Pulmonary Disease Pattern Recognition on X-Ray Radiography Image Using Artificial Neural Network (ANN) Method

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Abstract. This research aims to recognize the pattern of pulmonary disease on x-ray radiography image using artificial neural network (ANN) method. The images, which were used such as images of healthy pulmonary, pulmonary tuberculosis, and pulmonary tumour. Pattern recognition was using an extraction feature of GLCM (Gray Level Co-occurrence Matrix) and back propagation method. Before being identified, the images were processed by median filter and adaptive histogram equalization. The GLCM features that used were homogeneity, energy, contrast, variance and correlation. The parameters were learning rate and hidden layer. Learning rate was 0.3 and hidden layer was 25. Back propagation training showed 100% accuracy, which all of 44 images were used had been successfully identified. From the result, the healthy pulmonary showed 60% accuracy, 83.3% for pulmonary tuberculosis and 100% for pulmonary tumor. Hence, the overall result showed 81.25% accuracy, which 13 of 16 images had been successfully identified. From these result, extraction feature of GLCM using back propagation method was capable to recognize the pattern of pulmonary disease. However, due to narrow range of the feature, this application may not be used optimally for comparing features in every category of images. Therefore, the further research is needed to determine the best features and parameters of training back propagation.

1. Introduction
The medical image segmentation is well known as complicated things in the field of image processing and analysis [1]. In very specific area, this segmentation of the target image objects came before other image analysis and the false accuse in object detection could affect all the subsequent steps severely [2]. This paper was about chest X-Ray image processing, which known as chest radiographs. The several studies documented some result related to segmentation problem of lung component in X-Ray images [3, 4], most of their extraction result expressed unsatisfactory in many occasion. The problem of accurate segmentation became worsen even in the scheme of large screening of population [5] where related to advance big data domain [6]. The first attempt to employ some deep learning method
for image segmentation which similar to the ones. They tried to adopt deep learning architectures for small patches image or pixel neighbourhood to certain classes [7]. More recently, Vijay Badrinarayanan and colleagues from University of Cambridge have presented a novel and practical deep fully convolutional neural network architecture for semantic pixel-wise segmentation termed SegNet [8, 9]. X-ray digital radiography is a preeminent method for non-destructive detection for security check and medical imaging analysis, which could expressed the object structure and internal part detail [10]. The lungs are one of the important organ of human as respiratory organ, but the lungs also one of the organ that susceptible to various diseases. Some diseases that often attack the lungs are cancer, tuberculosis, inflammation (pneumonia), and others [11]. The important element that have to be done before treatment is diagnosis. One tool that can be used to diagnose lung disease is by using X-Ray. Nowadays, X-ray application widely used in some general field, such as in medical application field X-ray has been utilized for cancer diagnostic study. One of the utilization of X-ray is for radiotherapy treatment for cervical cancer cases by approaching this desease with Linac and brachytherapy treatment [12]. There are two types of X-ray such as X-Ray characteristic and X-ray bremsstrahlung [13]. The utilization of X-ray was usually used in various field such as medical, metallurgy, physics, chemistry, and many others [14]. One of the utilization of X-rays in medical field was to blacken film plates so that it can produce a good quality radiograph. Quality of the radiograph is very important in determining the accuracy of the diagnosis of an illness [15]. How to interpret radiographic films is still conventional, so it is very risky to bring up subjective factors and trigger differences of opinion between fellow interpreters. Computer vision is one of interpreting image method to obtain the desired information. Computer vision is a combination of image processing and artificial intelligence. Computers are able to do pattern recognition if image repair is done first to produce digital images that can be recognized by computers [16]. One of pattern recognition method with artificial intelligence is Artificial Neural Networks (ANN). The ANN is a system that adopts the ability of human brain tissue such as being able to process the information obtained, recognizing faces, learning certain conditions to determine a result so that it is expected to determine a solution to a non-deterministic problem [16]. ANN used in this study was the back propagation method by using the Gray Level Co-occurrence Matrix (GLCM) extraction feature.

The previous researches reported the using of back propagation method for diseases identification of through the introduction of medical images extraction [17-21]. The research was about identifying lung cancer and the level of accuracy reached up to 86.67%. Then the research about identifying Tuberculosis [18], the level of accuracy produced in these study was 77.5%. Zamani [20] found that this method which was to classifying breast cancer, the level of accuracy produced in those study was 97%. However, all of that research used many types of extraction feature. Riyani Hartadi [21] had conducted a study using the extraction of GLCM features to detect breast cancer, from the results of the study obtained an accuracy rate of 86%. Therefore, the aim of this research is to determine an applicative and easy application that can be used to help medical worker and researchers to introduce pattern of pulmonary disease. This research prioritizes image processing which includes image improvement and pattern recognition using the back propagation method by using the GLCM extraction feature extraction carried by MATLAB software.

