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Comparison of Mycobacterium Tuberculosis Image Detection Accuracy Using CNN and Combination CNN-KNN

Waluyo Nugroho[1], R. Rizal Isnanto[2], Adian Fatchur Rochim[3]
[1]Department of Electrical Engineering, Faculty of Engineering, Diponegoro University
[2,3]Department of Computer Engineering, Faculty of Engineering, Diponegoro University
[1]waluyo.programmer@gmail.com, [2]rizal_isnanto@yahoo.com, [3]adian@ce.undip.ac.id

Abstract

Mycobacterium tuberculosis is a pathogenic bacterium that causes respiratory tract disease in the lungs, namely tuberculosis (TB). The problem is to find out the bacterial colonies when the observation is still done manually using a microscope with a magnification of 1000 times. It took a long time and was tiring for the observer's eye. Based on this background, an automatic detection system for Mycobacterium tuberculosis was designed. Mycobacterium tuberculosis image data were obtained from the Semarang City Health Center. The dataset used is 220 sputum images, which are divided into 180 training data and 40 testing data. The method used in this research is a combination of Convolutional Neural Network (CNN) and K-Nearest Neighbor (KNN). CNN is used for image feature extraction. Furthermore, the results of the CNN feature extraction are classified using the KNN. The results of the accuracy of the combination of CNN-KNN and CNN were also compared. The stages of the process are color transformation, feature extraction, and data training with CNN, then classification with KNN. The results of the classification test between CNN and the CNN-KNN combination show that the CNN-KNN combination is better. The result of CNN-KNN accuracy is 92.5%, while CNN's accuracy is 90%.

Keywords: mycobacterium tuberculosis, automatic detection system, convolutional neural network, k-nearest neighbor

1. Introduction

Tuberculosis is an infectious disease caused by the bacterium Mycobacterium tuberculosis [1]. This disease can attack the lungs, circulatory system, lymphatic system, and respiratory tract, so if left unchecked it can cause human death [2]. Tuberculosis is caused by a dirty environment and humid areas. This disease can be transmitted between humans when coughing, sneezing, and talking [3].

Mycobacterium tuberculosis has a rod shape with varying curvature and a length between 1 to 10 mm [4]. Based on the 2019 WHO report, TB disease is still the most common cause of death. It is estimated that TB patients have increased to 10 million people, while deaths due to TB have increased by 208,000 people, from 88% of adults and 12% of children. Common countries with a large percentage are India (26%), Indonesia (8.5%), China (8.4%), Philippines (6.0%), Pakistan (5.7%), Nigeria (4.4%), Bangladesh (3.6%) and Africa South (3.6%) [5]. Every year, millions of people around the world are infected with tuberculosis, so WHO announced that tuberculosis is a global emergency disease.

The city of Semarang, Central Java, Indonesia has many tuberculosis patients. In 2019, male tuberculosis patients in Semarang reached 3,438, while there were 1,875 cases in women, and children have 840 cases [6]. The case value for men is higher, this is because men are less concerned about the aspect of maintaining individual health than women. Tuberculosis has the risk of being transmitted to all ages and genders, so prevention and treatment must be taken seriously. The dataset used in this research will be taken from the Semarang City Public Health Center.

Tuberculosis can be detected in several ways, including chest X-ray (CXR), sputum microscopy, GeneXpert MTB/RIF test, tuberculin skin test (TST), and interferon-gamma release assay (IGRA) [7]. Examination of tuberculosis patients using a microscope on sputum to detect Mycobacterium tuberculosis bacteria is still a popular diagnostic test in several countries, because of its low cost. Examination of tuberculosis with a microscope can be done with a Ziehl-Neelsen (ZN) staining process and a microscope magnification of 1000x [8]. The ZN staining process is used to change the color of Mycobacterium tuberculosis bacteria to red on a blue background, so that the

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examination of bacteria using a microscope can be seen clearly [8]. The technique of examining Mycobacterium tuberculosis bacteria using a microscope still uses the conventional system, namely checking manually through a microscopic eye lens with the naked eye, so it takes a lot of time and reduces the accuracy of detection [9].

Manual checking of Mycobacterium tuberculosis bacteria using a microscope also requires a lot of concentration of mind and body, for that it is necessary to develop an automatic detection system for Mycobacterium tuberculosis bacteria [10]. Mycobacterium tuberculosis detection results with automated procedures can improve accuracy and faster time [11]. Several methods in the detection of tuberculosis have been carried out, such as a classification system using K-Nearest Neighbor (KNN), artificial neural networks, and deep learning Convolutional Neural Network (CNN) [12],[13],[14].

