Texture Feature Extraction of CTB Radiograph Image Using Derivative Gaussian filter With NN Classification to Diagnose Osteoporosis

Kavita. Avinash. Patil, K. V. Mahendra Prashanth

Abstract*: *Texture feature based classification of bone radiograph images to diagnose osteoporosis is a challenge for researchers. The Calcaneus Trabecular Bone (CTB) micro architecture is one of the important factor to recognise osteoporosis because of which the entire structure of CTB is impaired. The method organized in this paper has two parts, to classify the normal (control cases) and abnormal (osteoporotic cases) CTB images. The first part of this method is to distinguish the CTB micro architecture predisposing using first and second order directional derivative of Gaussian filter with different standard deviation to obtain the extremum (maximum and minimum) responses. To differentiate the texture features of an image by transformation of extremum responses using linear and nonlinear operations on extremum responses. To reduce the entire dimension of the texture features, quantization and adjacent scale coding with weighted multipliers are used to reduce the intensity variations of features. The second part of this method uses the reduced histogram features as a training data set to classify the normal and abnormal CTB images using nearest neighbourhood (NN) classifier. The tested results gives effective classification accuracy of CTB images with less texture feature dimension. Since this method uses weighted multipliers and quantization to reduce the feature dimension of image texture. The selection of weighted multiplier plays an important role to improve the classification accuracy to diagnose osteoporosis for an input noisy and noiseless image. The overall system proposed in this paper results better diagnose accuracy than the existing system.

Index Terms*: *Classification, CTB images, Gaussian derivativefilters, Osteoporosis ,Quantization, Texture features,

I. INTRODUCTION

Osteoporosis is a disease condition which causes the trabecular bones to begin to fragile [1]. This condition is mostly seen in women, probably in menstruation ceases and men over the old age. It is characterized as loss of BMD and trabecular bone architectural variations [2]. When the trabecular bone density, thickness, and connectivity become low, the probability to get osteoporosis and femoral fracture becomes higher [3]. Fig. 1 shows the feet bones structure in which Calcaneus bone is the largest tarsal bone, which supports the full body weight and bear very high degree of force. Calcaneus is comprises almost 90 % of trabecular bone encapsulated by thin cortical bone as shown in Fig. 2. Further this bone is considered to reflect the mechanical property of the common osteoporotic fracture bones such as proximal femur and spine [4]. The trabecular bone thickness ranges from 100 – 150 µm, whereas the thickness of cortical bone ranges between 1 - 5 mm [5]. Metabolic rate of trabecular bone is 8 times more when compared to cortical bone. Commonly, Osteoporosis is diagnosed by measuring BMD of the trabecular bone with a standard measurement technique known as DXA and are represented as T-score [6]. The World Health Organization describes the person with T-score of -2.5 and below as osteoporotic and prominent to fracture risk. However, various investigators have found that only BMD estimation is not sufficient to determine fracture risk, and have suggested a role and importance of exploration of trabecular micro-architecture [7].Thus assessment of morphology and morphometric features of the trabecular and cortical bone provide substantial and useful information about severity of the osteoporosis and fractures [8]. Digital radiography is largely utilized modality for the analysis of bone related complications at various anatomical sites such as hip, femur, heel, spine and wrist. In particular, it has potential to fetch trabecular micro-architecture information that reflect in the Bio-medical imaging systems [8][9][10]. Thus, there has been ample scope for the research using radiography image analysis using texture based technique [11].Texture analysis is an effective method largely utilized for quantification of image features such as pixel intensity, pixel interrelationships, gray levels, and patterns etc which are distinguished by human vision. Applications of texture feature characterization are found in various medical and non-medical applications such as diagnoses using medical images, remote sensing, analysis of geological structures in images and microscope images [12]. Two techniques are commonly used to extract image texture features in spatial and spectral domain. Spatial methods are used to study the interrelationship between each pixel and its neighbours of an image with fine structures without apparent regularity. The spectral approaches based on various filters are utilized to record clinical measures with different imaging systems [13]. It provides a good spatial and frequency localization. Therefore, filters have extensively been used to epitomize image textures. Image texture classification