2. Experimental Method

This research was conducted from March 2014 until August 2014 at Computational Laboratory, Physics Department, Faculty of Science and Technology, Airlangga University and Dr. Soetomo Hospital Surabaya for observing digital chest radiograph images. The chest radiograph include normal pulmonary, pulmonary tuberculosis, and pulmonary tumor from X-ray machine. The X-ray radiation for Thorax applied high voltage of 65 kV, a current was 500 mA and irradiation time of 6.25 s. The imaging technique which been used in this recent study is the Focus Film Distance (FFD) technique, which the distance between the source and the film was about 1.5 m. The data obtained consisted of 60 photographs of 17 images of normal pulmonary, 17 images of pulmonary tumour and 26 images of
pulmonary tuberculosis (TBC). Then the result of image processing in the form of GLCM matrix would be extracted using GLCM feature. The features in extractions include homogeneity, energy, contrast, variance, and correlation. After that, the results of feature extraction became input value to trial interface. The trial interface used Artificial Neural Network (ANN) by empowering back propagation network method. The previous image was grouped into 3, namely normal pulmonary, pulmonary tumour, and pulmonary tuberculosis. After the program was given trial and error test, the program was ready to carry out testing of pulmonary radiographic images with certain diseases. The application was designed using a GUI (Graphics User Interface) which was designed to be applicative and user friendly. The GUI was designed with several windows consisting of testing window, image-processing window, and trial window. After going through several stages, both training and testing to ensure whether the software program was able to identify correctly with the accuracy level which could be calculated using the following equation:

\[
\text{Accuracy (i) } = \frac{\sum [i]_{\text{true}}}{n} \times 100 \%
\]

where Accuracy (i) stated the accuracy of the system for each i group which each represented each category, and n was the number of samples for each category. The test window is used to identify pulmonary disease patterns, the user only needs to enter the image to be identified, then by pressing the 'Process' button, and the results will be displayed in the results column at the bottom left of the application. From this test application, the user can see the value of each test image feature which includes homogeneity, energy, contrast, variance and correlation. The final results obtained from this test are groups of test images, so that it can be detected whether the image belongs to the normal image category, pulmonary TB or pulmonary tumor.

3. Result and Discussion
3.1 Specification of Artificial Neural Network (ANN) Architecture
The Artificial Neural Network (ANN) is a computational system whose architecture and operations biological nerve cells of human brain inspire. ANN can be described as mathematical and computational models for the non-linear approximation functions of cluster data classification and non-parametric regression or a simulation of a collection of biological neural network models [30]. The schematically arrangement of our ANN architecture specification was represented in Figure 1.

![Figure 1. The schematically arrangement of Artificial Neural Network (ANN) Architecture Specification](image)
Previous works have claimed that the utilization of ANN is a potential candidate as new method for kind of modelling consignment distribution and support other method in the same field of some kind spatial interaction modelling [30]. As you can see in Fig.1 there was one hidden layer and feed-forward back-propagation architecture was applied in this project. The number of input will be processed forward then the end was output result. The amount of neurons in the hidden layer as many as the input variables and the transfer equation for the activation process is kind of non-linear sigmoid equation [30].

3.2 Adaptive Histogram Equalization

The pulmonary radiographic image would be processed in order to have a better image intensity. Before the pattern recognition was done, the radiographic images have to be repaired. The extraction was carried out by cropping the image then using median filter, in the final touch the equalization adaptive histogram was applied to get a better quality image. The X-ray chest radiograph of normal lung, lung tumor, and TBC images are shown in Figure 2, Figure 3, and Figure 4 respectively.

**Figure 2.** X-ray chest radiograph images for normal lung (NL) in both original and processed images (n = 5 patients)

**Figure 3.** X-ray chest radiograph images for lung tumor (LT) in both original and processed images (n = 5 patients)
First step was cropping process, which was done manually and followed by resizing, so all of the images had uniform size, which was 640 x 640 pixels. The first step was pre-processing, which was cropping and resizing, then eliminated noise used the median filter to improve contrast after filtering, equalizing the adaptive histogram, then the repaired image was formed according to the Gray Level Co-occurrence Matrix (GLCM) to extract its features.

