Transfer Learning Analysis VGG16 For the Detection of Tuberculosis

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***Abstract* - Indonesia is still one of the countries with the highest growth of TB disease in the world. TB is an infectious disease that can cause severe lung damage, even death. TB is a critical case to be detected early so that patients immediately get the proper treatment. The challenge is the difficulty in diagnosing symptoms that are not specific and similar to other diseases. Therefore, further research is needed to find a faster, more accurate, affordable TB detection method. VGG16 is one of the Convolutional Neural Network (CNN) architectures that has the characteristic of recognizing delicate patterns of chest X-ray images of TB patients. Transfer learning on VGG16 can increase the accuracy of detecting TB disease even though it uses a small amount of training data. The trial results show that the VGG16 transfer learning technique can produce better performance with an accuracy of 94%. The accuracy value can be used to benchmark that the VGG16 transfer learning technique is proven effective in detecting TB disease**

Key words - TBC, Deteksi, VGG16, Transfer Learning

I. INTRODUCTION

Tuberculosis in Indonesia is still a serious health problem and is one of the leading causes of death. Tuberculosis, better known as TB, is an infectious disease that attacks the lungs. The bacteria Mycobacterium tuberculosis causes this disease. Early detection of TB disease can help patients get proper and regular treatment to prevent more serious complications. Rapid treatment can also prevent the transmission of TB to others.

VGG-16 is a convolutional neural network architecture that has great potential in medical diagnostic applications, including the detection of lung diseases such as tuberculosis (TB). VGG-16 consists of 16 convolutional layers designed to efficiently extract features from images [1], [2]. In TB detection, which often requires analysis of chest X-ray images to distinguish between healthy and infected lung tissue, VGG-16 can provide high accuracy by leveraging its ability to recognize patterns and fine details in images [3], [4].

Several studies have shown that VGG-16 provides effective results in lung disease classification and performs well in identifying various other medical conditions using image datasets, including pneumonia and COVID-19. For example, a study involving an X-ray dataset found that VGG-16 was able to detect pneumonia with high accuracy, reflecting its capabilities in tuberculosis detection [4],[5] and in radiographic image analysis for COVID-19 diagnosis [6]

In addition, the evaluation standards conducted on the VGG-16 model showed promising results with high sensitivity, specificity, and F1 value, which are important in a medical context [3], [7]. Thus, VGG-16 is an effective method in addressing the challenges in TB disease diagnosis, leveraging the power of deep feature extraction and a methodology that has proven efficient in various medical applications

In the context of TB detection, studies integrating VGG-16 with transfer learning methods have also shown positive results. For example, some works note that combining image processing techniques and effective feature selection can improve the accuracy of TB image classification, suggesting that using VGG-16 can contribute to more precise pattern recognition [7]. These results demonstrate the capability of the VGG-16 architecture to be adapted to different data, such as for the specific purpose of TB diagnosis [8].

X-ray is one of the diagnostic tools that can detect TB disease through X-ray photos of the lungs. When someone is infected with TB, the bacteria will cause inflammation and damage lung tissue. X-rays can capture these changes. X-rays help doctors assess how much damage has occurred to the lungs due to TB. This is very important to determine the proper treatment.

Image processing techniques can be implemented on chest X-ray results analyzing pixel intensity patterns to identify typical texture changes in lung tissue infected with TB through deep learning methods. Deep learning uses artificial neural networks to learn from large amounts of X-ray data and recognize complex patterns, thereby reducing diagnostic errors that may occur due to human factors [9]

A fairly popular deep learning model is the Convolutional Neural Network VGG16 architecture [7], [8]. VGG16 is designed with a stack of deep convolution layers that allow this model to extract very detailed features in lung X-ray images by performing transfer learning. The transfer learning technique in VGG16 makes it easier for the model to adapt to specific tasks such as TB detection even though it uses little training data. This study analyzes the effect of using transfer learning on VGG16 to detect TB disease and measures model performance with a confusion matrix.

II. MATERIALS AND METHODS

This study analyzes the results of implementing transfer learning VGG16 on the TB detection system

A. System Design

The research flow starts by preparing a dataset of lung X-ray images for the TB disease detection process, as shown in Figure 1. VGG16 model training uses transfer learning techniques so that when detecting TB with large data, there is no need to start training from the beginning again. The model's performance is then evaluated using a confusion measurement matrix.