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depends on the histogram of different filter techniques are used to analyse the image texture [14]. Co-occurrence matrix based image texture feature in dental panoramic radiographs and fractal dimension are measured within the cortex, cortical width measurement is one of the argument used to classify osteoporosis at femoral neck. Classification accuracy only cortical texture alone, cortical width alone with combined width and texture are 74.4%, 73.6 % and 80.0 % respectively [15]. Fractional Brownian motion model is used to compare isotropic and anisotropic images to distinguish normal and abnormal with image rotation [16]. Enhancement techniques are used as a pre-processing to intensify the detailed information present in the given image. Stacked Sparse Auto encoder with image subdivision is used to extract the feature of the image texture. These extracted features are used as a training data set to diagnose osteoporosis using SVM classifier. The experimental result shows diagnosis of osteoporosis accuracy rate around 90% [17]. Steerable pyramid filters are used to extract the texture information of the CTB images with SVM classifier to detect the osteoporosis [18]. Frequency separation method is incorporated to analyse the osteoporosis of the CTB images and SVM classifier is used to classify the normal and abnormal images [19]. Discrete dual tree wavelet transform (DDTWT) technique is used to decompose the texture information and SVM classifier to detect the osteoporosis [20]. Histogram based Gabor filter technique is used to analyse the trabecular structural information of CTB images with SVM classifier [21]. Both BMD and texture analysis of bone image gives better fracture assessments than only by bone mineral density (BMD) measurements [22]. Anisotropic Morlet [23] is used to analyse the intensity variations and neural network classifier is used to distinguish between normal and abnormal cases.

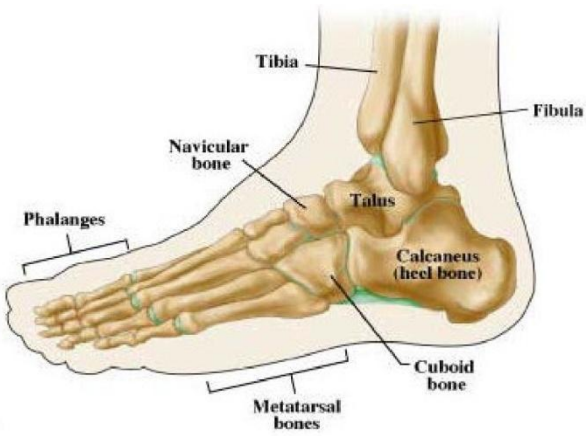

Fig.1: Feet bones Structure

In this paper, the proposed method uses features of CTB image texture as a training dataset to classify whether the given test images are normal or abnormal. The 2-D derivative of Gaussian filter responses in different directions are used to analyse the intensity variations of the CTB image texture. These filter responses are used further to obtain features like edges, lines, blobs and ridges of the texture by performing mathematical operations on filter responses .Since these texture features dimension are large in size for further processing, so this paper uses binary, uniform quantization and adjacent scale coding with weighted multiplier technique are used to reduce the feature dimension. In the second stage of the paper keeps reduced texture features as a training dataset for classification [24], in which nearest neighbourhood classifier is use to classify the normal and abnormal image.

