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Classification of Osteoporosis using Fractal Texture Features

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ABSTRACT

In our proposed method an automatic Osteoporosis classification system is developed. The input of the system is Lumbar spine digital radiograph, which is subjected to pre-processing which includes conversion of grayscale image to binary image and enhancement using Contrast Limited Adaptive Histogram Equalization technique(CLAHE). Further Fractal Texture features(SFTA) are extracted, then the image is classified as Osteoporosis, Osteopenia and Normal using a Probabilistic Neural Network(PNN). A total of 158 images have been used, out of which 86 images are used for training the network and 32 images for testing and 40 images for validation. The network is evaluated using a confusion matrix and evaluation parameters like Sensitivity, Specificity, precision and Accuracy are computed fractal feature extraction techniques.

I. Introduction

Osteoporosis is a progressive bone disease that is characterized by a decrease in bone mass and density which can lead to an increased risk of fracture. In osteoporosis, the Bone Mineral Density (BMD) is reduced, bone micro architecture deteriorates, and the amount and variety of proteins in bone are altered. The form of osteoporosis most common in women after menopause is referred to as primary type 1 or postmenopausal osteoporosis, which is attributable to the decrease in oestrogen production after menopause. Primary type 2 osteoporosis or senile osteoporosis occurs after age 75 and is seen in both females and males at a ratio of 2:1. Secondary osteoporosis may arise at any age and affect men and women equally, this form results from chronic predisposing medical problems or disease, or prolonged use of medications such as glucocorticoid, when the disease is called steroid or glucocorticoid-induced osteoporosis. So in order to detect the presence of osteoporosis we have to use image processing techniques on Digital radiographers contribute to the test values used for training the neural network. Thus Image processing is used to monitor the traits of the X-rays for possible infirmities that might occur and provide the necessary data for further treatment.

II. Literature Survey

According to AlceuFerraz Costa[1], a new and efficient texture feature extraction method called the Segmentation-based Fractal Texture Analysis, or SFTA is preferred than Haralick and Gabor filter. The extraction algorithm consists in decomposing the input image into a set of binary images from which the fractal dimensions of the resulting regions are computed in order to describe segmented texture patterns. The decomposition of the input image is achieved by the Two- Threshold Binary Decomposition (TTBD) algorithm, which we also propose in this work. The SFTA is evaluated for the tasks of content-based image retrieval (CBIR) and image classification, comparing its performance to that of other widely employed feature extraction methods such as Haralick and Gabor filter banks. SFTA achieved higher precision and accuracy for CBIR and image classification. Additionally, SFTA was at least 3.7 times faster than Gabor and 1.6 times faster than Haralick with respect to feature extraction time.

Histogram equalization, which stretches the dynamic range of intensity, is the most common method for enhancing the contrast of an image. An adaptive method to avoid this drawback is block-based processing of histogram equalization. In block-based processing, image is divided into sub-images or blocks, and histogram equalization is performed to each sub-images or blocks. Contrast Limited Adaptive Histogram Equalization (CLAHE), proposed by K. Zuierveld, has two key parameters: block size and clip limit. These parameters are mainly used to control image quality. In this paper, a new novel method was proposed by ByongSeok Min [2] to determine two parameters of the CLAHE using entropy of an image.

An Automatic Brain Tumor Classification using PNN and Clustering developed by P.Sangeetha [3] describes the Probabilistic Neural Network (PNN) will be employed to classify the various stages of Tumor cut levels such as Benign, Malignant or Normal. Probabilistic Neural Network with Radial Basis Function will be applied to implement tumor cells segmentation and classification. Decision should be made to classify the input image as normal or abnormal cells. Prediction of malignant cells or non-tumor cells can be executed using two variants: i) Feature extraction and ii) classification using Probabilistic Neural Network (PNN). The ability of their proposed Brain Tumor Classification method is demonstrated on the basis of obtained results on Brain Tumor image database. In their proposed method, only 5 classes of Brain tumors are considered, with respect to an example of 20 test images for instance but this method can be extended to more classes of Brain tumors.