In other research, a combination of machine learning and deep learning methods has been carried out to improve accuracy in image processing systems. This research was conducted by Sharifonnasabi, discussing the Hybrid CNN-KNN system to improve the accuracy of age estimation in orthopantomography [15]. The results of the accuracy of the method are compared with the CNN method and the SVM method. The result is that the combination of the CNN-KNN method has the highest level of accuracy [15]. The CNN-KNN combination research was also carried out by Shaila Shanjida, which compared the ANN method with the CNN-KNN combination for tumor detection in MRI images [16]. The result is that the CNN-KNN combination has the highest accuracy.

The CNN method has been widely used by researchers to classify images [17]. The CNN algorithm is claimed to be the best method for solving the problem of acquiring an object [18]. There are several CNN architectures used in image classification, including ImageNet, GoogleNet, AlexNet, VGGNet, and ResNet 101. CNN architecture using ResNet can be used for image classification on ImageNet image datasets with an accuracy of 80.62% and has won several competitions in 2015, beating the architectures of GoogleNet, AlexNet, and VGGNet [19].

The CNN method can perform feature extraction and classification automatically, but the CNN-Softmax classification has a large number of parameters that are difficult to set, so the results of the CNN classification are not perfect [20]. While classification using machine learning can be set several parameters for classification.

Based on the literature research, the researcher wants to develop a detection system for Mycobacterium tuberculosis by combining CNN and KNN. CNN method is used for feature extraction, then the results of the feature extraction will be classified using KNN [15]. The combination of CNN-KNN method is used to increase the accuracy of Mycobacterium tuberculosis detection. This research will compare the results of classification using CNN and the combination of CNN-KNN methods.

2. Research Methods

Mycobacterium tuberculosis detection process is carried out in several stages. The first stage is entering image data, then dividing the data into training data and testing data. The second stage is the image preprocessing process, namely image resizing, color segmentation, and image augmentation. Image resizing is used to equalize the size of the image to a size of 150×150 pixels. Color segmentation is used to change the background color and the color of the tuberculosis bacteria. The results of color segmentation will change the background color of the image to white, while the tuberculosis bacteria become black. After preprocessing the image, the feature extraction process is carried out using CNN.

The CNN feature extraction uses 6 convolutional layers, then the results from the convolutional layers will be converted into a single vector in the flattened layer. The result of feature maps in the flattened layer will be processed by KNN classification [21]. The KNN algorithm is used to classify tuberculosis bacteria and non-tuberculosis bacteria. The selection of the value of the K variable by doing several variations of the value of the K variable is used to get the highest accuracy in the CNN-KNN combination. The flow chart research method for the detection of Mycobacterium tuberculosis is shown in Figure 1.

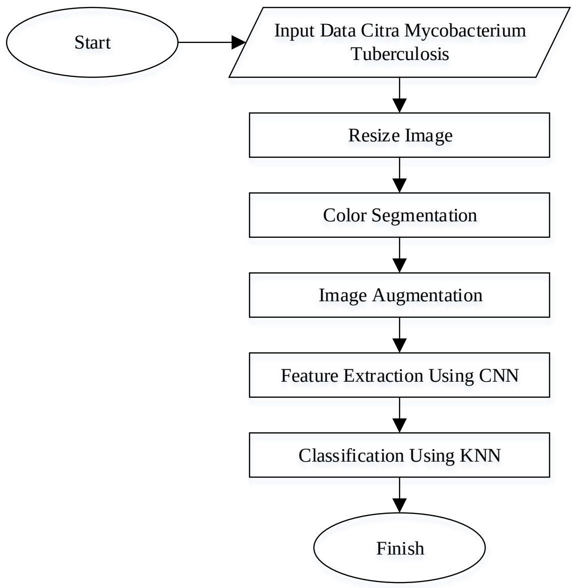

Figure 1. Flow chart research method detection mycobacterium tuberculosis

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2.1 Dataset Mycobacterium Tuberculosis

The dataset was obtained from the Semarang City Public Health Center. The total dataset is 220 images, namely 180 images for training and 40 images for testing. An example of a non-tuberculosis dataset is shown in Figure 2. While the tuberculosis image is shown in Figure 3.

