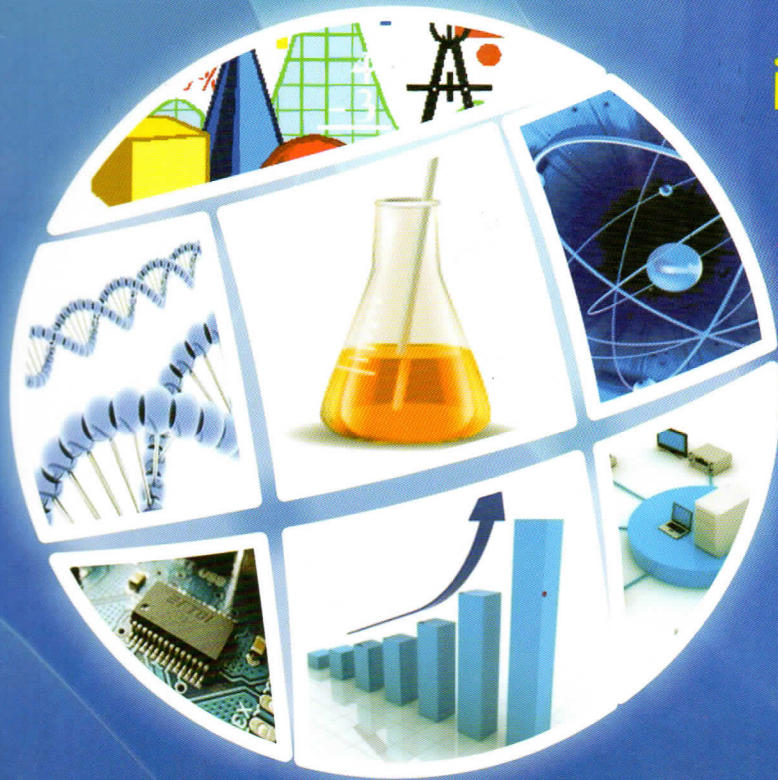


4th iSNPiNSA



International Seminar on New Paradigm
and Innovation on Natural Sciences
and its Application



Innovation
in Applied Science
for Environmental
Resource
Sustainability

PROCEEDINGS



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Application 2014*

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***“Innovation in Applied Sciences for Environmental
Resource Sustainability”***

Dr. Jatniko Endro Suseno, M.Si

Dr.Eng. Hendri Widiyandari, M.Si

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enhancement techniques, linear contrast techniques and non-linear contrast techniques. In linear contrast techniques applying three methods: Max-Min contrast method, Percentage contrast method and Piecewise contrast technique. Non-linear contrast techniques applying four contrast methods, Histogram Equalization method, Adaptive histogram equalization method, Homomorphic Filter method and Unsharp Mask, in the Homomorphic Filter method applying by using two type of filter, Low Pass Filter (LPF) and High Pass Filter (HPF). These methods are applied to choose the base guesses for contrast enhancement image [8].

Approaches for detection and classification of skin cancer images. The proposed work comprises of Pre-Processing, Segmentation, Feature extraction and Classification. In the Pre-Processing stage, Weiner Filter is implemented to remove noise and undesired structures from the images. In the Segmentation stage Distance Regularized Level Set (DRLS) method is implemented in order to acquire a contour by means of the gradient flow that minimizes an energy function with a distance regularization term and an external energy that drives the motion of the zero level set toward desired locations. Support vector machine (SVM) classifier is employed for the classification task, utilizing feature vectors derived from gray level co-occurrence (GLCM) features [9]. Indicated from his research that a small meniscus sign and a medial displacement of the costophrenic angle are the only subtle signs of small accumulations of fluid on post-anterior chest X-rays. On lateral views the finding of a small meniscus sign in the posterior costophrenic angle is the sign of small pleural effusion. In last decades ultrasonography of pleural space becomes a leading real-time method for demonstrating small pleural effusions [10].