Since medical X-Ray images are grayscale images with almost the same texture characteristics, conventional color or texture features cannot be used for appropriate categorization in medical X-Ray image archives. Therefore, a novel feature is proposed by Seyyed Mohammad Mohammadi [4] which is the combination of shape and texture features. The feature extraction process is started by edge and shape information extraction from original medical X-Ray image. Finally, Gabor filter is used to extract spectral texture features from shape images. In order to study the effect of feature fusion on the classification performance, different effective features like local binary pattern. It provides low computation complexity and straightforward implementation. Due to following advantages we can strongly claim that these features are the most powerful and reliable features for medical image X-Ray classification.

III. Proposed Method

The proposed approach starts first from preprocessing. It is then followed by Grayscale Conversion and the image is enhanced using a CLAHE filter. Then the features namely fractal features are extracted from the enhanced image and the fractal features are used to determine the category in which they fall determined by the PNN classifier for one sample. This is repeated for the stock of samples in which 2/3 of the samples are taken as Database samples.

Methodologies

A. Pre-processing
B. Grayscale conversion
C. Image Enhancement.
D. Feature Extraction
E. PNN Classifier.

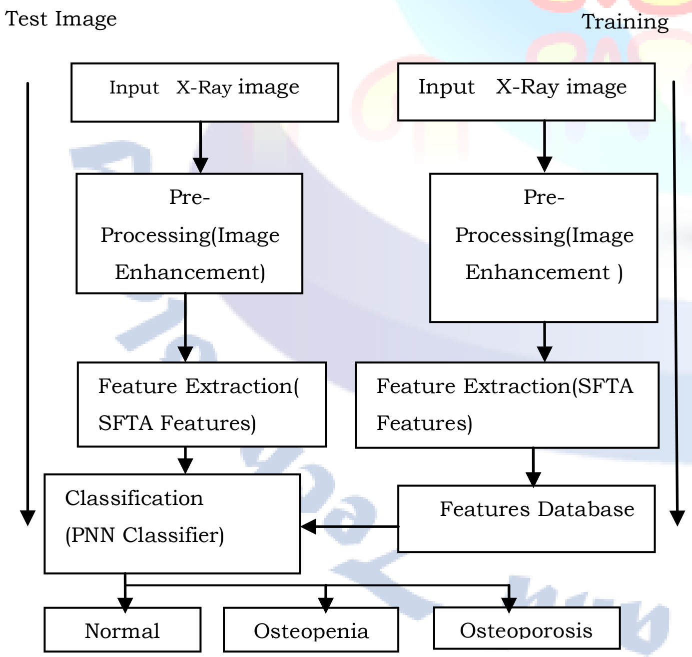


Figure 1.1 Block Diagram of proposed work

IV. Research Methodology

A. Preprocessing

Steps which are done prior to processing of an image are called preprocessing. It includes image enhancement and resizing. These are done in order to make the image more suitable than an original image for specific applications.

B. Grayscale Conversion

If the image selected is in three dimensions, it is converted to a grayscale image using 'rgb2gray' conversion command for feature extraction. Then the intensity variation of gray level image is shown in the graph. Its value varies from 0 to 255.Resizing of image is done for accurate processing of image. Image can be resized to any size of our interest.

C, Image Enhancement

Image enhancement is the process of adjusting digital images so that the results are more suitable for display or further image analysis. After resizing the image, we go for image enhancement. We use CLAHE (Contrast Limited Adaptive Histogram Equalization) technique. This method separates the image into a number of tiles, and then adjusts the contrast such that the tile histogram has the desired shape. The tiles are then stitched together using bilinear interpolation. The transformation function modifies the pixels based on the gray level content of an image. These techniques are used to enhance details over small areas in an image.

