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Osteoporosis Detection By Using CT Images Based On Gray Level Co-occurrence Matrix And Rule Based Approach

Maya Deoker[1], Prof.S.N.Patil[2]
[1]*M.E Student, Dept.of Electronics Engineering, P.V.P.I.T, Budhgaon, Maharashtra, India*
[2] *Associate Professor, Dept.of Electronics Engineering, P.V.P.I.T, Budhgaon, Maharashtra, India*

Abstract- **Image processing is an area of active research in which medical image processing is a highly challenging field. Medical imaging techniques are being used to image the inner portions of the human body for medical diagnosis. In this paper, Gray Level Co-occurrence Matrix (GLCM) features are effectively utilized for osteoporosis diagnosis. Early diagnosis of osteoporosis is important to protect bone loss. The proposed system uses four GLCM features such as Contrast, Correlation, Energy, and Homogeneity for the diagnosis. The classification of osteoporotic images into normal or abnormal is obtained by the Support Vector Machine (SVM) classifier. An internal database of images is utilized for the performance analysis. The results show that the proposed approach helps the doctors to make their decision very accurately. The system provides 93% classification accuracy.**

Index Terms - **Osteoporosis, GLCM, SVM classifier.**

I. INTRODUCTION

Osteoporosis is a bone disease that leads to an increased risk of fracture. In osteoporosis the bone mineral density is reduced and bone microarchitecture deteriorates. The areas of the bone architecture that are most affected by osteoporosis are the trabecular (spongy) bone and the cortical (compact) bone, where the trabecular bone is the sponge-like bone in the ends of long bones and vertebrae, and the cortical bone is the hard outer shell of bones. Osteoporosis causes the thinning of the cortical bone and deterioration of trabecular bone structure. The diagnosis of osteoporosis can be made using conventional radiography and by measuring the bone mineral density (BMD).Osteoporosis is nowadays a global health issue of humans, which affects especially the health condition and life quality of senior citizens. Accordingly, early diagnosis and prevention of osteoporosis has become significantly important. Bone histomorphometry is widely applied in osteoporosis research in common medical experiments, although this process is complicated and takes a long period from specimen making to measurement, image analysis and process techniques. In this paper, image texture analysis based on statistical analysis and a classification based on a Support Vector Machine (SVM) were introduced. The purpose of this paper is to develop a new method for texture analysis research and apply this result in clinical osteoporosis diagnosis in accordance with medical images. This paper proposes a method to distinguish normal and osteoporosis bone images by analyzing medical images acquired using conventional computed tomography machines, which can be found in most hospitals.

II. METHODOLOGY

The proposed method illustrates the basic steps followed by our automation system in clearly diagnosing a given tumor data set into its classes as shown in figure 1. It starts by loading the input MR images, image preprocessing, image segmentation, feature extraction; support vector machine (SVM) classifier

Fig 1 shows the basic block diagram of osteoporosis detection .CT scan images are taken for processing

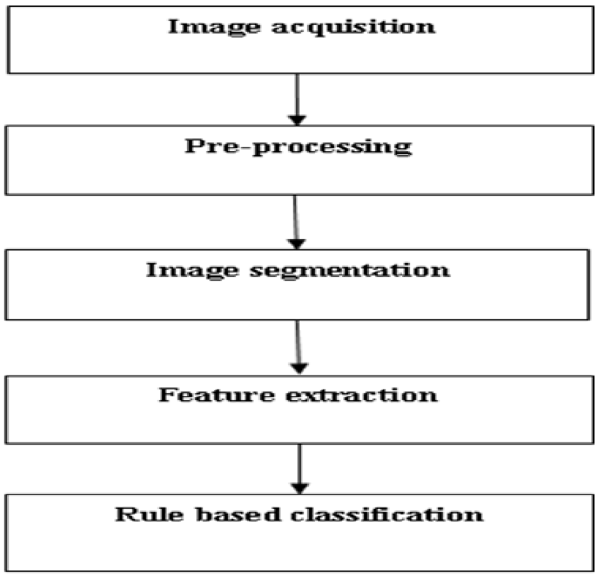

Fig 1: Block diagram

A. Image acquisition:

CT -images are acquired from various hospitals by visiting the hospitals frequently. Images are classified into normal bone images and affected bone images. The images are acquired on the cornerstone of factors like age and gender. The data linked to the patients including the patient's name, age and gender aren't revealed in the images used for training our system.

B. *Pre-processing:*

Preprocessing mentions to improvement of tumor intensity, noise, reduction, background removal, contrast manipulation, filtering and edges sharpening etc. Medical images are difficult to interpret the tumor, therefore preprocessing step is required with a specific end goal to make the picture segmentation and improve the quality of image results more precise. Usually the images which can be obtained during image data collection might not be ideal for classification purpose due to certain factors, such as for instance lighting intensity and size variations and some noise introduced by devices. Resize and cropping had done in pre-processing.

