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Osteoporosis Detection Using Combined Texture Features of Proximal Femur Radiographs

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ABSTRACT
This paper presents a computer-aided-detection system of osteoporosis. The proposed technique is implemented and applied to 79 proximal femur radiographs. A dual-energy x-ray absorptiometry (DEXA) scan is used to measure T-score of the images as a justification. Three feature extraction techniques are introduced to describe trabecular pattern changes in proximal femur recorded: wavelet-based hierarchical pyramid, Gabor filter, and intensity gradient map. The selected features were utilized in the design and training of support vector machine (SVM) classifier. The accuracy, sensitivity, and specificity are used to measure the quality of the proposed detection system. The best result and detect femur bone fractures and osteoporosis were obtained efficiently by using wavelet-based hierarchical approach combined with Gabor filter, and intensity gradient map features. The proposed system showed superior performance as compared to other related work.

Keywords
Dual-energy x-ray absorptiometry (DEXA), Bone mineral density (BMD), Feature extraction, Osteoporosis, X-ray imaging.

1. INTRODUCTION
Osteoporosis considered as one of the well-known and common public health problems due its high mortality, morbidity, and cost, with dangerous complications, e.g. fractures of hip, spine, and other skeletal locations. It is also known that elderly white women are more subject to fractures than others, with almost half of them are suffering osteoporosis related fracture in their life. [11].

Osteoporosis is ranked as the second biggest problem in the world as introduced in the World Health Organization. 13% of men and 40% of women are suffering from fractures that are resulting from the disease. In 1990, hip fractures resulting from osteoporosis totaled 1.7 million worldwide, expected to increase to 6.3 million by 2050 [1,2].

At Singapore General Hospital, physicians diagnose 350 cases of hip fractures annually. Usually, a physician spends two rounds or more in visual inspection of each X-ray image before the diagnosis [1]. This long time of the inspection may affect the patients. History of fracture, low calcium, low weight, and age are risk factors [1]. Physicians often focus on the fracture of hip, where in the UK about 260 000 are suffering from osteoporosis between women who are over 50, 70 000 of them are hip fractures [1]. National Health Service of treating osteoporotic fractures in the year 2000 estimated $3 billion as annual cost for treatment.

Bone density scanning, bone densitometry, and dual-energy x-ray absorptiometry (DEXA) are different names of the same x-ray technology which are to measure bone mineral density (BMD) [10].

T-score indicate of:

T-score of -1.0 or above = normal bone density

T-score between -1.0 and -2.5 = low bone density, or osteopenia

T-score of -2.5 or lower = osteoporosis

Another DEXA scan its result is Z score doctors may use. It's used to compare a person bone density score with a normal score for another person of the same age and body weight [10].

The shape, structure of the bone and the risk of falling are other factors that is very important to be predicted. The architecture of the bone is composed by the cortical bone shell and trabecular bone core. The Trabecular bone is a spongy, porous type, found at the ends of all bones, such as pelvis and spine also this bone that has differentiate in thickness and numbers as shown in Figure 1. In proximal femur [15].

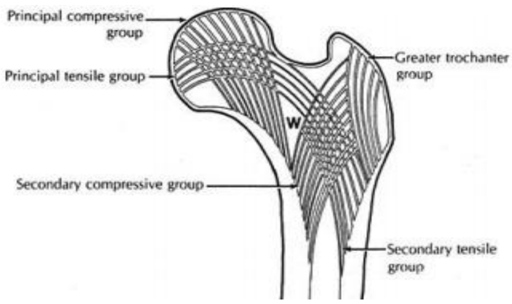

Fig 1: Trabecular Structure of The Femur [15].

Osteoporosis occur when the features in trabecular pattern changed, they used fractal dimension and Gabor filter to extract this feature in earlier research. Then compared to Singh index. The result for fractal dimension was around 70% [7].

