International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249 – 8958 (Online), Volume-9 Issue-4, April, 2020

Methods for Computer-Aided Osteoporosis Screening System

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Abstract: Osteoporosis is a disease that is not only a national issue but has also become a global issue. Although morbidity and mortality rates are relatively low in osteoporosis, fractures because of the disease makes the sufferer feel sick and suffering and affects socio-economic conditions in terms of health care systems and communities. Osteoporosis can be prevented by conducting early detection. Currently, DEXA is used to perform an osteoporosis test that becomes the World Health Organization (WHO) standard. However, the examination with DEXA is still relatively expensive. It technically can't show the bones' architecture. So that the examination method using a bone image that has trabeculae like wrist, thigh, jaw, hand, or foot is developed. Some research results on the osteoporosis examination system are presented in this article. The methods include such processes as image acquisition, image enhancement, image analysis (extraction and feature selection), as well as the classification process. Survey results showed that feature extraction, feature selection, and the classification method are selected based on the expected input and output system. Each method has a different level of accuracy

Keywords: osteoporosis, image, trabeculae, bone mass density.

I. INTRODUCTION

Osteoporosis is a reduction of progressive bone density so that the pores become fragile and easily broken/fractures. Usually, fractures occur in bones that have trabeculae, for example, on the wrist, spine, and *hip*. Bones consist of minerals such as calcium and phosphate, so the bones become hard and dense. If the body is unable to regulate the mineral content in the bones, then the bones become less dense and more fragile, resulting in osteoporosis. Osteoporosis is not only a national health problem alone but also one of the world's health problems.

The bone loss should be prevented and treated. Prevention of osteoporosis can be done early if the actual condition of the bone is known [1]. The negligence or unconsciousness results in many cases of fractures. Although morbidity and mortality rates for osteoporosis are relatively low, fractures make the sufferer feel sick and suffer and affect socioeconomic conditions in terms of health care systems and society in general [2].

Bone density examination should be done by measuring its BMD (Bone Mineral Density) [3] in order to reduce the prevalence of osteoporosis. The most accurate BMD examination and used as the gold standard by WHO is using DEXA (Dual-Energy X-ray Absorption) [4]. But in Indonesia, examination with DEXA is still an obstacle because it is expensive, and not all hospitals have this equipment. Furthermore, DEXA can't detect the bone architecture that became one of the parameters in bone density [5]. To overcome this problem, several methods of osteoporosis examination that have been developed are cheaper, namely the processing and analysis of radiographic (X-Ray) images of the hand bones [1,6], knee bones [1], jaw bones [1,7,8, 9, 10, 11, 12], femoral neck [13], hip bone [14, 15], spine [16], femur [17, 18,19]. In addition to using X-Ray images, some studies also use CT-Scan images [20,21], MRI images [22], and CBCT images [23] as input images. From these analyses, a characteristic pattern is obtained that can distinguish healthy bone from osteoporotic bone. In addition to using image data, osteoporosis detection can be done using text data such as demographic, anthropometric, or clinical data. The ability to automatically check these data is a characteristic of Computer-Aided Osteoporosis Screening (CAOS)

II. RESEARCH METHODS

CAOS research is rapidly progressing using artificial intelligence technology and techniques. The understanding of homemade intelligence is very diverse, one of which is a part of computer science that studies how computers can do work like, and as well as humans can do even better than humans can do. In general, the process carried out on CAOS if using bone images as input (figure 1) is to do image acquisition, image quality improvement, image analysis, and pattern recognition. At the same time, the efficiency of CAOS is usually measured by the parameters typically used in CAD, namely sensitivity and specificity [24]. Sensitivity (recall rate), used to measure the proportion of positive samples (suffering from osteoporosis) that have been identified. Specificity measures the proportion of negative samples (which do not suffer from osteoporosis) that have been identified. If the input data is in the form of text, the system does not need to perform feature extraction because the data has been determined by the researcher.

Revised Manuscript Received on April 25, 2020.
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A. Image Acquisition

Image acquisition is the initial stage to get digital images on bones. The purpose of image acquisition is to determine the data needed and choose the method of recording data. This stage starts from the object to be photographed, preparation of tools, to imaging. Imaging is the activity of transforming images into digital images. Several tools that can be used to produce bone images are radiographs carried out in research [1, 6, 7, 8, 10, 12,13, 14, 15, 17, 26, 27, 28, 29, 30, 31]. Computed Tomography Scan (CT-Scan) images have also been done by several researchers [21,32], Magnetic Resonance Imaging (MRI) by [22], Ultrasound by [33,34], and Cone Beam Computed Tomography (CBCT) by [23].