C. Image segmentation:

In image segmentation, the mandatory part is obtained by segmenting CT images. Grey level thresholding is used. It's a fundamental tool for segmentation of grey level images in which objects and background pixels can be distinguished by their grey level values. After cropping and resizing of the grey level image, grey level thresholding is applied. Through the use of thresholding the difference between the normal and affected bone images by calculating the total quantity of white and black pixels is identified. If the white pixels tend to be more in number and black pixels are lesser in number, in an image then it is recognized as to be a normal bone image. If the black pixels tend to be more in number and white pixels are lesser in number, in an image then it's regarded as affected bone image.

D. Feature extraction:

Features are said to be properties that describes the whole image. It can also refer as an important piece of information which is relevant for solving the computational task related to specific application. The purpose of feature extraction is to reduce the original dataset by measuring certain features. The extracted features acts as input to classifier by considering the description of relevant properties of image into feature space.

The Gray level co-occurrence matrix (GLCM) features are extracted. Among entropy, contrast, energy, homogeneity and correlation options that come with GLCM the contrast feature values provides accurate result. The input image's contrast values are then weighed against the obtained contrast values and the result is displayed as is the given input image is normal bone image or affected bone image. . If the image is affected bone image then it's further identified as whether it's severe bone image or non-severe bone image.

Gray Level Co-occurrence Matrix:

Gray Level Co-occurrence Matrix, GLCM is just a feature detector. This technique looks for intensity relation in the images. GLCM builds a new matrix that counts different intensity relations. The idea behind GLCM is to describe the texture as a matrix of "pair gray level probabilities". The GLCM is just a square matrix with Ng dimension, where Ng equals how many gray levels in the image. Each element of the matrix is the number of occurrence of the pair of pixel with values i and a pixels with value j. A co-occurrence matrix is just a two dimensional array where both rows and columns represent set of possible image values.

Different features can be extracted using GLCM as follows:

1) Entrophy:

- Entropy shows the total amount of information of the image that's necessary for the image compression.
- The entropy is large once the image isn't texturally uniform.
- Complex textures generally have high entropy.
- Entropy is strongly, but inversely correlated to energy.
- $Entropy = -\sum_i \sum_j p_{ij} \log_2 p_{ij}$

2) Contrast:

- Measures the neighborhood variations in the gray-level co-occurrence matrix
- Measures the spatial frequency of a picture and is difference moment of GLCM.
- It's the difference between the highest and the lowest values of a contiguous group of pixels.
- It measures the quantity of local variations within the image.
- Contrast(con)= $\sum_i \sum_j (i-j)^2 p_{ij}$

3) Correlation:

- It gives the joint probability occurrence of the specified pixel pairs

4) Homogeneity:

- Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Also called as Inverse Difference Moment.
- Measures image homogeneity since it assumes larger values for smaller gray tone differences in pair elements.
- It is more sensitive to the clear presence of near diagonal elements in GLCM.
- It has maximum value when all the elements in the image are same.
- Homogeneity decreases if contrast increases while energy is kept constant.
- Homogeneity $=\sum_i \sum_j \frac{1}{1+(i-j)^2} p_{ij}$

Quality measurement parameters are calculated to detect the quality of reconstructed image. Following quality parameters have been calculated

1. *MSE (Mean Square Error):* The MSE is the average of the square of the difference between the desired response and the actual system output (the error). The mean square error (MSE) is one way to evaluate the difference between an estimator and the true value of the quantity being estimated. MSE measures the average of the square of the "error," with the error being the amount by which the estimator differs from the quantity to be estimated.
   It is Defined as
   $$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{J=1}^{N}\left(X(i,j) - y(i,j)\right)^2$$
2. *PSNR (Peak Signal to Noise Ratio):* The term peak signal-to-noise ratio (PSNR) is an expression for the ratio between the maximum possible value (power) of a signal and the power of distorting noise that affects the quality of its representation. Because many signals have a very wide dynamic range, ratio between the largest and smallest possible values of a changeable quantity) the PSNR is usually expressed in terms of the logarithmic decibel scale.
   $$PSNR = 10 \log_{10} \frac{(2^n-1)\verb|^|2}{\sqrt{MSE}}$$
3. *AD (Average Difference):* This measure shows the average difference between the pixel values. Ideally it should be zero. It is defined as follows: -
   $$AD = \frac{1}{MN}\sum_{i=1}^{M}\sum_{J=1}^{N}\left(X(i,j) - y(i,j)\right)$$
4. *MD (Maximum Difference):* Maximum Difference is defined as follows:
   MD = MAX|(x(i, j) − y(i, j))|
5. *SC (Structural Content):* The large value of SC means that image is a poor quality. SC is defined as follows:-
   $$SC = \frac{\sum_{i=1}^{M}\sum_{J=1}^{N}\left(y(i,j)\right)^2}{\sum_{i=1}^{M}\sum_{J=1}^{N}\left(X(i,j)\right)^2}$$
6. *NAE (Normalized Absolute Error):* The large the value of NAE means that image is poor quality. NAE is defined as
   $$NAE = \frac{\sum_{i=1}^{M}\sum_{J=1}^{N}\left(X(i,j) - y(i,j)\right)}{\sum_{i=1}^{M}\sum_{J=1}^{N}\left(X(i,j)\right)}$$
7. *SNR(Signal to Noise Ratio):* The SNR measure is a calculation of the quality of a reconstructed image compared with the original image. The whole idea is to obtain a single number that

reflects the quality of the image by computing the ratio of the signal power to the noise power.

