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Identification of lung cancer using gray level co-occurrence matrix (GLCM) and artificial neural network with backpropagation algorithm

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ABSTRACT

Air pollution is a problem that occurs in various countries, including Indonesia. One of the consequences of poor air quality due to air pollution is health problems in the lungs, one of which is lung cancer. According to WHO data, lung cancer caused 1.80 million deaths in 2020. This is due to limited services to identify lung cancer early, resulting in delays in treatment. This study aims to identify lung cancer using CT-Scan image processing. The identification method uses a Backpropagation Artificial Neural Network (ANN BP) with Gray Level Co-occurrence Matrix (GLCM) feature extraction. Preprocessing is carried out to improve image quality by removing noise using a median filter. Segmentation of preprocessing results using Otsu threshold. Texture features from segmentation can be calculated from the resulting GLCM, such as Angular Second Moment (ASM)/energy, contrast, correlation, Inverse Different Moment (IDM)/homogeneity, and entropy. These values are obtained from angles of 0°, 45°, 90°, and 135°, and a distance between pixels of 2 pixels. Identification using ANN with Backpropagation algorithm. This study used images of normal lungs and lung cancer with 160 training data images and 40 test data images. The best test results were obtained with the best accuracy level of 92.5%.

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1. INTRODUCTION

Air pollution is a significant environmental problem worldwide with far-reaching impacts on human health and well-being [1], [2]. Air pollution is a problem that occurs every year. Pollution can occur in areas such as villages, mines, and even in big cities. Due to rapid technological advances before Industry 4.0, a company's production performance can increase by up to fifty percent. This is one of the causes of air pollution in Indonesia. Seventy percent of vehicle smoke that rises and pollutes the atmosphere is another cause of air pollution [1], [3], [4].

Human health is greatly affected by air pollution. Human mental and physical health is a big problem. Carbon monoxide (CO) levels are one of the most dangerous levels of air pollution. Inhaling a lot of carbon monoxide can worsen human health. In Indonesia, air pollution can kill up to 60,000 people every year. Air pollution has many dangers to lung health that should not be underestimated. This is because pollution contains substances or particles that can damage the lungs and cause diseases such as pneumonia, bronchitis and cancer [5], [6].

Cancer is a malignant disease that occurs when body cells grow without control. Worldwide, cancer is the most common cause of death, causing nearly 10 million deaths in 2020, or nearly one in six deaths. Breast, lung, colon, rectum, and prostate are the most common cancers [7]. Lung cancer is a malignancy in the lungs that occurs due to genetic changes in airway epithelial cells that cause uncontrolled cell proliferation. This malignancy can originate from primary (lung organs) or metastasis (from outside the lungs). According to WHO data, lung cancer caused 1.80 million deaths in 2020 [8]. The ever-growing technology sector aims to help in everyday activities and is continuously improved through research. One of the studies that continues to be carried out is to identify lung cancer. Image processing covers many things, such as photography, art, mathematics, physics, electronics, and computer technology, so it is very important for this research. Image processing and computer vision are interrelated. Object detection, segmentation, and classification are the main tasks of computer vision [9]–[11].

Doctors identify and classify lung cancer manually, which is less effective because they cannot distinguish morphological characteristics such as shape, texture and color in lung cancer. To solve this problem, research was carried out using image processing. Previous research used healthy lung and lung cancer datasets. Research using CTscan data by Fajri with the feature extraction method and Fuzzy Logic First Order classification obtained an accuracy of 66.67% [12]. Research by Yunianto and et al using the Gray Level Co-occurrence Matrix (GLCM) feature extraction method and naïve Bayes classification obtained an accuracy of 88.33% [13]. Research by Lavanya and Kannan using feature extraction methods Edge detection, Masking, Erosion and Back Propagation Network classification obtained an average accuracy of 87% [14]. Research using X-ray data by Akbar et al with the Local Binary Pattern (LBP) feature extraction method and Support Vector Machine (SVM) classification with test result accuracy of 62.5% [15]. Research by Zharfan using the Active contour segmentation method and 2D Fourier Analyst classification obtained an average accuracy of 58% [16]. Research by Wulan uses the wavelet haar feature extraction method and backpropagation artificial neural network classification with an accuracy of 86.67% [17]. Research by Kalaivani uses feature extraction of area, perimeter, major axis length, minor axis length, eccentricity and solidity. Backpropagation artificial neural network classification with an accuracy of 78% [18].

