

Analysis Influence Segmentation Image on Classification Image X-raylungs with Method Convolutional Neural

Fathur Rahman¹, Nuzul Hikmah¹, Misdiyanto¹

¹Studies Technique Electrical, Faculty Technique, University Panca Marga Probolinggo

Corresponding Author: Misdiyanto (misdie_id@yahoo.com)

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ABSTRACT

The impact of image segmentation on the classification of lung X-ray images using Convolutional Neural Networks (CNNs) has been scrutinized in this study. The dataset used in this research comprises 150 lung X-ray images, distributed as 78 for training, 30 for validation, and 42 for testing. Initially, image data undergoes preprocessing to enhance image quality, employing adaptive histogram equalization to augment contrast and enhance image details. The evaluation of segmentation's influence is based on a comparison between image classification with and without the segmentation process. Segmentation involves the delineation of lung regions through techniques like thresholding, accompanied by various morphological operations such as hole filling, area opening, and labeling. The image classification process employs a CNN featuring 5 convolution layers, the Adam optimizer, and a training period of 30 epochs. The results of this study indicate that the X-ray image dataset achieved a classification accuracy of 59.52% in network testing without segmentation. In contrast, when segmentation was applied to the X-ray image dataset, the accuracy significantly improved to 73.81%. This underscores the segmentation process's ability to enhance network performance, as it simplifies the classification of segmented image patterns.

Keywords: Convolutional Neural Network, Image Photo X-ray lungs, Network Nerves, Segmentation image



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INTRODUCTION

Today's image processing technology has developed increasingly advanced so that image processing technology has emerged to describe images into digital form. One of the most famous digital imaging applications in the medical field to date is X-ray tomography. X-ray tomography is used to record and examine the state and the human body as a whole using X-ray radiation (Watiningsih, 2012), (Anggarini, Muslim, & Mutanto, 2019). Results image X-ray or ray X-ray This often used For diagnose disease in body patient. Diagnosis This usually done by doctor/radiologist by analyzing X-ray images ray for find existing abnormalities.

The lungs are one of the organs that are difficult to detect and diagnose by most radiologists. The health field method used to capture the condition of the lung organs is one of them using X-ray technology (X-ray photos). This technology is a form of radiographic method based on X-ray absorption. The use of X-rays in lung examination is the most commonly used technique. The results of the X-ray process provide different images between healthy and unhealthy lungs, such as normal lungs or lung cancer (Ramdhan, 2016).

However, the examination of lung cancer from X-ray images still has shortcomings, namely some medical practitioners such as lung specialist doctors still rely on visual observations in reading X-ray results so that the results are very subjective. Previous research shows that the failure rate of radiologists to diagnose small nodules in the lungs is 30% of real cases (Khoiro, 2014). Lung specialists must observe X-ray images carefully and make truly accurate diagnoses in the detection of lung cancer in patients (Ramdhan, 2016). Therefore, software is needed that is able to detect lung cancer as a comparison of the work of medical practitioners, so that this software can help the accuracy of determining lung cancer detection (Listyalina, 2017).

On the other hand, Image segmentation is the separation of objects from one another in an image or between objects and the background contained in an image (Heryanto, Artama, Gunadi, & Segara, 2020), (Sinaga, 2017), (Kumaseh, Latumakulita, & Nainggolan, 2013), (Maria, Yulianto, Arinda, Jumiaty, & Nobel, 2018). In this research, the object to be taken is the lung. Therefore, segmentation may be very influential on the lung X-ray image classification process because after we separate the object, we will see the difference from the lung X-ray image.

The Convolution Neural Network (CNN) method is one of the most popular methods, especially in the identification process. For this case, identification is carried out on X-ray images that have been segmented. Researchers chose the CNN method because it has effectiveness in recognition, can extract features and classification automatically (Nugroho & Puspaningrum, 2021), (Mitra, 2021). Research using the CNN method has been conducted by (Lestyandy, 2022), (Riti & Tandjung, 2022), (Ramadhan, Mulyana, & Yel, 2022) and (Achmadiah, Hasan, & Setyawan, 2022). From the above explanation, research is proposed on "The effect of segmentation on the classification of lung X-ray images using the Convolutional Neural Network method" which is obtained by comparing the classification results of segmentation results with no segmentation. This research was conducted to determine the effect of image segmentation on the accuracy value in the classification of normal, cancer, and effusion type lung X-ray images using the Convolution Neural Network method.

