Feature Extraction and Classification of Thorax X-Ray Image in the Assessment of Osteoporosis

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Abstract — **Previous studies showed that it was possible to have a prediction or an early detection of osteoporosis by measuring the thickness of the cortex of the clavicle of thorax x-ray image. The drawback of this system was that it was still dependent on the operator of subjective vision applications in the measurement. In addition, the accuracy of the system very much relied on the x-ray image quality. Therefore, it is in urgent need of another system which can automatically classify x-ray image and another method of image processing to identify and acknowledge a certain texture of the based image using a set of classes or texture classification given. In this paper, calculation and analysis of a series of image processing algorithms to perform x-ray image classification are done using the K-Nearest Neighbor (KNN) and feature extraction techniques Gray Level Co-occurrence Matrix (GLCM) on small sample size data of 46 Thorax x-ray images of 44 females and 2 males with the average age of 63 years old. T-score of these images had been measured using DEXA scan before as a justification. The proposed method shows that the clavicle cortex thickness measurement using GLCM and KNN method as feature extraction and image classification has its sensitivity of 100% and specificity of 90%. Furthermore, the accuracy which is obtained from the entire implementation capability in correctly assessing osteoporosis is 97.83%. Thus, it is evident that it is significantly correlated with predetermined T-score of DEXA in the assessment of osteoporosis.**

Keywords — image classification; feature extraction; thorax x-ray; osteoporosis; K-Nearest Neighbour; Gray Level Co-occurence Matrix.

I. INTRODUCTION

Previous research by Delimayanti and Riandini (2014) produced a web-based software application for detecting osteoporosis using image data of Thorax x-ray by measuring the thickness of the cortex of the clavicle. This application comprised a series of image processing algorithms such as image filter, image enhancement, edge detection, and image rotation by allowing data retrieval of up to ten times (10x) and then calculating the average of the results of measuring the thickness of the cortex of the clavicle. Results of the application had been tested on the x-ray image using past data as well as real data from the hospital. The results revealed statistical calculation accuracy rate of up to 91.3% with a sensitivity of 94.4%. However, the system was still dependent on the operator of subjective vision applications in measuring the thickness of the cortex of the clavicle. In addition, differences in the techniques in taking x-ray image also affected the results, certainly affecting the image in the image processing cortical thickness measurement. Therefore, an alternative system which can automatically classify x-ray image and a new method of image processing to identify and acknowledge a certain texture based image using a set of classes or texture classification given.

Furthermore, research by Arriawati (Arriawati, et.al, 2011) performed a classification of digital images by using K-Nearest Neighbor (KNN) and extraction of features or textures using co-occurrence matrix of the image data. The result obtained from the learning image was the recognition rate of 100% for the value of k = 1, while the test result of the test images outside the learning image was the recognition rate of 55.557% for the value of k = 3. Additionally, Azahari (Azhari, et.al, 2014) did research on image analysis in mandibular bone panoramic radiography for the detection of osteoporosis by using Gray Level Co-occurrence Matrix (GLCM), and it resulted in relatively high accuracy of up to 85.71%. According to Smitha (Smitha, et.al, 2011) GLCM could be used in the extraction of features for classifying an image. Besides, the feature extraction techniques with GLCM were suitable for use in medical images automatically (Zare et.al, 2013).

This paper will discuss techniques of image classification and Thorax x-ray image feature extraction to obtain more precise, accurate, and automatic results of osteoporosis detection. X-ray image classification is performed by KNN, while feature extraction is done by GLCM.

II. THEORY

Lehman and Guld (Guld et.al, 2004; Lehman et al, 2003) stated that the classification of medical images was a grouping of medical images into class of image that had been defined previously. This was consistent with the categorization process of IRMA methods (Lehman et al, 2000, 2003). It was also consistent with the statement by Jain (Jain, 2000) which defined automatic image classification as mapping imagery into its class. Classification involves three basic principles, namely:

1. Representation, which means the extraction of certain features to describe the image content;
2. Adaptation, which is a subset of selecting the best feature to see what information is discriminatory;
3. Generalizing, which refers to training and evaluation of its classifiers.

