BMD Calculation for Osteoporosis detection from DXA Scan Images Using K-Means Clustering Bone Segmentation

A. Dr. Shubhangi D.C[1], B. Ayesha[2]

[1]*Head of the Department, Dept. of Computer Science and Engineering, VTU Regional Centre for PG Studies, Kalaburagi, Karnataka, India*

[2]*Student, Dept. of Computer Science and Engineering, VTU Regional Centre for PG Studies, Kalaburagi, Karnataka, India*

***Abstract* - A common systemic skeletal disorder called Osteoporosis leads to decrease bone strength and increase vulnerability to osteofragility fracture. A measure termed Bone Mineral Density is used to detect the disease (BMD). Several image processing and machine learning algorithms are used to estimate BMD in both X-ray and DXA pictures. This methodology comprises segmentation algorithms like k-means clustering and mean-shift algorithms, as well as a comparison of algorithm accuracy. In addition, a futuristic mathematical approach is presented to accurately detect the osteoporosis state by measuring the values of T–score in DXA pictures with a new metric 'S' derived from Bone Mineral Density(BMD) data.**

***Index Terms* - BMD(Bone Mineral Density), DXA, T-Score, X-ray.**

INTRODUCTION

The disease osteoporosis meaning 'porous bone', which make bones weak, and brittle is triggered by loss of bone strength. Bone Mineral Density (BMD) is a metric that measures the porous quality of the bone and is a measure of the inorganic mineral content in bone. Osteoporosis increases the risk of fractures in both males and females. Women, on the other hand, are more likely to notice it. BMD is measured and osteoporosis is diagnosed using a variety of ways. Bone Mineral Density is measured using Diagnostic radiography/X-ray, Quantitative ultrasound (QUS), Compton scattering, Quantitative Computed Tomography (QCT), Single Energy X-ray Absorptiometry (SXA), high resolution peripheral quantitative CT(HR-pQCT), Magnetic resonance imaging (MRI), Dual Energy X-ray Absorptiometry (DXA), Neutron activation, peripheral quantitative CT (pQCT) and Radiographic Absorptiometry (RA) are the most commonly used imaging techniques nowadays. DXA is the optimum method for measuring BMD among these methods, although it is highly expensive when compared to other approaches. DXA machines are made by a variety of companies.

Osteoporosis can be discovered early on, which reduces the chance of a fissure. Image processing technologies are used to measure BMD in the early phases. Pre-processing, segmentation, and BMD measurement are only a few of the processes involved in image processing. The development of deep learning algorithms aids in the recognition of diseases with more accuracy than classical methods. For proper illness diagnosis, ROI segmentation is critical. As a result, there is a nececity to offer faithful segmentation methods which are automatic for segmenting bone regions and enhancing the accuracy of BMD calculation.

In this paper,segmentation algorithms like k means clustering & mean –shift algorithms are used and a futuristic mathematical approach is presented to accurately detect the osteoporosis state by measuring the T–score values in DXA pictures with a new metric 'S' derived from Bone Mmineral Ddensity(BMD) data.

RELATED WORK

S.M.Nazia Fathima et al [1] aims to link digital image processing approaches to the assessment of BMD using X-ray data. A database of X-Ray images consist of the spine, clavicle bones, hip and knee is considered for the research. A shock filter is added in the image Preprocessing, to enhance the image strength. To study the impact of image noise, the Peak Signal to Noise Ratio (PSNR) is used. To calculate BMD, segmentation methods like Active Contour and Mean Shift segmentation can be used. For the identification of osteoporosis, unprocessed and segmented pictures are evaluated, and the findings are compared. The planned effort also includes using gold standard methodologies to calculate T and Z scores. The proposed procedure has been tested on 78 people, and the results are promising.

Dildar Hussain et al [2] uses a Pixel Label Decision Tree (PLDT) method. PLDT creates seven new feature maps utilizing certain high energy (HE) and low energy (LE) X-ray features to find hidden patterns in DXA images and determine the optimum feature set for the model. Image segmentation methods like Global Threshold, Region Growing Threshold, and artificial neural networks are used to estimate the performance of PLDT in femur segmentation. PLDT achieved excellent results of femur segmentation (91.4%) than either Global Threshold (68.4%), Region Growing Threshold (76%) or artificial neural networks (84.4%) in DXA imaging.

T Hegemann et al. [3] To ascertain osteoporosis from X-ray images, the researchers introduced support vector machine 60 (SVM), a machine learning technique for classification. Also, simulated annealing technique 61 was utilised to divide training set into separable classes and choose best number of features.

Li Chen et al [4] presents a new measure for BMD analysis with DXA images. This research provided a novel method for calculating a scalar value from DXA pictures that reveals the connectivity of bone mineral elements. This approach determines the bone's quality in terms of average bone density intensity and also calculates T and Z values. The λ-measure is a suggested new metric that opens up new possibilities for measuring how well bone components are connected. λT and λZ can be used to represent T and Z scores which are used to construct conventional values. When this method was combined with the λ-connected maximum entropy approach, good segmentation results were discovered. The λ-measure should be in range of [0.962,0.977] based on the outcomes of the experiments and data received.

