ORIGINAL RESEARCH PAPER — **Engineering**

A SUPPORT VECTOR MACHINE BASED TECHNIQUE FOR EARLY STAGE OSTEOPOROSIS CLASSIFICATION FROM PELVIC BONE X-RAY IMAGES

KEY WORDS: Medical imaging, Neural Network, SVM, Femur, X-Ray Osteoporosis, Fracture

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ABSTRACT

Osteoporosis is one of the very common pathophysiological traits which is getting observed in the modern urban population. Although over the years, several sophisticated diagnostic techniques are being developed to effectively detect Osteoporosis, the adaptation is not wide due to time, money and skill complexities with these methods. X-ray is one of the most widely available medical imaging methods but it has been traditionally used in detecting fractures and other severity in the bone structure. Osteoporosis deals with weakening of the bones which are not essentially always get detected through X-ray at the early stage. In this paper we present an efficient technique for early stage Osteoporosis detection with an accuracy of 84% that leverages the texture and structure properties of the pelvic section X-ray image, a prior knowledge and binary SVM classifier to classify a given pelvic section X-ray of a subject to asses if that subject has Osteoporosis or not. Our method relies on extracting high dimensional feature vectors using fractal dimension from the bone X-ray image and training a SVM classifier with linear kernel to classify the image data into normal or Osteoporosis.

1. NTRODUCTION

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.

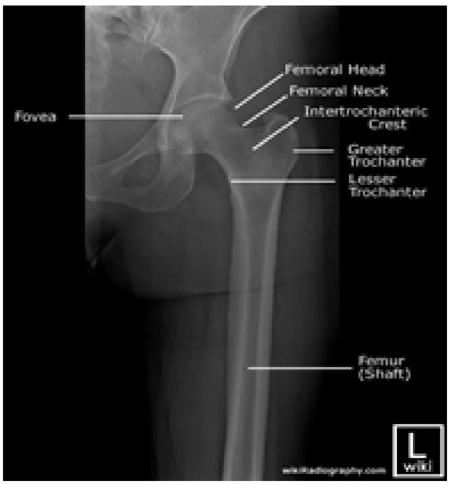


Figure 1: Radiographic Anatomy of a Femur bone

Osteoporosis is a progressive disease where the bone mass of a patient is reduced. It is more visible at the lower limbs, particularly in the joints as the disease inherently weakens them. The process of bone cell metabolism involves death of old bone cells and replacement of them. Osteoporosis is often caused by factors like Vitamin D deficiency where the dead bone cells are not being replaced by new cells. Figure 1 shows a typical femur bone Structure.

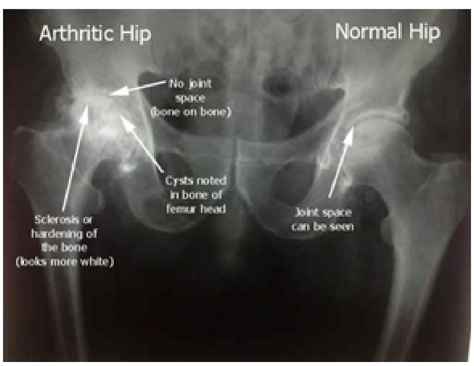


Figure 2: Typical Anatomy of Normal and Arthritic Hip bone.

Figure 2 shows an X-ray of a subject where the right limb is severely affected by Arthritis which is one of possible outcome of a prolonged Osteoporosis. It can be seen in the image that an abnormal bone reflects light with different density which can be observed by the naked eye if it is significant, but often it is not detected at the early stage.

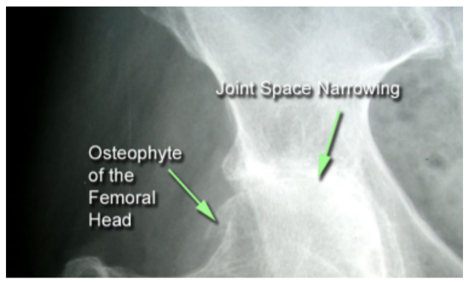


Figure 3: Typical Osteoporosis induced Hip area abnormality.

Figure 3 shows a typical X-ray image of an Osteoporosis bone. It can be seen from the comparison of figure 2 and 3 that Osteoporosis is much more difficult to detect due to the fact that weak bones not necessarily have a different photo sensitivity than the normal bones at the early stage.

Often detection of such fractures at an early stage is difficult from the X-Ray image as 2D Xray 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.

