Texture Feature Extraction of Lumbar Spine Trabecular Bone Radiograph Image using Laplacian of Gaussian Filter with KNN Classification to Diagnose Osteoporosis

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Abstract. The human bones are categorized based on elemental micro architecture and porosity. The porosity of the inner trabecular bone is high that is 40-95% and the nature of the bone is soft and spongy whereas the cortical bone is harder and is less porous that is 5 to 15%. Osteoporosis is a disease that normally affects women usually after their menopause. It largely causes mild bone fractures and further stages lead to the demise of an individual. The detection of Osteoporosis in Lumbar Spine has been widely recognized as a promising way to frequent fractures. Therefore, premature analysis of osteoporosis will estimate the risk of the bone fracture which prevents life threats. The paper is systematized in two different sections to classify normal (non-osteoporosis) and abnormal (osteoporosis) Lumbar spine trabecular bone. In this method, the first section is based on discriminating the lumbar spine trabecular bone micro-architecture predisposing by means of first and second order directional derivative of Laplacian of Gaussian filter with different standard deviation to acquire the minimum and maximum responses. The dimension reduction of texture features, quantization and adjacent scale coding with weighted multipliers are used to lessen the intensity variations of texture features. The second section is based on the reduction of histogram features as a training data set for classification of normal and osteoporotic images of lumbar spine (L1-L4) using K-Nearest Neighborhood (KNN) classifier. The tested dataset result gives effective classification accuracy of 97.22% with lesser texture feature dimension. The usage of weight multiplier as well as quantization technique plays a major role for the improvement of accuracy to diagnose osteoporosis for an input noisy and noiseless image.

Keywords: Osteoporosis; Lumbar Spine; DXA; CT; Machine learning algorithms; MRI; Detection.

1. Introduction

Osteoporosis is a bone disease which affects the structure of the bones as a person gets older. It weakens the strength and decreases the size of the bones, which leads to fracture [1]. The anatomy of the spine is the most commonly affected part of the human body. It is divided into three major sections: the beginning part of the spine is cervical bones (C1-C7), the middle part of the spine is thoracic bones (T1-T12) and the lower part of the spine [2] [3] is lumbar bones (L1-L5) as shown in figure 1 and each individual bone is called vertebrae [3]. The Trabecular (cancellous or spongy) bone quantity is 40-95%
compared to the cortical (compact or dense) bones which lies between 5-15% [4]. The internal trabecular structures of different stages of normal, osteoporotic and osteoporotic compression fracture [5] of the vertebra are as shown in figure 2. Most of the body weight is carried by the lumbar spine. This gives flexibility for the movements and hence there is a chance of getting osteoporosis which commonly affects the lower part of the spine. The mortality rate of the lumbar spine is 0.13% [6].

Figure 1. Anatomy of the Spine [2] [3]

Figure 2. 3D View of Stages of Osteoporosis [5]