A. K-Nearest Neighbour Classification Method

K-Nearest Neighbor (KNN) method is a method to classify the object based on the learning data that are located close to the object, according to the number of nearest neighbors or value of k. Then, near or far neighbors are usually calculated based on Euclidean distance with the following equation (Ganis, 2011):

$$d(x-y)=\sqrt{\sum_{j=1}^{n}(x_j-y_j)^2} \qquad (2.1)$$

where:
d: distance learning data to the test data
xj: test data j with j = 1, 2, ..., n
yj: learning data all j, j = 1, 2,. , , , n

KNN classification is done by searching k nearest neighbors of testing data and selecting the class with the most members. The steps of the KNN classification are as follows:
1. If a set of training data y has N data points overall, then it is required to introduce the k nearest neighbors of x testing data.
2. From the k nearest neighbors, the data are identified in the class ω x i, i = 1, 2,. , ., M. M is the number of classes.
3. The test data x are included in the class with the highest number of members.
4. If there are two or more classes ω in the immediate neighborhood of the test data x, then there is a balanced condition (conflict) and the use of conflict resolution strategies.
5. For the classes involved in the conflict, the distance d is determined between the test data x to ωi class members involved in the conflict, which amounted E.
6. Data training of class ωi involved in the conflict is indicated by
$y^{im}=\left\{y_1^{im},...,y_j^{im}\right\}$ .Therefore, the distance between x to ωi is:

$$d_i=\frac{1}{E}\sum_{j=1}^{N}(x_j-y_j^{im}) \qquad (2.2)$$

7. The test data x is included in the class with the smallest distance.

B. Feature Extraction

Feature is divided into feature "natural" and feature "artificial." The former is part of the image, such as brightness and edges of objects, while the latter is referred to as a feature that is obtained with certain operations on the image, for example, the gray level histogram. Feature extraction is the process to get the distinguishing features that distinguish an object from other objects (Darma Putra, 2010).

Furthermore, in the context of this extraction of texture features, the distinguishing feature is the texture which is a defining characteristic in the image. The technique of feature extraction is performed by scanning process to search for traces of the gray degree of every two pixels, separated by a fixed distance *d* and angle θ.

C. Gray Level Co-ocurance Matrix

Gray Level Co-occurrence Matrix (GLCM), which Haralick et al. introduced in 1973, is one of the statistical methods that can be used for texture analysis in image analysis applications, especially in the biomedical field. Co-occurrence matrix is formed from an image with respect to the paired pixels which have certain intensity. This method is based on the hypothesis that the texture will occur in a looping configuration or a pair of gray cedar. Suppose d is defined as the distance between the two pixel positions (x_1, y_1) and (x_2, y_2) and θ as the angle between them, and then the co-occurrence matrix is declared as $P_{d\theta}(i,j)$. A neighboring pixels that have the distance d between them can be located in eight different directions, as shown in Fig.1.

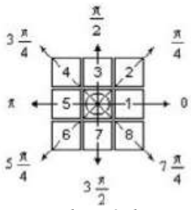


Fig. 1. *Neighboring pixels in 8 directions (Ganis, 2011)*

In co-occurrence matrix, there are eight characteristic features which are extracted. There are mean co-occurrence matrix, standard deviation, entropy, angular second moment (ASM), energy, contrast, homogeneity, dissimilarity. These characteristics are used to differentiate the images with a particular class and other images with another different class (Ganis, 2011).

D. Osteoporosis

There are many methods used in diagnosing osteoporosis. Among them is the Dual-energy X-ray Absorptiometry (DEXA). The gold standard for diagnosis of osteoporosis is measurement of Bone Mineral Density (BMD) using DEXA even though low bone mass or osteopenia can be detected through radiological tests such as radiographs (x-rays) and CT-Scan. Lately, numerous research have been done to detect osteoporosis by measuring the thickness of clavicle cortex from x-rays of the thorax (Fig.2).