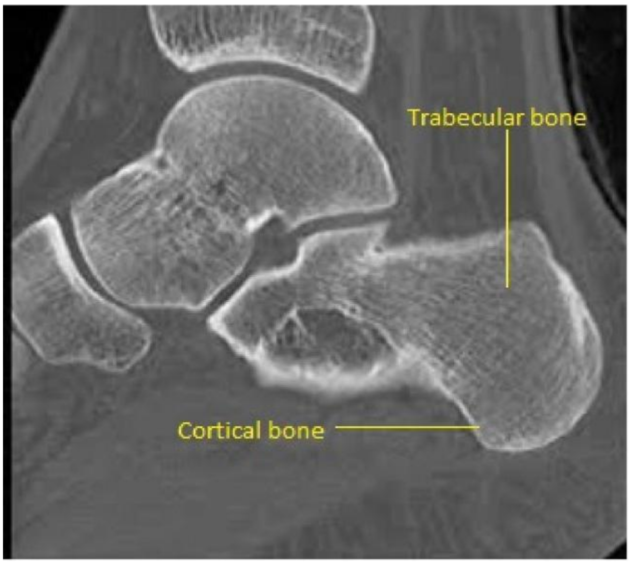

Fig.2: Internal Structure of Calcaneus bone

II. PROPOSED METHOD

The training dataset consists of calcaneus radiograph images (N=116) of 58 different osteoporotic patients and 58 different normal images with the resolution of 350x350 pixels. Each pixel has 16-bit tiff format. Osteoporosis disease of calcaneus bone cause to predisposing of trabecular bone micro architecture leads to fracture the bone ,so in this paper the following proposed method are used to classify normal and abnormal images. The proposed method consist of four stages 1) Extremum Gaussian filters 2) Texture feature extraction 3) Reduction of Texture feature Dimension.

4) Classification using NN.

A. *Extremum Gaussian filters*

The 2D Gaussian filter with mean μ = 0 and different scale of sigma (σ) as in (1) is used to derive extremum Gaussian filters.

$$F(u, v) = \frac{1}{2\pi\sigma^2} \; e^{-\frac{u^2+v^2}{2\sigma^2}} \qquad (1)$$

The extremum Gaussian filters of five different sets are derived by considering first derivative of Gaussian function as F_u as in (2) and F_v as in (3) and second derivatives are F_{uu} as in (4) , F_{vv} as in (5) , F_{uv} as in (6).

$$F_u = -\frac{u}{2\pi\sigma^4} \; e^{-\frac{u^2+v^2}{2\sigma^2}} \qquad (2)$$

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$$F_v = -\frac{v}{2\pi\sigma^4}\, e^{-\frac{u^2+v^2}{2\sigma^2}} \quad (3)$$

$$F_{uu} = -\frac{1}{2\pi\sigma^4}\, e^{-\frac{u^2+v^2}{2\sigma^2}} \left(1-\frac{u^2}{\sigma^2}\right) \quad (4)$$

$$F_{vv} = -\frac{1}{2\pi\sigma^4}\, e^{-\frac{u^2+v^2}{2\sigma^2}} \left(1-\frac{v^2}{\sigma^2}\right) \quad (5)$$

$$F_{uv} = -\frac{1}{2\pi\sigma^4}\, e^{-\frac{u^2+v^2}{2\sigma^2}} \left(\frac{uv}{\sigma^2}\right) \quad (6)$$

To obtain minimum and maximum response of the above mentioned filters for a given input images are

$I_u = F_u * I$, $I_v = F_v * I$,
$I_{uu} = F_{uu} * I$, $I_{vv} = F_{vv} * I$ and $I_{uv} = F_{uv} * I$

B. *Texture feature extraction*

Predispose of CTB feature extraction is obtained by performing linear and non-linear mathematical operations on extremum filter responses [25].The linear operations are like gradient, extremum difference and the non-linear operations gives curved regions of the bone.

a) *Gradient of image*

Gradient of image along horizontal and vertical direction of first order derivative of Gaussian filter responses gives a maximum edge variation of the image texture as in (7).

$$G = \sqrt{(I^2u + I^2v)} \quad (7)$$

b) *Extremum Difference*

The maximum intensity variation of the texture information is achieved by considering the difference between the maximum and minimum second order derivative of Gaussian filter responses gives lines of image texture as in (8).

$$D = \sqrt{(I_{uu} - I_{vv})^2 + 4I_{uv}^2} \quad (8)$$

c) *Curved Region*

The blobs and ridges in the curved region of the Calcaneus trabecular bone in different directions are represented as a C_B and C_R respectively, which are obtained by using derivative of Gaussian filter responses represented as in (9) and (10).

$$C_B = 0.5 - \frac{1}{\pi}\tan^{-1}\left[\frac{-I_{uu} - I_{vv}}{D}\right] \quad (9)$$

$$C_R = \frac{2}{\pi}\tan^{-1}\left[\frac{D}{G}\right] \quad (10)$$

C. *Reduction of Texture feature Dimension*

The aim is to reduce the memory size to store features of the CTB image with reduction in the computation cost for further processing. Since G and D are the linear features of an image texture, hence two-level thresholding is sufficient to reduce the feature dimension without loss of texture information as in (11).

