Computer aided diagnosis (cad) ct images for abnormal cervix using region-based snake model and support vector machine (svm)

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Abstract. Tumors are an abnormally growing cells and are divided into two types, benign and malignant. Cervical cancer is one of the types of malignant tumors. It is a type of cancer with the highest prevalence in the world. Nevertheless, most cervical cancer patients came to doctors with end-stage cancer conditions. Various diagnostic imaging modalities are used to determine the location, the size and the severity of cervical cancer that affects patients, one of them is CT-Scan. There are not many researches on digital image processing of cervical cancer used CT-Scan images so that makes this research different from others. The process of segmentation, feature extraction, and classification are some examples of digital image processing techniques applied to cervical cancer for further analysis. This study created a program which used CT-Scan image data and Region-based Snake Model as the segmentation method. It also used Support Vector Machine (SVM) and feature extraction in the form of Gray Level Co-occurrence Matrix (GLCM) of texture analysis. The segmentation process was used to obtain the region of cervical abnormalities. The classification process was expected to categorize the image data onto normal images and cervical abnormalities images. Results of segmentation process which gave limits of the region of the cervical abnormalities was quite appropriate and fit to diagnosis of specialists or radiologists. The classification process gave good statistical results in distinguishing normal images and cervical abnormality images, i.e., sensitivity, specificity, accuracy, precision, overall error, and Area Under Curve (AUC) reached 88\%, 92\%, 90\%, 91.67\%, 10\%, and 90\%.

1. Introduction
Tumors are an abnormally growing cells. They are divided into two types, benign and malignant. Cervical cancer is one of the type of malignant tumors. It is one of the highest prevalence cancers in the world. It becomes the fourth cancer of the most commonly found in women in the world [1]. In Southeast Asia, cervical cancer is ranked first among cancer patients in women. In Indonesia, the number of cases of cervical cancer reaches 20,928 cases of 92,200 cases of female deaths as a whole. It makes cervical cancer be the second leading cause of death in Indonesia after breast cancer, with an age range of 15 to 44 years [2]. The Ministry of Health of the Republic of Indonesia estimates that the current number of women with new cervical cancer ranges from 90 to 100 cases per 100,000 population and there are 40,000 cases of...
cervical cancer per year [3]. However, the dangers of cervical cancer are not widely known by people because patients generally do not feel symptoms leading to cervical cancer. It causes many cervical cancer patients came to the doctor with end-stage cancer.

Various diagnostic imaging modalities are used to determine the location, the size, and the severity of cervical cancer that affects patients. CT-Scan is one of those technologies. We know that MR images are superior to CT images on many aspects, especially for tumor localization in patient’s body. MRI gives a very good and clear edges of soft tissues on its image. However, not all hospitals in Indonesia are equipped with MRI, especially remote areas in Kalimantan, Sulawesi, and Papua. Many cervical abnormalities patients in remote areas are examined using CT-Scan to know how severe their tumors and to make a contour of tumors for radiotherapy treatment planning. In this study, we want to maximize CT images of cervical cancer patients to be sharper and clearer so it can help doctor to make a decision on the abnormalities, such as cancer staging of patients.

There are many studies of medical imaging, especially cervical cancer, using MR images, USG images, pap smear images and PET/CT images. MR images are used in many studies, such as in [4]-[10]. [11]-[14] used pap smear images of cervical cancer patients and USG images are used in [15]. Beside that, PET/CT images are used in [16]. Therefore, an innovation is needed in terms of segmentation and classification between the normal and cervical abnormalities of the CT images. The program that we developed is expected to be used by obstetricians and radiologists as a part which is able to provide information on how big cervical abnormalities have spread in decision-making stages of cervical abnormality and the type of therapy to be administered to patients. The program is targeted to used by remote area hospitals with only CT-Scan facilities and without radiotherapy facilities. The prediction decided by the program is expected to be one of the preliminary information for doctors in remote area hospitals to decide the status of a patient before being referred to a government general hospital. Study using CT images data for segmentation and classification of cervical cancer has not been much done because it is quite difficult to do. It needs to be investigated more deeply [17]. This study used CT images data with region-based snake model as segmentation method and Support Vector Machine (SVM) as classification technique using feature extraction in the form of Gray Level Co-occurrence Matrix (GLCM) of texture analysis.