METHODS

A. Object Study

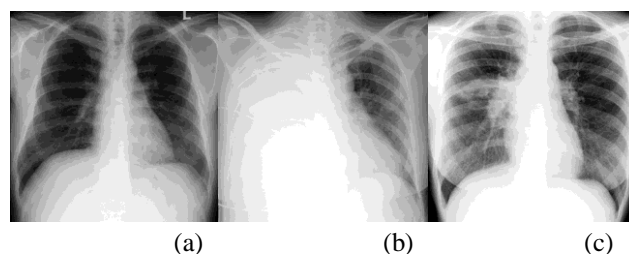


Figure 1. Example image digital results X-ray lungs: (a) normal, (b) effusion, (c) cancer

Source : Study

The objects used are 150 X-ray images of the lungs that have been diagnosed by a doctor before. The digital images are stored in BMP (Bitmap) format with 8 bit resolution. The images are divided into three categories, namely X-ray images of normal lungs, lungs affected by effusion

and lungs affected by cancer. Figure 1 is an example of image data processed in this study. The lung X-ray image data is then divided into several parts for the purposes of the CNN classification process, namely training data, validation data and test data. The specifications of the number of datasets used in this study are shown in Table 1. As for the programming, two kinds of software are used, namely Matlab R2017b for image processing in the segmentation process and Google Colab in Python for the CNN classification process.

Table 1. Lung X-ray Image Dataset Specification for CNN Classification Process

Process	Efussion image	Cancer Image	Normal image
Training	26	26	26
Validation	10	10	10
Testing	14	14	14
Amount	50	50	50

Source : Study

B. Processing Beginning Image

Image preprocessing is very important to improve the visual quality of the image and highlight some aspects of the information contained in the image so that it can facilitate the process that will be carried out next. The first thing to do in this process is to convert the image which was originally an RGB type into a grayscale image in order to facilitate the further analysis process. Then the Adaptive Histogram Equalization process is carried out to show the details in the image. Comparison of the original image and the results of the initial processing can be seen in Figure 2.

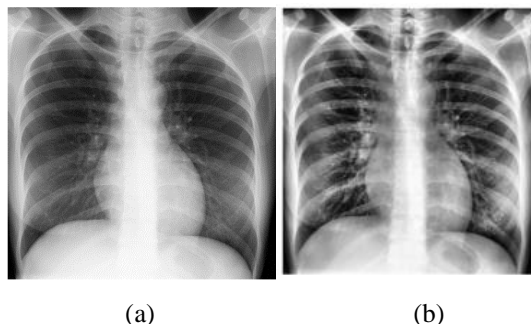


Figure 2. (a) Original image, (b) Preprocessed image

Source : Study

C. Segmentation Area Lungs

Segmentation is an image processing technique used to partition an image into distinct regions, primarily for the purpose of isolating or identifying objects within the image. In this study, the segmentation process is employed to delineate the lung region within the image, with the intention of aiding the subsequent classification process. To achieve the desired segmentation results, the researchers implemented various processes within the segmentation method, including thresholding and morphological operations such as hole filling, area opening, labeling, and contouring. In the thresholding process, the pre-processed image is transformed into a binary image using a specific gray level threshold value derived from the characteristics of lung X-ray images. In this research, a threshold value of 110 gray levels was utilized. Subsequently, the image undergoes multiple morphological manipulations. The first of these is hole filling, which serves to solidify the segmented object in the thresholded image. Following this, the image is refined to retain only the lung area based on the results of the thresholding segmentation. In the

subsequent stage, the image from the preceding process is smoothed, and small extraneous spots that do not pertain to the lungs are eliminated using the morphological area opening method. The lung region is then identified through the labeling process, which provides information about the position and area of the segmented regions. Finally, the preprocessed image is marked by contouring specific to the segmentation results obtained earlier. Figure 3 displays the segmentation outcomes in relation to the classification of diagnosed diseases.