$$T_G(i) = \begin{cases} 1, & \text{if } G(i) > \mu_g \\ 0, & otherwise \end{cases} \quad (11)$$

Where μ_g is the average value of gradient features and 'i' 'varies from 1 to M×N size of image. Similarly two-level thresholding approximation is applied for D features. Since noise degrades the perception quality and also it affects the intensity range of CTB image especially for C_B and C_R features. However C_B gives blob region of bone which requires three-level thresholding i.e. $L_B = 3$ for proper approximation as in (12) to reduce C_B dimension.

$$T_B(i) = \begin{cases} 0, \text{if } C_B(i) \le \frac{1}{L_B} \\ 1, \text{if } \frac{1}{L_B} < C_B(i) \le \frac{2}{L_B} \\ 2, \text{if } C_B(i) \ge \frac{2}{L_B} \end{cases} \quad (12)$$

Osteoporosis affected CTB images usually appear like ridge region. Since C_R 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 (13).

$$T_R(i) = \begin{cases} 0, \text{if } C_R(i) \le \frac{1}{L_R} \\ 1, \text{if } \frac{1}{L_R} < C_R(i) \le \frac{2}{L_R} \\ 2, \text{if } \frac{1}{L_R} < C_R(i) \le \frac{3}{L_R} \\ 3, \text{if } \frac{1}{L_R} < C_R(i) \le \frac{4}{L_R} \\ 4, \text{if } C_R(i) \ge \frac{4}{L_R} \end{cases} \quad (13)$$

D. *Histogram Feature Extraction*

Three different histogram feature F_1, F_2 and F_3 are calculated by considering the adjacent thresholding of T_G, T_D and T_C with different scales as in (14), (15) and (16).

$$F_1 = T_B(\sigma_1;\sigma_2) \times w_B + T_G(\sigma_1;\sigma_2) \times w_G + T_D(\sigma_1;\sigma_2) \times w_D \quad (14)$$

Where $T_B(\sigma_1;\sigma_2) \times w_B$, $T_G(\sigma_1;\sigma_2) \times w_G$, $T_D(\sigma_1;\sigma_2) \times w_D$ are threshold levels of $\sigma_1 = 1$, $\sigma_2 = 3$ of curvedness, gradient and extremum difference of image respectively and w_B, w_G, w_D are weight multipliers. Similarly F_2 is calculated with adjacent thresholding of $\sigma_2 = 3$, $\sigma_3 = 5$.

$$F_2 = T_B(\sigma_2;\sigma_3) \times w_B + T_G(\sigma_2;\sigma_3) \times w_G + T_D(\sigma_2;\sigma_3) \times w_D \quad (15)$$

F_3 is calculated with adjacent thresholding of $\sigma_1 = 1$, $\sigma_2 = 3$ and $\sigma_3 = 5$ of T_R with w_R weight multiplier.

$$F_3 = T_R(\sigma_1;\sigma_2;\sigma_3) \times w_R \quad (16)$$

Where w_B, w_G, w_D, w_R are the weight multipliers to adjust the range of F_1, F_2 and F_3 feature levels so that less number of features are sufficient to keep as a training data set for classification. where $w_B = (L_B)^i$, $i = 1$ to 0, $w_G = (2)^i$, $i = 3$ to 2, $w_D = (2)^i$, $i = 1$ to 0 and $w_R = (L_R)^i$, $i = 2$ to 0. Feature extraction depends on the weight multipliers, so selection of weight multipliers are playing important role to extract the significant histogram features of F_1, F_2 and F_3. These histogram feature are the training data feature H_f as in (17) by appending histogram features h_{F_1}, h_{F_2} and h_{F_3}. The dimension of H_f is playing important role during the testing process because, less dimension of H_f takes less time to diagnose whether the given CTB is normal or abnormal.

$$h_{F_1} = \text{hist}\,(F_1, 0:[L_B^2 \times 2^4] - 1)$$
$$h_{F_2} = \text{hist}(F_2, 0:[L_B^2 \times 2^4] - 1)$$
$$h_{F_3} = \text{hist}\,(F_3, 0:L_R^3 - 1)$$
$$H_f = [h_{F_1}, h_{F_2}, h_{F_3}] \qquad (17)$$