The current study aims to inform an osteoporosis detection system. Figure 2. describe the framework for classification system for femur X-ray images. A pre-processing step is utilized using median filter to prepare the images for further processing. A segmentation step is carried out by differentiating structure of the filtered image and applying energy function algorithm to help snake algorithm in extracting the contours of femur bones. Three bone trabecular feature extraction algorithms are utilized to extract features from images: intensity gradient map, Gabor filter, and wavelet decomposition. A support vector machine classifier is used for training and testing to decide if the image is osteoporosis or not. Assessing the performance for each feature extraction technique has been achieved using three evaluation criteria the accuracy, sensitivity, and specificity.

The present study is constructing as follows: Section 2 focuses on sample collection of femur X-ray images. The use of image pre-processing methods is explained in Section 3. Mechanisms of feature extraction are described in Section 4 while Section 5 describes the support vector machine classifier, finally, conclusion of the comparative study of different techniques to extract the features is given in Section 6.

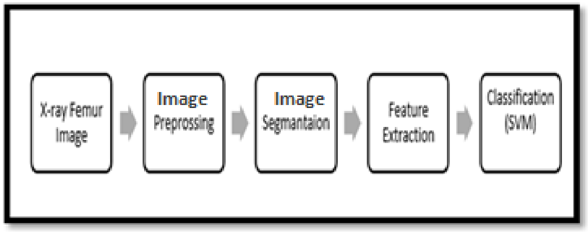

Fig 2: The Proposed system for automatic classification of femur images.

2. RELATED WORK

Sadat-Ali M, Elshaboury E without of dual energy X-ray that total cortical thickness was carried out in 50 Saudi Arabian females ≥ 45 years with DXA scans whose radiographs of the upper tibia were available for analysis. Average T score of the hip and the spin was taken. A comparison was made between age, T score. Inter cortical distance (ICD) was measured and compared in both groups. Data were analyzed for predictive value for diagnosis of osteopenia and osteoporosis. The disadvantages of this system, beside with the weak percentage of detection that the age of patient > 45 and depend on specific number. The result for fractal dimension was around 90% [13](Research 1).

A research in 2017 that osteoporosis detection model using dental panoramic radiography, they used fractal dimension and the gray level co-occurrence matrix using regions of interest and to develop an osteoporosis detection model based on panoramic radiography. The drawback of this system was that dental panoramic is expensive and inaccurate Because many dental problems are not related to osteoporosis index, thus This leads us to a wrong osteoporosis classification, the accuracy of this study were 96% using support vector machine [16](Research 2).

With the aid of calculating the thickness we manage to detect osteoporosis by a web-based software application produced by past research by Riandini and Delimayanti [8]. Scientists tested results of the application on the x-ray image from the hospital. Rate of accuracy up to 91.3%, but this result is affected by x-ray image taking techniques differentiate (Research 3).

In this study, they analyzed hip DXA scans from 29 older [3]. They performed image texture analysis applied to various regions of interest. Feature selection was used to determine which method, or combination of methods, was the best. Texture features derived from Gabor filters in combination with total T-score Estimates of risk were more accurate when the texture was measured overall femoral neck compared to other regions This study shows that image texture based on Gabor filters can complement the standard measures to improve fracture risk estimation. The disadvantages of this study that we must to calculate DXA scan and this operation expensive and not easy for every one so we need another study to predict without using DXA as a prerequisite (Research 4).

Osteoporosis is caused by decreased density of bone which can lead to fracture in many caused due to minimal forces. probability of being affected by osteoporosis increases by age for both genders, but has higher probability for females. One of the main parameters used to formalize and identify bone strength is BMD, which stands for Bone Mineral Density, and it is being measured by Dual Energy X-ray absorptiometry (DXA). Osteoporosis is being evaluated by comparing low-cost digital hip radiograph with DXA Dual Energy X-ray absorptiometry.

1) evaluate morphometry of femur using digital radiograph.

2) evaluate morphometry of metacarpal using digital radiograph.

3) apply and calculate energy function on trochanter, head and neck on proximal femur using anisotropic Morlet wavelet transform, this filter also applies enhancements on femur, after that, features are being extracted using Morlet wavelet transform. They also conducted a free osteoporosis screening camp at SRM Medical College and Research Institute at India. 50 women participated this camp, 18 of them were healthy premenopausal, and 32 postmenopausal [12] (Research 5).