J. Wu et al[5] uses active shape model(ASM) for segmentation. To characterize object's shape, active shape model landmark points are used. Each landmark refers to the definite anatomical position. To find out the final position of an object, merging of landmark points is needed. Active shape model matches landmarks from a model sample to a collection of pixels in the test image using a statistical metric called Mahalanobis distance (MD). ASM sometimes can links to the false edges of an object. When the ASM model's covariance matrix is sparse, defining MD can be challenging. The ASM model assumes Gaussian appearance spaces, but this inference went wrong due to differences in bone structure, especially in patient's with bone spurs.

Proposed System

The proposed technique consists of the following key stages: Image enhancement, Data augmentation, segmentation, BMD measurement and classification. For segmentation of bone, algorithms like k-means clustering and mean-shift are used in this methodology and also accuracy of algorithm used is calculated. Also in addition, a futuristic mathematical approach is presented to accurately detect the osteoporosis state by measuring the T–score values in DXA pictures with a new metric 'S' derived from Bone Mineral Density(BMD) data.

System Architecture

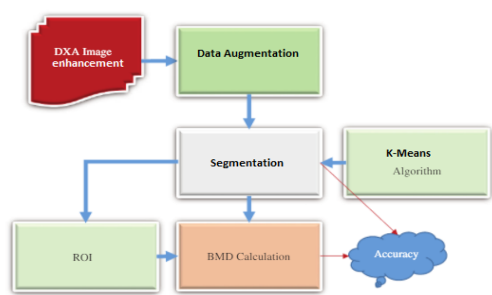


Figure 1: System Architecture

Methodology

Image segmentation is a critical step in distinguishing between related and unrelated features in an image. Scanning in bone pictures entails the separation of bone composition from other areas like muscle and backdrop. In the field of bone X-ray imaging, this is a significant difficulty. The region of interest (ROI), crack, bone mineral density (BMD), fracture, and deformation can be anticipated by segmenting the bone region.

One of the best unsupervised classification techniques is K-means clustering. The approach is a desired method because it works in a simple and effective way in the unsupervised learning methods.

K-Means Algorithm: The k-means algorithm uses the mean value of each cluster's components to represent the cluster's centre.

Input:

k: total volume of clusters.

D: a collection of n objects in a data set

Output: a collection of k clusters.

Method:

1. Pick k objects at random from D to serve as the initial clusters centers.
2. Repeat
3. Using the algorithm below, re-assign each item to the cluster to which it is almost closely connected, depending on the mean value of the item in the cluster.
4. Find the mean value of the items for each cluster to update the cluster means.
5. Until no action.

The output of k-means approach is divided into segments based on cluster size. cluster size has an effect on performance. The larger the cluster, the higher the accuracy %.