E. Classification using NN

Nearest Neighbourhood classifier is used to classify the normal and abnormal (Osteoporosis) CTB images. This classifier is very simple, it measures the minimum distance between the test and train image features. The distance vector D_v is calculated as in (18)

$$D_v = \sum_{i=1}^{L} \frac{F_{sub}^2(i)}{F_{add}(i)} \qquad (18)$$

Where $F_{sub} = F_{test} - F_{train}$, $F_{add} = F_{test} + F_{train}$ and L is the length of the feature vector. F_{test} and F_{train} are test and train feature vector. The minimum value of distance vector D_v decides the given test image is normal or abnormal image.

F. Test image classification

Each test image is rotated by 20 times with different degrees. For each rotation there is abnormal or normal classification depending on the input image. Like this 20 classification are occurring but greater than or equal 0.5 probability of occurrence are treated as that of class .Table I: shows the one of the example to test Image with rotation in different degrees to classify the given test image is normal or abnormal. In Table I the N_r represents Normal and AN_r represents Abnormal.

III. RESULTS

The experimental results are carried out on 58 normal and 58 abnormal CTB images with region of interest for different patients are considered as a training database to diagnose the Osteoporosis with zero mean. However to improve the diagnose accuracy, images are rotated a 0°,1°, 2°, 3°, 4°, 90°, 91°, 92°, 93°, 94°, 180°, 181°, 182°, 183°, 184° and 270°, 271°, 272°, 273°, 274° so that total number of trained images becomes 2320 (116×20) and 37 images are used to test the Osteoporosis by rotating each image 20 times. In this paper the proposed method uses directional extremum Gaussian filters of three different sizes 7×7 for $\sigma = \sigma_1$, 13×13 for $\sigma = \sigma_2$ and 25×25 for $\sigma = \sigma_3$ are used to calculate minimum and maximum responses with different scale . The Fig.3 shows filter response of size 25×25 for σ = 5. The 2×3 images are like abnormal input image, first derivative filter response I_x, I_y and second derivative filter response I_{xx}, I_{yy}, I_{xy} respectively. Similarly the Fig.4 shows filter responses for normal CTB input image. From these responses there is a texture intensity variations between normal and abnormal images in different directions are helpful to give the information of predisposing of CTB images.

The significant features like edges ,lines ,blobs and ridges in CTB image is one of the criterion to analyse the texture information .The transform features G, D, C_B and C_R are calculated using above mentioned equations for three different size of filters responses. Fig. 5 and 6 shows 1×4 images are G, D, C_B and C_R of abnormal and normal image features for filter size 25×25 respectively. Since G and D are linear operations .The lines and edges are dense in normal CTB images than abnormal because the abnormal bones are porous and C_B and C_R are non-linear operations gives the curvature parts of the texture image information. The C_B gives the blob portion of curvature information, with more spacing in abnormal than normal image. The C_R gives ridge portion of information, which is more in abnormal image.

Table I

Test Image Rotation in different Degrees

Table I (a)
Test image = Normal (N_R)

Test image rotation in degrees	0	1	2	3	4
Classification of each image	N_R	N_R	N_R	N_R	N_R
Actual classification	Normal (N_R)				

Table I (b)
Test image = Normal (N_R)

Test image rotation in degrees	90	91	92	93	94
Classification of each image	N_R	AN_R	N_R	AN_R	N_R
Actual classification	Normal (N_R)				

Table I (c)
Test image = Normal (N_R)

Test image rotation in degrees	180	181	182	183	184
Classification of each image	AN_R	N_R	N_R	AN_R	AN_R
Actual classification	Normal (N_R)				

Table I (d)
Test image = Normal (N_R)

Test image rotation in degrees	270	271	272	273	274
Classification of each image	AN_R	N_R	N_R	N_R	N_R
Actual classification	Normal (N_R)				

The proposed method uses quantization to reduce feature dimension to save storage space for trained dataset.