If the effusions persist for more than three days, thoracentesis is indicated. The initial thoracentesis is usually performed for purposes of diagnosis; unless the patient has shortness of breath when at rest, in which case therapeutic thoracentesis to remove up to 1500 ml of fluid is indicated. Thoracentesis can be performed at the bedside with the aid of diagnostic imaging. Ultrasonographic guidance is indicated if difficulty is encountered in obtaining pleural fluid or if the effusion is small. An exception is patients with a clinical diagnosis of left ventricular failure; it is reasonable to treat these patients initially with diuretics, reserving pleural aspiration for those with 'atypical' features (such as asymmetrical bilateral effusions, unilateral effusion, chest pain or fever) or whose effusions fail to respond to diuresis within several days [11].

1 METHODOLOGY

1.1 Image Processing Thorax

1.1.1 Image Enhancement

Image processing begins with the process of changing the format of an RGB image to Grayscale. Samples were taken from the hospital in the form of an RGB image that must be converted to grayscale for next processing. One of the sample images and the results are shown in Figure 1.

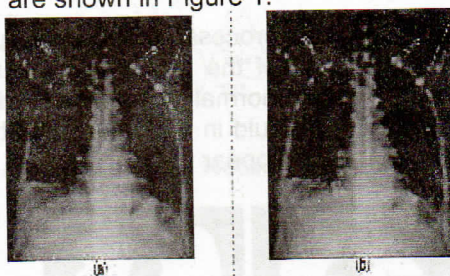


Figure 1: The process of RGB to Grayscale (a) RGB image, (b) grayscale image

The next process carried out the histogram equalization process. This process is carried out for a uniform histogram. One sample image and histogram equalization results are shown in Figure 2.

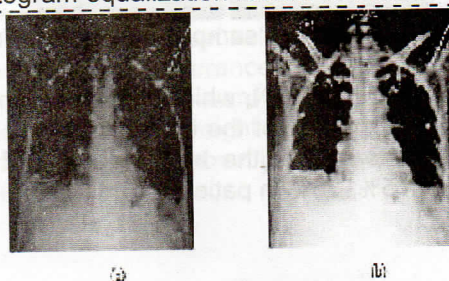


Figure 2: Histogram equalization process (a) Grayscale image, (b) image histogram equalization Results

Histogram equalization process is not enough to improve the contrast of the image of the next process is set contrast enhancement in Figure 3. The difference absorption of X-rays of each patient sample because each image has a different intensity values. Therefore, the contrast setting is done automatically so that each sample can be set uniformity contrast.

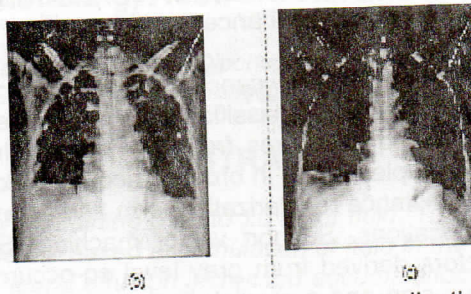


Figure 3: The process of contrast enhancement (a) Histogram equalization image, (b) Result image contrast enhancement settings

3.1.2. Level Set Segmentation

The Image will be segmented thorax must have uniformity of contrast. The segmentation process starts with determining the limits on each sample image initialization, initialization of the level set method will meet the border of the image of the thorax, so that the image will be obtained pattern of the right lung and the left lung. The result of this pattern of lung binary image where each pixel is white is 1 and each black pixel is 0. Process and level sets segmentation result is shown in Figure 4.

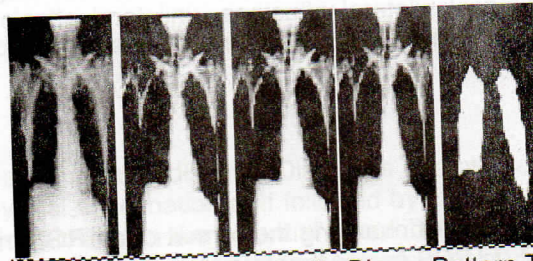


Figure 4: Segmentation Process and Results Binary Pattern The Image Thorax

After the segmentation process performed extraction process binary image pattern of the thorax. The extraction process is intended to determine the characteristics of the thorax with pleural effusion and normal thorax, the difference between the image of the sample indicated normal and pleural effusion is located at the tip of pointy or inefficacy of thorax image, as shown in Figure 5, the fluid in the pleural cavity will cover the bottom of the lungs when the volume of fluid increases the lung image will appear flat.