Referring to previous research using CT scan and X-ray data, better results were obtained using CT scans. CT-Scan is an imaging modality in the field of radiodiagnostics that can produce axial, coronal and sagittal slices of the object or patient being examined. CT-Scan can be applied to diagnose trauma in cancer cases [19], Meanwhile, based on X-Ray images of the lungs, it is difficult to do because it has many similarities with other diseases [20]. So the level of accuracy is low and the time is longer. The highest level of accuracy from previous research was 88.33%, from these results the researchers tried to increase the accuracy. The method used is by taking CT scan data using a combination process of the Gray Level Co-occurrence Matrix (GLCM) feature extraction method and for identification using a Backpropagation Neural Network. The Gray Level Co-occurrence Matrix (GLCM) feature extraction method was chosen because it can extract several second order features. Identify Backpropagation Artificial Neural Networks (JST BP) because they can carry out systematic training for multiplayer artificial neural networks. Therefore, this research aims to create a system that is able to identify lung cancer and produce a better level of accuracy.

2. METHOD

Designing and creating a flow diagram for a lung cancer identification system using the Gray Level Co-occurrence Matrix (GLCM) method and Backpropagation Artificial Neural Network (JST BP) can create a flow or steps in the research. The system design flow in this research can be outlined in the flow diagram in Figure 1.

