

Evaluation of Fracture Risk Condition using Bone Mineral Content and Standard Deviation

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Abstract: Bone is a most important anatomical structure in human body and a challenge in the medical world is the concern in the bone density called as osteoporosis. This disease in the bone is detected by medical image techniques. The main objective of this paper is to measure the bone mineral density (BMD) from X-ray images and thereby, evaluate the value of T-score, with an emphasis on scaling of images of DXA and X-ray for the measurement of BMD and T-score. The anticipated method comprises the succeeding steps: Region of Interest(ROI) of the bone region from X-ray and DXA images, Calculation of BMD using scale factor, Evaluation of T-score value and finally, the risk condition of bone.

Index Terms: BMD, DXA, osteoporosis, scaling factor T-score, X-ray images.

I. INTRODUCTION

Osteoporosis is one of the pandemic diseases, which is the skeletal disorder caused by low calcium level termed as bone mineral density (BMD). Osteoporosis can lead to bone fracture due to bone loss and fragility. It affects men and women equally and can happen at any phase of the life. The probability of bone fracture with osteoporosis above age 50 is high, especially in menopausal women. It is found that, 1 in every 3 women and 1 in every 5 men of age above 50 are affected by osteoporotic fractures. Worldwide, 200 million cases cause more than 8.5 million fractures [1]. The condition of risk of osteoporosis can be determined by measuring mineral density in the bone. The density level can be evaluated by different method and at different undernourished sites where BMD can be measured. A bone density test is the only test that can diagnose osteoporosis before a broken bone occurs. This test estimates the density of the bone and the chance that bone will break. Bone density test gives the report as normal bone density, low bone density (osteopenia) or osteoporosis. The lower the bone density, the greater the risk of breaking a bone [2]. Conventional radiographs which is the oldest method, limits to the visual interpretation of the physician thereby can give erroneous prediction. This disease can also be diagnosed by X-ray imaging technique in a limited dosage called dual-energy X-ray absorptiometry (DXA), but,

DXA has limitations such as inconsistent database, need of standardisation among various manufacturers, need of expert physicians to take the scan and it is not widely available as the cost of machine is high. Hence there is a need for a low cost method for earlier diagnosis of the disease to reduce the burden in the society. It is proposed in this work, that by analysing digital radiographs and DXA images, we can evaluate bone mineral density [3].

II. LITERATURE REVIEW

Very few works are done to evaluate bone mass and internal structure on X-ray images and DXA images by applying digital image analysis techniques. By measuring changes in statistical texture parameters and fractal dimensions of X-ray images it is possible to monitor changes in calcium contents and internal structure of the bone. Some works were done to analyze texture features of DXA images. Texture is analyzed to estimate the variation of the intensity levels of an image. Texture analysis of images will give an idea of the variation of grey scale patterns.

El Hassani et.al [4], developed a texture analysis method for the trabecular bone X-ray images. The work studied the effect of pre-processing the data of X-ray images for the diagnosis of osteoporosis. The image is enhanced by using Retinex algorithm which are then analyzed by using anisotropic morlet wavelet. Then, the renyi entropy has been used for the description of anisotropic textures. After extracting the texture features Neural Network classifier is used for classification. Results show this method is 92% efficient in classifying patient with osteoporotic fracture from that of normal subject. Kavya et.al [5], proposed another texture based analysis for the assessment of osteoporosis. The 2D images pre-processed using Weiner filter and contrast is enhanced by using histogram equalisation. Then both the first order texture features and second order statistical features are extracted. Two feature selection methods are proposed in this work are Wrapper method and Fischer Ratio method. Both the methods gave same features which were then used for classification by feed forward neural network. Results show

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that the proposed algorithm efficiently discriminated healthy and osteoporotic subjects. Bandyopadhyay et.al [6], proposed a fully automated X-ray image segmentation technique based on a variant of entropy measure of the image. It segmented the bone region in a digital X-ray image from its surrounding flesh region. The method performs as first it produces an entropy image from an input X-ray image, and then uses thresholding for segmenting the bone region. Jahan, F[7], proposed a partitioning method for defining texture measures of DXA images based on the variation of grey level patterns of pixels. These measures seem to produce better results and thresholds which help to discriminate normal and osteoporotic total hip DXA image. Bromiley et.al [8] suggested Random Forest Regression Voting Constrained Local Models (RFRV-CLMs) for more accurate vertebral fracture assessment (VFA). Vertebra and femurs are often segmented using an Active Shape Model (ASM) or Active Appearance Model (AAM). These methods require prior knowledge of the object shape and close initialization of the landmark set to the object shape to be segmented, and are unsuitable for separation of bone and soft tissue. Hussain et.al [9], presented a new method namely, a Pixel Label Decision Tree (PLDT), and test its accuracy in femur