Osteoporosis diagnosis is conducted using a **T-score value**, which is a BMD standard deviation (SD) value of a patient compared with an average BMD of young population, i.e. population whose bone mass/density is reaching its highest period (20-30 years old) (Nathan, 2003, Sariningsih, 2004).

$$T-Score = \frac{patient's\ measured\ BMD - mean\ BMD\ of\ young\ normal\ population}{SD\ of\ BMD\ of\ young\ normal\ population} \quad (2.3)$$

According to WHO Working Group Criteria, osteoporosis diagnosis criteria are on the basis of the following T-score values:

- Normal: providing that bone mass/density is over -1 SD (T-Score > -1 SD)
- Osteopenia: providing that bone mass/density lies between -1 SD and -2.5 SD
- Osteoporosis: providing that bone mass/density is -2.5 SD or less
- Severe Osteoporosis: osteoporosis with fracture

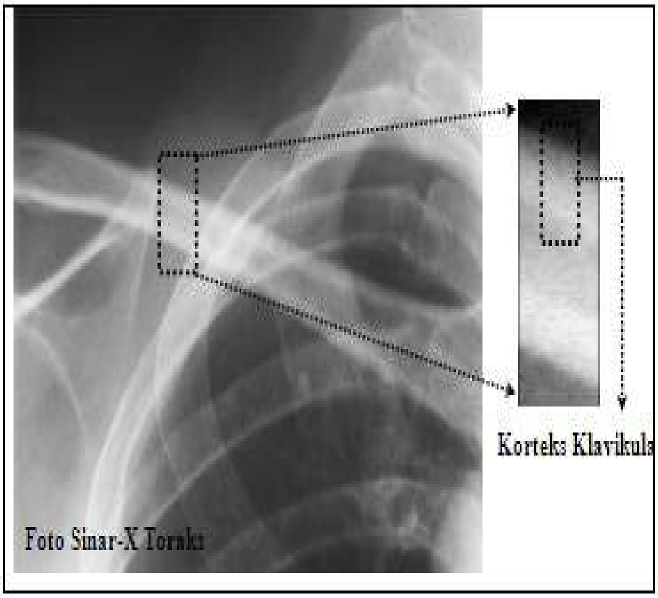


Fig. 2. *Clavicle Cortex on a Thorax X-ray Photo*

III. Methodology

A. Materials used

This research utilizes small sample size data. The data are obtained from 46 images of thorax x-ray patients, 44 females and 2 males with average age of 63 years old, who have been diagnosed using DEXA to determine the T-score of bone health. Digital images used have 800 dpi resolution and 8 bit intensity depth (gray scale) and are stored in Windows Bitmap (* .bmp) format.

In addition according to the previous studies (Nathan, 2003, Sariningsih, 2004, Widita, 2005), clavicle cortex of thorax x-ray image with thickness less than or equal to 3 mm (≤ 3 mm) indicated the presence of osteoporosis".

B. Research Implementation

Below is the proposed schema of the implementation of feature extraction and image classification of thorax x-ray image in the assessment of osteoporosis.

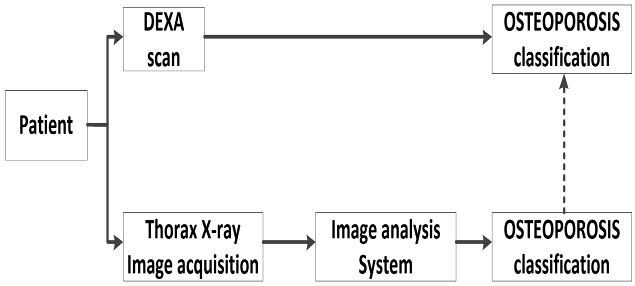


Fig. 3. *Diagram block system*

The implementation in this research is divided into several stages:

1. The image input in the form of x-ray image of the thorax with the Region of Interest (ROI) in the cortex region of the clavicle with a predetermined format. The ROIs are detected automatically based on the applied algorithm using Matlab of the previous research by Widita, 2005 and Delimayanti, Riandini, 2014.
2. Feature extraction method GLCM i.e. by converting the input image into a level of gray. The GLCM is formed by first determining the parameters of the distance (*d*), the direction (θ), and the degree of gray (*g*). The gray level determines the size of the co-occurrence matrix.
3. Image storage with feature extraction results as training data / reference data.
4. The final stage is the classification. The method which is used to classify the input data is K-Nearest Neighbor (KNN). KNN algorithms classify the input data into a class with the highest number of members.

All of the above stages can be illustrated in flowchart in Fig. 4. Fig. 5, on the other hand, presents samples of stages 1 and 2 of research implementation.