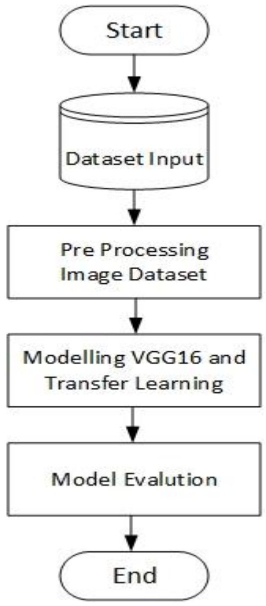
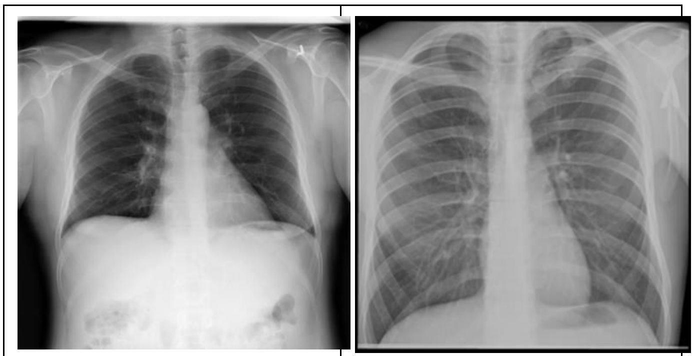


Figure 1. Research Flow

B. *TB Dataset*

The data used in this study were taken from the Kaggle public dataset. The description of the dataset includes a database of lung X-ray images with a total of 3500 normal images and 3500 images of TB patients. The total number of images entered into the database is 7000 files. The following are examples of normal lung and lung X-ray images of TB patients.



(a) (b)

Figure 2. a) Normal Lung Image, b) Lung Image of TB Patient

C. *Preprocessing of TBC Dataset Image*

Before the training process with the VGG16 model and transfer learning, the image is first prepared by separating the dataset into two groups according to the normal and tuberculosis labels. Furthermore, an augmentation process is carried out where each dataset image is preprocessed in the form of shear_range, rotation_range, width_shift_range, height_shift_range, horizontal_flip and vertical_flip. In addition, image resizing is carried out to change the image size and adjust it to the input of the model to be trained.

The lung X-ray image dataset totalling 7000 with 3500 per class will be subjected to 10-fold cross-validation so that the dataset will be divided into 9:1 parts. The 9:1 division of the dataset will consist of 6300 *training* and 700 validation

D. *VGG16 Architecture Modeling*

The VGG16 architecture is one of the models in artificial neural networks widely used in image classification, including in practical applications in various fields. VGG16, designed by the Visual Geometry Group in Oxford, is known for its capacity to extract detailed features from images through cascaded convolutional layers, allowing it to perform well in visual pattern recognition. The VGG16 model is often used in image classification tasks by applying transfer learning techniques. In transfer learning, a model previously trained on a large dataset, such as ImageNet, is used as a starting point for training a more specific task. For example, Madhuri et al. used VGG16 for chilli leaf disease classification, where they adjusted the final layers of the model for the new dataset, thereby improving classification accuracy [10]. Similarly, Riyadi et al. applied VGG16 for weather category classification, finding that this architecture effectively processed images to classify weather conditions based on visual details [11].

Other studies have shown that VGG16 can also be implemented for skin disease classification. Nurkhasanah and Murinto used this architecture to detect five types of facial skin diseases, demonstrating its reliability in a medical context [12]. In addition, Supirman et al. reported using VGG16 to classify seven types of skin diseases, with an accuracy of 82.14% and showing promising results [13]. This shows that VGG16 is a strong choice in medical and agricultural applications, especially when combined with image augmentation techniques to improve training results [14]. Furthermore, recent studies have explored the combination of VGG16 with other architectures, such as ResNet34, to improve accuracy in detecting plant diseases. The results showed that the combination of these two models performed better than using a single architecture alone, confirming the flexibility and adaptability of VGG16 in more complex contexts [15]. With an accuracy of 95.93% on a specific test dataset, VGG16 is a very effective tool in image-based classification models across many disciplines, from agriculture to health.