In table 1 comparison between result accuracy of mentioned research in above.

Table 1. Results of Research

Research1	Research2	Research3	Research4	Researc5
90%	96%	91.3%	95%	92%

3. DATA ACQUISITION

Real database contains 79 X-ray femur images taken from the Orthopedic department, Mansoura University Hospital. The images taken were of size 500 pixels by 700 pixels. 44 images were used for testing and 35 for training. Table 2. illustrates the classification of database images used. Figure 3. depicts a typical example of femur X-ray images.

Table 2. Images classification

Image Class	Number of Images
Normal bone density	26
Low bone density	31
Osteoporosis	22

Fig 3: A typical example of femur X-ray images.

4. PRE-PROCESSING

Pre-processing is fundamental for decreasing the complexity and computation time. Patients and imaging sequences are the main contributors to the radiograph images quality, background level, noise level and the pixel value domain all these items are variable. We can smooth non-impulsive noise and maintain detail and using spatial processing performed by the Adaptive Median. The small part in the image done by Adaptive Median Filter is one of its prime benefit. In order to know the idea of adaptive median filtering, we should know the composition and function of it. In various types of processing of digital image, the prime process is: we place a neighborhood around a point, that point is composed of pixel in image, then an analysis is done in the neighborhood to amount of all the pixels, and then the original pixel's amount is replaced with one based on the process of analysis we done on the pixels in the neighborhood.

Data is smoothed by these filters while details is still sharp and small. The middle value of the pixels in the neighborhood is referred as The Median. Also, using median is getting more accurate results than average. Then, we can remove various kinds of noise using median filtering [6].

5. SEGMENTATION

The process of partitioning image into various segmentation to make the exemplification of an image easier to something that is more significative and softer is known by Segmentation. The main steps used in segmentation process to extract contours, are shown in Figure 4. The first step is to generate single-pixel thick continuous edges using canny edge detector algorithm, as shown in Figure 5 [9].

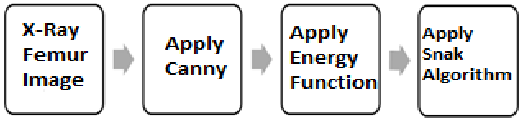

Fig 4: Segmentation Data Flow Diagram.

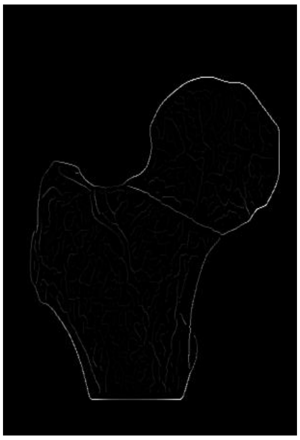

Fig 5: Output of Canny Edge Detector.

The next step is using energy function algorithm. This function helps the snake algorithm to converge correctly towards the contour and dramatically improves the performance [14]. The target for this function is to create a gradient direction towards the contour points to help the snake moving towards the right direction. First, defining the edges created by the canny edge detector as a first level direction. The algorithm then moves to all points around the first level to generate the second level direction with less intensity, and so on until reaching the final level of direction, as illustrated in Figure 6.

Fig 6: The output of using Energy function.

Active Contours (Snake Algorithm) after applying the energy function on edges produced by Canny edge detector the image now is ready for exacting contour. The following step is to use snake to extract active contour with an initial rectangular mask (bounding box) which is applied automatically based on edges produced by Canny detector.

We set the initial mask and then the algorithm decides the radius based on image size. For each pixel, snake searches for another pixel inside circle boundaries to move to base on the intensity and gradient direction. It keeps moving towards the edges until extracting the exact contour, as shown in Figure 7.

Fig 7: Output of segmentation process.

6. FEATURE EXTRACTION

This is the most important stage, in which feature algorithms are introduced seek to get a top degree of efficiency the diagnosis of osteoporosis, as discussed below.

6.1 Intensity Gradient Map

The direction that has the largest gradient magnitude in the region is referred as the intensity gradient direction of a region. The algorithm of extracting intensity gradient direction can be summarized in the following stages:

- Adaptive sampling – dividing the femur into constant number of sub-regions.
- Intensity gradient direction extracted from a sub-region compilation of intensity gradient maps [14].