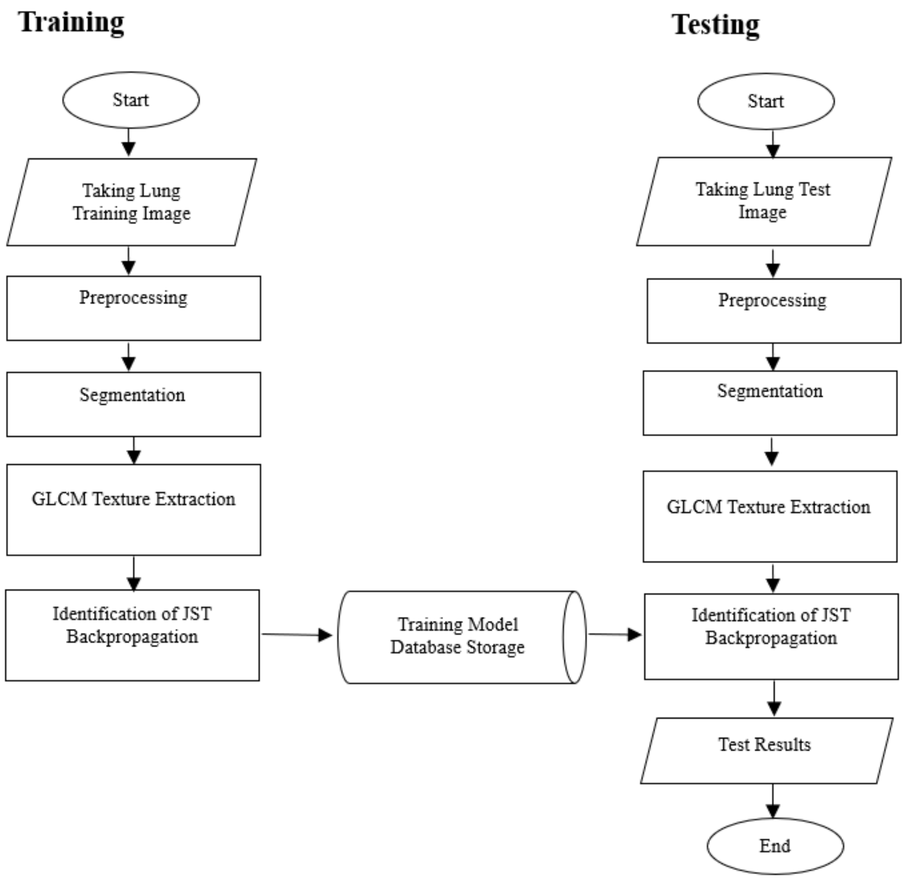


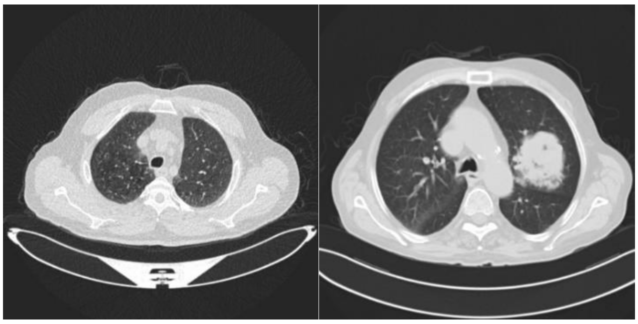
Figure 1. Research design flow diagram

The algorithm from Figure 1 explains the design of the research carried out, which is as follows:

1. **Start**: for training.
2. **Taking lung training image**: as the image to be processed.
3. **Preprocessing**: to make images easy to analyze by changing from RGB to grayscale, removing noise with a median filter.
4. **Segmentation**: to make it easier to analyze using the Otsu thresholding method.
5. **Feature extraction**: using the Gray Level Co-occurrence Matrix (GLCM) method.
6. **Identify Backpropagation Neural Networks (ANN BP)**: to determine healthy lungs or lung cancer.
7. **Training Model Database Storage**: normal lung and lung cancer training outcomes. saved as a training model which will later be used as a testing load.
8. **Start:** for testing.
9. **Taking lung testing image**: as the image to be processed.
10. **Preprocessing**: to make images easy to analyze by changing from RGB to grayscale, removing noise with a median filter.
11. **Segmentation**: to make it easier to analyze using the Otsu thresholding method.
12. **Feature extraction**: using the Gray Level Co-occurrence Matrix (GLCM) method.
13. **Identification of Backpropagation Neural Networks (ANN BP)**: to determine healthy lungs or lung cancer. The training data that has been saved as a model is then loaded into the program for the test data identification process.
14. **Result**: The test results are in the form of accuracy levels in identifying healthy lungs and lung cancer.
15. **End.**

Image Acquisition

The image acquisition process is the initial stage for taking or obtaining digital images using certain additional devices or tools, in research taking secondary data from Mendeley. The material used is CT scan image of lung data under license from Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) [21]. The CT scan image of the lungs is converted into JPEG format (ekstensi*.jpg). The total data used in the research was 200 data. The data is divided into two data, namely 100 normal image data and 100 cancer image data. Each normal data and cancer data is divided into training data and test data with a ratio of 80:20. So in total each type of image consists of 80 training data and 20 test data. For example, 2 normal lung samples in Figure 2(a) and lung cancer in Figure 2(b).



(a) (b)

Figure 2. Lung image (a) normal lung, (b) lung cancer

Preprocessing

Preprocessing is used to enhance an image by removing the background. This feature is used to enhance images so that they are easy to process and analyze [22]. The initial step is changing the image from RGB to grayscale, removing noise with a median filter. By removing noise, objects will be seen clearly and can help facilitate the image segmentation process [23], [24]. The median filter process uses the MATLAB program, with the first step of making a read data program, namely reading CT - Scan images in format.jpeg taken from Kaggle.com [12], [25].

Segmentation

After the image improvement process is carried out, image segmentation is then carried out. The segmentation process makes it easier to analyze further and recognize the information contained in the image. The thresholding method is the simplest image segmentation technique. Thresholding can be used to form binary images. In this study, thresholding was used. The concept of otsu thresholding is to automatically group binary images based on the shape of the histogram, assuming the image contains two basic classes of bimodal histograms (foreground and background). Otsu thresholding creates a binary image from a gray level one by changing all pixels below the threshold to zero and all pixels above the threshold to one [13], [26], [27]. Figure 3 shows segmentation using Otsu thresholding to make it easier to analyze images.

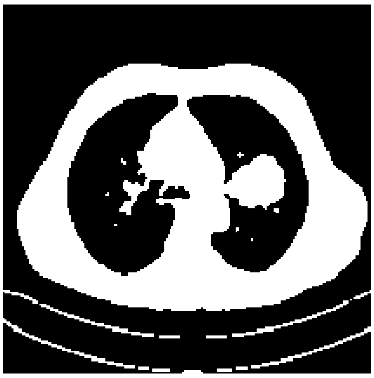


Figure 3. Segmentation using otsu thresholding

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Feature Extraction

The next process is that the segmentation results are extracted to obtain information about the parts affected by the disease. Texture extraction was carried out using the GLCM method. Gray Level Co-occurrence Matrix (GLCM) is a feature extraction method used for textures that produces statistical calculations. Texture features can be calculated from the resulting GLCM, such as Angular Second Moment (ASM)/energy, contrast, correlation, Inverse Different Moment (IDM)/homogeneity, and entropy. This value is obtained from angles of 0°, 45°, 90°, and 135°, as well as the distance between pixels of the segmented image.