The median filter method was very useful for eliminating noise, which were extreme pixel values [22]. Figure 2, 3, and 4 (original image) shows that the pulmonary radiographic image was not disturbed by noise, this can be seen from the median filter image. Adaptive histogram equalization aims to improve image quality so that the pattern was clearer (see Fig 2, 3, and 4 processed image). This can be seen from the equivalent image of the adaptive histogram, where the resulting image was clearer and brighter so that it can be used for the next step of pattern recognition process. Images that had been processed using the median and equal filter adaptive histograms had a very large matrix size of 256 x 256. The feature can be recognized well, with an accuracy of 86%. The G matrix formed can be seen in table 1. The formation of the GLCM matrix must be done so that the image can be recognized by its features. The MATLAB function used to form the GLCM matrix was: G = graycomatrix (E, ‘offset’, [0,1], ‘Symmetric’, true);

|   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|
| 10006 | 2437 | 9 | 2 | 0 | 0 | 0 | 0 |
| 2437 | 52134 | 6114 | 108 | 5 | 0 | 0 | 0 |
| 9 | 6114 | 72246 | 8581 | 200 | 10 | 1 | 0 |
| 2 | 108 | 8581 | 102582 | 9917 | 227 | 17 | 0 |
| 0 | 5 | 200 | 9917 | 113166 | 9224 | 116 | 2 |
| 0 | 0 | 10 | 227 | 9224 | 149054 | 10147 | 47 |
| 0 | 0 | 1 | 17 | 116 | 10147 | 110342 | 2647 |
| 0 | 0 | 0 | 0 | 2 | 47 | 2647 | 9648 |

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix.
The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix [23]. The GLCCM matrix for our project can be seen in Table 1.

The texture filter functions, described in Texture Analysis, cannot provide information about shape, that is, the spatial relationships of pixels in an image. GLCM describes the frequency of occurrence of pairs of two pixels with a certain intensity in distance $d$ and direction orientation with a certain angle $\theta$ in the image [24]. The $G$ matrix is formed using the orientation angle ($\theta$) of 00 and pixel distance ($d$) of 1 pixel. Previous research by Riyan [21] used the same orientation angle and distance. The $G$ matrix then normalized to obtain a probability value for each pixel. The results of the formation of a normalized GLCM matrix can be seen in Table 2.

### Table 2. The Normalized GLCM Matrix

$$G =$$

|       | 0.0139 | 0.0034 | 0.0000 | 0.0000 | 0   | 0   | 0   | 0   |
|-------|--------|--------|--------|--------|-----|-----|-----|-----|
| 0.0034 | 0.0725 | 0.0085 | 0.0002 | 0.0000 | 0   | 0   | 0   | 0   |
| 0.0000 | 0.0085 | 0.1005 | 0.0019 | 0.0003 | 0.0000 | 0.0000 | 0 |
| 0.0000 | 0.0002 | 0.0119 | 0.1427 | 0.0138 | 0.0003 | 0.0000 | 0 |
| 0     | 0.0000 | 0.0003 | 0.0138 | 0.1574 | 0.0128 | 0.0002 | 0.0000 |
| 0     | 0     | 0      | 0.0000 | 0.0003 | 0.0128 | 0.2074 | 0.0141 | 0.0001 |
| 0     | 0     | 0      | 0      | 0.0000 | 0.0002 | 0.0141 | 0.1535 | 0.0037 |
| 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0001 | 0.0037 | 0.134 |

Each matrix is 256x256, assuming the image has 256 grey degrees. If each matrix has a size of 256x256, it will require large memory to store it and need a long time to do the next process. This is where GLCM plays a role in reducing the degree of grey image from 256 to 8 degrees grey [25].

### 3.3 Feature Extraction

Feature extraction was done to find the value of the features of each image for training. Feature extraction was performed on each image that will be used for training. Feature extraction, which were used such as homogeneity, energy, contrast, variance and correlation. Correlation between homogeneity and energy feature each image category are showed on Figure 5. The homogeneity feature attempt to measure the closeness of the distribution of elements in the GLCM diagonal. Hence, the energy extraction feature provides the sum of squared elements in the GLCM. It also known as uniformity or the angular second moment [23]. The homogeneity graph shows that the normal pulmonary image has the greatest homogeneity value compared to the other images. The homogeneity range of normal pulmonary image was from 0.94-0.96, while pulmonary tumour images were between 0.94-0.95, and the image of pulmonary TBC had a homogeneity value between 0.91-0.97. The greater the value of homogeneity, the greater the uniformity of image intensity. Normal pulmonary image had a large uniformity of intensity, because normal pulmonary image did not show white spots in diseased pulmonary images. From the range of each image category, it can be seen that in certain values normal pulmonary images, tumour and TBC are not significantly different; the value of homogeneity was 0.94-0.97.