2. Proposed Method

In this study, we used 200 CT images consisting of 100 normal cervical images and 100 abnormal cervical images. We divided those images of two datasets, i.e., training dataset and testing dataset. The training dataset consist of 50 normal images and 50 abnormal images as well as the contain of the testing dataset. All images must go through the preprocessing, segmentation, feature extraction and classification process. The flow diagram of the proposed method is shown in Figure 1.
FIGURE 1. The flow diagram of the proposed method

In the preprocessing, CT images of DICOM type were changed into TIFF type to reduce computational load. After that, images were normalized, denoised and sharpened using second order filter. Normalized images were cropped so that the next process was focused only on the object areas. The cropped image was used as an input for segmentation process. We used snake model as segmentation method. The snake model used a spline of energy reduction to find the shape of the object of the image. It determined an area on abnormalities cervix using a spline of energy reduction to determine the shape of the target. It was believed by many researchers for its ability to find well-segmented object variations, as had been done in [16], [18]-[21]. Formula 1 was mathematical form of region-based snake model by [18].

\[
E_{\text{region}}(x, y) = \lambda_1 \int_{R_1} (I - \mu_1)^2 \, dx + \lambda_2 \int_{R_2} (I - \mu_2)^2 \, dx + \lambda_3 \int_{\partial R_1} \mu_1 \, ds + \lambda_4 \int_{\partial R_2} \mu_2 \, ds
\]

I was the input image, \(\mu_1\) was the average intensities of the contoured region of \(R_1\) and \(\mu_2\) was the average intensities of the outer region of \(R_2\), \(\lambda\) was the smoothness determinant parameter of the spline.

In this study, the set of snake model control points was not used at the beginning of the iteration; instead, it was replaced by a circle line that detected abnormalities based on the relation of energy values around the line. If there was a considerable difference between the regional energy on the line and the outer region of the line, then the algorithm stopped to run and displayed the result of segmentation. However, if during the iteration of the outer region the line had the energy or gray degree almost equal to the region in the line, then iteration still carried-out until it found a considerable energy difference between the two regions. The expected result was the contour generated by the snake model algorithm showing the predicted region of cervical abnormalities and normal cervix.

We used a texture analysis as a feature extraction method. Texture analysis measured various variations in the intensity of the surface of the image. An image had many textures, such as rough, smooth or wavy, especially in medical images. It was known as Gray Level Co-occurrence Matrix (GLCM). There had been some previous studies that used texture analysis in feature extraction, i.e., [7], [8], [12] and [13] . The function of GLCM stated that the texture features had information about the spatial distribution of the gray degree variations on the image. It calculated how often pixel pairs with specific values and in certain spatial relationships occur in the image, process the GLCM and extract the statistical value of the matrix to get the texture of an image. We generated 4 GLCM matrices at angles 0°, 45°, 90° and 135°. The GLCM features worked in the image spatial domain so that the value of each pixel was very
influential in calculating the GLCM parameter values. Some statistical parameters in GLCM explained the
texture of an image in terms of “Contrast”, “Correlation”, “Energy” and “Homogeneity” values. Formula
2 to 5 were the mathematical equation of each GLM features used in this study.

\[ f_{\text{contrast}} = \sum_{i,j=0}^{N-1} P(i,j)(i-j)^2 \]  
\[ f_{\text{correlation}} = \sum_{i,j=0}^{N-1} P(i,j) \frac{(i-\mu)(j-\mu)}{\sigma^2} \]  
\[ f_{\text{energy}} = \sum_{i,j=0}^{N-1} |P(i,j)|^2 \]  
\[ f_{\text{homogeneity}} = \sum_{i,j=0}^{N-1} \frac{P(i,j)}{N} \]  

Where

\[ \mu = \sum_{i,j=0}^{N-1} P(i,j) \]  
\[ \sigma^2 = \sum_{i,j=0}^{N-1} P(i,j)(i-\mu)^2 \]  

\(P_{ij}\) was the element i, j of the normalized symmetric GLCM. I and j were the coordinates that had the
pixel value of each position, N was the number of gray levels available on the image, \(\mu\) was the average of
GLCM which was the approximate intensity of all connected pixels with GLCM and \(\sigma\) was a variance of
the intensity of all pixels that contribute to GLCM.

The result of feature extraction was used as an input for machine learning to classify these data. In this
study, we used Support Vector Machine (SVM) as machine learning. The SVM principle was to find a
hyper plane between two classes, through the selection of hyper plane with the maximum limit. SVM
succeeded in classifying an image of a type of category based on its feature extraction in [7], [8] and [11]-
[13]. We classified images data onto two groups, i.e., normal group and abnormal group. SVM decision
function on two dimensional field is shown in Figure 2.

