

Machine Learning Technique for Osteoporosis Caused Bone Fracture Detection in Femur Bones from 2D X-Ray Images

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ABSTRACT

Osteoporosis is becoming an epidemic in the urban population due to improper diet, unhealthy food and lifestyle and minimum exposure to sun which results in low Vitamin D metabolism in the body. Osteoporosis causes depletion of the bone mass which eventually results in weakening of the bones. This weak bone leads to minor to severe cracks and fractures in the bones. Detecting such minor fractures at the early stage from the X-Ray images is a significant challenge for the Orthopedics. In this work we propose a unique machine learning technique to detect early stage bone fracture caused by Osteoporosis using machine learning and image processing techniques by combining image preprocessing, segmentation and segmented ROI classification techniques.

General Terms

Medical imaging, Neural Network, Osteoporosis, Fracture

Keywords

Bone fracture, noise removal, segmentation, classification.

1. INTRODUCTION

Femur bones are the strongest bones of the body and are the thigh bones. They are also part of the lower limb. A typical femur bone anatomy is shown in figure 1.

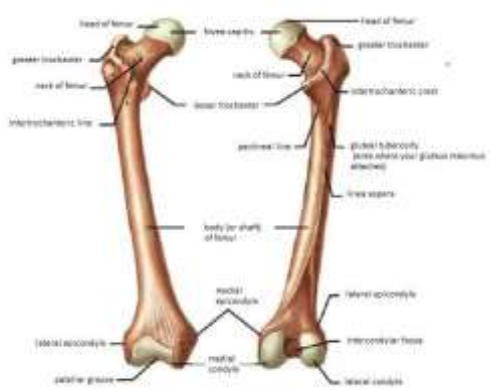


Figure 1: Typical Femur Bone Anatomy

An Osteoporosis is the loss of the Bone mass density and is often related to the improper bone metabolism. A bone metabolism is the process of death of Bone cells and replacement of them with new cells. In case of improper Vitamin D and other deficiencies in the body, the bones lose their inner mass and several dead cells are not being replaced, weakening the bones from inside. A Typical

anatomy of Normal and Osteoporosis bone is displayed in figure 2. This condition is also due to fewer and thinner trabeculae.

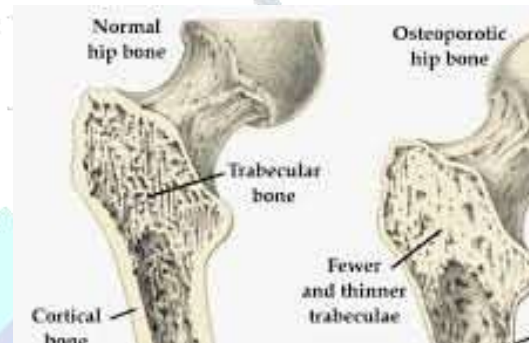


Figure 2: Typical Anatomy of Normal and Osteoporosis Femur bone.

Weak femur bones are vulnerable to hip fractures as the part of the structure is not capable of taking the load of the body in the lower limb. A Typical Osteoporosis driven femur fracture is displayed in figure 3.



Figure 3: Typical Osteoporosis induced Hip fracture illustration(L) and corresponding 2D X ray(R).

Often detection of such fractures at an early stage is difficult from the X-Ray image as 2D X ray images do not present the BMD difference suitable for the diagnosis of the Osteoporosis induced fracture.

Many of the past works have presented computer assisted diagnosis mechanism for bone fracture detection and classification. However very few research is being found in the areas of early stage fracture detection from the X-Ray imaging for the Femur bones caused by Osteoporosis. As it is obvious that an early detection can help fighting the disease through clinical intervention, we

propose a unique and novel framework for detection of Osteoporosis induced fracture detection of the femur bones.