Zbigniew Omiotek [7] et al stated to detect osteoporosis of thoraco-lumbar portion of the spine using computed tomography (CT) images is carried out based on the fractal analysis to extract texture features. This produces a set of feature descriptors based on linear regression and three descriptors are calculated. The variation method is used to calculate two fractal dimensions from grey images and the box-counting is used to determine a third fractal lacunarity from binary images. These feature descriptors are used to classify the osteoporotic bone (abnormal) and normal bone in CT images with the help of six different classifiers. The performance results are varied depending on the classifiers, but k-NN (k the nearest neighbours with k=10) classifier gives better performance than other classifiers. Machine learning tools (Tensor flow and Python programming) was utilized to detect osteoporosis of spine in terms of HU (Hounsfield units) of lumbar CT and information of QCT (Quantitative Computed Tomography). Several regression algorithms were used to detect osteoporotic or non-osteoporotic vertebra by calculating the T-score by independent inputs (sex, age, and Hounsfield units of vertebrae on CT) incorporated with that of QCT. Kyoung Hyup Nam [8] et al proposed that substantial increase in data set would provide more accurate results. The experimentally calculated Recall was 96.9%, which is a positive outcome predicted appropriately to all inspections of the given subject and F1-score of 95.4% is the subjective normal of Precision with Recall being better system performance. Hence, machine learning is one of the most significant modality for research in medical field. Atheel Sabih Shaker [9] et al stated that recurrent neural network was used to predict osteoporosis of AP lumbar spine using Magnetic Resonance Imaging (MRI). This network was implemented with five different models, the
first three were custom models designed to characterize different depths, and the remaining two models were designed for fine-tuning at different levels. This design process increased the representational capacity to analyse osteoporosis with better fracture prediction and bored the convenience of transfer learning which included fast training process and aptness for larger datasets. There were some practical challenges for deep learning for instance lower training process and insufficiencies of precision was conveyed. Auto-diagnostic techniques made use of morphometric features extracted from CT images to measure three parts of vertebral structure for diagnosis of vertebral compression and anomaly was located using segmentation and vertebral edges was determined. Hamid Yousefi [10] et al recommended procedure consisted of noise reduction and preference to the best slice of CT image, identification of the lumbar region in the spine, estimation of six points on the contour of the vertebral body and each vertebral morphometric features such as crush, wedge and biconcave were extracted to be used in the diagnosis of vertebral compression fractures. Osteoporotic and normal bones were classified based on SVM and KNN classifiers to obtain better system performance. KNN classifier (k=5) is better than SVM. It can be concluded from survey paper that the challenging task for researchers is to collect datasets which improves system performance and alignment of images. Redouan Korchiyne [11] et al proposed Machine learning-based Legendre’s Multifractal spectrum model was developed to diagnose osteoporosis in CT and MRI images. This system was developed to extract the texture features of the trabecular bone structure using Multifractal features and Support Vector Machine to diagnose osteoporosis and normal bones. Here by improving the system performance. Yinong Wang [12] et al suggested a method for acquiring features such as volumetric parameter (morphological) and bone density determinants to classify Vertebral Compression Fractures (VCF) of Osteoporotic origin. Although it is observed from the data that misclassifications produced by longitudinal feature set is more in comparison with other features (Demographic and Measured) yet on inclusion of longitudinal feature in committee of SVM, provides ease to accurate classification but advancement is not significant by data. The hybrid type classifier model is developed to diagnose osteoporosis using an artificial neural network (ANN) based monarch butterfly optimization (MBO) technique built on individual attribute values like trabecular separation, trabecular number, age, body mass index, etc. D.Devikanniga [13] et al suggested model is experimented and verified by ten-fold cross-validation of lumbar spine data sets. Outcomes of the model are better analogized using receiver operating characteristics (ROC) and Wilcoxon signed-rank verified with existing approaches. Paper by A. Valentinitsch [14] et al is based on combination of three-dimensional texture features extracted using wavelets (WL), local binary patterns (LBP), Histogram of Gradients (HoG), grey-level co-occurrence matrix Haralick features (HAR) and local volumetric BMD of CT images to detect osteoporosis. These features are registered on to random forest classifier which is a high discriminative applied to improve the overall system performance. The fourfold cross-validation is conducted for system verification to distinguish the features for significant improvements. Sangwoo Lee [15] et al explored different machine learning models to forecast BMD utilizing DEXA and X-ray image features of spine obtained by three Deep learning algorithms. Systems to predict highly risked society with abnormal BMD was identified. This system achieves 0.75 Recall and 0.73 F1-score for its better performance. Maha M. Saad [16] et al performed a quantitative study on detection of lumbar spine osteoporosis using MRI-based score (M-score) and calculation of relative correlation between lumbar spine signal intensity measured from MRI on sagittal plane of T1WI, T2WI and BMD, Z-score, T-score from DEXA in post-menopausal women. The statistical quantitative method significantly improves distinguishing osteoporotic from non-osteoporotic bones. Table 7. shows the performance comparison with different methods and Table 8. shows comparison of AUC for Different methods.