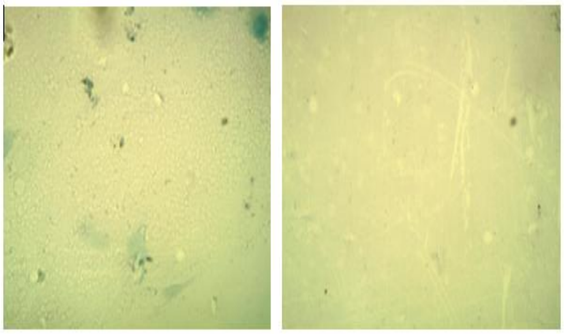

Figure 2. Non-tuberculosis images

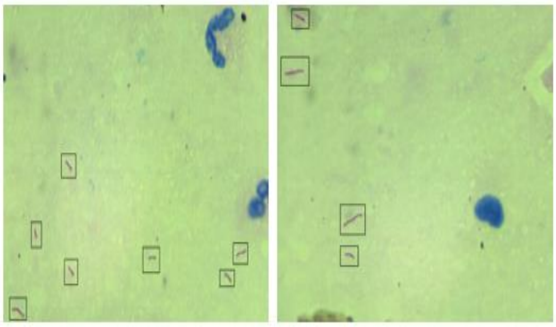

Figure 3. Tuberculosis image

The training data of 180 images is divided into 115 tuberculosis images and 65 non-tuberculosis images. While the testing data is 40 images, namely 20 images of tuberculosis and 20 images of non-tuberculosis. The graph of the amount of training data is shown in Figure 4. While the graph of the amount of testing data is shown in Figure 5.

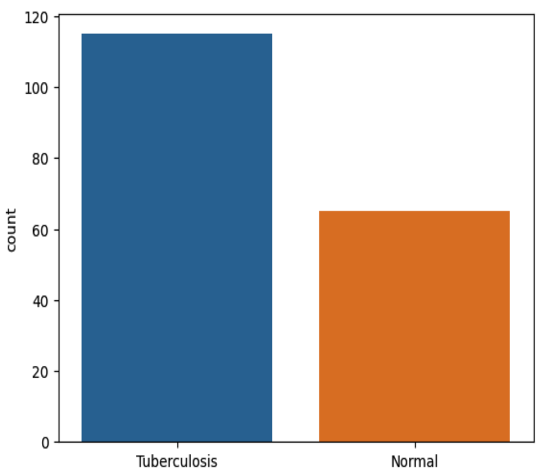

Figure 4. Total training data

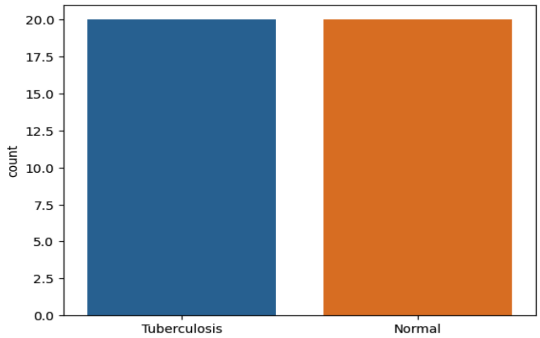

Figure 5. Total testing data

2.2 Preprocessing

In the preprocessing stage, the image resizing process is carried out to equalize the image size, which is 150×150 pixels, then the color segmentation process is carried out. The RGB color image will be converted into a grayscale image, then converted into a binary image. The results of the binary image will be augmented by image augmentation to increase the dataset and increase the accuracy of the model [22]. After the augmentation process, the resulting image will be processed into CNN.

2.3 Color Segmentation

Color segmentation is a method in image processing that is used to separate objects from the background in digital images [23]. Color segmentation used in this research is a binary image. RGB image input data will be converted into a grayscale image. Furthermore, the grayscale will be converted into a binary image [24]. The binary image at the preprocessing stage will be carried out by an image augmentation process, then the image augmentation results will enter the CNN. An example of an image conversion image is shown in Figure 6.