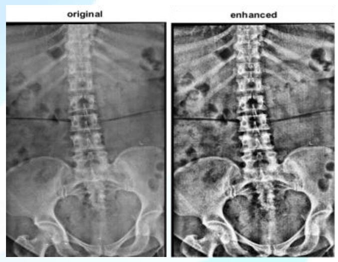


Figure 1.2 Image after Enhancement

D. Feature Extraction

Feature is a parameter of interest to describe an image. Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task. The Segmentation-based Fractal Texture Analysis or SFTA method is a feature extraction algorithm that decomposes a given image into a set of binary images through the application of what the authors call the Two Threshold Binary Decomposition (TTBD). For each resulting binary image, fractal dimensions of its region boundaries are calculated that describe the texture patterns.TTBD takes an input greyscale image and returns a set of binary images by first computing a set of T threshold values from the gray level distribution information in an input image. This is accomplished by recursively applying to each image region the multilevel Otsu algorithm, an algorithm that quickly finds the threshold that minimizes the input image intra-class variance until the desired number of thresholds is obtained. The input image is decomposed into a set of binary images by selecting pairs of thresholds from T and applying two-threshold segmentation.Fractal measurements are used to describe the boundary complexity of objects, with each region boundaries of a binary image represented as a border image. The fractal dimension is computed from each boarder image using a box counting algorithm.

A. Haussdorf fractal dimension

Haussdorf dimension serves as a measure of the local size of a set of numbers, taking into account the distance between each of its members. The Haussdorf dimension of an n-dimensional inner product space equals n. This underlies the earlier statement that the Haussdorf dimension of a point is zero, of a line is one, etc., and that irregular sets can have non integer Haussdorf dimensions. Haussdorf fractal dimension of an object represented by the binary image. Non-zero pixel belongs to an object and zero pixel constitute the background.

$$dim_H(X) = \inf\{d \ge 0 : C_H^d(X) - 0\} \qquad (1)$$

Where 〖 dim〗 _H(X) is the infimum of the set of d∈ [0, ∞) such that the d-dimensional Haussdorf measure of X is zero.

B. OTSU'S Segmentation

Otsu's method is used to automatically perform clustering-based image thresholding i.e., the reduction of a graylevel image to a binary image. The algorithm assumes that the image contains two classes of pixels following bi-modal histogram, it then calculates the optimum threshold separating the two classes so that their combined spread is minimal.In Otsu's method, we exhaustively search for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances of the two classes.

$$\sigma_w^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t) \qquad (2)$$

Weights ω_i are the probabilities of the two classes separated by a threshold t and σ_i^2variances of these classes. Otsu thresholding returns a set of thresholds for the input image employing the multilevel Otsu algorithm. The multilevel Otsu algorithm consist in finding the threshold that minimizes the input image intra-class variants. Then, recursively, the Otsu algorithm is applied to each image region until total thresholds are found.

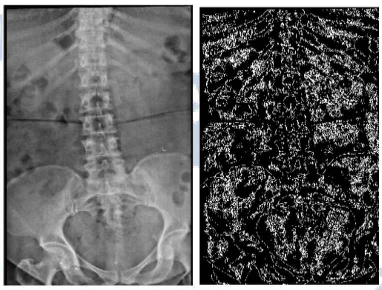


Figure 1.3 Image after OTSU Segmentation

C. Edge detection

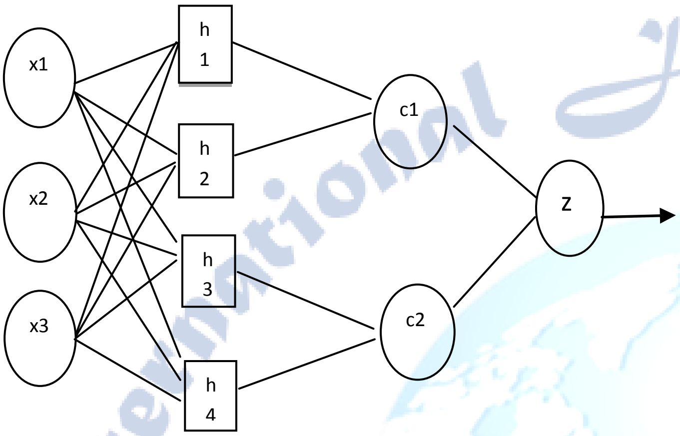
Edge detection is an image processing technique for finding the boundaries of objects within images. It works by detecting discontinuities in brightness. Edge detection is used for image segmentation and data extraction in areas such as image processing, computer vision, and machine vision.Edge detection returns a binary image with the regions boundaries of the input image. The input image must be a binary image. The returned image takes the value 1 if the corresponding pixel in the image has the value 1 and at least one neighbouring pixel with value 0. Otherwise takes value 0.