2. Proposed Method
The training dataset comprises of lumbar spine radiograph images (N=116) of 58 different osteoporotic patients and also 58 different normal images with resolution of 450x450 pixels. Each pixel has 16-bit tiff format. Osteoporosis disease of lumbar spine (L1-L4) cause to predisposing of trabecular bone micro architecture which leads to fracture bone. In this paper the subsequent proposed method is used to classify normal as well as abnormal images. The proposed technique consists of four stages 1) Maximum
and Minimum responses of Laplacian of Gaussian filters (LOG) 2) Texture feature extraction 3) Dimension Reduction in Texture feature 4) Feature Extraction histogram 5) K-NN Classifier.

2.1 Maximum and Minimum responses of Laplacian of Gaussian filters (LOG)
The 2-D Gaussian filter with mean (µ = 0) and with different scales of sigma (σ = 2, 4, 6, 8) as shown in equation (1) and is used to derive extremum responses (Maximum and Minimum) LOG.

\[ G_0(x, y) = e^{-\frac{-(x^2+y^2)}{2\sigma^2}} \]  

(1)

The extremum LOG filters of five different sets are derived by considering a first derivative of Gaussian function as \( G_x \) in equation (2) and \( G_y \) in equation (3) and second derivatives are \( G_{xx} \) as in equation (4) \( G_{yy} \) as in equation (5).

\[ G_x = \frac{x^2}{2\pi \sigma^4} e^{-\frac{-(x^2+y^2)}{2\sigma^2}} \]  

(2)

\[ G_y = \frac{y^2}{2\pi \sigma^4} e^{-\frac{-(x^2+y^2)}{2\sigma^2}} \]  

(3)

\[ G_{xx} = \frac{x^2 - \sigma^2}{\sigma^4} e^{-\frac{-(x^2+y^2)}{2\sigma^2}} \]  

(4)

\[ G_{yy} = \frac{y^2 - \sigma^2}{\sigma^4} e^{-\frac{-(x^2+y^2)}{2\sigma^2}} \]  

(5)

The overall Laplacian of Gaussian (LOG) filter is given in equation (6)

\[ \text{LOG} = G_{xx} + G_{yy} \]  

(6)

The minimum and maximum response of the above stated filters for a given input image I are calculated in equation (7) and equation (8)

\[ I_{xx} = G_{xx} * I \]  

(7)

\[ I_{yy} = G_{yy} * I \]  

(8)

The filter response with respect to Laplacian of Gaussian filter is given in equation (9)

\[ I_{LG} = \text{LOG} * I \]  

(9)

The Filter responses \( I_{xx}, I_{yy} \) and LOG of Normal and Abnormal Image for different sigma values (σ = 2, 4, 6, 8) as shown in figure 3 and 4. From these responses there is a texture intensity variation between normal and abnormal images in different directions are helpful to give the information of predisposing of Lumbar spine trabecular bone images.
**Figure 3. Filter responses of Normal Image**
(a) Input Normal Image (b) $I_{xx}$ filter response for sigma = 2 (c) $I_{xx}$ filter response for sigma = 4 (d) $I_{xx}$ filter response for sigma = 6 (e) $I_{xx}$ filter response for sigma = 8 (f) $I_{yy}$ filter response for sigma = 2 (g) $I_{yy}$ filter response for sigma = 4 (h) $I_{yy}$ filter response for sigma = 6 (i) $I_{yy}$ filter response for sigma = 8 (j) Laplacian of Gaussian (LOG) filter response for sigma = 2 (k) LOG filter response for sigma = 4 (l) LOG filter response for sigma = 6 (m) LOG filter response for sigma = 8.