segmentation in DXA imaging. Pixel classification is a method often used in medical image segmentation to identify anatomical structures. Pixel classification with decision tree is widely used in osteoporosis risk analysis with DXA images. Pixel Label Decision Tree (PLDT) is machine learning based segmentation method is used to automatically segment femur from DXA images. Results show that this method is better than the conventional techniques with an accuracy of 91%. But this method requires optimal supervised selection of features. It is evident from the above survey, only very few works are done on applying image processing algorithms on X-ray and DXA images for the evaluation of bone mineral density.

III. PROPOSED METHODOLOGY

The proposed method is depicted in Fig.1. This work includes the following steps:

1. Image segmentation
2. BMD (Bone Mineral Density) calculation
3. Computation of scaling factor
4. Evaluation of T-score
5. Classification of condition of risk.

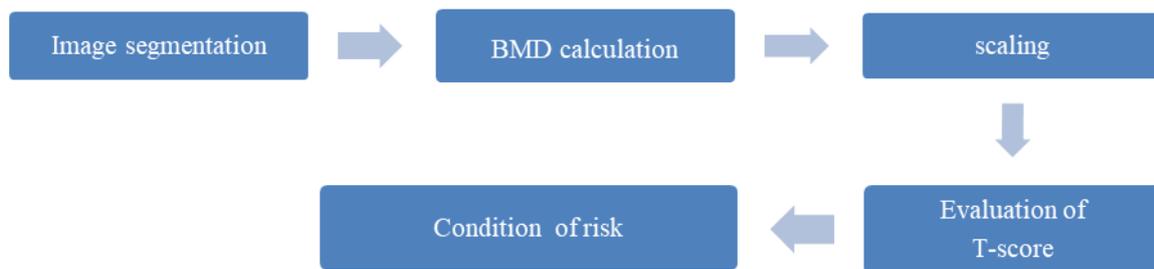


Fig.1 . Overall Block diagram of the proposed method

The input for this scheme is the X-ray and DXA images of same subject. The input X-ray images are segmented using watershed algorithm. From the segmented images the values of BMD are calculated, thereby the T-score is evaluated. Finally, based on the value of T-score the condition of risk of disease is determined. Segmentation process involves the partitioning of a bone from the soft tissues. Segmentation process is a needed process in image processing. The segmentation separates the digital image into multiple segments. Segmentation plays a vital role, by using optimal segmentation algorithm one can extract the bone parts accurately from the X-ray and DXA images. In this proposed work, global thresholding method is employed to segment the images. Global method is used as the image has a two levels of modal histogram. The area of interest is separated from the background by comparing the distribution level of each pixel in the image with a onset. Some pixels, whose intensity values are greater than the threshold, are classified as presence of class 1 - object of interest (with an intensity value of 1), and the rest of the pixels as being part of class 2-background (with an intensity value of 0). Fig.2 is the segmented output of knee

of X-ray image and Fig.3 is the segmented output of right femur of DXA image.

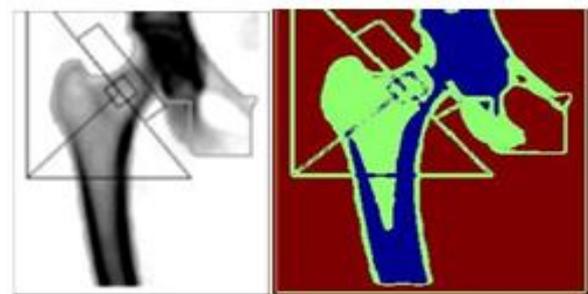


Fig.2 Segmented output of knee of X-ray image



Fig.3 Segmented output Knee of DXA image

From the segmented DXA image, the amount of bone mineral content can be calculated using the Equation (Eqn.1).

$$BMD_{DXA} = \frac{BMC_{DXA}}{(avg * 0.026)^2}$$

(1)

Where, *BMD* is the bone mineral density, *BMC* is the bone mineral content and *avg* is the average of the number of pixel counts in the segmented image. The value of BMC of DXA image for Indian women aged between 40-49 is 5 [10].