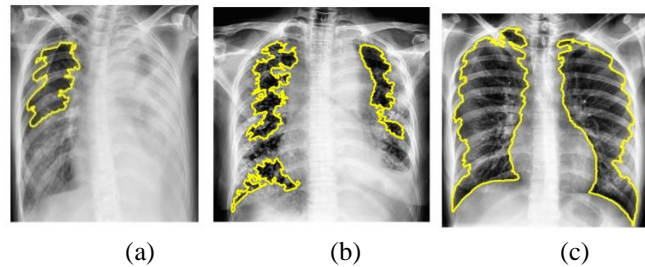


Figure 3. Segmentation results for lung X-ray images (a) normal, (b) cancer, and (c) effusion

Source : Study

D. Image Classification with Convolution Neural Network

In this study, lung X-ray image classification is conducted on datasets with and without prior segmentation using the CNN method. The CNN method is implemented in several stages: Pre-processing, Model Development, Model Training and Validation, and Testing, leading to the final model prediction. Unlike the initial image preprocessing, this classification process involves preparing the image data for testing to enhance classification accuracy. This stage includes two processes: resizing and augmentation. Resizing is applied to all images in the dataset, reducing them to 100 x 100 pixels. Augmentation, on the other hand, is exclusively performed on the training dataset to generate additional data, improving CNN model generalization and thereby enhancing training accuracy. Subsequently, the images undergo convolution and pooling processes. In the convolution process, five convolution layers are established with dimensions of 16, 32, 64, 128, and 256. In the pooling process, the input image size is significantly reduced. Following this, the flatten process converts the results from the pooling layer, presented as feature maps, into a vector format. This marks the transition to the fully connected layer stage. During the training process, both segmented and non-segmented lung X-ray image datasets are trained using the architectural model developed, involving 30 repetitions or epochs. The outcomes of this training process are stored for later use in the prediction phase.

RESULTS AND DISCUSSION

A. Training Network System

CNN classification in this research uses an architecture that uses 5 convolution layers with each layer dimension used has a 3x3 kernel size and uses "Relu" activation. For the classification stage in this study using a fully connected layer with several functions, namely flatten, dense and dropout. After going through the fully connected layer stage, it is found that the total number of parameters used in the model building process and suitable for input in the training process is 525,731 parameters.

In this study, the network training process consists of 30 epochs, indicating that the data is trained 30 times. Figure 4 illustrates the training performance using the lung X-ray image dataset without the segmentation process. In Figure 4 (a), after 30 epochs, the final accuracy results for training

and validation stand at 65% and 40%, respectively. Conversely, Figure 4 (b) displays the training and validation data with a loss of 0.7601 for training and 1.9756 for validation after 30 iterations.

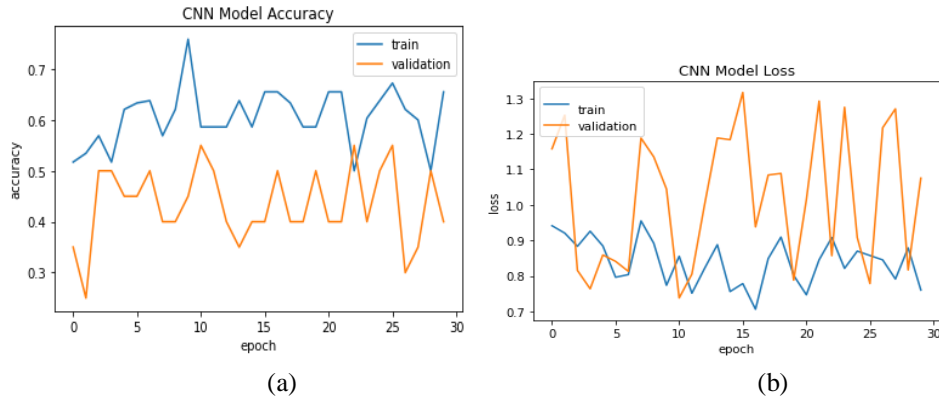


Figure 4. Graphs of (a) accuracy and (b) loss of CNN model for classification of lung X-ray image dataset without segmentation

Source : Data processed, 2023

It's worth noting that the training accuracy exceeds the validation accuracy, while the training loss is lower than the validation loss. Furthermore, there is a significant imbalance between the training and validation graphs. These conditions collectively indicate overfitting at each epoch, leading to lower testing accuracy than in training. In simpler terms, the CNN model created does not perform satisfactorily. Several factors can contribute to this, including limited data, an inappropriate learning rate, and an insufficient number of layers in the model.

