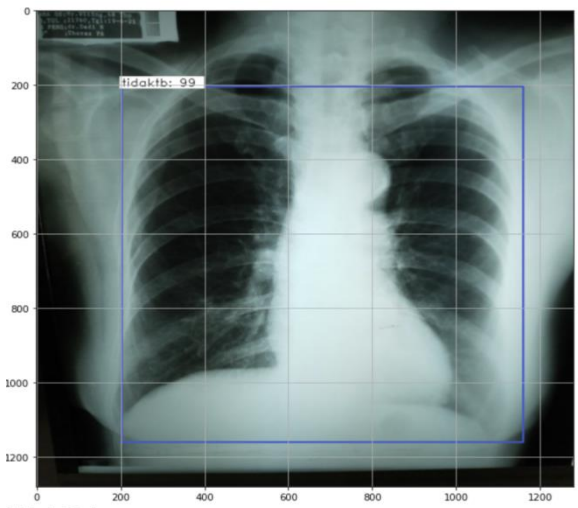
```
from sklearn import metrics
confusion_matrix = metrics.confusion_matrix(prediksi_df['y'], prediksi_df['prediksi'])
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display_labels = ['tb', 'tidaktb'])
cm_display.plot()
plt.show()
```

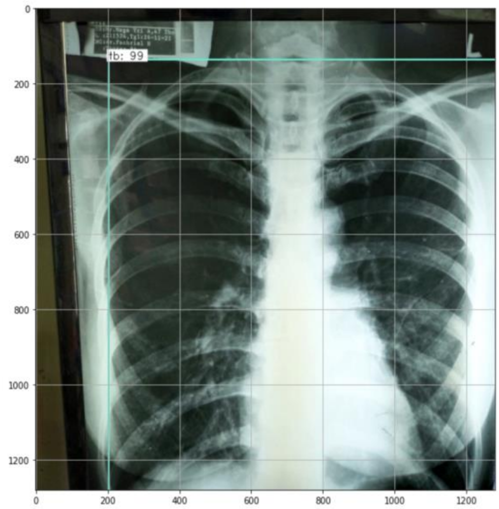



```
#Faster R-CNN
print("---FasterRCNN (Resnet-50)---")
# accuracy: (tp + tn) / (p + n)
accuracy_FasterRCNN = metrics.accuracy_score(prediksi_df['prediksi'], prediksi_df['y']) * 100
print("Accuracy with FasterRCNN: {0:.2f}%".format(accuracy_FasterRCNN))
# precision tp / (tp + fp)
precision_FasterRCNN = metrics.precision_score(prediksi_df['prediksi'], prediksi_df['y'], pos_label="tb") * 100
print("Precision with FasterRCNN: {0:.2f}%".format(precision_FasterRCNN))
# recall: tp / (tp + fn)
recall_FasterRCNN = metrics.recall_score(prediksi_df['prediksi'], prediksi_df['y'], pos_label="tb") * 100
print("Recall with FasterRCNN: {0:.2f}%".format(recall_FasterRCNN))
# f1: 2 tp / (2 tp + fp + fn)
f1_FasterRCNN = metrics.f1_score(prediksi_df['prediksi'], prediksi_df['y'], pos_label="tb") * 100
print("F1-Score with FasterRCNN: {0:.2f}%".format(f1_FasterRCNN))
print("---------")
```

```
---FasterRCNN (Resnet-50)---
Accuracy with FasterRCNN: 62.04%
Precision with FasterRCNN: 40.00%
Recall with FasterRCNN: 64.52%
F1-Score with FasterRCNN: 49.38%
---------
```

Prediction Result: Normal
Prediction Result: TB





Actual Results: Normal (No TB) Actual Results: TB

Figure 5. Faster RCNN Test Results

The next stage is a testing process that uses test data to determine the extent to which the classifier model has succeeded in classifying correctly. Each model's performance will be measured by calculating the accuracy of its predictions. The results of testing the Faster RCNN model are in the form of a confusion matrix which can then be used for testing by calculating accuracy, precision, recall and F1 score values. The accuracy value obtained on the Faster RCNN model during the testing process using the ResNet 50 model has an accuracy value of 62.04%, Precision of 40.00%, Recall of 64.52% and F1-score of 49.38% can be seen in Figure 4.4.

2. Discussion

a. Training

In this research, the training process was built using Google Collaboration with 100 epochs, Adam optimizer, learning rates 0.0001 and 220 batch sizes in training using the Resnet architectural process which obtained the "*.h5" model. Calling the training image then the image is divided by 220 from the batch size so that 1 epoch goes through a process of 220 images then it is completed up to 100 epochs where with the Resnet architecture we get the lowest value of total loss which is divided into loss in training 0.0001 and for the lowest value the total loss function is 0.3 . Training is carried out for 7 hours. The model that has been obtained in this research is still in the classification and diagnosis stage using x-ray images to determine the level of accuracy obtained from the model. In Figure 4.3 the accuracy results and Figure 4 show the loss results as the results from training on the Resnet architecture.

b. Faster RCNN Model Testing

In Figure 5, there is a testing process that uses test data to determine the extent to which the classifier model has succeeded in classifying correctly. The performance of each model will be measured by calculating the accuracy of its predictions. An example of the prediction results in the testing process can be seen in Figure 5. After going through the testing process, each image in the test data will receive an additional prediction result label in the form of the class name, normal or TB. .The results of testing the Faster RCNN model are in the form of a confusion matrix which can then be used for testing by calculating the values of accuracy, precision, recall and F1 score. The accuracy values obtained on the Faster RCNN model during the testing process can be seen in Figure 3. Using the ResNet 50 model has an accuracy value of 62.04%, Precision of 40.00%, Recall of 64.52% and F1-score of 49.38% can be seen in Figure 4.4 .

4. CONCLUSION

From the results of this research, it was concluded that the Faster RCNN model test results using the ResNet 50 model had an accuracy value of 62.04%, Precision of 40.00%, Recall of 64.52% and F1-score of 49.38%.

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