Because of the variation in femur size due to variation of patient's age, gender, etc. We should first perform a size normalization technique. The only issue in size normalization is that it could reduce image quality or generate some noise, especially that this feature is so sensitive to noise. We performed another technique called adaptive sampling as shown in Figure 8.

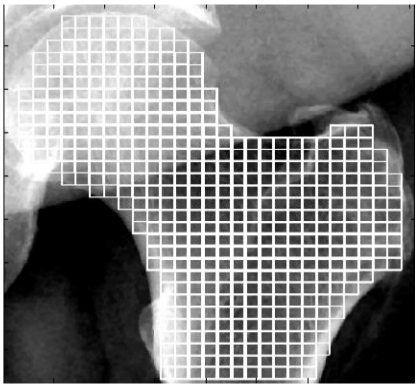

Fig 8: Adaptive sampling for femur bones.

In order to apply the adaptive algorithm of sampling to the femur. The femur was enclosed in bounding box. The value is the size of the bounding box is defined by the values x_{max} , $x_{min}, y_{max}, y_{min}$ where p is the contour points and the edge of the bound box is femur contour of the image are referred as the edges of that bounding box:

$$x_{max} | (x_{max}, y) \epsilon p \vee (x, y) \in p, x_{max} \geq x$$

$$x_{min} | (x_{min}, y) \epsilon p \vee (x, y) \in p, x_{max} \leq x$$

$$y_{max} | (x, y_{max}) \epsilon p \vee (x, y) \in p, y_{max} \geq y$$

$$y_{min} | (x, y_{min}) \epsilon p \vee (x, y) \in p, y_{max} \leq y \tag{1}$$

After locating the bounding box, we calculate the size of the sub-region using the following Equations:

$$s_x = \left\lfloor \frac{x_{max} - x_{min} + 1}{n_x + 1} \right\rfloor$$

$$s_y = \left\lfloor \frac{y_{max} - y_{min} + 1}{n_y + 1} \right\rfloor \tag{2}$$

The n_x,n_y is numbers of row-wise and column-wise .By defined $s_x$and s_y the number of regions column-wise and row-wise have to be constant [5].

Next, the sub-regions of the size $s_x$by Sy in the candidate image are generated, starting from the top left corner of the bounding box around the femur (x_{min}, y_{min}) until reaching the bottom right corner of the bounding box (x_{max}, y_{max}) and advancing by s_x/2 horizontally and s_y/2 vertically. For each sub-region, we must check if the four corners of the sub-region are located within boundaries of femur contour to make sure that it fully located inside the contours of the femur. The value we used for n_x andn_y is 14 and 16 respectively, to detect the changes that happened in small area, the sub-region should be smaller by increasing these values, but would also lead to more computational complexity. After adaptive sampling, the next stage is extracting intensity gradient direction from a sub-region. For each sub-region that is located inside the femur contour, the point with the greatest differentiate from the center computed. Center of the sub-region can be computed using the following equations [5]:

$$angel = \tan((s_1 - s_2)/(1 - s_1 * s_2)) \qquad (3)$$

where s1 is the slope of the shaft's left side and s2 is the slope of the shaft's right side.

If the direction is towards the center, we add 180 degrees on the resulting degree so the classifier can differentiate it from the other direction. The intensity gradient direction store in computer that deal with it. As computer usual treat all values as numbers so it cannot understand it. Direction stored in the form of degrees. For example, if we compare 2 points distance to 0◦ like 355◦ and 90◦, the computer would tell as that 90◦ is nearer than 355◦. To get rid of this problem, Two-dimensional vector has used to store the data. This vector is denoted by

$$U\, ij = \begin{bmatrix} \cos\phi_{ij} \\ \sin\phi_{ij} \end{bmatrix} \qquad (4)$$

Single map generated by the combination of various sub-regions. U = [$U\, ij$] With the aid of the computed intensity gradient directions. We pass intensity gradient maps to the classifier after processing all the images. In this feature we get four valid value for support vector machine. Output of Intensity Gradient Map for femur bones as shown in Figure 9.