The energy graph shows the image of pulmonary tumour has the greatest energy value compared to other pulmonary images. The energy range of pulmonary tumour images is from 0.13-0.18, while normal pulmonary images are between 0.12-0.14, and the image of pulmonary TBC has an energy value between 0.11-0.17. Energy is a measure of the concentration of a couple with a certain intensity on the matrix [26]. The greater the energy value, the more intensity pairs are formed. From the range of each image category, it can be seen that in certain values normal pulmonary images, tumour and TBC are not significantly different; the energy value is 0.12-0.14.
Figure 5. The feature extraction graph which expressed both homogeneity and energy feature extraction of GLCM. The left y axis is homogeneity and the right side is energy. The inserted images are Xray chest radiograph of normal lung (top left) and TBC’s (right below).

Other feature extractions are contras, variants and correlation. The contrast measures the local variation in the grey level co-occurrence matrix. The correlation measures the joint probability occurrence of the specified pixel pairs [23]. The contrast graph (Figure 6) shows that the image of pulmonary TBC has the greatest contrast value compared to other images. The value of each GLCM feature extraction was displayed in Table 3. The range of image homogeneity of pulmonary TBC is 0.06-0.17, while the image of pulmonary tumour between 0.11-0.12, and normal pulmonary imaging has a contrast value between 0.08-0.12. The greater the contrast value, the greater intensity of an image. This is inversely proportional to homogeneity. The image of Pulmonary TBC has the most random intensity value, this is because in the image of pulmonary TB is darker than other pulmonary images. From the range of each image category, it can be seen that in certain values normal pulmonary images, tumour and TB are not significantly different, the contrast value is 0.11-0.12.

Figure 6. The feature extraction graph of normal lung and TBC’s cases

The variance graph shows that the normal pulmonary image has the greatest variance value compared to the other images. The range of variance in normal pulmonary image is from 6.3-8.7, while the image of pulmonary tumour between 6.3-7.3, and the image of pulmonary TB has a variance between 6.1-7.3. Variance is a value that shows the distribution of pixel values in the image [27]. When compared with the graph in Figure 5 the pattern of the value of variance and the value of homogeneity are the same. In other words, the more homogeneous an image is, the more evenly distributed the pixels in an image. From the range of each image category, it can be seen that in certain values normal pulmonary image, tumour and TB are not significantly different; the variance value is 6.3-7.3.

The correlation value (Table 3) shows that the image of pulmonary tumour has the highest correlation value compared to other pulmonary images. The correlation range of pulmonary tumour
image is from 4.4-5.2, while normal pulmonary image is between 4.1-4.6, and pulmonary TB is between 3.8 to 5.4. The correlation states the relation of the pixel size with neighbour pixels [26]. When compared with the graph in Figure 5.6 the pattern of correlation values and energy values are the same. Both values state the relationship between neighbour pixels. From the range of each image category, it can be seen that in certain values normal pulmonary images, tumour and TB are not significantly different; the correlation value is 4.4-4.6.

**Table 3. Test Imaging Feature Extraction Result**

| Imaging’s code | Homogeneity | Energy | Contrast | Variation | Correlation |
|----------------|-------------|--------|----------|-----------|-------------|
| NL-1           | 0.9507      | 0.1492 | 0.0992   | 6.9153    | 4.7441      |
| NL-2           | 0.9519      | 0.1811 | 0.0976   | 6.7800    | 5.1097      |
| NL-3           | 0.9618      | 0.1837 | 0.0768   | 5.9377    | 5.3250      |
| NL-4           | 0.9477      | 0.1535 | 0.1050   | 6.4352    | 5.3196      |
| NL-5           | 0.9575      | 0.1906 | 0.0851   | 6.0360    | 6.0880      |
| TBC-1          | 0.9367      | 0.1336 | 0.1276   | 6.8322    | 4.5958      |
| TBC-2          | 0.9452      | 0.1534 | 0.1169   | 6.9465    | 4.8118      |
| TBC-3          | 0.9438      | 0.1413 | 0.1134   | 7.0557    | 4.4247      |
| TBC-4          | 0.9396      | 0.1276 | 0.1261   | 6.6770    | 4.4572      |
| TBC-5          | 0.9348      | 0.1312 | 0.1370   | 6.9634    | 4.6012      |
| LT-1           | 0.9493      | 0.1598 | 0.1046   | 7.1373    | 4.5844      |
| LT-2           | 0.9430      | 0.1571 | 0.1152   | 7.2157    | 4.7821      |
| LT-3           | 0.9640      | 0.2256 | 0.0731   | 5.9652    | 4.7284      |
| LT-4           | 0.9469      | 0.1381 | 0.1077   | 6.9623    | 4.7675      |
| LT-5           | 0.9586      | 0.1979 | 0.0840   | 7.2010    | 5.1132      |