B. Image Enhancement

This step is necessary to ensure the smoothness in subsequent processes. Image improvement aims to improve the image display quality for the human view or to convert an image to have a better format so that the image is easier to be processed [35]. The operations performed at this level are

- **Point Operation** – includes brightness adjustment, negation, contrast, thinning intensity, bit separation, gamma correction, range compression, histogram equalization, local sharpening [14], image reduction, and image- out scaling.
- **Spatial Operation** – includes linear filters [13,33], non-linear filters, Gabor transformation, filtration in the frequency domain.

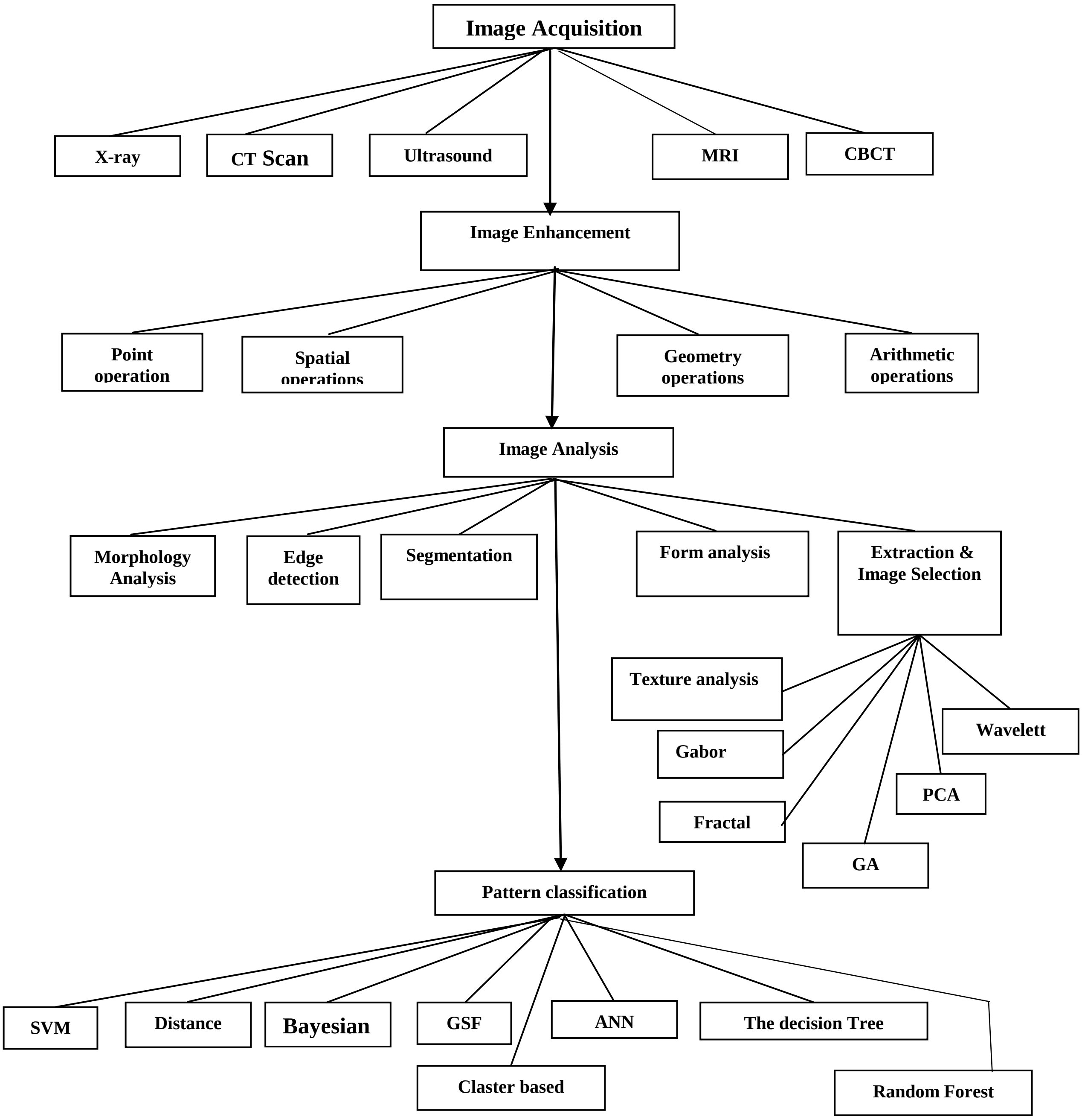

Fig 1. CAOS system development phase with image input

Retrieval Number: D7453049420/2020©BEIESP
DOI: 10.35940/ijeat.D7453.049420
Journal Website: www.ijeat.org