After pre-processing the dataset, the next step is to design the model and architecture of the Convolutional Neural Network (CNN) used, the Visual Geometry Group (VGG-16) model. This model has special characteristics in its deep learning model, which consists of 16 layers, including 13 convolutional layers and three fully-connected layers. These layers are arranged into blocks, each containing several convolutional layers followed by a max pooling layer for down.

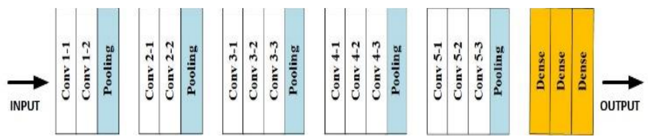


Figure 3. VGG-16 Architecture Diagram

The following are the details of the VGG-16 architecture, including:

1. Input layer with input dimensions: (224, 224, 3)
2. Convolutional layer (64 filters, 3x3 filters) padding same with 64 filters, each with a filter size of 3x3

3. Max pooling layer (2x2, stride 2)
4. Convolutional layer (128 filters, 3x3 filters, padding "same")
5. Max pooling layer (2x2, stride 2)
6. Convolutional layer (256 filters, 3x3 filters, padding "same")
7. Convolutional layer (512 filters, 3x3 filters, padding "same")
8. Max pooling layer (2x2, stride 2)
9. Stack of convolutional and max pooling layers
10. Flattening
11. Fully-connected layer

E. *Transfer Learning*

Transfer learning is an increasingly popular technique in developing Convolutional Neural Network (CNN) models, especially in image processing. In a basic sense, transfer learning allows the use of information already obtained from a previously trained model to improve the model's performance on a new dataset that may be smaller or more difficult. This is especially useful when the training dataset for a particular application is insufficient to produce a performant model. One example of the application of transfer learning can be found in a study conducted by Hasanat et al., who evaluated using a CNN model pre-trained on spectral data for land cover classification with a limited dataset. This study showed that transfer learning can significantly improve classification accuracy on imbalanced data [16]. In a similar context, Naufal and Kusuma also applied transfer learning to classify facial images with masks, showing how this technique can speed up the training process and improve classification results [17].

Transfer learning is effective in a variety of applications, including disease detection. For example, Apostolopoulos and Mpesiana applied this method to detect COVID-19 from X-ray images, trying to maximize the performance of an existing CNN by adapting the model to a new, smaller dataset [18]. In addition, Pane and Sihombing conducted a study on bird species classification using the transfer learning approach, comparing several CNN architectures and confirming how this technology leverages existing models to produce accurate classifications [19].

Transfer learning in Convolutional Neural Networks (CNN) is a machine learning technique where a model trained on one task is used as a starting point for another related task without having to retrain it from scratch. The use of transfer learning in CNNs can save time and computation. Models that utilize this feature representation can achieve higher accuracy on other new tasks, especially when the dataset for the new task is limited.

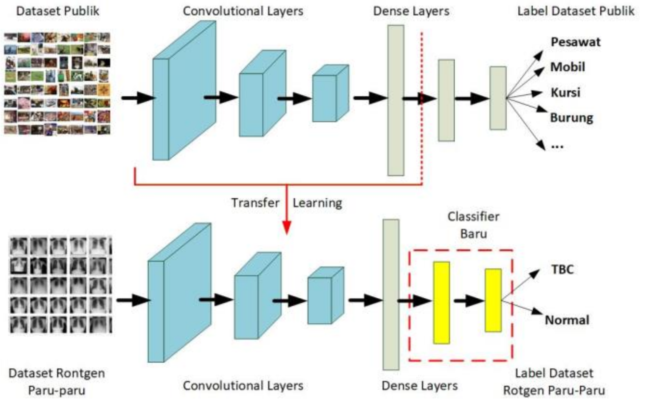


Figure 4. VGG16 Transfer Learning Model Architecture

Here is how VGG16 transfer learning works as in the architecture of Figure 4 above:

- Feature Extraction.
  The initial layer in a pre-trained CNN will extract high-level features from the input images of the public dataset. These features are generally general and can be applied to various types of images.
- Layer Freezing
  The initial layer in a trained model is usually frozen, meaning that the weights in that layer are not updated during training. This is done because the initial layer has learned very good features.
- Adjusting the Final Layer
  The final layer in the trained model is replaced with a new layer (new classifier) appropriate for the new task, namely for detecting TB disease based on the lung X-ray dataset.