E. Artificial Neural Network

Artificial neural networks (ANNs) are a family of statistical learning algorithms inspired by biological neural networks. They are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. Artificial neural networks are generally presented as systems of interconnected "neurons" which can compute values from inputs, and are capable of machine learning, as well as pattern recognition thanks to their adaptive nature. After being weighted and transformed by a function (determined by the network's designer), the activations of these neurons are then passed on to other neurons. This process is repeated until finally, an output neuron is activated.

A.PNN classifier

PNN is a useful neural network architecture with slightly different in fundamentals from the back propagation. The architecture is feed forward in nature which is similar to back propagation, but differs in the way that learning occurs. PNN is supervised learning algorithm but includes no weights in its hidden layer.



Input nodes Hidden nodes Class nodes Decision node

Figure 1.4 Block Diagram of PNN Classifier.

Basically, PNN consists of an input layer, which represents the input pattern or feature vector. The input layer is fully interconnected with the hidden layer, which consists of the example vectors (the training set for the PNN). The actual example vector serves as the weights as applied to the input layer. Finally, an output layer represents each of the possible classes for which the input data can be classified. The output class node with the largest activation represents the winning class. In PNN algorithm, calculating the class-node activations is a simple process. For each class node, the example vector activations are summed, which are the sum of the products of the example vector and the input vector. The hidden node activation, shown in the following equation, is simply the product of the two vectors (E is the example vector, and F is the input feature vector).

$$h_i = E_i F \qquad (3)$$

The class output activations are then defined as:

$$c_j = \frac{\sum_{i=1}^{N} e^{\frac{(h_i - 1)}{\gamma^2}}}{N} \qquad (4)$$

Where N is the total number of example vectors for this class, h_i is the hidden-node activation, and γ is a smoothing factor. The smoothing factor is chosen through experimentation. If the smoothing factor is too large, details can be lost, but if the smoothing factor is too small, the classifier may not generalize well . It's also very easy to add new examples to the network by simply add the new hidden node, and its output is used by the particular class node. This can be done dynamically as new classified examples are found. The PNN also generalizes very well, even in the context of noisy data.

V. Results And Discussion

Here, totally 158 images have been used out of which 86 are taken for training and remaining have been used for testing and validation. Calculated feature values of various input X-Ray images are tabulated. Results show that images are normal, are Osteopenia and osteoporosis. Comparison of various features for normal, Osteopenia and osteoporosis images can be seen.