Published By:
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C. Image Analysis

This stage is one of the most important stages. Some of the image analysis techniques used are as follows

- Morphology analysis: porosity, connectivity and orientation, Dimension of Fractal, and the total number of "bright" pixels (ET), Mandibular Cortical Width (MCW), Mandibular Cortical Index (MCI), and Mandibular Cortical Degree (MCD) using support vector regression (SVR). Research using morphology analysis with several parameters including [46,47,48,49,50,51,52-52]
- Texture Analysis: first-order statistic (*mean, Variance, coarseness, skewness, kurtosis, energy, entropy*), second-order statistic (*moment, contrast, correlation, angular second*), high order statistic (GLRLM: *short-run emphasis, long-run emphasis, grey level distribution*), Fourier Spectrum [36], gray level co-occurrence matrix (GLCM), histogram and fraction [55], intensity and texture (intensity histogram, local binary pattern, the histogram of oriented gradient) [45], Melakukan anatomical landmarks with multi ROI, Hybrid of feature (Haar feature and Local feature, and Long Range Context feature and short-range context feature) [54]
  Research using texture analysis with several parameters including [1,7, 8, 10, 17, 19, 23,27,28,29]
- Fractals: Box-counting, Lacunarity based on Glinding Box Algorithm (GBA) [9], 17, 18, 21, 26, 28, 53, 58]
- Gabor: [14, 18, 22, 30, 37].
- Wavelett: [8, 14, 18, 19, 22, 25]
- ROC [13,38].
- Feature Selection: Principal Component Analysis (PCA) [29], and heuristic techniques [39].

D. Pattern Recognition Methods

Some of the pattern classification methods used in CAOs are as follows:

- Distance measure – distance is used to determine the level of similarity or dissimilarity of two feature vectors. The degree of similarity is a value, and based on the value, two vector traits will be said to be similar or not. One of the distance methods that can be used to measure the level of the resemblance of the two vectors is the Euclidian distance [13].
- Support Vector Machine (SVM) [45], SVM with multi-kernel [55], a combination of Bayes and SVM [37,58].
- Clustering Techniques – This is a method of grouping data into several unknown clusters (groups). In clustering, the number and characteristics of the group will be derived from the data, and usually, the groups are not yet known. The clustering method may be categorized into two classes i.e., hierarchy-based and partition-based methods. One of the most commonly used hierarchy-based methods is the agglomerative hierarchical clustering, while the method based on a partition is the K-Means clustering algorithm [25,58].
- Neural Networks – ANN is a model of neural networks that mimic the working principle of neurons of the human brain. ANN first appeared after a modest model of an artificial neuron introduced by McCulloch and Pitts in 1943. Some of the ANN methods used to detect osteoporosis are multi-layer perceptron (MLP) [11, 12, 40], backpropagation [29,34,51], *Linear Vector quantization* (LVQ) and *probabilistic Neural Network* [38], ART MAP [7], and *Multi-Version System* [41]. Besides, [42] used the hybrid system that integrates ANN and cryptic logic.
- The decision tree has also been investigated by [43,44]
- Random forest [54]
- The geometrical attributes of both the mandibular cortical bone and trabecular bone were acquired. Designing an automated system for osteoporosis screening involved the partitioning of the input attributes to generate an initial membership function (MF) and a rule set (RS), classification using a fuzzy inference system, and optimization of the generated MF and RS using the genetic swarm algorithm. Fivefold cross-validation (5-FCV) was used to estimate the classification accuracy of the hybrid GSF classifier. The performance of the hybrid GSF classifier has been further compared with that of individual genetic algorithm and particle swarm optimization fuzzy classifiers Hybrid genetic swarm fuzzy (GSF) classifier [56]

III. RESULT AND DISCUSSION

The following are the review results of several journals discussing the detection of osteoporosis.

In the bone structure analysis of osteoporosis, [29] applied the Fourier transformation to extract the image features and subsequently use the PCA to select the main features. The classification process is carried out using the backpropagation ANN. The method was tested on 100 bone trabeculae patients with osteoporosis, osteopenia, and healthy. The results of this study showed an accuracy of 77%-84%.