![FIGURE 2. SVM decision function in two dimensional field [22]](image)

The method of this study has been assessed statistically to know its performance in solving the
problem. The most common approach was Receiver Operating Characteristics (ROC). In this study, we
used the 10-fold cross validation to evaluate performance of SVM. It used 100 images consisted of 50
normal images and 50 abnormal images. Cross validation was one of methods that used to measure the
stability of SVM for predicting testing data images. From these data, 90 images were training data set and
the remaining ones were testing data set. There were chosen randomly and we did not know members of
both data sets.
Measured ROC parameters in this study were accuracy, sensitivity, specificity, accuracy, precision, overall error and Area Under Curve (AUC). Beside that, we tested all images of testing data set and recorded them manually. After that, we calculated ROC parameters and compared to the result of cross validation. Formula 8 to 13 were the mathematical equation of measured ROC parameters in this study [23].

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}
\]

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \tag{9}
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \tag{10}
\]

\[
\text{Precision} = \frac{TP}{TP + FP} \tag{11}
\]

\[
\text{Overall Error} = \frac{FP + FN}{TP + TN + FP + FN} \tag{12}
\]

\[
\text{Area Under Curve (AUC)} = \frac{\text{Sensitivity} + \text{Specificity}}{2} \tag{13}
\]

True Positive (TP) meant an image was detected and diagnosed as an abnormal image by program and doctor. True Negative (TN) was an image detected and diagnosed as a normal image by program and doctor. False Negative (FN) meant an image was detected and diagnosed as a normal image by program, but was diagnosed as an abnormal image by doctor. True Positive (FP) was an image detected and diagnosed as an abnormal image by program, but diagnosed as a normal image by doctor.

### 3. Result

Figure 3 presents result of each step of the preprocessing. An abnormal image of DICOM format was changed into TIFF format and it filtered to reduce noises, sharpened and normalized by second order filter. Beside that, Figure 3 showed the result image of cropping process. This image was used as an input for snake model segmentation that showed in Figure 4.
FIGURE 3. Steps of preprocessing. (a) image with DICOM type. (b) image with TIFF type. (c) image result of normalization. (d) choose a region in image for cropping. (e) cropped image.

FIGURE 4. Image result of snake model segmentation. The red line is the contour line that moves on iteration and looks for energy similarities between adjacent pixels.

The result of extraction feature process was a feature matrix of 100 X 4 for each group. We took mean values of all features to avoid dependence on neighboring pixels. This matrix was an input for SVM. We used the training set matrix consisted of 50 normal images and 50 abnormal images to train SVM model. The 10-fold cross validation is used to evaluated the stability of machine. It gave results, i.e., ROC parameters value from the number of TP, TN, FP, and FN. In this part, we found that the TP was 4, FP was 0, FN was 1, and TN was 5. Based on these values, the SVM model had a sensitivity of 0.833, specificity of 1, accuracy of 0.9, precision of 1, error of 0.1, and Area Under Curve (AUC) of 0.917. Figure 5 presents the data grouping charts performed by SVM based on the 10-fold cross validation.
On the second part of evaluation, we used 100 images of testing data set to know how good SVM to classify data set. The result of this technique evaluation gave the TP value of 44, FP value of 4, TN value of 46, and FN value of 6. Therefore, SVM model had a sensitivity of 0.88, specificity of 0.92, accuracy of 0.9, precision of 0.9167, error of 0.1, and AUC of 0.9. These values were simply a guarantee that SVM model could be used to classify normal and abnormal cervical images accurately.

4. Conclusion
CT images of normal cervixes and abnormal cervixes were used in segmentation and classification using this CAD program. A region of abnormal cervix on cervical CT image was segmented using snake model algorithm. This algorithm gave good results of all images of both dataset. Texture analysis as a part of feature extraction was used in this study to give information about the difference between feature of normal images and feature on abnormal images, especially texture features. The values of texture features were used as an input of SVM model to classify images of testing dataset into two groups, ie. normal group and abnormal group. Based on the results of cross validation and tested all images of testing data set, we believed that this program can be trusted to classify and predict images accurately. The method which was used in this CAD had sensitivity of 88%, specificity of 92%, accuracy of 90%, precision of 91.67%, error of 10%, and AUC of 90%.

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