**Figure 4. Filter responses of Abnormal Image**
(a) Input Abnormal Image (b) $I_{xx}$ filter response for sigma = 2 (c) $I_{xx}$ filter response for sigma = 4 (d) $I_{xx}$ filter response for sigma = 6 (e) $I_{xx}$ filter response for sigma = 8 (f) $I_{yy}$ filter response for sigma = 2 (g) $I_{yy}$ filter response for sigma = 4 (h) $I_{yy}$ filter response for sigma = 6 (i) $I_{yy}$ filter response for sigma = 8 (j) Laplacian of Gaussian (LOG) filter response for sigma = 2 (k) LOG filter response for sigma = 4 (l) LOG filter response for sigma = 6 (m) LOG filter response for sigma = 8.
2.2 Texture Feature Extraction

2.2.1 Shape Index (curved region): The edges, ridges and blobs in the curved region of the Lumbar spine (L1-L4) trabecular bone are shown in the shape index(SI) of equation (10).

\[
SI = \tan^{-1}\sqrt{\left(I_{LGE}\right)^2}
\]  

(10)

The significant features like edges, lines, blobs and ridges in Lumbar spine trabecular bone image is one of the criteria to analyse the texture information as shown in figure 5. The white portion shows the amount of bone present in Lumbar spine trabecular bone.

![Figure 5](image)

**Figure 5.** Feature Extraction like edges, lines blobs and ridges for different sigma values: (a) Internal shape of the bone for sigma=2 (b) Internal shape of the bone for sigma=4 (c) Internal shape of the bone for sigma=6 (d) Internal shape of the bone for sigma=8

2.3 Dimension Reduction in Texture Feature

Osteoporosis affect Lumbar spine trabecular bone images generally seem like ridge region. Since shape index (SI) gives a ridge portion of the image feature, it requires five-level thresholding i.e., \( L_R = 5 \) to obtain finest texture information as in equation (11). The objective is to reduce the memory size to store features of the Lumbar spine trabecular bone image by reducing the computation cost for further processing. The five-level i.e. \( L_R=5 \) thresholding is adequate to reduce the feature dimension without losing the texture information as in equation (11).

\[
T_R(i) = \begin{cases} 
0 & \text{if } SI(i) \leq \frac{1}{L_R} \\
1 & \text{if } \frac{1}{L_R} < SI(i) \leq \frac{2}{L_R} \\
2 & \text{if } \frac{1}{L_R} < SI(i) \leq \frac{3}{L_R} \\
3 & \text{if } \frac{1}{L_R} < SI(i) \leq \frac{4}{L_R} \\
4 & \text{if } SI(i) > \frac{4}{L_R} 
\end{cases}
\]

(11)

The figure 6 shows the quantized features of an image for filter size 25×25 with \( L_R = 5 \).

![Figure 6](image)

**Figure 6.** Quantization for \( L_R=5 \): (a) Sigma=2 (b) Sigma=4 (c) Sigma=6 (d) Sigma=8
2.4 Feature Extraction Histogram
The histogram feature $F$ is calculated by considering the adjacent thresholding of $\sigma_1 = 2$, $\sigma_2 = 4$, $\sigma_3 = 6$ and $\sigma_4 = 8$ of $T_R$ with $w_R$ weight multiplier as in equation (12).

$$F = T_R(\sigma_1; \sigma_2; \sigma_3; \sigma_4)W_R$$

(12)

Where, $W_R = [L_R]^i$, $i = 0$ to $3$, $w_R$ is the weight multipliers to adjust the range of feature level ($F$) so that less number of features are sufficient to keep as a training data set for classification. Feature extraction depends on the weight multipliers, so selection of weight multipliers is playing important role to extract the significant histogram features of $F$. The histogram feature $H_F$ is the training data feature as shown in figure 7.