A computer-aided diagnosis was also proposed by [11] using novel morphology of fuzzy thresholding to identify 100 menopausal women with low bone mass. This system can automatically determine the cortical erosion of the mandible on dental panoramic. The Fuzzy inference system integrates with MLP to identify menopausal post women in normal categories or suffering from osteoporosis. The average *sensitivity* and *specificity* are 95% and 95%, respectively.

On [12] the web-based *Intelligent Medical Diagnosis System* is developed to determine whether the 245 *Dental panoramic* image suffers from osteoporosis or not. The feature extraction is using morphological mathematics, and classification process using 4-layer *Fuzzy Neural* Network. The results showed that from 200 training data had an accuracy rate of 71%, while the test data had an accuracy value of 66.7%. The overall recognition rate is 70.2 % Detection of osteoporosis using the JST Weighted Fuzzy ART Map classification was also carried out by [7] in 100 women.

The images used are dental panoramic radiographs. Fourier and FSeg transformations are used to perform feature extraction. At the end of the study, it was found that the sensitivity and specificity were 93.33% and 83.33%, and in general, the accuracy value was 87.88%.

Research using the KNN method was carried out by [25] to classify images of normal or reduced bone density. The feature extraction used is wavelet. This study concludes that wavelet can be used for osteoporosis detection with an accuracy value of 70.83%.

Texture analysis (mean, standard deviation, skewness, energy, entropy) and Fourier transform were applied by [28] to detect whether the bones were in the healthy category, osteopenia, or osteoporosis. Input on this system is 50 X-ray images, and to find out the detection results used statistical analysis between the results of feature extraction and DEXA measurements.

Classification of bone into healthy, osteopenia, and osteoporosis is presented in [9]. The researchers use dental panoramic images samples from perimenopausal and postmenopausal persons. The pixel intensity (PI) and box-counting fractal dimension (FD) are used as features. The results are compared to DEXA measurements and conclude that pixel intensity yields better results than FD.

Other researchers [33] developed a detection system with ultrasonic input. Two parameters are obtained from the samples, namely Speech of Sound (SOS) and Broadband Ultrasonic Attenuation (BUA). The results are compared with those obtained from DEXA using statistical analysis. The research concludes that SOS and BUA can be used to distinguish bone characteristics.

Researchers in [21] extracted seven types of features from 3D CT-Scan trabecular bone using topological analysis. The seven types of features are I (Isolated), C (curve), CE (curve edge), SE (surface edge), CC (curve-curve), SS (surface-surface joint), and SC (surface-curve). The experiment using 289 data shows that the number of false positives and false negatives are 83 and 7, respectively.

Classification of dental panoramic X-ray based on the first and second-order statistics is presented in [1]. The discriminant analysis is performed to classify the sample into healthy bone or osteoporosis. The results showed that the skewness and the angular second moment could be used to distinguish healthy bone from osteoporosis with an accuracy of 78.9%.

X-ray images of the lumbar spine, femoral neck, and total hip are analyzed, and features (h-mean, co-occurrence, short-run emphasis) are extracted. The features are used to detect osteoporosis, and results are compared to those obtained based on BMD measured with DEXA. The comparison is based on ROC. The author states that this method can be used to detect osteoporosis well [27].

Thirty-seven dental images were analyzed to search for Region of Interest (ROI) [13]. Detection of osteoporosis is carried out by applying the concept of distance. The vector being compared is the result of feature extraction and the measurement of DEXA.

A CAD system is developed to process hip bone image information in 50 Indian patients [14]. The image quality is improved using histograms and local contrast. Gabor filter is applied, and wavelets are used as features. The results of detecting whether the bone is in the osteoporosis or osteopenia category are compared with the results of DEXA measurements. The results showed that 20% of the sample had osteoporosis, and 34% had osteopenia.

MLP is used to classify 704 cervical X-Ray and lumbar spine images into normal or abnormal categories [16]. Then, the morphological analysis method was applied to obtain 72 main features. Research shows that 92% are categorized as healthy.

Medical image analysis of trabecular bone from MRI using fractals, Gabor, and wavelet filters is presented in [22]. The feature selection output is then correlated with Singh's index. The results show that Gabor and wavelet can be used to detect normal or osteoporotic bone categories. The same thing was done by [18], but the input used was the proximal femur. In this study, the authors utilize Gabor, Wavelet, and Fractal. The result is that the Gabor method is closer to Singh's index.

The image from a 3D CT scan is used by [21] to detect whether the bone is in normal condition or suffering from osteoporosis. Multifractal Spectrum is used for feature extraction and selection, while the selection process uses C4.5. The classification uses the RBF ANN.