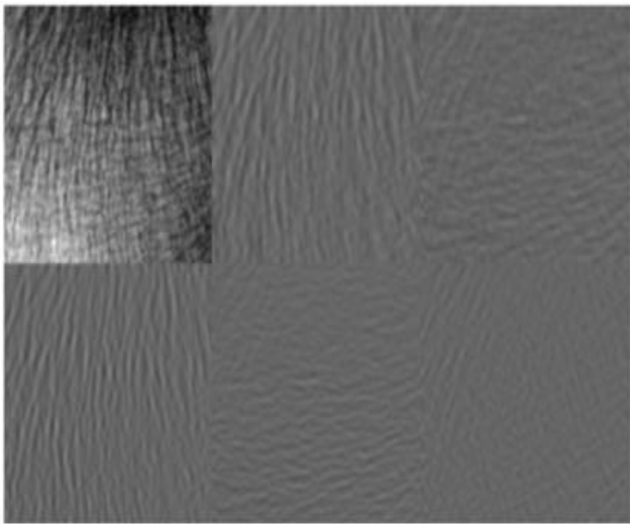

Fig. 3: Abnormal image filter responses

Since G and D are linear operations, the two-level quantization is sufficient to keep the significant information and C_B and C_R are non-linear operation, which requires uniform quantization to keep curvature portion effectively.Experimentally the quantization levels are adjusted by L_B and L_R . If $L_B \leq 1$ and $L_R \leq 1$ no

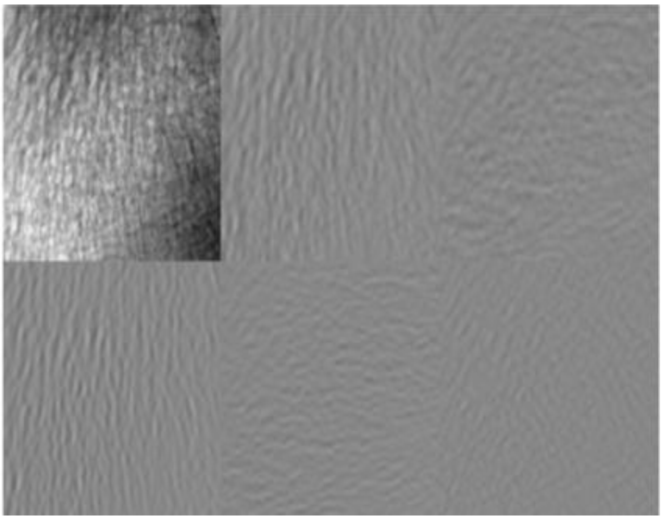

Fig. 4: Normal image filter responses

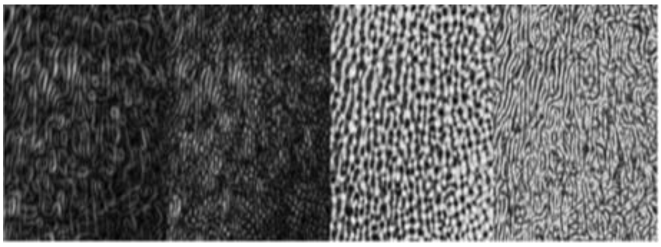

Fig. 5:Features of abnormal image

quantization used. If $L_B = 2$ and $L_R = 2$ two level quantization, $L_B = 3$ and $L_R = 3$ three level quantization like this will continue till seven level quantization.