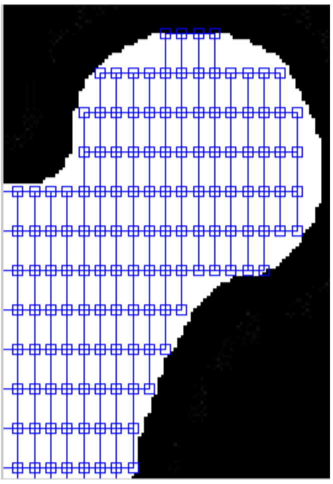

Fig 9: Output of Intensity Gradient Map for femur bones.

6.2 Bone Trabecular Feature Extraction

6.2.1 Gabor Filter

We use Gabor filter a linear filter used for texture analysis, it analyses if there are any specific frequency content in the image in specific directions in a localized region around the point or region of analysis [4].Contemporary vision scientists claim that orientation and frequency representations of Gabor filters to be as human visual system, but still there is no functional rationale to support the idea and no empirical evidence. Gabor filters found to be particularly convenient for texture representation and differentiation. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. A Gabor filter, named on name of Dennis Gabor.

$$g(x,y) = s(x,y)\, w_r(x,y) \qquad (5)$$

where is $s(x,y)$ complex sinusoid(carrier), and $w_r(x,y)$ is a 2-D Gaussian-shaped.
The complex sinusoid is

$$s(x,y) = \exp(j(2\pi(u_0x + u_0y) + p)) \qquad (6)$$

where $(u_0 + u_0)$ and p is the spatial frequency and the phase of the sinusoid respectively.

The Gaussian envelope

$$(x,y) = K\exp(-\pi(a^2(x - x_0)_r^2 + b^2(y - y_0)_r^2)) \qquad (7)$$

$$(x - x_0) = (x - x_0)\cos\theta + (y - y_0)\sin\theta$$
$$(y - y_0) = (x - x_0)\sin\theta + (y - y_0)\cos\theta \qquad (8)$$

θ : rotation angle of the gaussian envelop.
(a,b) : scale the two axes of the gaussian envelop.
p : phase of the sinusoid carrier.
K : scales the magnitude of the gaussian envelop.
$(x_0 - y_0)$: location of the peak of the gaussian envelop.

The magnitude and phase response of a Gabor filter is computed by Gabor function which is Gaussian modulated sinusoid. Input for this function is grayscale image, identified as a real, 2-D matrix. Wavelength is described in pixels/cycle of the sinusoidal carrier. on the other hand, in the range from 0 to 360 degrees orientation of the filter is specified. Useful features can be extracted by using a set of Gabor filters with different frequencies and orientations as shown in Figure10.
In this research Gabor filter was used with normalized center frequencies of $\frac{\sqrt{2}}{2^5}$ and $\frac{\sqrt{2}}{2^6}$ with $0^0, 30^0, 60^0, 90^0, 120^0, 150^0$orientations.

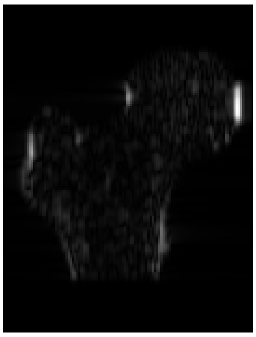

Fig 10: Output of Gabor filter for femur bones.

6.2.2. Wavelet Decomposition

The discrete signal such as digital image is being analyzed by the discrete wavelet transforms (DWT) or Wavelet Decomposition. In signal processing, we can recover weak signals from noise with the aid of wavelets. The input of wavelet decomposition the image, level of composition and mother wavelet function. Haar wavelet as mother wavelet function. The wavelet features from level 2 decomposition. Matrix s and vector c are outputs of the decomposition that return approximation coefficients image [4].
The details in three orientations (horizontal, vertical, and diagonal) and the approximation at level j+1, are four components of decomposition.

Basic decomposition step for images in following chart Figure 11.