F. *Performance Measurement*

The proposed model in the study was measured using 10-fold cross-validation, which is most commonly used in evaluating machine learning models. The lung X-ray image data was divided into 10 equal parts. Furthermore, the training and testing process was carried out 10 times. Each iteration used one fold as test data, while the remaining nine folds were used as training data. The performance matrix, namely accuracy, precision, recall, F1-Score, was calculated at each iteration. After completing all iterations, the matrix values were averaged to estimate the model's performance

Confusion Matrix

A table that compares the predicted values with the actual values allows for a more detailed and accurate analysis of the model's success in predicting the correct class [9], [20].

TABLE I. CONFUSION MATRIK

Actual	**Predictions**	
	Positive	**Negative**
Positive	True Positive (TP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TN)

Accuracy

Accuracy is a comparison of success in guessing the truth in all classes. The higher the accuracy value, the better the model predicts the correct label.

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

Precision

Precision shows how many optimistic predictions the model makes are positive.

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

Recall

Recall shows how capable the model is in detecting all objects that should be classified as positive

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

F1-Score

An indicator that shows the balance of the model in detecting objects with precision and its level of sensitivity.

$$F1\ Score = 2 \times \frac{Presisi \times Recall}{Presisi + Recall} \quad (4)$$

Results and Discussion

The test was carried out by comparing the accuracy between the CNN model and the VGG16 Model using transfer learning. The following is the CNN model configuration with the parameters shown in Table 2.

TABLE II. CNN PARAMETER CONFIGURATION

Parameter	Value
Padding	Same
Pooling	Max
Activation	Relu & Sigmoid
Optimizer	Rmsprop
Loss	Binary cross-entropy
Metics	Accuracy
Epoch	20
Step_per_epoch	100

According to the CNN model used in this experiment, in epoch one, it achieved a loss of 0.79 with an accuracy of 58% and a validation loss of 0.77. With a validation accuracy of 55%. However, in epoch 8, there was a significant increase with a loss of 0.43, an accuracy of 77%, and a validation loss of 0.56, with a validation accuracy of 82%. In epoch 14, fluctuations were seen with a loss of 0.30. And an accuracy of 86% and a validation loss of 0.62. And a validation accuracy of 72%. At the end of training, the model achieved a loss of 0.30 and an accuracy of 87%, with a validation loss of 0.55 and a validation accuracy of 74%. This process shows that the model has successfully learned during training but fluctuates at some point.

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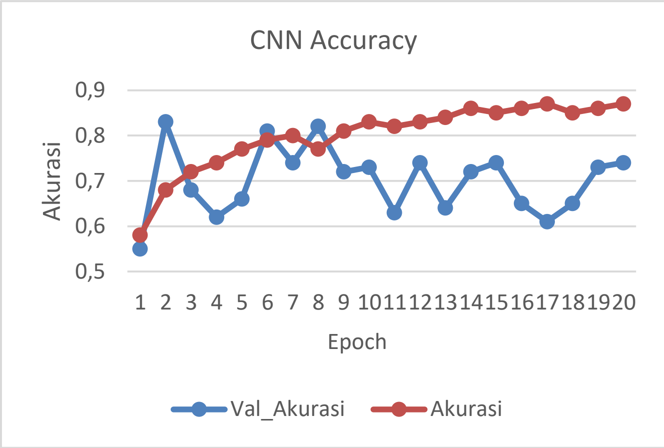

Figure 5. CNN Model Accuracy Graph

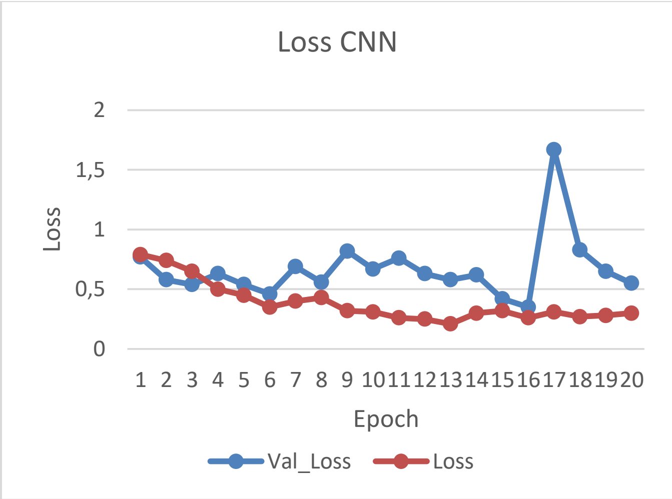

Figure 6. CNN Model Loss Graph

The next stage is a trial with the VGG16 transfer learning model. This VGG16 model uses pre-training weights from ImageNet, which will later be used as the starting point for training the TB disease detection model. The following is a table of the VGG16 transfer learning model configuration