![Histogram features](a) normal (b) abnormal

2.5 K-NN Classifier
Nearest Neighbourhood classifier is used to classify the normal and abnormal (Osteoporosis) Lumbar Spine trabecular bone images. This classifier is very simple, it measures the minimum distance between the test and train image features. The Table 1. shows the classification accuracy for an input image without noise for different values of $L_B$ and $L_R$. The feature dimension of each image, TP is true positive, FN is false negative, TN is true negative, FP false positive. In this paper the selection of $L_B$ and $L_R$ are very important to keep the intensity range of feature in order to maintain a maximum number of features within the bins, which in turn reduces the feature dimension. For small value of $L_B$ and $L_R$ gives the less dimension since the maximum number of features present within a single bin. But this less dimension feature is not sufficient to diagnose Osteoporosis, even abnormal test image is treated as normal as shown. Table 1. For $L_B = 2$ and $L_R = 3$, the proposed system gives better accuracy with less dimension. However, less accuracy with more dimension results of increasing $L_B$ and $L_R$ values. Because of quantization, this in turn gives more number of histogram bin which leads to change in the texture information. For $L_B = 2$ and $L_R = 3$, the overall percentage accuracy of the system is 97.22.

| Sigma = [2 4 6 8] | Total=36 , Abnormal=18 and Normal=18 |
|-------------------|--------------------------------------|
| $L_B$ | $L_R$ | Feature Dimension | % of Accuracy | TP | FN | TN | FP | % of Accuracy |
| 0.4 | 0.1 | 5 | 63.15 | 44.44 | 8 | 10 | 12 | 7 | 54.04 |
| 2 | 3 | 10 | 97.22 | 97.22 | 18 | 0 | 17 | 1 | 97.22 |
| 2 | 1 | 128 | 52.63 | 77.77 | 14 | 4 | 10 | 9 | 64.86 |
| 3 | 2 | 296 | 63.15 | 83.33 | 15 | 03 | 12 | 07 | 72.97 |
| 0.6 | 0.1 | 5 | 63.15 | 44.44 | 8 | 10 | 12 | 7 | 54.04 |
The Table 2. shows percentage of standard measures for without noisy input. The method gives better results for $\sigma = 2, 4, 6, 8$ with 100% sensitivity for abnormal test images, 95% specificity for normal test images. 95% positive predictive value (PPV) gives probability of exactly abnormal test images. 100% negative predictive value (NPV) gives probability of exactly normal test images. 97.43% F1 score gives precision which signify the normal and abnormal rate. Even for less value of $L_B$ and $L_R$ gives less accuracy because of less texture information. But the proposed method works for $L_B$ must be greater than $L_R$. The Table 3. shows accuracy for different $\sigma$ values. The proposed method gives better accuracy 97.22 for $\sigma = 2, 4, 6, 8$ with $L_B = 2$ and $L_R = 3$.

### Table 2. Percentage of standard measures without noise

| Sigma | Sensitivity(%) | Specificity(%) | F1-Score(%) | PPV(%) | NPV(%) |
|-------|----------------|---------------|------------|--------|--------|
| 2,4,6,8 | 100            | 95            | 97.43      | 95     | 100    |
| 0,5,1,5,2,5 | 61.11        | 63.15         | 61.11      | 61.11  | 63.11  |
| 1,2,3  | 72.22          | 57.89         | 66.66      | 61.90  | 68.75  |

The Table 4. shows the classification accuracy with additive white Gaussian noise of varying SNR for $L_B = 2$ and $L_R = 3$ with $\sigma = 2, 4, 6, 8$. Since noise affects the intensity of an image, the accuracy also increasing by increasing the SNR. However, it gives better accuracy at 50 dB. There is some amount of false positive and false negative due to this there is a reduction in the accuracy as well as it gives less specificity. For a little amount of increasing SNR, the proposed method gives better performance as shown in Table 5. The Table 6. shows the comparison between different methods to diagnose the osteoporosis. The proposed method gives better accuracy and also less feature dimension than the other methods.