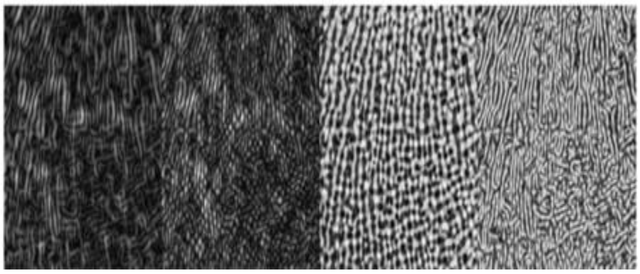

Fig. 6: Features of normal image

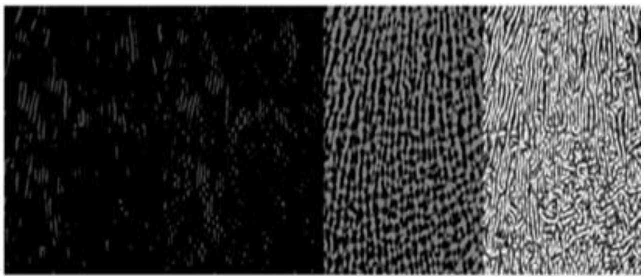

Fig. 7:Abnormal Quantized feature image

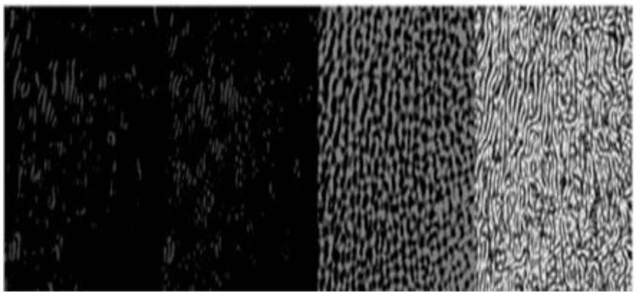

Fig. 8: Normal Quantized feature image

The fig. 7 and 8 shows the abnormal and normal quantized features of an image for filter size 25×25 with $L_B = 0.8$ and $L_R = 0.1$.

The Table II: shows the classification accuracy for an input image without noise for different values of L_B and L_R. FD is feature dimension of each image, TP is true positive, FN is fasle 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 feature 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 in

Table II : For $L_B = 0.8$ and $L_R = 0.1$ the proposed system gives better accuracy with less dimension. However

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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 LB = 0.8 and L_R = 0.1, the overall percentage accuracy of the system is 94.59.

Table II
Classification accuracy without noise

Sigma values = 1,3,5. Feature Dimension (FD). Total =37. Abnormal (AN) = 18. Normal (N) = 19.								
L_B	L_R	FD	Percentage of accuracy		TP	FN	TN	FP
			N	AN				
0.4	0.1	5	63.15	44.44	8	10	12	7
0.6	0.1	11	68.42	72.22	13	05	13	6
0.8	**0.1**	**21**	**94.73**	**94.44**	**17**	**01**	**18**	**1**
1	0.5	33	63.15	83.33	15	03	12	7
2	1	128	52.63	77.77	14	04	10	9
3	2	296	63.15	83.33	15	03	12	7

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 III: shows accuracy for different σ values. The proposed method gives better accuracy for σ = 1,3,5 with L_B = 0.8 and L_R = 0.1. The Table IV: shows percentage of standard measures for without noisy input.The method gives better results for σ = 1,3,5 with 94.44 % sensitivity for abnormal test images, 94.73 % specificity for normal test images. 94.44 % positive preidctive value (PPV) gives probability of exactly abnormal test images. 94.73% negative preidctive value (NPV) gives probability of exactly for normal test images. 94.44 % , F_1 score gives precision which signify the normal and abnormal rate. The receiver operating characteristics (ROC) curve for L_B = 0.8 and L_R = 0.1 with different σ values as shown in fig. 9. ROC is one of the objective measures for viewers evaluation. This curves gives trade offs between the sensitivity and the specificity of a test images. The curve shows better diagnose rate for σ = 1,3,5 because it occupies entire region in the graph. The Table V: shows the classification accuracy with additive white gaussian noise of varying SNR for L_B = 0.8 and L_R = 0.1 with σ = 1,3,5.Since noise affects the intensity of an images,the accuracy also increasing by increasing the SNR .However it gives better accuracy at 50 dB.There is a 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 VI. By increasing SNR the proposed method gives better ROC curve as shown in fig.10. The Table VII shows the comparision between different methods to diagnose the osteoporosis. The proposed method gives better accuracy and also less feature dimension than the other methods.

Table III
Classification accuracy for three sigma values

L_B=0.8 L_R=0.1 Total = 37 Feature Dimension (FD). Abnormal (AN) = 18. Normal (N) = 19.							
Three sigma values	FD	Percentage of accuracy		TP	FN	TN	FP
		N	A N				
0.5,1.5, 2.5	21	63.15	61.11	11	07	12	7
1,2,3	21	57.89	72.22	13	05	11	8
1,3,5	**21**	**94.73**	**94.44**	**17**	**01**	**18**	**1**
2,4,6	21	84.21	61.11	11	07	16	3

Table IV
Percentage of standard measures for without noise.