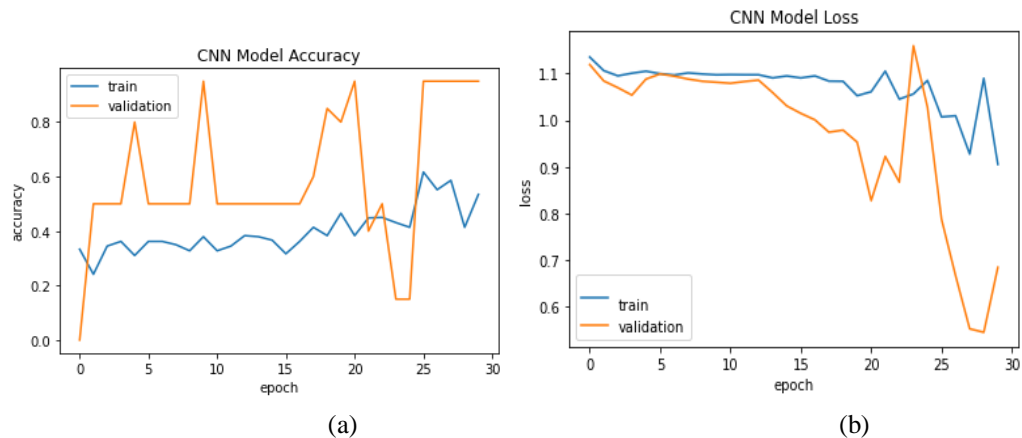


Figure 5. Graphs of (a) accuracy and (b) loss of CNN model for classification of segmented lung X-ray image dataset

Source : Data processed, 2023

Figure 5 shows the training performance on the lung X-ray image dataset resulting from the segmentation process. This network training also uses 30 epochs, which means that the data will be trained 30 times. The results of the network training graph can be seen in Figure 5. Figure 5 (a) above shows that data training and data validation after going through 30 times obtained accuracy results for training data reached 53% while validation accuracy reached 95%. While Figure 4.10 (b) shows that training and validation data after 30 times get a loss or loss of 0.9055 for training and 0.6848 for validation. From the graph it can be seen that the validation accuracy value is higher than the training accuracy. In addition, both losses are quite stable until the 13th

epoch. While above it the CNN model experiences overfitting. This shows that the CNN model formed is good enough until the 13th epoch.

B. Final Predictions

The testing process is used to test and predict test data using the model that has been obtained in the previous training process. This process is carried out using 42 test image data from X-ray image data without segmentation and X-ray image data with pre-selected segmentation. By using the weights obtained in the previous training process, the test image classification results were obtained, as shown in Table 2 below.

Table 2. Classification testing report of lung X-ray image without segmentation

Class	Precision	Recall	F1-Score	Accuracy
Efussion	0.83	0.71	0.77	71,43%
Cancer	0.25	0.07	0.11	7,14%
Normal	0.54	1.00	0.70	100%
Overall accuracy				59,52%

Source : Data processed, 2023

Table 3. Classification testing report of lung X-ray image segmentation result dataset

Class	Precision	Recall	F1-Score	Accuracy
Efussion	1.00	0.79	0.88	78,57%
Cancer	0.59	0.71	0.65	71,43%
Normal	0.71	0.71	0.71	71,43%
Overall accuracy				73,81%

Source : Data processed, 2023

From the testing process, it is found that the normal lung class has the largest number of True Positives, predicted entirely correctly, and the class that has a low value in the cancer class only predicts 1 image data that has True Positives from the entire test data. This can be due to poor image conditions, especially in cancer lung X-ray images. From the results generated from the testing process, the overall accuracy results are not good enough. One of the reasons is because of the True Positive value of each class, only the cancer class cannot be predicted properly. In addition, it can also be due to overfitting in the training process which causes the CNN model used to be less good as previously explained.

By comparing the values in Tables 2 and 3, we can compare the classification performance between images without segmentation and segmentation results. Overall accuracy in the classification of images without segmentation is 59.52%, while classification using the segmented image results in a greater accuracy of 73.81%. This shows that the segmentation process carried out has an impact on the classification process by increasing the accuracy results obtained. This can be because the segmented image contains different contouring marks in each class so that it is easier to classify.

CONCLUSIONS

Key findings from the conducted research include the lung X-ray image classification accuracy of 73.81% achieved through the application of Convolutional Neural Network-based segmentation. This contrasts with the accuracy of 59.52% obtained when classifying lung X-ray images without

segmentation. The segmentation process notably enhances network performance. This improvement is attributed to the segmentation process, which facilitates easier recognition of input patterns by the network due to the presence of distinct contouring marks in each class within the image.

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