Similarly for X-ray image, the BMD is calculated as follows:

$$BMD_{XRAY} = \rho * \left(\frac{\alpha * BMC_{DXA}}{(avg * 0.026)^2} \right)$$

(2)

A scaling factor is derived based on the resolution and zooming factor of the DEXA and X-ray images, where, $\rho = 15$, and $\alpha = 10$ are the scaling factors. Here the BMC of X-ray image for Indian women aged 40-49 is scaled to 50, by multiplying the value of BMC for DXA image by 10.

T-Score is usually derived using mean and standard deviation of the mentioned population, hence any changes in these values will be reflected in the corresponding T-scores, and perhaps diagnoses and management. T-score is the number of units called standard deviations that the bone density is based on the average value. In the proposed work, the predefined mean and standard deviation of the reference population is not considered and a new parameter is defined to evaluate the value of T-score for DXA and X-ray images.

$$T - score_{DXA} = \frac{(BMD_{DXA} - (0.9 + 0.7))}{0.7}$$

$$T - score_{XRAY} = \frac{(BMD_{XRAY} - (0.9 + 0.5))}{\beta}$$

Where $\beta = 10$.

According to World Health Organisation (WHO), the value of T-score more than -2.5 is considered as osteoporosis, the value between -1.0 and -2.5 is considered as Osteopenia, and the value between +1.0 and -1.0 is considered as normal. Thus, based on the obtained value of T-score, the condition of risk of the disease is determined as either normal or osteopenia or osteoporosis.

IV. EXPERIMENTAL RESULTS

The database includes 60 images from 10 subjects. The proposed methodology was validated with a set of 10 images

of DXA and X-ray of same subjects of Indian women aged between 40 - 49. The images of AP spine, right and left femur are taken in the study. The proposed method is implemented on MATLAB R2015b. In the fig. 4, a sample knee image BMD and T-score of DXA, X-ray images and DXA Clinical report is shown. In fig.5 and 6, a sample right femur & left femur subjects BMD and T score of DEXA, X-ray and DEXA clinical report is shown. From the acquired values it is inferred that there is a small deviation in the values of BMD and T score, when compared with the clinical report values. The small difference is in tolerance level when the risk condition is analysed. So the proposed work justifies the obtained results with the clinical value.

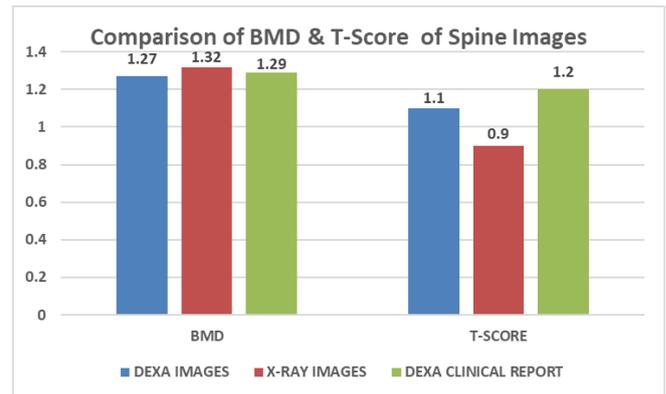


Fig.4 BMD and T-Score Values of a sample DXA and X-ray spine images

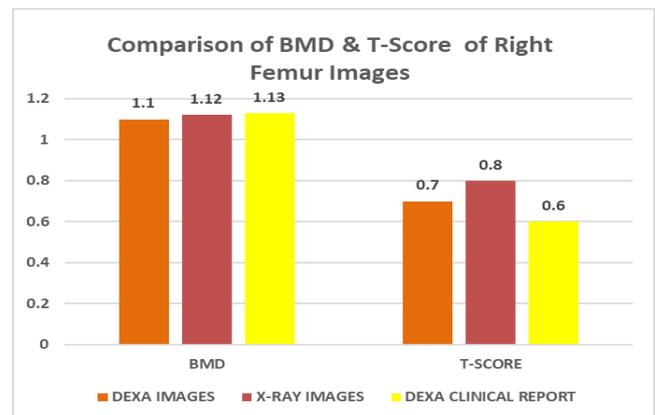


Fig.5 BMD and T-score values of a sample DXA and X-ray right femur images

V. CLASSIFICATION OF RISK CONDITION

The results are validated with the DXA report and with the interpretations of the physician. Table.1 gives the risk of condition of disease using our proposed method and validated against the results in the report.