*the abbreviation remarks: NL: normal lung; TBC: tuberculosis; LT: lung tumour;

One of the causes of deviations is the result of the extraction of features obtained in other image category range. In the NL-1 and NL-2 image, the test results (see Table 3) stated that the results should be a tumours in the pulmonary. The feature that keeps the difference is homogeneity, the value of homogeneity of the NL-1 and NL-2 image is at the tumour with the image range of 0.94-0.95 (Fig. 1). The small range of the image homogeneity of pulmonary tumours resulted in this feature in the category of pulmonary tumour image. The TBC-2 image shows some features that have a prominent difference are correlation. The TBC-2 image correlation value is in the normal image range of 4.1-4.6. The small range of normal pulmonary image correlation causes the feature to be grouped in the normal pulmonary image category. Result analysis of features obtained from the test image, giving an overview that the range of feature values obtained in the training process affects the results of grouping imagery by category. The smaller the range of the resulting fittings, the more likely the occurrence of error grouping features for each category.

Despite of there is no mathematical definition of acceptable texture, it can be said that texture is a repetitive pattern of spatial relations (distribution) of grey degrees on neighbour pixels [28]. So that the features obtained in this study have represented the texture of the observed image. From the results of extraction of features obtained, the image cannot be grouped separately. From the synergy of the role of ANN to group images based on features that have been obtained. The neural network training used in this research employed the Back Propagation method. The training imagery used was 44 images, consisting of 12 normal pulmonary images, 20 pulmonary TB images and 12 pulmonary tumour images. To conduct training using backpropagation, each image category has a different target value. On the normal image of the target used is 1, the image of the target pulmonary TB used is 0 and the image of the target lung tumor used is -1. The initial weight determination was done randomly with a small value [29-31]. To get maximum results, the training is done by varying the value of the learning rate and the number of neurons on the hidden layer, so that the smallest MSE (Mean Square
Error) value is the least number of epoch. The learning rate variation uses the number of hidden layers and the maximum of the same epoch, which are 5 neurons and 1000 iterations. The second variation is the number of neurons on the hidden layer, i.e. using learning rate 0.3 from the previous variation, the maximum error tolerance of $10^4$ and the maximum epoch is 1000. From the results of variations of the parameters performed, obtained the best parameter value for conducting artificial nerve network training backpropagation namely, learning rate of 0.3, hidden layer amounted to 25 and maximum epoch is 1000. The training process resulted in a chart of MSE relationships with the number of epoch in the 4.11 image, with minimized error tolerance to $10^8$. From the results of the training on phyto-set data, obtained the training accuracy of 100%. Where each image is grouped correctly based on the target of each category. The testing part was done using the input parameters obtained in the training process is the learning rate of 0.3, neurons on the hidden layer amounted to 25, maximum error tolerance is 10-8 and the maximum epoch 1000 times. Image data for testing amounted to 16 data, with 5 normal pulmonary images, 6 pulmonary TBC images and 5 pulmonary tumour images. It also employed back propagation method which should gave the same Y-output result value as the desired target, in order to achieve a high level of accuracy.

From the results of the calculation analysis, the accuracy of this study results is 81.25%. The results of this accuracy are quite good when compared with the previous research conducted by Argisraha [32], namely identification of TBC using ANN with a rate of 77.5%. In addition, this study adds to the category of pulmonary abnormalities tested, namely pulmonary tumour.

4. Conclusion
This study successfully applied the extraction of the GLCM feature using the back propagation ANN method that can to recognize pulmonary disease patterns. The features were homogeneity, energy, contrast, variance and correlation. While the best parameters obtained from this study include learning rate = 0.3, the number of hidden layers = 25 and tolerance errors = 10-8. From the test results, the accuracy of training for normal pulmonary image, pulmonary TBC, and pulmonary tumour were 60%, 83.3% and 100%. Indeed, the accuracy of the research results was 81.25%.

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