Table 1.1 Table Showing Result Set

Class	Number Of Images
Normal	55
Osteopenia	46
Osteoporosis	57

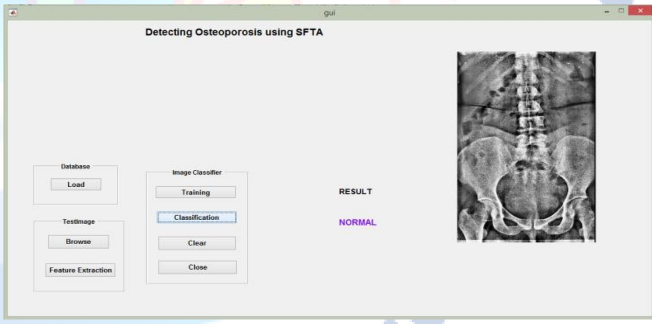


Figure 1.5 GUI Result shows Normal

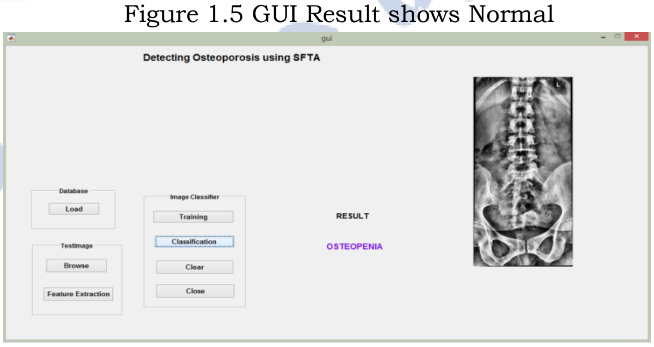


Figure 1.6 GUI Result shows Osteopenia

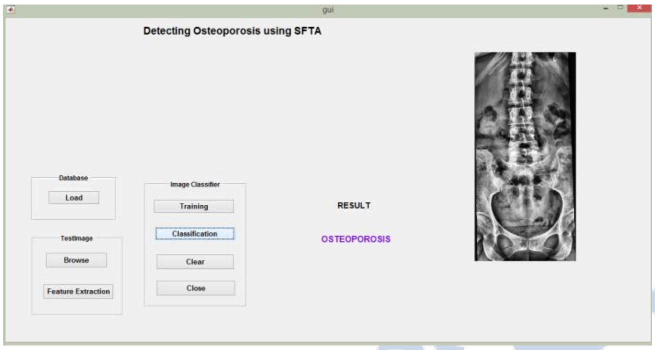


Figure 1.7 GUI Result shows Osteoporosis

A. Confusion Matrix

Confusion matrix is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one. Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class. Evaluation parameters such as Sensitivity, Specificity, Precision and Accuracy are calculated for the confusion matrix.

Table 1.2 Three Class Confusion Matrix of SFTA

45	2	0
4	65	4
0	2	34

Table 1.3 Table Showing Validation result of SFTA

Parameter	Formula	SFTA
Sensitivity	TP/ (TP+FN)	88.2%
Specificity	TN/ (FP+TN)	94.2%
Precision	TP/ (TP+FP)	97%
Accuracy	(TP+TN)/ (TP+TN+FP+FN)	94.3%

VI. Conclusion And Future Work

In this work, the suitability of texture features in classification of Lumbar spine digital radiographs is analyzed. The Experimental results during testing and theoretical analysis prove in perspective of time, accuracy of system being a main concern the fractal features are more precise and more accurate. In medical imaging or in diagnosis, the important factor is accuracy rather than speed, hence present fractal features as a more suitable technique for feature extraction. The results on classification have a combined accuracy of 93%. This value is obtained by validating our practical results with DEXA results. Hence our system can assist in diagnosis of osteoporosis. In future the work can be implemented for distal and thoracic digital radiograph, the system can also be embedded in a Digital radiography machine to diagnose osteoporosis on the fly.

References

[1] AlceuFerraz Costa, Gabriel Humpire-Mamani andAgmaJuci Machado Traina, (2012) 'An Efficient Algorithm for Fractal Analysis of Textures', Conference on Graphics, Patterns and Images (SIBGRAPI), pp. 39-46.

[2] ByongSeok Min, Dong Kyun Lim, Seung Jong Kim and Joo Heung Lee, (2013)'A Novel Method of Determining Parameters of CLAHE Based on Image Entropy', International Journal of Software Engineering and Its Applications, Vol.7, No.5, pp.113-120.

[3] Sangeetha. P, (2014) 'Brain Tumor Classification using PNN and Clustering', International Journal of Innovative Research in Science, Engineering and Technology, Vol. 3, No.3, Mar 2014.

[4] Seyyed Mohammad Mohammadi, Mohammad SadeghHelfroush and Kamran kazemi, (2012) 'Novel shape-texture feature extraction for medical X-Ray image classification', International Journal of Innovation Computing, Information and Control (ICIC), Vol.8, No.1, ISSN 1349-4198.