### Table 3. Classification accuracy for different sigma values

| Sigma | Feature Dimension | Normal % of Accuracy | Abnormal % of Accuracy | TP | FN | TN | FP | % of Accuracy |
|-------|-------------------|---------------------|------------------------|----|----|----|----|---------------|
| 2,4,6,8 | 10                | 97.22               | 97.22                  | 18 | 0  | 17 | 1  | 97.22         |
| 1,2,3  | 21                | 57.89               | 72.22                  | 13 | 5  | 11 | 8  | 64.86         |
| 0,5,1,5,2,5 | 21           | 63.15               | 61.11                  | 11 | 7  | 12 | 7  | 62.16         |

### Table 4. Classification accuracy with noise

| SNR (dB) | % of Accuracy | L_B=2 and L_R=3 |
|----------|---------------|-----------------|
| 40       | Normal: 38.44 | Abnormal: 77.77 |
|          | TP: 04       | FN: 07          |
|          | TN: 12       | FP: 12          | 56.75 |
| 43       | Normal: 47.36| Abnormal: 83.33 |
|          | TP: 03       | FN: 09          |
|          | TN: 10       | FP: 10          | 64.86 |
| 44       | Normal: 52.63| Abnormal: 83.33 |
|          | TP: 03       | FN: 10          |
|          | TN: 09       | FP: 09          | 67.56 |
| 50       | Normal: 89.47| Abnormal: 94.44 |
|          | TP: 17       | FN: 01          |
|          | TN: 17       | FP: 17          | 91.89 |

The Table 5. shows the percentage of standard measures with noise.

| SNR(dB) | Sensitivity | Specificity | F1-Score | PPV | NPV |
|---------|-------------|-------------|----------|-----|-----|
| 40      | 77.7        | 36.8        | 63.3     | 53.8| 63.6|
| 43      | 83.3        | 47.3        | 69.7     | 60.0| 75.0|
| 44      | 83.3        | 52.6        | 71.4     | 62.5| 76.9|
| 50      | 94.4        | 89.4        | 92.0     | 89.4| 94.4|
### Table 6. Accuracy for different methods

| Method                | Classification | % of Accuracy |
|-----------------------|----------------|--------------|
| Steerable Pyramid     | SVM            | 93           |
| Frequency Separation  | SVM            | 94           |
| Gaussian Method       | NN             | 94.44        |
| DDTWT                 | SVM            | 93           |
| Proposed Method       | KNN            | 97.22        |

2.6 Test image classification

Each test image is rotated by 10 times with different degrees. For each rotation there is abnormal or normal classification depending on the input image. Like this 10 classification are occurring but greater than or equal 0.5 probability of occurrence are treated as that of class. The trained images are 116 images [0-58 is normal and 59-116 is abnormal i.e. 116x10= 1160] and the test images are 36 (36X10=360). The Overall dimension = 116x10 for training images and 36x10 for test images.

### Table 7. Performance Comparison with different methods

| Methods and features | Imaging modalities | Classifiers | Accuracy | Sensitivity | Specificity | Cross validation |
|----------------------|--------------------|-------------|----------|-------------|-------------|------------------|
| Fractal Analysis [7] | CT                 | k-NN        | 81       | 78          | 90          | 3-fold           |
| Morphometric [10]    | CT                 | k-NN        | 88.3     | 92.5        | 83.3        | 10-fold          |
| Multifractal [11]    | CT and MRI         | SVM         | 95.2     | N           | N           | 10-fold          |
| Morphometric with global descriptors [12] | CT | SVM | 82.0 | N | N | 10-fold |
| MBO-ANN approach [13] | Person attribute values | Hybrid | 97.9 ± 0.14 | 98.33 ± 0.03 | 98.33 ± 0.03 | 10-fold |
| 3D feature with vBMD [14] | CT | Random forest | - | 77 | 78 | 4-fold |
| DCN [15]             | DEXA and X-ray     | SVM, KNN, RFC | 71 | 81 | 60 | 4-fold |
| Statistical Quantitative Analysis [16] | MRI and DEXA | N | N | 94 | 60 | 2-fold |