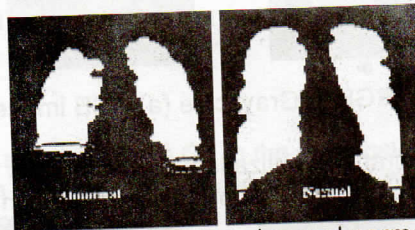


Figure 5: Differences pleural effusion samples and normal image that has binary

Then a binary characteristic pattern recognition of ANN, which was trained binary characteristic pattern that is part of the 5% -30% below the size of the image pattern of the thorax, obtained the best accuracy for the introduction and testing of ANN pattern that is characteristic of the binary pattern of 15%. In Figure 6. will be shown to characterize binary patterns extracted from 5% -25% in patients 1.

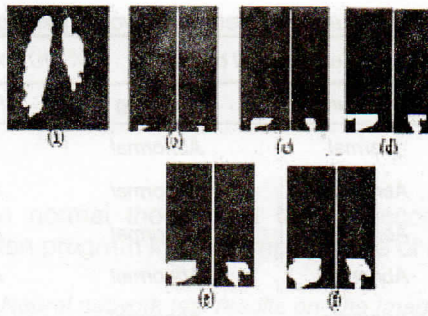


Figure 6: (a) characteristics of the binary image size, (b) 5% of the bottom image, (c) 10% of the bottom image, (d) 15% of the bottom image, (e) 20% of the bottom image, and (f) 25% of the bottom image

12. Training Artificial Neural Network (ANN)

12.1 Network Architecture

In training the neural network for this study using the network architecture shown in Figure 7. Figure 7 shows the parameters of the ANN in this study which has 100 input ANN architecture, composed by two screens hidden (hidden layers) containing 10 neurons in each hidden layers. Using binary sigmoid activation function in the hidden screen and identity activation function on the output display, the maximum number of training epochs with a time of approximately 12 and 11 second iteration process.

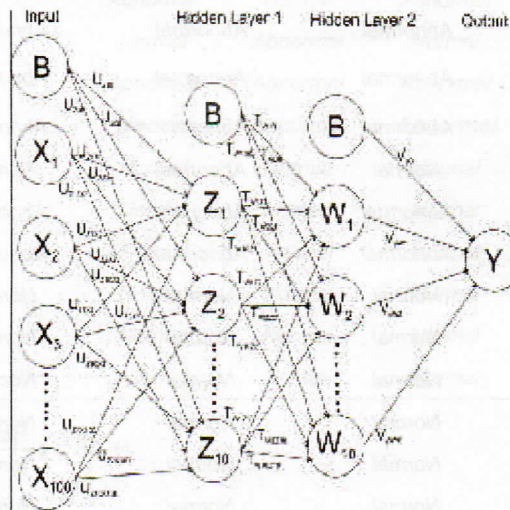


Figure 7: Neural Network Architecture.

12.2. Propagation Network

Propagation ANN involves three phases which forward propagation, backward propagation and weight changes. During the forward propagation, input signals are propagated to the hidden screen using binary sigmoid activation function next propagated forward again to the next hidden screen to produce a network output. Next, the network output compared with the target to be achieved (where the image of the targeted pleural effusion is 0 and normal image of the targeted value is 1). The difference between the network output and the target is the error that occurred. If this error is smaller than the tolerance limit (set value of tolerance $1e-6$) is specified, then the iteration is stopped. However, if the error is still greater than the tolerance limit, then the weight of each line in the network will be modified to reduce errors, this is done through backward propagation. Backward propagation will change the weight values are derived from the hidden units to the weight of all lines simultaneously modified, this process is a phase change in weight, after all modified weights above the third phase are repeated continuously until the termination condition (minimum error value) are met.

4. RESULT

After the binary characteristic of pattern recognition process on the results of accuracy the ANN training neural network and diagnosis of doctors in the table 4.1

Table 1. Accuracy of Neural Network Training.