2. RELATED WORK

Many algorithms and research works in the past have proposed different techniques for bone fracture detection and classification. In this section we present some of the past works in this direction. Vijay Kumar et al. [1] proposed medical image denoising techniques that are essential as first step towards any medical image processing. The filtering not only enables noise removal but also helps in smoothing the image which is essential for the segmentation process. Al-Khaffaf H et al [2], Zain, M. L. et al. [3] presented image d-noising and enhancing algorithms. Chan, K.-P. et al [4] elaborated the framework for feature extraction using Haar, wavelet and curvelets transform. Haar method was found to be having highest accuracy in comparison to the other two when used in classification. Tian, T.[5] presented fracture demarcation in femur bone X-ray image using geometric measurement of the femur's neck-shaft angle. Lim, S. et al [6], Yap, D. et al [7] and Lum, V. L. F et al [8] proposed Gabor filter coefficients, Markov Random Field, and gradient intensity features respectively which were extracted from x-ray images. SVM was used for the classification. Based on this observation, He at al. [9] proposed to use a "hierarchical"

SVM classifier system for fracture detection in femur bones. Mahendran, S. et al [10] presented a fusion classification technique for automatic detection of fracture in the Tibia bones. Chai, H. Y. et al [11] presented GLCM based segmentation for the x-ray images of the hand for separating bone and tissue regions. Hao, S. et al [12] presented an edge mitigation based segmentation for X-ray images. Bielecki, A. et al [13] proposed Joint feature extraction for the hand X-ray images.

From the review it is apparent that by using preprocessing, segmentation, feature extraction and classification a framework for X-ray or 2D medical imaging model can be built towards automatic detection of the bone issues. The very same model is used in the proposed work. However, unlike the past method that relies on binary SVM classifier for classifying a segmented region as fracture or not, we used machine learning based technique with feedforward neural network. As our objective is to detect the fracture at an extremely early stage that are resulted from the Osteoporosis rather than generic fracture identification, the model needs not only to separate between the normal and the fracture bones but also at the same times should be able to distinguish between osteoporosis and natural fractures. We use combination of geometric features and texture features to train and classify our neural network model.

The work is presented in detail in the next section.

3. PROPOSED METHOD

We collected three different types of samples of bone X-ray from Haddy Hospital, Gaya, India. Haddy hospital and Dr. Navneet Nischal provides specialized care for Osteoporosis and organize several free camps for BMD and X-Ray. We collaborated with the hospital to obtain fracture X-ray images of Femur bone, weak femur bone X-ray with or without hairline crack/fracture. All the images are manually classified by the doctor. We collected total 73 subject's anonymized data over a period of 8 months. The database was divided into two major parts: Training and testing. In the training phase, features were extracted the labeled features were given as training to neural network. We used proposed technique of Neural network as classifier with Hough line and circle statistics, fractal texture feature as feature vector and compare it against GLCM with SVM based method.

Proposed system framework is presented in figure Fig 4.

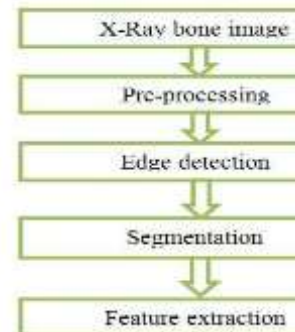


Figure 4: Proposed Framework for Femur femur bone fracture detection

Pre-processing

The preprocessing step involves a high pass filter which detects the edges in the image and a low pass filter using median filter. The preprocessing then combines these two results to provide an image that is sharp at the edges and smooth in the inner boundary. Figure 5 presents the result of the preprocessing step.



Figure 5: Preprocessing of X-ray Image by combining Low pass and High pass filter results.

Segmentation

We use an edge fitting algorithm for segmenting the femur part of the X-ray. In Edge fitting algorithm first all the possible edge candidates are located using sobel edge operator. Then region labelling technique is used to separate the connected

regions of the preprocessed image. Hough lines are estimated in the region. Hough angle of each of the lines are calculated and one between 70° to 105° degree is retained. The area that contains these Hough lines are marked as probable femur area. Location of all the Sobel edges are calculated and only the edges that falls in the marked area are retained. Rest of the area are eliminated.

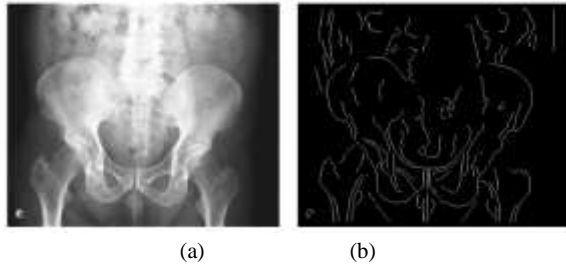


Figure 6: Result of Edge Detection Process



Figure 7: Femur bone registration and segmentation process

Feature Extraction

Features are extracted as fractal features and Hough lines from the segmented images. One of the primary quality of the Osteoporosis is that the bone density reduces significantly in the bones. This is characterized by change in micro pour density from one part of the bone to another part. Therefore, for accurate classification of Osteoporosis, such texture extraction is essential. Fractals are the mathematical equations that can define complex shapes. By fitting a fractal equation into an image, texture of the image can be well defined.



