Computer-Aided Diagnosis (CAD) to Detect Abnormality on CT Image of Liver

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Abstract. Liver cancer on CT-scan image has different shapes, locations and textures in every image. The contrast difference between abnormal and healthy liver is often indistinguishable, making it difficult to evaluate. Liver abnormalities are such as swelling, fibrosis, and the presence of benign or malignant tumor. The difference of low contrast with wide size on the image is easily known as abnormality, but it is very hard to evaluate for small mass and low contrast. In this research, CAD was conducted to help the evaluation on liver abnormality, especially abnormality in small size. The research method used was active contour-based segmentation method. The research data were secondary data, the abdomen image was produced from the modality of Computed Tomography Scanner (CT-Scan) in Regional Public Hospital of Cibinong, Bogor. The data collection techniques were through observation on the image data of abnormal liver from either liver cancer patients, normal liver patients, as well as patients of other diseases as diagnosed by the doctor. Meanwhile, the data was processed through feature extraction process using the texture analysis of Gray-Level Co-occurrence Matrix (GLCM) with machine learning of Artificial Neural Network (ANN) to detect abnormality on image. The research stated that ANN can be used to categorize the images into normal and abnormal groups at 89% accuracy, 86% sensitivity, 92% specificity, 91% precision, and 10% overall error. Keywords: Segmentation, Active Contour, GLCM, Classification, ANN.

1. Introduction
Tumor is an abnormal cell growth. Basically, tumor is divided into two types: benign or malign. If the growth is benign and it does not harm its surrounding area, then it is a benign tumor. On the opposite, if the tumor grows malignant and quickly spreads to the other area (metastases), then it is malignant tumor. An example of malignant tumor case is liver cancer. In Global Cancer Statistics, it was reported that “Liver cancer in men is the fifth most frequently diagnosed cancer worldwide but is the second most frequent cause of cancer death. In women, it is the seventh most commonly diagnosed cancer and the sixth leading cause of cancer death”. According to the mentioned research, in 2008, there were estimated to be 748,300 new liver cancer cases in the world, and 695,900 people died from liver cancer [1]. A technology that is used to analyze and diagnose liver cancer is Computed Tomography Scanner (CT-Scan). CT0-Scan is a modality of x-ray which provides three-dimensional image [2]. The quality of CT-Scan image is determined by the resolution and contrast [3]. The contrast difference between abnormal and health liver is often indistinguishable, making it difficult to evaluate
Liver abnormalities are such as swelling, fibrosis, and the presence of benign or malignant tumor. The difference of low contrast with wide size on the image is easily known as abnormality, but it is very hard to evaluate for small mass and low contrast. Therefore, this research conducted the initial study to detect liver abnormality on CT-Scan image using CAD method, which have recently and rapidly become of growing interest. They include many techniques of image analysis, such as thresholding, organ segmentation, and tissue characterization, often based on texture analysis [5], combined with classification algorithms. A large number of publications on the subject proved that the (semi) automatic CAD systems appear to be a powerful tool for supporting medical decisions. In addition, this program also calculates the area and volume of liver abnormalities, so it is expected to be used by radiology specialists as a tool that can provide information about the spread of liver abnormalities, because the area and volume of liver abnormalities were not calculated in previous studies [6].

2. Material and Methods

This research consists of five stages. The first stage was categorizing normal and abnormal images based on the Hounsfield Unit (HU) value. Abnormal image was determined for every image of slice amount which detected abnormality. Liver CT image samples came from 6 normal liver patients and 12 abnormal liver patients with contrast media. The total images were 203 images which consisted of 150 normal liver images and 156 abnormal liver images. These images were divided into two: images for training and for testing. Within this research, the radiology specialist doctor only provided the information on two types of abnormality, which were abscess and Hepatocellular Carcinoma (HCC), which occurred to 6 and 4 patients respectively.

The second stage was thresholding process which aimed to distinguish the liver image with the surrounding tissues using MatLab program and then followed with liver image cropping process. The third stage was feature extraction using Gray Level Co-occurrence Matrix (GLCM) method. The image GLCM result could be characterized by four parameters, which are contrast, correlation, energy, and homogeneity [7]. Classification through Artificial Neural Network (ANN) was conducted to determine whether the liver image was normal or abnormal. In this study, ANN is used for classification because, massive parallelism, distributed representation, learning ability, generalization ability, and fault tolerance. The accuracy of ANN result was tested using Receiver Operating Characteristics (ROC) method which referred to the evaluation result from the radiology specialist doctor.

In order to know the abnormality volume, abnormality image area was measured on each slice. With 0.95 mm² pixel size and 5 mm slice thickness, then the liver volume or the abnormality could be determined.

3. Result and Discussion

3.1. Preprocessing

Figure 1 shows the CT image sample of abnormal liver, and the result of threshold process is shown in Figure 2.
Figure 1. Initial image in DICOM format.

Figure 2. Image after thresholding process.

3.2. Segmentation

The segmentation method or image cropping used was active contour or also known as region-based snake model. Active contour is vector \((x, y)\) which aims to encircle the liver area and describe it in object contour. The result of cropping treatment can be seen in Figure 3.

Figure 3. Liver image cropping from Figure 2.

Figure 4. Binarization image result from suspected area of abnormal liver which was provided for determining volume.

3.3. Feature Extraction

GLCM extraction feature process was performed using 4 angles at 0°, 45°, 90° and 135° of which the average result was used for classification process [8]. The result of feature extraction is presented on Table 1.