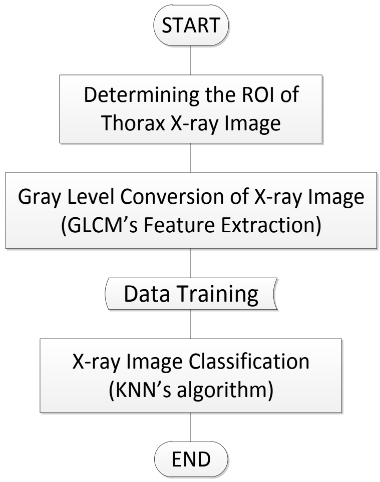
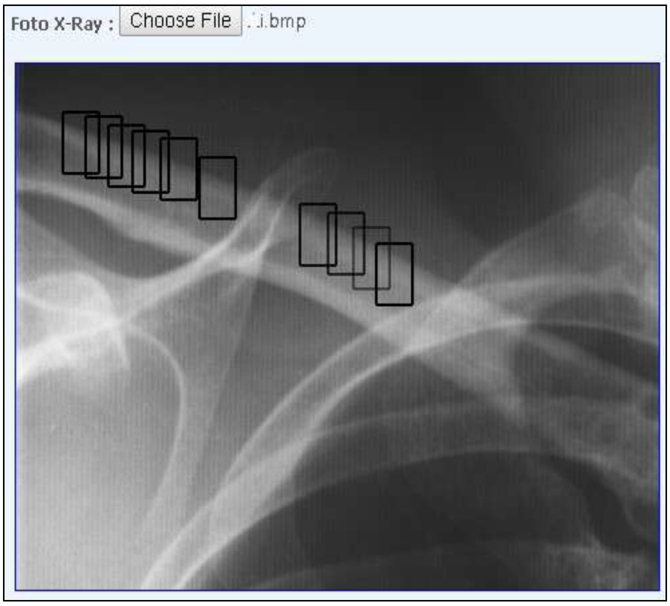
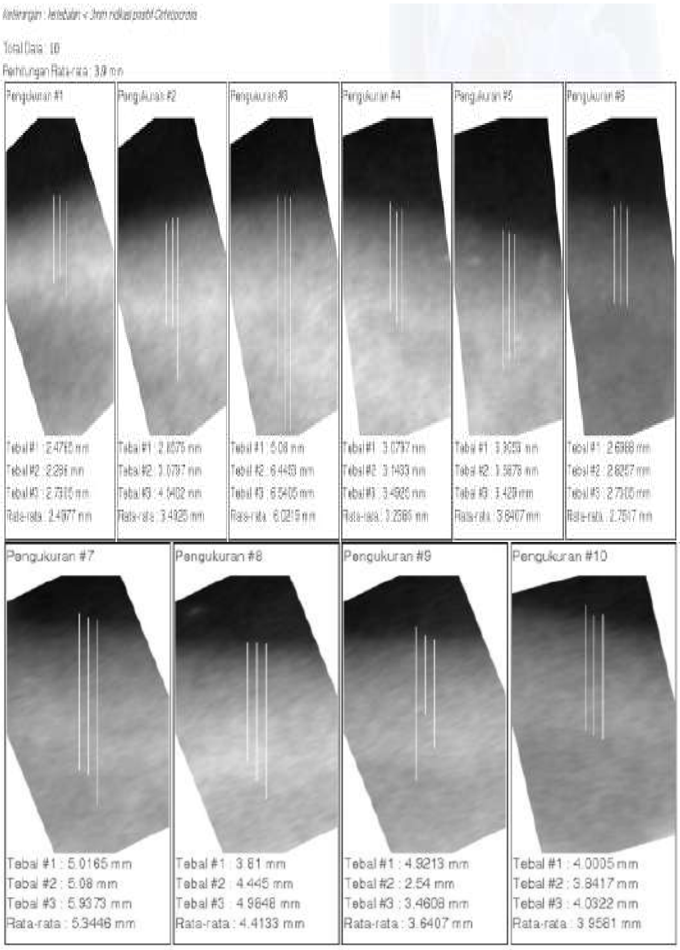


Fig. 4. *Research Implementation Flowchart*



(a)



(b)

Fig. 5. Sample of System Implementation on Patient-1.
(a).Determining ROI; (b) Thickness measurement of ROI for 10 measurements