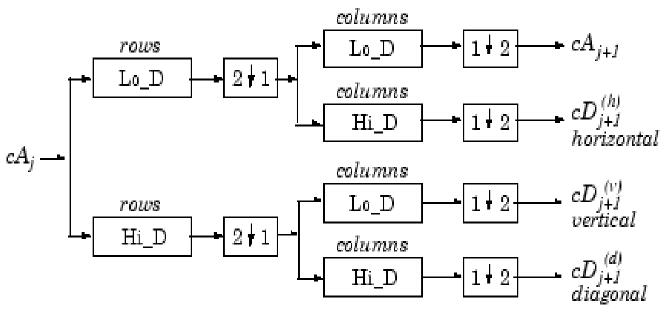

Fig 11: decomposition scheme for the calculation of 2-D wavelet coefficients.

Using energy to extract Gabor and wavelet filter features calculation as follows

$$e(x) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}|x(m,n)|^2 \quad (9)$$

For image x(m,n) with $1 \leq m \leq M$ and $1 \leq n \leq N$. A certain region of interest of proximal femur known as Ward's triangle and femoral neck, this region is highly sensitive to any change in bone mass [1], that's why wavelet and Gabor features were performed on such a region [4]. Figure 12 shows a typical example of a ROI detected in a proximal femur radiography.

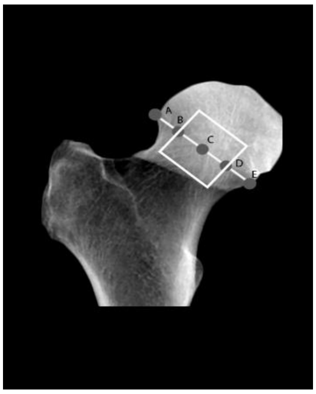

Fig 12: region of interest for a proximal femur X-ray image.

ROI related to the main trabecular systems in locations near to the Ward's triangle. To make sure of reproducibility, this region is in the center of the narrowest part of the femoral neck. Points A to E were chosen to determine the femoral neck and used to locate the ROI. Points A and E mark the femoral neck width. Points B, C and D lie at ¼, ½ and ¾ along this line. The ROI is in the form of square box with its sides equal to ½ of the line AE and point C located in the center.

7. CLASSIFICATION

This is the module that performs the final process of the system. It classifies the given radiograph image of the bone as: normal bone, osteoporosis, or Osteopenia. This was achieved using Support Vector Machines (SVM) classifier. SVMs are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis [13]. Using a group of training examples, each one is marked and belongs to one of the two categories, new model is built by SVM training algorithm, this model is allocated to one category or the other, making it a non- probabilistic binary linear classifier (although other methods like Platt scaling uses SVM in a probabilistic classification setting). An SVM model is a simulation of the examples as points in space, located so that the examples of the different categories are divided by a clear gap which must be as wide as possible. New examples are then mapped into the created space, then we predict to which category these examples belong to according to the side of the gap where they fall. Plus performing linear classification, we can use SVMs in getting a non-linear classification [13]. We made combination by extract 4 value from intensity map with the wavelet and Gabor filter results in vector and using support vector machine to test the data.

8. TEST RESULTS

A real database of 79 X-ray femur images has been illustrated in this study. The data set is classified into 35 images for training phase and 44 images for testing phase. Three different trabecular pattern feature extraction techniques were used: Intensity Gradient Map, Gabor filter, and wavelet decomposition. The three feature vectors were utilized separately and combined, for training and testing SVM classifier. Accuracy, we can evaluate the classifier results for

different features set in a specific and sensitive way given by equations (11), (12), and (13).

Accuracy = number of true classification/total number of data. (11)

Specificity = true negatives / (true negative + false positives). (12)

Sensitivity = true positives/ (true positive + false Negative). (13)

The results in Table 3 shows that using Gabor filter features could be more useful with a percentage of 62% as average correct classification rate while Intensity Gradient Map features could achieve only 50%. On the other hand, 77% of the images were correctly classified when using wavelet decomposition features. The optimal results were obtained by combining all features together. The combined features resulted in 97% correct classification rate. Figure13 depicts the test results of SVM classifier for each database class using different feature extraction techniques.