1. RELATED WORK

Many algorithms and research works in the past has proposed different techniques for bone fracture detection and classification. In this section we present some of the past works in this direction. Vijaykumar 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 denoising 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 of fractures 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 section, we learn that by using a standard machine learning framework, X-ray bones can be classified effectively. However, the challenge is to classify an X-ray bone into Osteoporosis or normal at the early stage. Because Osteoporosis is often detected as the apparent cracks in the hip joint. In this work we propose a unique technique of classifying early stage Osteoporosis from the X-ray images by using Radius mass and grid (number of boxes) features of the fractal dimension extracted from the X-ray images, training a binary SVM classifier with the features and known classes and then classifying a supplied pelvic X-ray image.

2. 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 SVM. We used proposed technique of SVM as the classifier and used combined geometric and fractal features as feature vectors for the classifier. Before extracting the feature vectors, we used preprocessing with Histogram Equalization The overall framework is presented in figure 4.

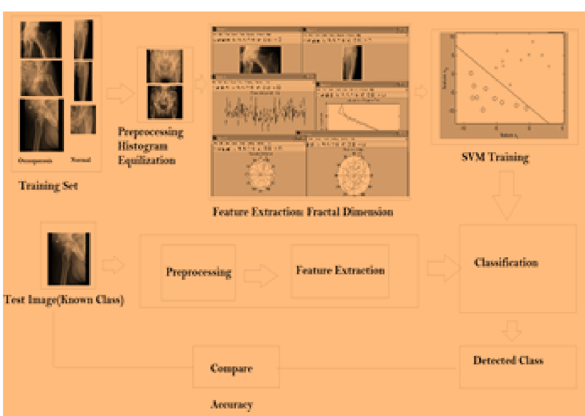


Figure 4: Proposed Framework for Femur bone fracture detection

Pre-processing

Preprocessing step involves adaptive local histogram equalization. An histogram equalization is the process of adjusting the contrast level of an image such that details are much more prominent in the image.

Figure 5: Preprocessing of X-ray Image by histogram equalization. a) Actual image b) Equalized image.

It can be seen from the figure that histogram equalization process enhances the image and makes the edges and joints more prominent. Therefore, even the faintest of trace of the bone weakening has better chances of being detected by a machine learning model by adapting this simple preprocessing step.

Feature Extraction (Fractal Dimension)

Bone structures in its elementary form is essentially a Micro-Porous structure. The composition of the micro structure is definite for each tissues and bone structure. An abnormality in the bone either through physical damage or due to pathological abnormalities essentially changes the structure of the bones which are also highlighted in the change in their elementary micro-structure. Such a micro-structure in image processing is known as the texture of the image. Though a bone X-ray looks very monotonous and homogeneous from the onset, structural changes can be identified through high level transform and modelling.

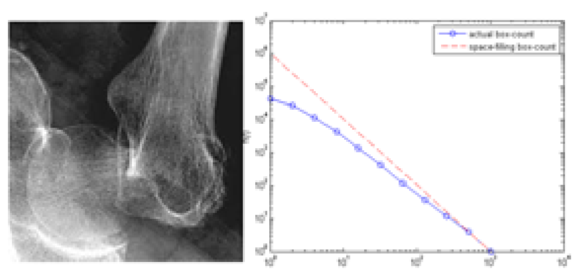
One such model of representing this texture is called a fractal dimension.

Fractal is an irregular geometric form which can be subdivided into distinct and finite sets of irregular shapes. Fractal exposes the self-similarity of these shapes.

There are many established and popular fractal shapes such as like Cantor set, Sierpinski gasket, Koch curve etc. Fractals are identified from their measurement properties. A measurement property is essentially the center, length, shape structure of the fractal descriptor. These are considered as a function of scale. The value of the scale then can be used as the feature vectors for training a classifier and for testing purpose.

The differential box counting technique used here is adapted from [14].

We use radius mass and grid numbers as two feature vectors.



(a) (b)

Figure 8: X-Ray image of Femur and corresponding fractal fitting. a) Pelvic X-ray b) Box count features

Figure 8 shows a fractal box counting curve of an Osteoporosis Hip.

Due to apparent joint and bone issues an Osteoporosis image would present significant increase in the number of boxes or the structure representing the image fractals.

Therefore, they make the features linearly separable in the hyperspace. Either a mean v/s standard deviation of the box counting can be used as the feature or any other properties can also be used. However, our experiments show that mean radius mass and mean box count are the most optimal sets of vectors which are separable linearly in the hyper dimensional feature space.