E. Rule Based classification:

The classifier used for our system is Rule based approach. Initially in the classification phase we classify the image into normal and affected bone images.If the bone is osteoporotic we then find whether the disease is severe or non-severe. For classification of images, SVM classifier is used

Support Vector Machines:

Support Vector Machine (SVM) is supervised learning models with associated learning algorithms that analyze data and recognize patterns, useful for classification and regression analysis. The original SVM algorithm was invented by Vladimir N. Vapnik and the present standard incarnation (soft margin) was proposed by Vapnik and Corinna Cortes in 1995. The basic SVM takes some input data and predicts, for every single given input, which of two possible classes forms the output. The classification process is split into the training phase and the testing phase. The known data is given in the training phase and unknown data is given in the testing phase. The accuracy depends upon the efficiency of classification.

Aim of SVM classifier is to group items that have similar feature values into groups. Classifier achieves this by making a classification decision based on the value of the linear combination of the features.

III. RESULTS AND DISCUSSION

The fig2 depicts the result of a normal bone image. By comparing the features of test image with trained dataset ,the system outputs the result.

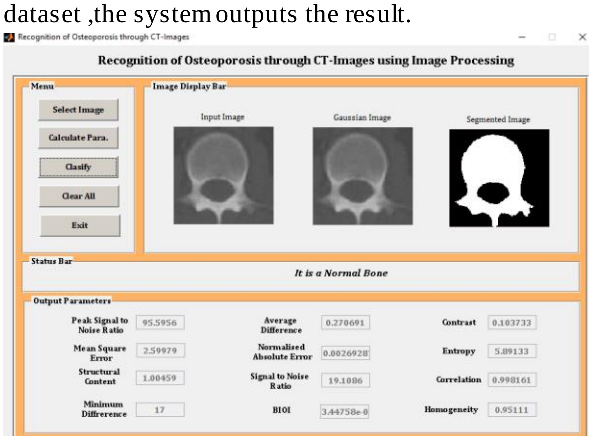

Fig 2:Normal bone image detected

The fig3 depicts the result of an osteoporotic image with the case of nonseverity.

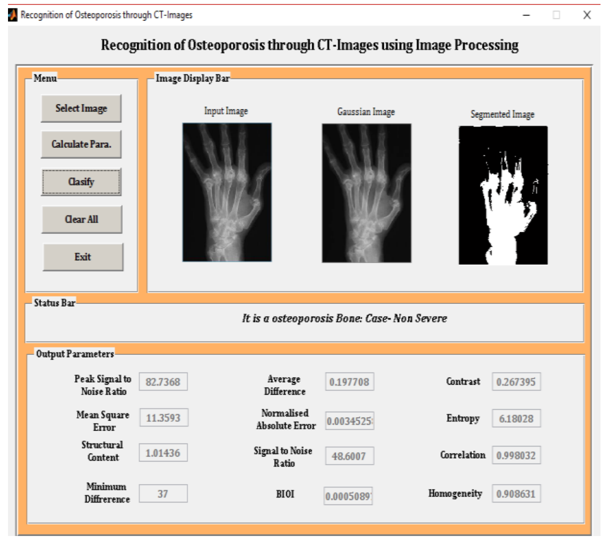

Fig 3: Non- severe osteoporotic bone image detected

For the proposed work some images were choosen randomly. Texture Features are obtained for the segmented part . GLCM features are extracted and its classification was obtained. From Table III, we observe the feature values for the various sample images.

Table: Feature Extraction

Feature	Image1 (Normal)	Image2 (Normal)	Image 3(Ost.)	Image 4(Ost)
Contrast	0.1037	0.2237	0.076	0.079
Entrophy	5.891	5.56	5.17	5.04
Correlation	0.998	0.982	0.990	0.993
Homogeinity	0.951	0.944	0.9616	0.960

From Table , the images are classified as normal and abnormal using SVM Classifier

IV. CONCLUSION

In this paper, an efficient approach for the diagnosis of osteoporosis is presented using GLCM and SVM classifier. For classification, SVM classifier which automatically classifies the given image into normal or abnormal is used. The proposed approach is an non-invasive approach and it gives an second opinion to the doctors to make their decision efficiently . The proposed approach is computationally less expensive and yields good result. SVM provides the accuracy of 93%.The accuracy of system can be improved if training is performed by using a very large image database.

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