Figure 8: X-Ray image of Femur and corresponding fractal

fitting

Also, as Hough lines defines the most prominent line structures in the bones, a fractured bone will have more Hough line than the other. A thumb rule for identifying the Osteoporosis fracture and other fracture is that in Osteoporosis fracture, the texture variation in either part of the legs will be significant along with the fracture. Whereas a natural fracture will not have this quality. Therefore, combining texture and edge images is one of the best ways of performing this classification.

Classification

The objective of the classification stage is to find the closeness of the features from the given image and match them against the features of known trained set of images. As the correlation of the parameters in images that belongs to a particular category are not linear, linear distance based classifiers often fails to categorize complex images. Artificial Neural Networks are popular learning and classification techniques. In this work we propose to classify the combination of fractal texture and Hough based structural features by using feed forward neural network. The objective of the network is to classy any given image as normal or having probability of Osteoporosis traces. Further non Osteoporosis images are classified as one having fractures and the other without any fractures.

4. RESULT AND ANALYSIS

Figure 9 displays a sample database for the work. It can be seen from the images that not all the images are full pelvis samples. Few of the samples contains complete X-ray of the full pelvis section, yet few images have particular side of the body. Few X-rays contains only the femur section of the pelvis. Therefore, the segmentation process must be clearly able to distinguish this and provide robust result.



Figure 9: Sample Database: Top Images shows Osteoporosis femur whereas the bottom row shows normal femur and pelvis section.



Figure 10: Training v/s Accuracy comparison of present and proposed systems.

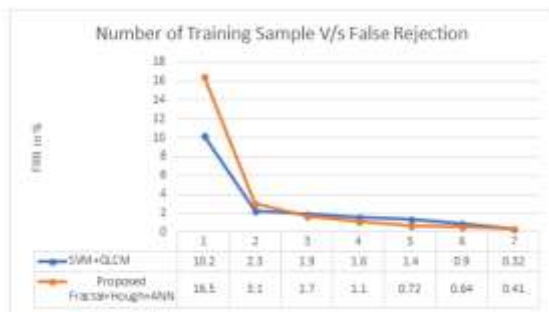


Figure 11: Number of training sample v/s False Rejection Rate

Figure 10 and 11 presents the result analysis of the proposed system with GLCM and SVM combination of current state of art. It can be seen from the results that the performance of Neural network improves significantly with the increase in the number of samples. In all the cases a total of 35 images are classified and are tested for true classification. It was also seen that the proposed method has much better false rejection rate performance which is very important for the medical imaging. The Performance analysis also shows that the proposed system can also be improved with sufficient trained data.

5. CONCLUSION

Osteoporosis is becoming one of the most prominent and widely seen disorders in urban India. Unhealthy lifestyle, low exposure to sun and various other factors are contributing towards this. There have been various methods which has been proposed in the past for efficient detection of Osteoporosis. Most commonly Bone Mass Density and several blood tests are used in the conjunction for accurately detecting this disorders. However, most of the techniques are not adequate to offer a good understanding of the actual effect on the bone of these methods. In this work we have presented a very robust technique for analyzing Osteoporosis from the femur bone structure. Our framework offers preprocessing, segmentation and separation of the femur bone from the pelvis X-ray and perform both crack detection as well as texture driven analysis for the Osteoporosis trace detection. The overall accuracy of our system was found to

be close to 96% whereas the False rejection rate was found to be as low as 0.6%. The method can be further improved by increasing more number of training sample. Deep learning based method can also help to improve the performance of the technique.

6. ACKNOWLEDGMENTS

We thank Dr. Navneet Nischal and Haddy Hospital, Gaya, Bihar, India for providing us with Labeled real data of the patients and helping us with this work. We also thank Mr. Rupam Das and Acculi Labs for providing us lab, research platform as well as for coordinating with the medical and radiology stuff for creating the dataset and permitting us a research on the same.

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