L_B=0.8, L_R=0.1					
Three sigma values	Sensitivity	Specificity	F1 -Score	PPV	NPV
0.5,1.5,2.5	61.11	63.15	61.11	61.11	63.15
1,2,3	72.22	57.89	66.66	61.90	68.75
1,3,5	94.44	94.73	94.44	94.44	94.73
2,4,6	61.11	84.21	68.74	78.57	69.56

Table V
Classification accuracy with noise

Sigma=1,3,5 L_B=0.8, L_R=0.1							
SNR (DB)	Percentage of accuracy		TP	FN	TN	FP	% of Accuracy
	N	AN					
40	38.84	77.77	14	04	07	12	56.75
43	47.36	83.33	15	03	09	10	64.86
44	52.63	83.33	15	03	10	09	67.56
46	63.15	83.33	15	03	12	07	72.97
47	78.94	88.88	16	02	15	04	83.78
50	**89.47**	**94.44**	**17**	**01**	**17**	**02**	**91.89**

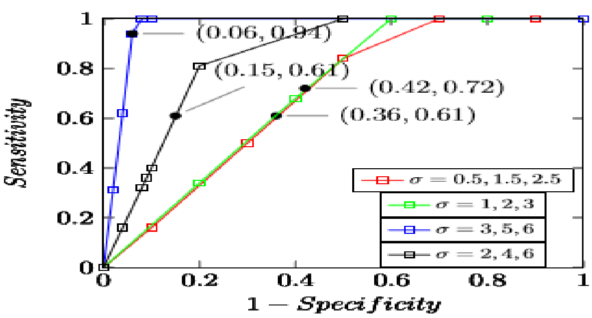

Fig. 9: ROC curve for different σ values

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Table VI
Percentage of standard measures with noise

N=37					
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
46	83.3	63.1	74.9	68.1	80.0
47	88.8	78.9	84.1	80.0	88.2
50	**94.4**	**89.4**	**92.0**	**89.4**	**94.4**

Table VII
Accuracy for Different methods

Method	Classification	% of Accuracy
Steerable Pyramid	SVM	93
Frequency Separation	SVM	94
DDTWT	SVM	93
Gabor Filters	SVM	93
Proposed	**NN**	**94.44**

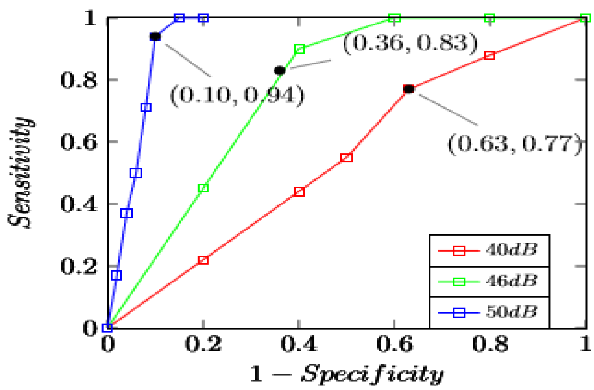

Fig. 10 :ROC curve for different SNR

IV. CONCLUSION

Diagnose of osteoporosis CTB images based on texture analysis is still challenging field since there is no difference between normal and abnormal images for human perception. Many researchers have proposed different methods to diagnose osteoporosis accuracy depending on computation complexity. The proposed methods depends on image texture,which results better classification accuracy in the presence and absence of noise with exsiting methods because texture analysis is based on three different gaussian derivative filter size of different scale with different directions to produce the maximum and minimum responses. Further texture features are reduced by applying quantization .This in turn helps to keep significant texture feature as a training dataset to diagnose osteoporosis. Finally a simple NN classifier is used to detect whether the given test image is normal or abnormal.Lastly the proposed method in terms of accuracy, reduction in dimension ,with respect to sensitivity and specificity etc. in all aspects the performance measures are better than the existing.This methodology could be used to diagnose osteoporosis for other anatomical sites which are rich in trabecular structure. By selecting appropriate code map is a further challenging to diagnose osteoporosis in the given CTB images.

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