Twenty-six (26) X-Ray images were improved in quality using a Gaussian low-pass filter. Feature extraction used is Gabor filter, while KNN is used to classify the image into normal image patterns, osteoporosis, and osteopenia [30].

Trabecular structure extraction in dental panoramic radiograph images using morphological mathematics (median filter, structuring element, erosion, opening, dilation) was done by [31]. Statistical analysis is then used in correlating the results of feature extraction and DEXA measurements.

In [19], texture feature (energy) and wavelet features obtained through a 4-level wavelet decomposition were extracted from 55 femoral radiograph images and used for assessment. The results were compared with Singh's index in grades 3-6.

With 94 wrist radiograph images [6] conducted an initial study to classify fractures due to osteoporosis. The features extracted for the study are the fractal dimension (surface area, box-counting, energy scale), histomorphometric, and skeletal. The research concludes that the 32 features obtained are correlated with BMD values.

An osteoporosis assessment using a Fuzzy Neural Network-based hierarchical tree classified hip images with 100% accuracy. The method used Contrast Limited Adaptive Histogram

Equalization (CLAHE) for enhancing the image and texture features (GRGL, energy, mean, standard deviation, skewness, kurtosis) [15].

Osteoporosis classification using Fuzzy Rules and ANN Backpropagation is conducted by [34]. The parameters taken as characteristics are SOS radius, tibia, and phalax. The method was tested on 66 data, and the classification results show 97% accuracy.

Retrieval Number: D7453049420/2020©BEIESP
DOI: 10.35940/ijeat.D7453.049420
Journal Website: www.ijeat.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249 – 8958 (Online), Volume-9 Issue-4, April, 2020

The use of a rule-based inference engine was reported in [43] to develop Intelligent Data Analysis to classify the density of human bones. The data used for evaluating the method was 100. The accuracy of this research is 82%.

A system for predicting osteoporosis using Multilayer Perceptron was reported in [39]. The data processed were in the form of patient clinical data (menopausal status, steroid use, smoking activity, alcohol consumption, coffee consumption), demographic data (gender, age), and anthropometric data (weight, height, and BMI). By utilizing statistical analysis, seven features are obtained for the prediction. By using an optimization algorithm, the architecture of the ANN is 7-13-1. The ANN output is compared with the T-Score value. The results of the study have a sensitivity and specificity of 76.2% - 80% and 12.5% - 55.5%.

The experiment in landmark detection for osteoporosis detection is reported by [54]. A random forest with 10 decision trees learned from 100 training images. The proposed approach is tested using 50 images and achieves an average detection error of 2.9 mm.

In [56], a Hybrid GSF classifier is evaluated for identifying low BMD or osteoporosis at the lumbar spine and femoral neck. The sensitivity, specificity and accuracy of the hybrid GSF with optimized MF and RS in identifying females with a low BMD were 95.3%, 94.7%, and 96.01%, respectively, at the lumbar spine and 99.1%, 98.4%, and 98.9%, respectively, at the femoral neck BMD. The diagnostic performance of the proposed system with femoral neck BMD was 0.986, with a confidence interval of 0.942–0.998. The highest mean accuracy using 5-fold cross-validation was 97.9% with femoral neck BMD.

To predict the risk of osteoporosis, [38] uses ROC (Receiver Operating Characteristics) to select the most influencing factors of osteoporosis. These factors are classified using LVQ and PNN. The results showed that the accuracy rate of PNN was 96.58%, and LVQ was 96.03%.

Osteoporosis detection using age, height, weight, height lost, and year menopause was reported in [40]. A multi-version system (MVS) was employed for the detection. Initially, 20 factors were considered and analyzed, which resulted in the five most influencing factors. The classification results are compared with the qualitative ultrasound using regression analysis [40].

In [39], a decision tree and ANN are used to analyze the 31 factors influencing osteoporosis. The results are compared with the T-Score to decide whether or not a patient has osteoporosis. The results show an accuracy of 80% in abnormal data (suffering from osteoporosis) and 90% in normal data (not suffering from osteoporosis).

IV. THE CONCLUSION

In this paper, surveys are conducted on an osteoporosis screening system that uses artificial intelligence approaches. The feature extraction, feature selection, and classification method are presented, and the results are reported. This study shows that improvement could be done using different method, especially using the latest machine learning approaches.

V. FUTURE WORK

From this study, we conclude that

- There is a need to develop methods for a more efficient examination of osteoporosis and have a better level of accuracy
- There is a need to establish a method for osteoporosis examination based on bone trabeculae images for economic reasons.

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DOI: 10.35940/ijeat.D7453.049420
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