### Table 8. Comparison of AUC for Different methods

| Methods                          | Image type          | Accuracy | Area Under the Curve (AUC) | Cross validation |
|----------------------------------|---------------------|----------|----------------------------|------------------|
| Multivariable Regression Algorithm [8] | CT and QCT         | 92.5     | 90                         | 4-fold           |
| DCN [15]                         | DEXA and X-ray      | 71       | 0.74                       | K-fold           |
| Statistical Quantitative Analysis [16] | MRI and DEXA       | N        | 90.4                       | 50               |

3. Conclusions

Osteoporosis is a chronic metabolic bone disease which is characterized by bone fragility. The factors which cause osteoporosis are menopause and aging. Due to increased life span and aging population, this disease is taking the shape of a pandemic. Over 200 million people all around the globe are suffering
from this bone disease. The data published by International Osteoporosis Foundation, shows that above the age of 50 years one in three women and one in five men are affected by osteoporotic fractures in their lifetime. All fractures are an indication of subsequent disasters. This bone disease is asymptomatic until there is a fracture. This disease makes human lead a lower quality of life, makes them adjust to disabilities and puts the health insurance systems of the countries in financial trouble. Osteoporosis can be prevented by early detection leading to early treatment which can prove helpful to women for a better quality of life. Many technologies are currently working to diagnose osteoporosis to evaluate skeletal healthiness. One of them is DEXA and it is put to more regular usage. It deals with hip, spine, and total body with faster, accurate and highly precise BMD of a particular region. Although DXA is standard method of analyzing osteoporosis. It has certain drawbacks such as low accessibility, very costly and 2-D processing techniques with in-built limitations such as it cannot differentiate between trabecular and cortical bone and the changes due to bone geometry. The characteristics which are micro-structural like size, trabecular shape, orientation and number cannot be examined and hence radiographs based subjective analysis of osteoporosis is cost effective which is substitute to DXA. As BMD quantitative measures from DXA is not the micro-architecture bone quantity so it is inefficient to diagnose osteoporosis. Hence the texture features extraction evaluation measures are able to give the complete micro structural design of the trabecular bone. In addition, osteoporosis also affects the trabecular bone structure in comparison with the cortical bone and furthermore DXA provides an areal BMD. Hence, integration of BMD measurement with texture attribute analysis of the trabecular bone will afford a better and additional responsive evaluation for premature detection of osteoporosis. Even though MRI and QCT techniques results in a true bone mass density, but have limitations like expensive cost.

4. Future work

There are still potential challenges in the research field to come out with new techniques to achieve detailed information about micro architecture of trabecular bone with cost-effective diagnostic tools required to diagnose osteoporosis. Looking at the opportunities to predict osteoporosis and advancement in the technologies it is possible to investigate the true measurements of volumetric bone density (BMD) and would also help the global population to reduce their disabilities. This analysis is used to obtain bone indices which classifies the bone quality and also describes new methods of extracting trabecular bone texture features to evaluate the standard methods to classify the bones. Hence, developing a system for an early diagnosis of osteoporosis in order to improve the analysis of accuracy, reliability, sensitivity, correct geometric measurements, strength evaluation and prediction of risk of bone fracture is significant. This could remarkably help medical field in advancements of clinical trials, cost management and also in accounting the number of osteoporotic fractures in health system. Hence it reduces the financial burden in the upcoming years.

Acknowledgements

This work was supported by Dr. A Ramalingaiah M.S (ortho)Orthopaedic Doctor, Bangalore. No.271 Abhilasha Orthopaedic Hospital 5th Block 100ft Rd Banashankari 3rd Stage Bangalore - 560085, Bangalore.

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