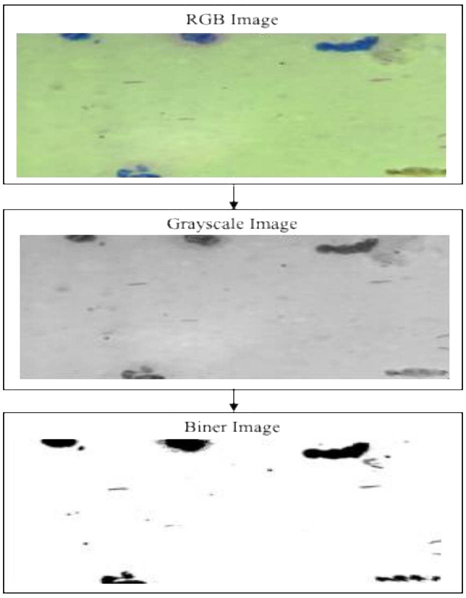

Figure 6. Mycobacterium tuberculosis image conversion

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2.4 Image augmentation

Image augmentation is used to add datasets, so as to increase the accuracy of the model [21]. The parameters used in this image augmentation are rescale = 1./255, zoom_range = 0.2, rotation_range = 30, width_shift_range = 0.1, height_shift_range = 0.1, horizontal_flip = True.

2.5 CNN feature extraction model architecture

Convolutional Neural Network (CNN) is a feature extraction method that belongs to the deep learning group that uses convolution layers to convolution an input with filtering [25]. CNN consists of two main stages, namely feature extraction, and classification.

The feature extraction stage consists of a convolution layer, ReLU (activation function), pooling layer, and flatten layer. While at the classification stage it consists of dense layers. The CNN architecture in this research uses 25 layers, there are 6 convolutional layers 2D with reLu activation functions and max-pooling layers. The filter used in convolutional 2D is 3×3. The hyperparameter table on the CNN model feature extraction is shown in Table 1.

Table 1. Hyperparameters in CNN model feature extraction

Layer (type)	Output Shape	Param #
1stConvolution (Conv2D)	(None, 150, 150, 16)	448
1stMaxPool (MaxPooling2D)	(None, 75, 75, 16)	0
2ndConvolution (Conv2D	(None, 75, 75, 32)	4640
Dropout1 (Dropout)	(None, 75, 75, 32)	0
2ndMaxPool (MaxPooling2D	(None, 38, 38, 32)	0
3rdConvolution (Conv2D)	(None, 38, 38, 64)	18496
3rdMaxPool (MaxPooling2D)	(None, 19, 19, 64)	0
4thConvolution (Conv2D)	(None, 19, 19, 128)	73856
Dropout2 (Dropout)	(None, 19, 19, 128)	0
4thMaxPool (MaxPooling2D)	(None, 10, 10, 128)	0
5thConvolution (Conv2D)	(None, 10, 10, 256)	295168
Dropout3 (Dropout)	(None, 10, 10, 256)	0
5thMaxPool (MaxPooling2D)	(None, 5, 5, 256)	0
6thConvolution (Conv2D)	(None, 5, 5, 512)	1180160
Dropout4 (Dropout)	(None, 5, 5, 512)	0
6thMaxPool (MaxPooling2D)	(None, 3, 3, 512)	0
Flatten (Flatten)	(None, 4096)	0

The output of the convolutional layer will be processed by the flatten layer to convert 3 dimensions into 1 dimension. In the CNN classification system, the value of the flatten layer will be classified in the fully connected layer with sigmoid activation. While the CNN-KNN combination method, will take the value of the feature map from the flatten layer as a feature extraction, then classified by the KNN method [15].

2.6 Classification using CNN

The CNN classification system uses the value of the flatten layer feature maps and then it will be processed in a fully connected layer using 3 reLu activation dense layers and 1 sigmoid activation dense layer using the rmsprop optimizer. The hyperparameter table Hyperparameters in the CNN model classification is shown in Table 2.

Table 2. Hyperparameters in the CNN model classification

Layer (type)	Output Shape	Param #
Dense1 (Dense)	(None, 128)	524416
Dense2 (Dense)	(None, 64)	8256
Dropout6 (Dropout)	(None, 64)	0
Dense3 (Dense)	(None, 32)	2080
Dense4 (Dense)	(None, 1)	33

As shown in table 2, the fully connected layer uses 4 Dense layers. Dense = 128 with relu activation, Dense = 64 with relu activation, Dense = 32 with relu activation, Dense = 1 with sigmoid activation and rmsprop optimizer. The epoch is 40 and uses the binary_crossentropy classification. The total CNN architecture parameters for feature extraction and classification studied are 2,173,089. The Max-Pooling layer and the dropout layer have no parameters to learn.