Table 1. Value range of four feature parameters on abnormal and normal liver image.

| Feature    | Abnormal liver image     | Normal liver image    |
|------------|--------------------------|----------------------|
| Correlation| 0.9905 – 0.9943          | 0.9706 – 0.9921      |
| Energy     | 0.6038 – 0.9802          | 0.6614 – 0.9909      |
| Homogeneity| 0.8516 – 0.9926          | 0.8748 – 0.9965      |
| Contrast   | 101.66 – 458.15          | 67.07 – 463.66       |
Figure 5 is a graph of data distribution on the feature extraction result using GLCM based on the features of correlation, energy, homogeneity and contrast. Based on the graph above, normal and abnormal liver images had not been clearly distinguished, there were overlaps on normal and abnormal liver images; therefore, a classification method to recognize the normal and abnormal liver images is required.

3.4. Classification
Classification was performed for the accuracy test of the used program. By retesting 100 abnormal and normal liver images, the accuracy result of the program was obtained and shown on in Table 2.

| Data     | Samples | Error (%) |
|----------|---------|-----------|
| Training | 200     | 10.7      |
| Testing  | 106     | 3.8       |

Classification using ANN produced error percentage which is the error value on the usage of machine learning at 10.7% on training data and 3.8% on testing data. Through ANN, confusion matrix value was produced—it is the categorization of normal and abnormal image based on the diagnosis from doctor and program—and was also used as the success measurement for the ANN classification program’s result on the liver images.
To ensure the produced error percentage, ANN model had to be tested to assure its stability in providing the prediction result. The evaluation used within this research was through ROC statistic model as shown in Table 4.

Table 3. Confusion matrix of ANN classification result

| Parameter            | Number of confusion matrix |
|----------------------|----------------------------|
| TP (True Positive)   | 44                         |
| TN (True Negative)   | 51                         |
| FP (False Positive)  | 4                          |
| FN (False Negative)  | 7                          |

Table 4. The measurement of program performance based on ROC parameter

| Parameter    | The percentage of (%) |
|--------------|------------------------|
| Accuracy     | 89 %                   |
| Sensitivity  | 86 %                   |
| Specificity  | 92 %                   |
| Precision    | 91 %                   |
| The overall error | 10 %                 |

Figure 6. Cross entropy in ANN classification

Figure 6 is the performance of ANN validation on epoch 32. Iteration or epoch stopped because the error percentage was met. Cross entropy is the error calculation method used within this ANN model.
On the graph of performance, the data of training and testing have to meet in one equilibrium point to reach the error stability.

3.5. The calculation of area and volume abnormality

Table 5. Number of images and volume of abnormal liver.

| Patients | Image Slice Amount | Area (mm$^2$) | Distance between slice (mm) | Volume (mm$^3$) |
|----------|-------------------|---------------|----------------------------|----------------|
| 1        | 19                | 203.293       | 5                          | 1016465        |
| 2        | 20                | 210.953       | 5                          | 1054765        |
| 3        | 29                | 221.864       | 5                          | 1109320        |
| 4        | 16                | 253.621       | 5                          | 1268105        |
| 5        | 21                | 212.043       | 5                          | 1060215        |
| 6        | 9                 | 259.412       | 5                          | 1297060        |
| 7        | 27                | 212.643       | 5                          | 1063215        |
| 8        | 3                 | 219.472       | 5                          | 1097360        |
| 9        | 8                 | 229.136       | 5                          | 1145680        |
| 10       | 27                | 207.413       | 5                          | 1037065        |
| 11       | 3                 | 209.396       | 5                          | 1046980        |
| 12       | 8                 | 207.820       | 5                          | 1039100        |
| Average  |                   | 220.588       |                            | 1102940        |

Table 6. Number of images and volume of normal liver.

| Patients | Image slice number | Area (mm$^2$) | Distance between slice (mm) | Volume (mm$^3$) |
|----------|--------------------|---------------|----------------------------|----------------|
| 1        | 30                 | 200.435       | 5                          | 1002175        |
| 2        | 31                 | 201.080       | 5                          | 1005400        |
| 3        | 37                 | 202.393       | 5                          | 1011965        |
| 4        | 32                 | 212.486       | 5                          | 1062430        |
| 5        | 33                 | 215.047       | 5                          | 1075235        |
| 6        | 37                 | 200.871       | 5                          | 1004355        |
| Average  |                   | 205.385       |                            | 1026926        |

The measurement of liver volume was determined using ImageJ software, where the pixel distance had to be heeded because it affected the measurement result. Based on the baseline, the liver volume size for Indonesian men and women are 1161.252 cm$^3$ and 1347.221 cm$^3$, with percentage at 16.01%, and the Hounsfield unit on liver is $+69.80 \pm 11.21$ HU with the range at $+58.13$ HU to $+75.91$ HU [9]. Based on IAEA, Hounsfield Unit of liver is $+60$ HU ($+50$ HU to $+70$ HU) [10].
As an example, the calculation result on a patient with abscess abnormality was visible on 13 slices with the total abnormality volume of 1268 mm$^3$. The liver volume calculation result on this patient was seen from the total image volume of 1145680 mm$^3$ which means that the abnormality volume was only 0.1% out of the total liver volume. Within this research, the smallest area that the program was able to detect was up to 5.8 mm$^2$.

4. Conclusion
The CAD evaluation result using ROC method has discovered that the accuracy is 89%, sensitivity is 86%, specificity is 92%, precision is 91%, and overall error is 10%. Abnormal liver tends to have relatively bigger volume than normal liver. For the information, normal liver has 1002 and 1026 cm$^3$ volume. From the CAD result, liver CT image was able to detect abnormality with the smallest size at 5.8 mm$^2$.

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