IV. RESULTS

TABLE I. SYSTEM IMPLEMENTATION COMPARED WITH THEIR CORRESPONDNG DEXA'S T-SCORE IN THE ASSESSMENT OF OSTEOPOROSIS

Patient	DEXA scan		System Implementation's Results	
	T-Score	Osteoporosis (T-Score < -1)	Average (10x measurements)	Osteoporosis (Thickness < 3mm)
1	-0.6	NEGATIF	3.8889	NEGATIF
2	-0.9	NEGATIF	3.3472	NEGATIF
3	-2.3	POSITIF	2.1557	POSITIF
4	-1.6	POSITIF	2.0501	POSITIF
5	-1.9	POSITIF	1.9456	POSITIF
6	0.8	NEGATIF	3.3091	NEGATIF
7	-2.8	POSITIF	2.2473	POSITIF
8	-1.7	POSITIF	2.5400	POSITIF
9	-1.2	POSITIF	2.5467	POSITIF
10	-2.7	POSITIF	2.2252	POSITIF
11	-1.2	POSITIF	2.8619	POSITIF
12	-1.4	POSITIF	2.3033	POSITIF
13	-2.1	POSITIF	2.1994	POSITIF
14	-0.2	NEGATIF	3.2095	NEGATIF
15	-1.3	POSITIF	1.8817	POSITIF
16	-2	POSITIF	2.2972	POSITIF
17	-2.8	POSITIF	2.1630	POSITIF
18	-3.2	POSITIF	2.2071	POSITIF
19	-1.2	POSITIF	1.9216	POSITIF
20	-4.1	POSITIF	1.8877	POSITIF
21	-0.4	NEGATIF	3.2206	NEGATIF
22	-2	POSITIF	2.5011	POSITIF
23	0.7	NEGATIF	3.2575	NEGATIF
24	-2.7	POSITIF	2.4940	POSITIF
25	-3.6	POSITIF	2.8873	POSITIF
26	-3.7	POSITIF	1.8400	POSITIF
27	-1.4	POSITIF	2.7001	POSITIF
28	-3.7	POSITIF	2.2206	POSITIF
29	-3.6	POSITIF	2.0303	POSITIF
30	-2.7	POSITIF	2.3916	POSITIF
31	-2.7	POSITIF	1.8725	POSITIF
32	-3.2	POSITIF	2.7282	POSITIF
33	-4.5	POSITIF	2.2508	POSITIF
34	-1.5	POSITIF	2.2545	POSITIF
35	-0.8	NEGATIF	3.7939	NEGATIF
36	-2.8	POSITIF	2.5071	POSITIF
37	-2.3	POSITIF	2.5514	POSITIF
38	-3.4	POSITIF	1.7424	POSITIF
39	-0.8	NEGATIF	3.3253	NEGATIF
40	-1.1	POSITIF	2.3155	POSITIF
41	-1.2	POSITIF	2.7555	POSITIF
42	-0.9	NEGATIF	1.8238	POSITIF
43	-2.6	POSITIF	2.3253	POSITIF
44	-3.2	POSITIF	2.0911	POSITIF
45	0.2	NEGATIF	3.1363	NEGATIF
46	-1.4	POSITIF	2.6549	POSITIF

TABLE II. STATISTICAL RESULTS OF THE SYSTEM IMPLEMENTATION COMPARED TO DEXA

		DEXA		Total
		Osteoporosis	Normal	Total
System Implementation	Osteoporosis	36	1	37
	Normal	0	9	9
Total		36	10	46

Statistically, from Tables I and II, it is evident that the clavicle cortex thickness measurement using GLCM and KNN method as feature extraction and image classification has its sensitivity of 100%, specificity of 90%. Furthermore, the accuracy which is obtained from the entire implementation capability in correctly assessing osteoporosis is 97.83%. Therefore, both GLCM and KNN can be usedas feature extraction and classification of Thorax x-ray image solely as a decision support tools in the assessment of osteoporosis. The advantage of using them is to reduce subjectivity of observers. As DEXA measures the change of T-score, this computerized feature extraction and image classification algorithm will be able to assess the bone quality (osteoporosis). However, the accuracy of this assessment considerably depends on the x-ray image quality.

V. Conclusion

Both Gray Level Co-occurrence Matrix (GLCM) and K-Nearest Neighbour (KNN) are successfully applied to extract the feature and classify the Thorax x-ray image. The extracted features from clavicle cortex of thorax x-ray image in the form of its thickness are able to give information about the quality of the bones for the assessment of osteoporosis.

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