Table: Risk Condition Validation from Clinical Report, DXA Image and X-Ray Image

Subject Id	DXA Clinical report	DXA-Proposed Method	X-Ray-Proposed Method
SUB_1	Normal Bone	Normal Bone	Normal Bone
SUB_2	Osteoporosis	Osteoporosis	Osteoporosis
SUB_3	Osteoporosis	Osteoporosis	Osteoporosis
SUB_4	Normal Bone	Normal Bone	Normal Bone
SUB_5	Normal Bone	Normal Bone	Normal Bone
SUB_6	Normal Bone	Normal Bone	Normal Bone
SUB_7	Osteopenia	Osteopenia	Normal Bone
SUB_8	Normal Bone	Normal Bone	Normal Bone
SUB_9	Normal Bone	Normal Bone	Normal Bone
SUB_10	Normal Bone	Normal Bone	Normal Bone

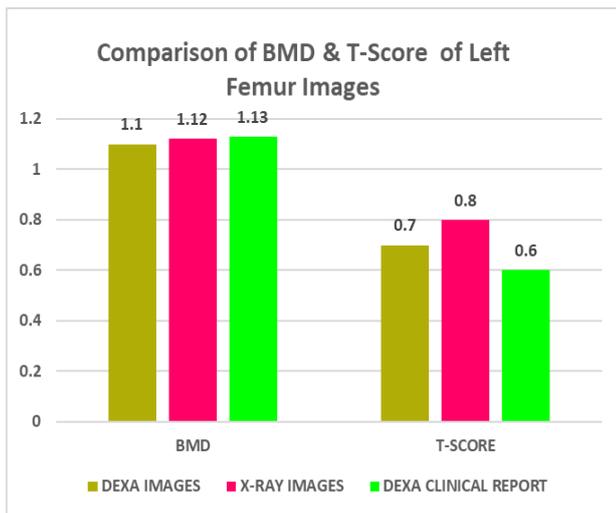


Fig.6 BMD and T-score values of a sample DXA and X-ray left femur images

VI.CONCLUSION

Lot of research challenges exist in the medical field for the detection of osteoporosis condition. This work has been made to attempt to evaluate the values of BMD and T-score from the X-ray and DXA images using image processing algorithms and mathematical model is determined for an accurate measurement of these values. The work has to be trained with a larger dataset and the performance of the method need to be evaluated.

REFERENCES

1. <https://www.nof.org>
2. Adams, J. E “Single-and dual-energy: X-ray absorptiometry in Bone densitometry and osteoporosis”, Springer, Berlin, Heidelberg, pp. 305-334,1998.
3. Nazia Fathima S.M., Tamilselvi R., Beham M.P, “Role of X-Rays in Assessment of Bone Mineral Density—A Review”, In: Saini H., Singh R., Kumar G., Rather G., Santhi K. (eds) Innovations in Electronics and Communication Engineering. Lecture Notes in Networks and Systems, Vol. 65, Springer, Singapore, 2019.
4. El Hassani, A. S. E. B., El Hassouni, M., Jennane, R., Rziza, M., & Lespessailles, E, “Texture analysis for trabecular bone X-ray images using anisotropic morlet wavelet and entropy”, International Conference on Image and Signal Processing ,Springer, Berlin, Heidelberg, pp. 290-297, 2012.
5. Kavya R, Joshi Manisha Shivram, “Texture Based Bone-Radiograph Image Analysis for the Assessment of

Osteoporosis”, International Journal of Engineering & Technology, Vol. 4, No. 06, 2015.

6. Bandyopadhyay, O., Chanda, B., & Bhattacharya, B. B, “Automatic segmentation of bones in X-ray images based on entropy measure”, International Journal of Image and Graphics, Vol.16,No.01, 2016.
7. Jahan, F, “An Investigation of Bone Image Texture Analysis for Predicting Fracture Risk”,2010.
8. Bromiley, P. A., Adams, J. E., & Cootes, T. F, “Localisation of vertebrae on DXA images using constrained local models with random forest regression voting” Recent Advances in Computational Methods and Clinical Applications for Spine Imaging ,Springer, Cham, pp. 159-171,2015.
9. Hussain, D., Al-antari, A. M., Al-masni, A. M., Han, S. M., & Kim, T. S, “Femur segmentation in DXA imaging using a machine learning decision tree”, Journal of X-ray science and technology, (Preprint), pp.1-20, 2018.
10. Lekamwasam, S., Rodrigo, M., de Silva, K. I. S., & Munidasa, D, “ Comparison of phalangeal bone mineral content and density between the dominant and non-dominant sides”, Ceylon Medical Journal, Vol.50,No.4,2009.

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