In earlier research [10] they used fractal dimension and Gabor filter the result for fractal dimension was around 70%. Another research in [2] a total cortical thickness was carried out in 50 Saudi Arabian females with DXA scans the result for fractal dimension was around 90%. A research in 2017 [1] illustrated an osteoporosis detection model using dental panoramic radiography. The accuracy was around 93%. Another web-based software application was researched By Delimayanti and Riandini used to detect osteoporosis with aid of data x-ray image that resulted from calculating the thickness of the cortex of the clavicle. The results were statistically accurate by 91.3%. Another research in this study, they analyzed hip DXA scans from 29 older [10]. They performed image texture analysis applied to various regions of interest. Feature selection was used to determine which method, or combination of methods, was the best. Texture features derived from Gabor filters in combination with total T-score Estimates of risk were more accurate when the texture was measured overall femoral neck compared to other regions This study shows that image texture based on Gabor filters can complement the standard measures to improve fracture risk estimation. The disadvantages of this study that we must to calculate DXA scan and this operation expensive and not easy for every one so we need another study to predict without using DXA as a prerequisite. So, it can be concluded that the proposed system gave a superior performance as compared to other related work.

Table 3. Comparison of SVM classification results using different feature extraction techniques.

Image Class	**Gabor Filter Features**		**Wavelet-based Features**		**Intensity Gradient Map Features**		**Combined Features**	
	Classification Rate [27/44] (62%)		**Classification Rate** [34/44] (77%)		**Classification Rate** [22/44] (50%)		**Classification Rate** [43/44] (97%)	
	Sensitivity	**Specificity**	**Sensitivity**	**Specificity**	**Sensitivity**	**Specificity**	**Sensitivity**	**Specificity**
Normal	[5/27] (19%)	[4/17] (23%)	[10/34] (29%)	[2/10] (20%)	[7/22] (32%)	[11/22] (50%)	[17/43] (40%)	[0//1] (0%)
Osteopenia	[4/27] (15%)	[2/17] (12%)	[12/34] (35%)	[3/10] (30%)	[5/22] (23%)	[8/22] (36%)	[19/43] (44%)	[0/1] (0%)
Osteoporosis	[7/16] (44%)	[7/16] (44%)	[6/10] (60%)	[2/1] (13%)	[4/13] (31%)	[4/13] (30%)	[9/9] (100%)	[0/17] (0%)

9. CONCLUSION

This paper presented an osteoporosis detection system using combined texture features of proximal femur radiographs. The proposed system was implemented on 79 X-ray femur images that different in classification, some with normal bone and others has osteoporosis or osteopenia. First, we applied median filter to smooth the data image and keep sharp and small details. Three steps are used in Segmentation process to extract contours: Canny edge detector, energy function, and snake algorithm. Three different feature extraction algorithms have been utilized separately and combined: wavelet decomposition, Gabor filter, and intensity gradient map. Discrete 2D wavelet decomposition was performed on femur imams to the second resolution level. For this research, Haar Wavelet is used as mother function in wavelet decomposition. Gabor Filter is used later as texture properties. Extracting useful properties from an image will be easier through using of many Gabor filters with different frequencies and orientations. In this study Gabor filter was used with 0^0, 30^0, 60^0, 90^0, 120^0, 150^0 orientations. Certain Region of Interest of femur which is known as Ward's triangle was extracted. This region is sensitive to any change in bone mass. Then Gabor and wavelet features were calculated on region. The Ward's triangle is the region that is most sensitive to bone mass lost.

Intensity Gradient Map is the third technique we used in the system the algorithm of extracting intensity gradient direction can be summarized in the following stages: adaptive sampling by dividing the femur into constant number of sub-regions.

Three different feature extraction algorithms where used to compare between results obtained from the proposed technique. The estimation of osteoporosis could be identified by the information we get in the form of energy that resulted to us from features of trabecular pattern. The extracted features from trabecular pattern combined with Intensity Gradient Map reached accuracy of 97%. These Algorithms will have a vital role in getting healthcare better by detecting the change in the trabecular bone. Based on the above, our project might be used in lieu of normal BMD measurements due to our high results in the screening of osteoporosis.

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