TABLE III. VGG16 PARAMETER CONFIGURATION

Parameter	Value
Weight	ImageNet
Pooling	Max
Activation	Relu & Sigmoid
Optimizer	adam
Loss	Binary cross-entropy
Metics	Accuracy
Epoch	20
Step_per_epoch	100

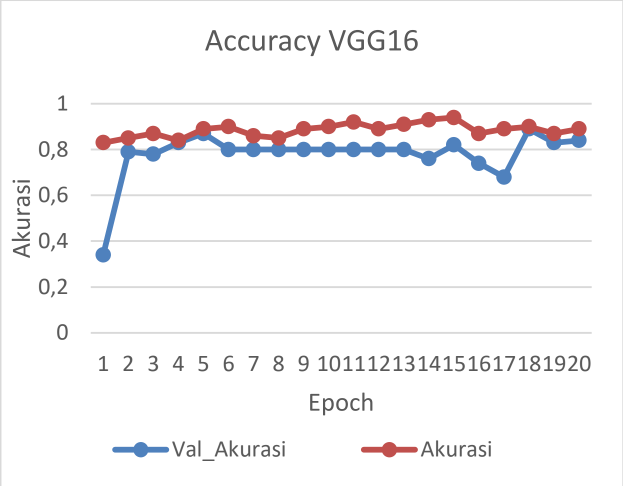

Figure 7. VGG16 Accuracy Chart

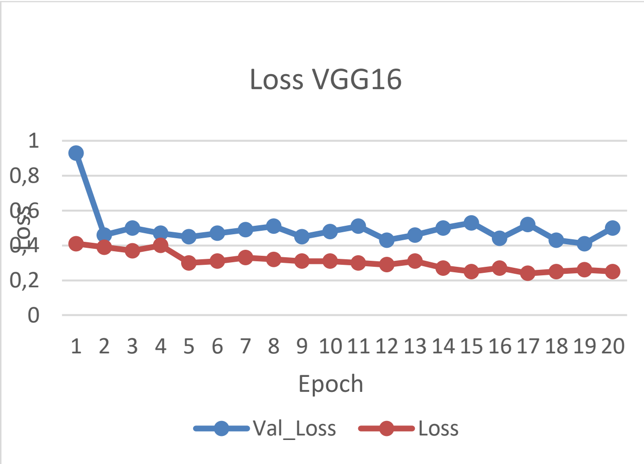

Figure 8. VGG16 Loss Chart

Figures 7 and 8 show that in Epoch 1, the model achieved a loss of 0.41 with an accuracy of 83% and a validation loss of 0.93 with a validation accuracy of 0.34. However, there was a significant increase in epoch 7, where the model achieved a loss of 0.33 with an accuracy of 86%, a validation loss of 0.49 and a validation accuracy of 80%. In epoch 20, the model achieved a loss of 0.25 with an accuracy of 89%, a validation loss of 0.50 and a validation accuracy of 84%.

The results of the evaluation and comparison of the CNN and VGG16 models with transfer learning are listed in Table 4.

TABLE IV. CONFUSION MATRIX EVALUATION RESULT

Model	Acuuration	Presisi	Recall	F1-Score
CNN	87 %	86 %	93 %	0,89
VGG16-transfer leaning	94 %	95 %	95 %	0,95

III. CONCLUSION

The results of TB disease detection on the CNN model in this study achieved the highest accuracy of 87%, Precision of 86%, Recall of 93% and F1 Score of 0.89. At the same time, VGG16 with transfer learning reached 94%, Precision and recall of 95% and F1 score of 0.95. Based on these values, both models can be said to have good performance. However, in terms of accuracy obtained, the VGG16 model with transfer learning can detect TB disease more accurately when compared to the conventional CNN model.

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