Texture feature extraction [28]–[31]:

1. Angular Second Moment/Energy/Uniformity
   ASM or energy has the ability to measure gray intensity or texture uniformity and image density in the GLCM matrix. If the change in intensity in the image is small, the ASM value will be large. Following is Equation 1 to calculate the ASM value:

$$f_1 = \sum_i \sum_j \{p(i,j)\}^2 \tag{1}$$

2. Contrast/Inertia
   Contrast shows the size of the spread (moment of inertia) of the image matrix elements. If it is located far from the main diagonal, the contrast value is greater. Visually, the contrast value is a measure of the variation between the degrees of gray in an image area. Following is Equation 2 to calculate the contrast value:

$$f_2 = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{\substack{i=1 \\ |i-j|=n}}^{N_g} \sum_{j=1}^{N_g} p(i,j) \right\} \tag{2}$$

3. Correlation
   Correlation shows a measure of linear dependence between gray scale values in an image. Following is Equation 3 to calculate the correlation value:

$$f_3 = \frac{\sum_i \sum_j (ij)\, p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{3}$$

4. Inverse Difference Moment/Homogeneity
   The inverse difference moment or what is usually called uniformity, is a characteristic that shows the uniformity of images with the same degree of gray in the co-occurrence matrix. The energy value increases when pairs of pixels that satisfy the requirements of the co-occurrence intensity matrix are concentrated on a small number of coordinates, and decreases when they are scattered. Therefore, we can conclude that a homogeneous image has a large IDM value. The following is Equation 4 to calculate the IDM value:

$$f_5 = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j) \tag{4}$$

5. Entropy
   Entropy functions to measure the irregularity of the gray level intensity distribution of an image in the co-occurrence matrix. If the GLCM elements have relatively the same value then the value will be high. If the GLCM element is close to the value 0 or 1 then the value is low. This means that if the change is also small, the gray degree transition is also small. Following is Equation 5 to calculate the entropy value:

$$f_9 = -\sum_i \sum_j p(i,j) \log(p(i,j)) \tag{5}$$

Where:

$p(i,j)$ = (i,j), input in the normalized grayscale spatial dependence matrix, $P(i,j)/R$.

$p_x(i)$ = i input to the marginal probability matrix obtained by adding the rows of $p(i, j), = \sum_{j=1}^{N_g} P(i, j)$.

N_g = number of different gray levels in a quantized image

$\sum_i$ and $\sum_j$ $\sum_{i=1}^{N_g}$ and $\sum_{j=1}^{N_g}$

Haralick's research proposed 14 extraction features, in another journal [32], the 5 best features to use were obtained, namely Angular Second Moment (ASM)/energy, contrast, correlation, Inverse Different Moment (IDM)/homogeneity, and entropy. The use of these five properties is based on the MATLAB program function, namely graycoprops, which has a relatively small number of properties, thereby reducing the time required for training and testing.

Identification

After extracting texture features, identification is carried out using the Backpropagation Neural Network (ANN BP) method. ANN BP is a systematic method for training multiplayer artificial neural networks. This method has a strong, objective, mathematical basis and this algorithm obtains the form of the equation and the coefficient values in the formula by minimizing the sum of the squared errors through the model developed [17], [33], [34].

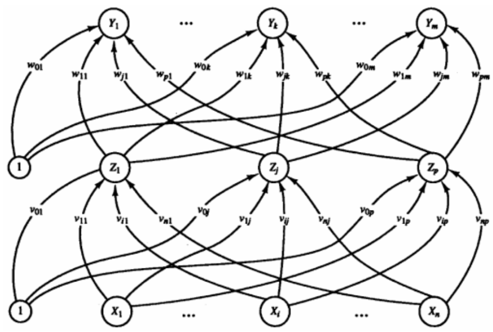

Figure 4. Backpropagation architecture

The backpropagation architecture is depicted in Figure 4, which has n input layers (plus bias), a hidden layer consisting of p units (plus bias), and m output layers. Activation functions can be used to bring input from the input layer to the layer above it to get the desired output. The activation function of a backpropagation neural network must be continuous, easily differentiated, and non-decreasing. This activation function will change the size of the weight.