2.7 Classification using Combination CNN-KNN

The CNN-KNN combination system uses the CNN process as feature extraction and KNN as a classification. The KNN classification is used to replace the classification on the dense layer CNN. This is because the CNN classification contains a large number of parameters that are very difficult to set so it is not always perfect as a classifier [20]. On the other hand, K-NN requires very little parameter adjustment to provide high classification accuracy for one-dimensional feature vectors, so in this research, KNN is used for classification by taking feature extraction from CNN.

The output feature map in the flattened layer on CNN will be classified using the KNN method. In the CNN-KNN classification, to get high accuracy results, it is seen from the K value variable.

Training and testing were carried out on the CNN-KNN model with different K values to get the K value with the highest accuracy. To find the value of K in the KNN classification using the Euclidean distance [26]. The equation for finding the Euclidean distance is shown in equation 1.

$$D\left(d_x, d_y\right) = \sqrt{(f_{x,1} - f_{y,1})^2 + \ldots + (f_{x,j} - f_{y,j})^2} \quad (1)$$

This research will compare the classification of Mycobacterium tuberculosis with the CNN method with the CNN-KNN combination method. The image input after preprocessing will be processed by CNN to get the feature extraction results.

Furthermore, the CNN feature extraction will be carried out with the sigmoid activation CNN classification and

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the KNN classification. Figure 7 shows a block diagram of CNN and CNN-KNN classification.

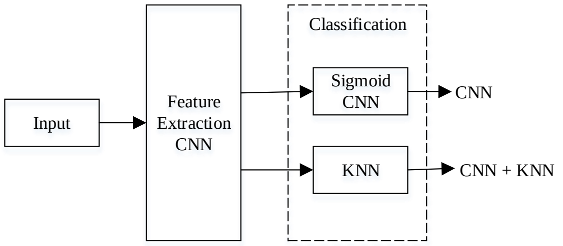

Figure 7. CNN and CNN-KNN classification block diagram

2.8 Performance Test

The method used in the performance test is the confusion matrix model. The parameters measured are accuracy, precision, recall, and f1-score using equations (2), (3), (4), and (5). TP is True Positive, FP is False Positive, TN is True Negative and FN is False Negative [27].

Accuracy shows the accuracy of the results obtained from the closeness of the value obtained with the actual value. Precision is the suitability of the data taken with the required information. Recall is success in getting information back. F1-score is a comparison of the average precision and recall [28].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (5)$$

3. Results and Discussions

Research on this system has been carried out using the python language. The training data used 180 images with 2 classes, namely 115 images of tuberculosis and 65 images of non-tuberculosis. While the data testing uses 40 images with 2 classes, namely 20 images of tuberculosis and 20 images of non-tuberculosis.

The results obtained show that the classification results using the CNN method produce an accuracy of 90%. CNN training uses 40 epochs with sigmoid classification activation and rmsprop optimizer. After training and testing, a plot is made to show a graph of the results of training and testing. The CNN training and the testing graph are shown in Figure 8.

Figure 8. CNN training and testing graph

CNN accuracy results can be seen with the confusion matrix. The confusion matrix shows the evaluation results between correct predictions and wrong predictions. The results of the CNN confusion matrix show 3 false positives and 1 false negative. CNN's performance confusion matrix is shown in Figure 9.

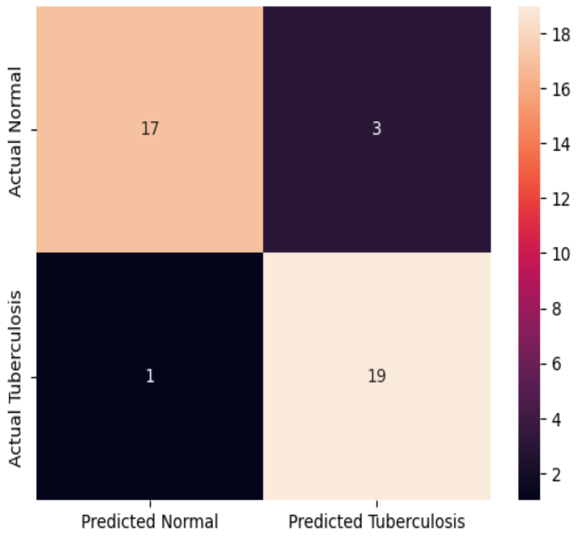

Figure 9. Confusion matrix CNN

In the CNN-KNN combination method, a test was carried out with several K-value variables on KNN. The selection of the value of the K variable on the KNN is done by looking at the value of the accuracy of each K [29]. So that the value of K with the highest accuracy will be taken. The graph of the accuracy of the combination of the CNN-KNN method with variations in the value of K is shown in Figure 10.