Number of patients	Testing ANN output		Diagnosis Doctors	
	Right lung	Left lung	Right lung	Left lung
1	Normal	Abnormal	Normal	Abnormal
2	Abnormal	Abnormal	Abnormal	Abnormal
3	Abnormal	Abnormal	Abnormal	Abnormal
4	Abnormal	Abnormal	Abnormal	Abnormal
5	Abnormal	Abnormal	Abnormal	Abnormal
7	Abnormal	Normal	Abnormal	Normal
8	Abnormal	Abnormal	Abnormal	Abnormal
9	Abnormal	Normal	Abnormal	Normal

Number of patients	Testing ANN output		Diagnosis Doctors	
	Right lung	Left lung	Right lung	Left lung
11	Abnormal	Abnormal	Abnormal	Abnormal
12	Normal	Abnormal	Normal	Abnormal
13	Normal	Abnormal	Normal	Abnormal
14	Abnormal	Normal	Abnormal	Normal
15	Abnormal	Abnormal	Abnormal	Abnormal
16	Abnormal	Abnormal	Abnormal	Abnormal
17	Abnormal	Abnormal	Abnormal	Abnormal
18	Normal	Abnormal	Normal	Abnormal
19	Abnormal	Abnormal	Abnormal	Abnormal
20	Abnormal	Abnormal	Abnormal	Abnormal
21	Normal	Normal	Normal	Normal
22	Normal	Normal	Normal	Normal
23	Normal	Normal	Normal	Normal
24	Normal	Normal	Normal	Normal
25	Normal	Normal	Normal	Normal
26	Normal	Normal	Normal	Normal
27	Normal	Normal	Normal	Normal
28	Normal	Normal	Normal	Normal
29	Normal	Normal	Normal	Normal
30	Normal	Normal	Normal	Normal
31	Normal	Normal	Normal	Normal
32	Normal	Normal	Normal	Normal
33	Normal	Normal	Normal	Normal
34	Normal	Normal	Normal	Normal
35	Normal	Normal	Normal	Normal
36	Normal	Normal	Normal	Normal
37	Normal	Normal	Normal	Normal
38	Normal	Normal	Normal	Normal
39	Normal	Normal	Normal	Normal
40	Normal	Normal	Normal	Normal

$$\begin{aligned}
 \text{Accuracy (\%)} &= \frac{\text{COUNTING THE EXACT NUMBER}}{\text{Number of counting}} \times 100 \% \\
 &= \frac{40}{40} \times 100\% \\
 &= 100 \%
 \end{aligned}$$

ANN testing performed to identify the normal thorax and thorax accompanied by pleural effusion diagnosis radiologist. The results of the identification program in the sample image of the thorax indicated by Table 4.2.

Table 2. Neural network test results on The Image Thorax.

Number of patients	Testing ANN output		Diagnosis Doctors	
	Right lung	Left lung	Right lung	Left lung
1	Abnormal	Abnormal	Abnormal	Abnormal
2	Abnormal	Normal	Abnormal	Normal

Number of patients	Testing ANN output		Diagnosis Doctors	
	Right lung	Left lung	Right lung	Left lung
4	Abnormal	Abnormal	Abnormal	Abnormal
5	Abnormal	Normal	Abnormal	Abnormal
6	Abnormal	Normal	Abnormal	Normal
7	Normal	Abnormal	Normal	Abnormal
8	Abnormal	Abnormal	Abnormal	Abnormal
9	Normal	Abnormal	Abnormal	Abnormal
10	Normal	Normal	Normal	Normal
11	Normal	Normal	Normal	Normal
12	Normal	Normal	Normal	Normal
13	Normal	Normal	Normal	Normal
14	Normal	Normal	Normal	Normal
15	Normal	Normal	Normal	Normal

$$\begin{aligned}
 \text{Accuracy (\%)} &= \frac{\text{COUNTING THE EXACT NUMBER}}{\text{Number of counting}} \times 100 \% \\
 &= \frac{14}{15} \times 100\% \\
 &= 93,33 \%
 \end{aligned}$$

CONCLUSION

Program in this study succeeded in identifying pleural effusions with methods of artificial neural network back propagation through the binary image feature extraction thorax. Neural network training process is performed to identify the appropriate patient data 40 of the 40 patient data are trained. Process of identification of pleural effusion by testing the neural network on the condition of setting two hidden layers, each of which contains 10 hidden layers of neurons, the data obtained from 15 patients who tested 14 correctly identified the 93.33% of data identification value.

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