According to Siang, there are three phases of backpropagation training. The first phase is forward propagation, where each forward propagation input signal is calculated forward using an activation function determined from the input layer to the hidden layer to the output layer. The second phase is backpropagation, where the error, namely the distance between the network output and the desired target, backpropagation starts from the line that is directly related to the units in the output layer. Each output layer checks activations against predefined output targets to find out if there are any errors in the input and output patterns during training. The third phase is weight propagation. In this phase, weight modification is used to reduce errors. To change the weight between the output and hidden layers, the error obtained in the second step is used [35], [36].

Training with backpropagation is the same as training other neural networks. Feedforward networks are trained to calculate weights so that they have the right weight at the end. During the training process, weights are set iteratively to reduce errors. The mean of the squares of errors (MSE), which is also used to calculate the work of the activation function, is the basis for calculating errors [37].

3. RESULTS AND DISCUSSIONS

The research carried out used CT scans of normal lungs and lung cancer. The Artificial Neural Network architecture used in this research uses the Backpropagation algorithm with a structure as shown in Figure 5. The artificial neural network used consists of 10 first hidden layers with 5 second hidden layers and 2 output layers. Input consists of Angular Second Moment (ASM)/energy, contrast, correlation, Inverse Different Moment (IDM)/homogeneity, and entropy using angles of 0°, 45°, 90°, and 135° with 2 pixel distances. The output is normal lungs and lung cancer. The epoch in this ANN structure reaches 10,000 iterations.