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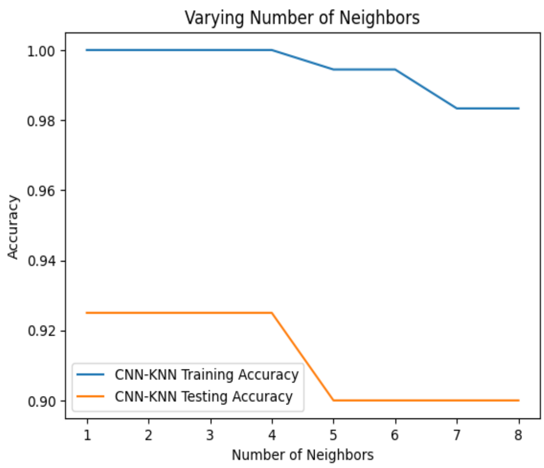

Figure 10. Varying number of neighbors

The graph in Figure 10 shows the accuracy of the CNN-KNN combination with a K value of 1 to 9. Based on the results of the accuracy graph, the highest accuracy value is the value of K = 1 to 4. The value of K = 4 is used in the CNN-KNN combination method. The accuracy performance of the CNN-KNN method can be seen in the confusion matrix image. The evaluation of the model in the confusion matrix is used to measure the performance of deep learning or machine learning models in knowing whether predictions are true or false from the total data [30]. The CNN-KNN confusion matrix shows higher accuracy when compared to CNN. The CNN-KNN confusion matrix has 3 false positives and 0 false negatives. The results of the confusion matrix are shown in Figure 11.

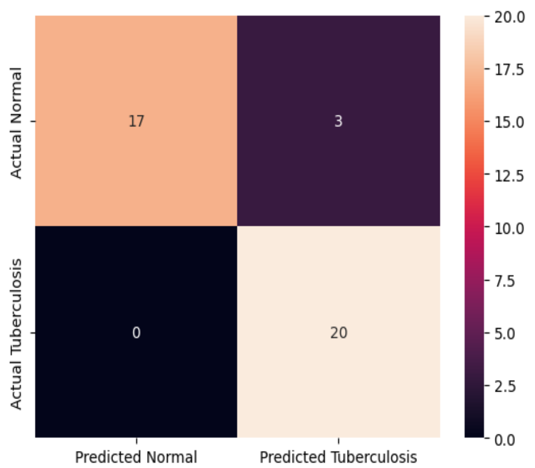

Figure 11. Confusion matrix CNN-KNN

Based on the comparison results of the CNN confusion matrix and the CNN-KNN combination, shows that the accuracy of the CNN-KNN combination method has higher accuracy than CNN. The accuracy of the CNN-KNN combination method is 92.5%, while the CNN accuracy is 90%. The results of the comparison of accuracy, precision, recall, and F1-score between the CNN method and the CNN-KNN combination method are shown in Table 3.

Table 3. CNN and CNN-KNN classification accuracy results

Measurement Average	CNN	CNN-KNN
Accuracy	90%	92.5%
Precision	90%	93.5%
Recall	90%	92.5%
F1 Score	89.5%	92.5%

4. Conclusion

This research compares 2 methods for the detection of Mycobacterium tuberculosis, namely the CNN method and the CNN-KNN combination. The CNN training used 40 epochs with sigmoid activation and rmsprop optimization for classification. While the combination of CNN-KNN uses the results of the flattened layer feature extraction on CNN, then the results of the feature extraction are classified with KNN. The value of the K variable in KNN with the highest accuracy is K = 1 to 4, so the value of K = 4. The results of the confusion matrix comparison of the accuracy values between CNN and the CNN-KNN combination show that the CNN-KNN combination results are better. The CNN-KNN accuracy result is 92.5%, while the CNN accuracy is 90%.

Suggestions for further research on the same topic, it can be done by adding datasets to the CNN-KNN combination method. This research still uses a total of 180 images of Mycobacterium tuberculosis. The addition of the dataset is expected to increase the performance and accuracy of the Mycobacterium tuberculosis detection system.

Acknowledgment

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