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. Support vector machine is a kernel based data fitting method. Given a set of marked dataset, the machine takes a kernel and changes the parameters of the kernel iteratively till the vectors from two distinct classes are separable linearly. There are various kernels such as Gaussian Kernel, Polynomial Kernel which can be used in SVM to create a model that transforms linearly inseparable feature vectors into a separable hyperspace through a non-linear transform. We use a linear Kernel which is a model of line curve with

$y=wx+b$

The objective of the kernel is then iterating and change the parameters w and b in a way that all the vectors from both classes have maximum inner distance. Once transformed, the new domain of vectors is known as the hyper dimension. Figure 9 shows an SVM kernel operation in the given problem space.

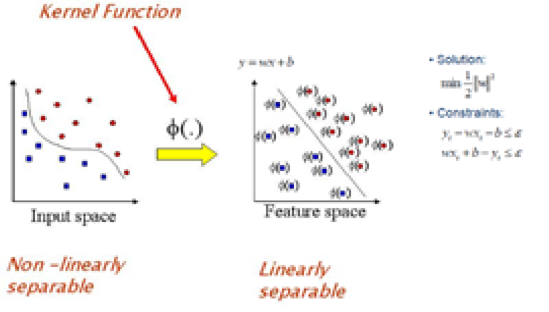


Figure 9: SVM Objective function for the classification problem

1. RESULT AND ANALYSIS

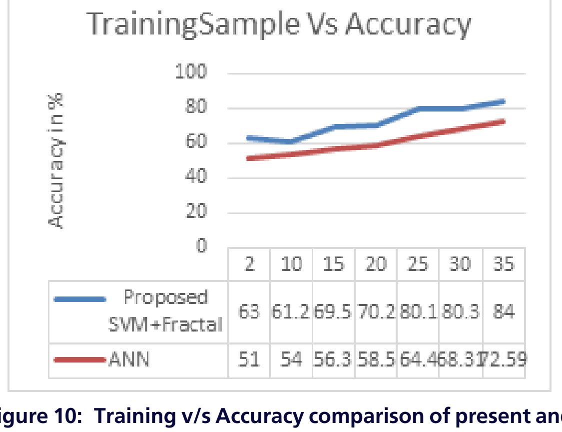


Figure 10: Training v/s Accuracy comparison of present and proposed systems.

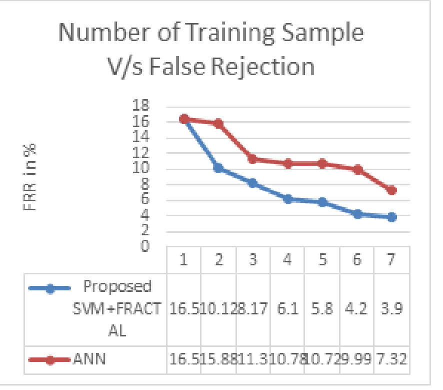


Figure 11: Number of training sample v/s False Rejection Rate

Figure 10 and 11 presents the result analysis of the proposed system of Fractals and SVM combination with popular Neural Network technique. It can be seen from the results that the performance of SVM improves significantly with the increase in the number of samples.

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.

2. 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 is an immediate need therefore to develop more automated methods to detect Osteoporosis from widely available imaging techniques. In this work we address this issue by developing and analyzing a machine learning based framework for detection of Osteoporosis using structural and texture features combined into a high dimensional optimized feature space and being classified by support vector machines.

Most often in a finite problem of binary classification, support vector machines have proven to be more effective than the other machine learning techniques when cost of implementation, adaptation and mathematical and computational complexities are all considered in coalition. Even though a cloud based deep learning framework could be more natural choice of selection in today's advanced stage of deep learning frameworks, however such cloud based techniques need centralized infrastructure with high internet speed. Considering that India still doesn't have the necessary infrastructure for adapting such core driven solution, we used Support Vector Machines as classifiers in this work. Support vector machines gives the agility of implementation of a decision system at the edge using an algorithmic approach. Such a framework can be used by future researchers to experiment with other sets of features vectors and associated techniques like combining semi-supervised model with the supervised model. Our model gives an overall accuracy of 84% which can be considered as within acceptable limits considering that no other techniques or standard clinical procedure is able to do this today with existing infrastructure. The system accuracy can and should obviously be improved over time with the use of better feature selection and classification techniques.

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