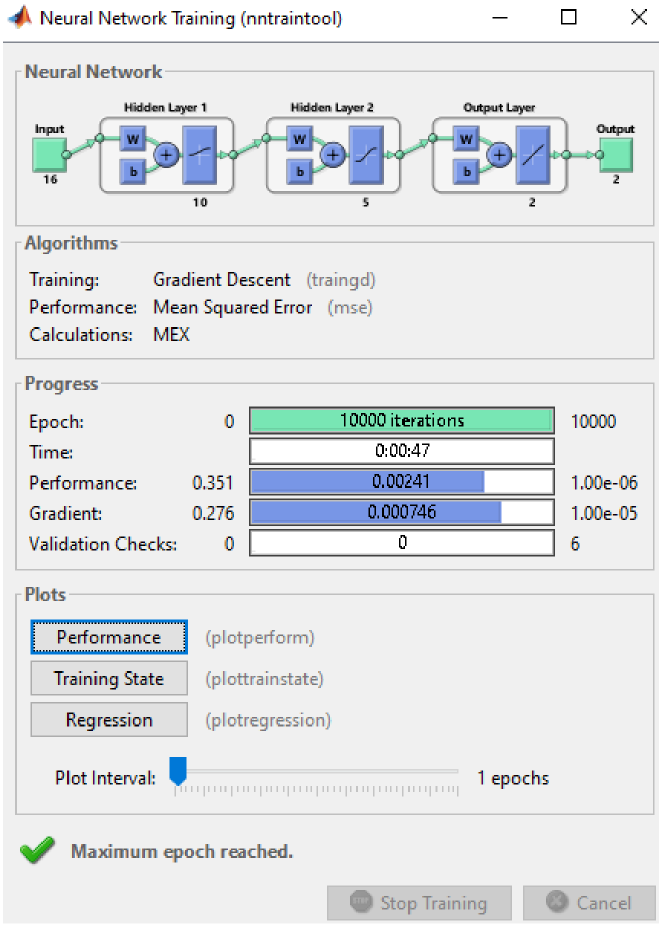

Figure 5. Artificial neural network structure

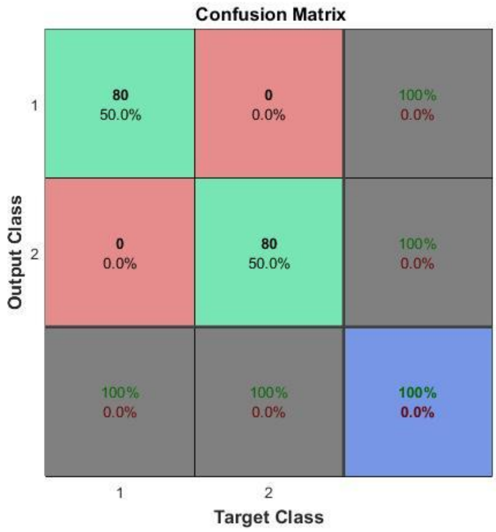

Figure 6. Confusion matrix training data accuracy

Based on the data shown in Figure 6, it is clear that the image training results in identifying normal lung types and lung cancer using the Artificial Neural Network backpropagation algorithm obtained training results with a success percentage of 100%. The data consists of class 1 normal lungs with 80 data and class 2 lung cancer with 80 data. All data is in accordance with the desired target.

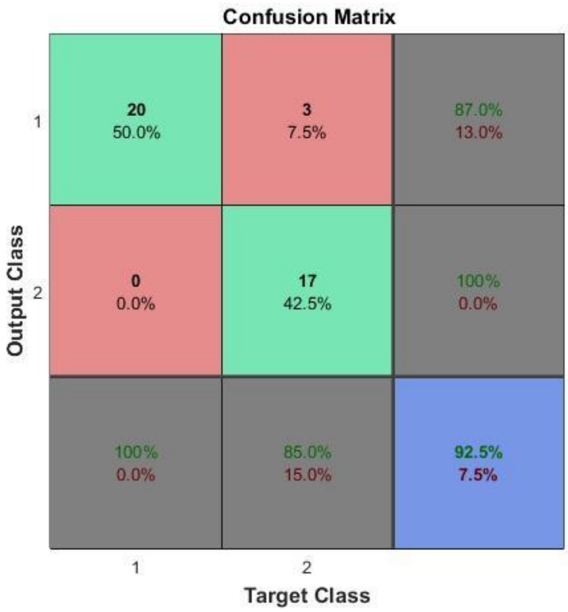

Figure 7. Counfusion matrix test data accuracy

Based on the test data shown in Figure 7, it can be seen that the image test results in identifying normal lung types and lung cancer using the Artificial Neural Network Backpropagation algorithm obtained test results with a success percentage of 92.5%. The data consists of class 1 normal lungs with 20 data and class 2 lung cancer with 20 data. The normal lung data all match the target, but for the lung cancer data there are 3 images where normal lungs are detected. So, the image data that detected lung cancer was 17 images. The percentage of unsuccessful detection was 7.5%. Failure to occur in the testing process can be caused by many factors, one of which is that the part of the lung cancer that is detected is small so that it almost resembles a normal lung.

In the previous study, the highest accuracy of the results showed the highest accuracy level of 88.33%, namely the classification of lung cancer from 120 CT Scan image data. At research, the preposition process begins with a variety of filtering using a low pass filter, median filter, and high pass filter. The segmentation used is Otsu Thresholding which then the texture will be extracted using the Gray Level Co-occurrence Matrix feature (GLCM) with variations in angular direction. The results of GLCM extraction are used as a database that will become a dataset for image classification using Naive Bayesian classification [13]. Therefore, it can be concluded that the lung cancer identification research using the Gray Level Co-occurrence matrix method and Backpropagation Artificial Neural Network on CT-Scan images has higher results because the accuracy level reaches 92.5%.

4. CONCLUSION

In research identifying lung cancer due to air pollution based on the Gray Level Co-occurrence Matrix (GLCM) and Backpropagation Neural Network (JST BP) methods. The artificial neural network must carry out a training process first before carrying out the testing process with a maximum number of epochs of 10,000 iterations. Image processing uses 2 types of lungs with a total of 40 image test data. Normal lung data 20 images and lung cancer data 20 images. The test results proved that the identification of the type of lung cancer was successfully detected with a percentage accuracy of 92.5%, while 7.5% were declared not successfully detected. This shows that the combination of GLCM feature extraction and identification using BP ANN can increase accuracy compared to previous research. Although these results show high effectiveness, it is recommended for further research to explore a combination of feature extraction and identification techniques using other methods.

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