Implementation

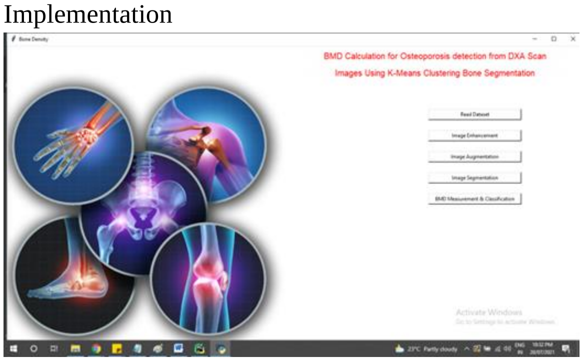


Figure 2: Home Screen

Menu consists of Image enhancement, Augmentation, segmentation and BMD

Figure 3: Read Dataset

Reads the dataset

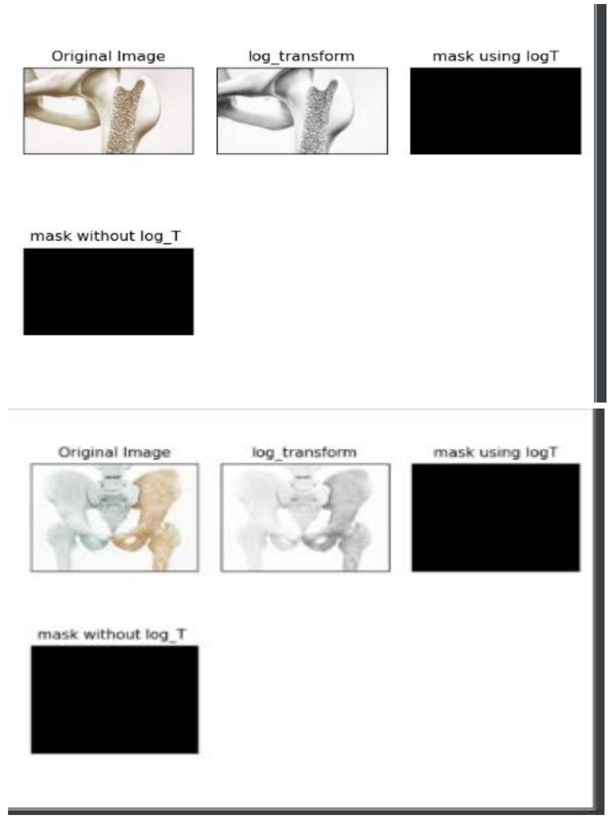


Figure 4: Image Enhancement

This enhances the images

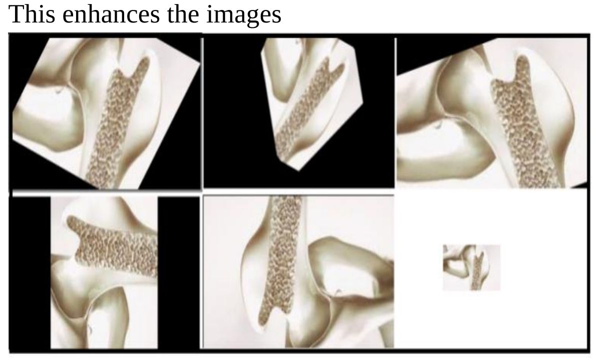


Figure 5: Image Augmentation

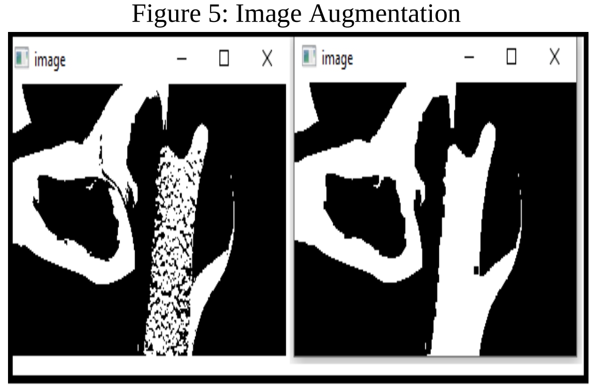


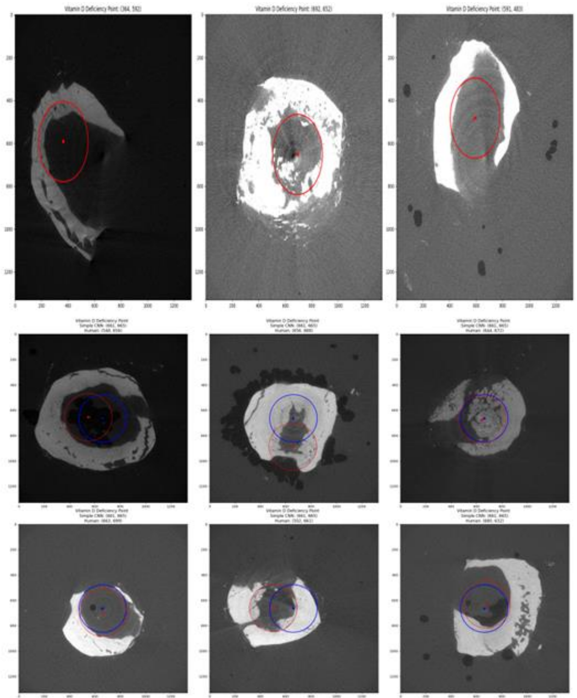
Figure 6: Image Segmentation

```
   img_id cx_pxl cy_pxl      cx      cy
  0 C00055300022   859   1059 0.419434 0.51709
  1 C00055300023   859   1059 0.419434 0.51709
  2 C00055300024   859   1059 0.419434 0.51709
  3 C00055300025   859   1059 0.419434 0.51709
  4 C00055300026   859   1059 0.419434 0.51709
        img_id cx_pxl cy_pxl      cx      cy
  0 C00055300022   500    700 0.37594 0.526316
  1 C00055300023   500    700 0.37594 0.526316
  2 C00055300024   500    700 0.37594 0.526316
  3 C00055300025   500    700 0.37594 0.526316
  4 C00055300026   500    700 0.37594 0.526316
        img_id  pxl0  pxl1  pxl2  pxl3  pxl4  pxl5  pxl6
pxl7 pxl8 \
  0 C00056340107  0.0  0.0  0.0  0.0  0.0  0.0  0.0
0.0 0.0
  1 C00055390113  0.0  0.0  0.0  0.0  0.0  0.0  0.0
0.0 0.0
  2 C00055400079  0.0  0.0  0.0  0.0  0.0  0.0  0.0
0.0 0.0
  3 C00056530106  0.0  0.0  0.0  0.0  0.0  0.0  0.0
0.0 0.0
  4 C00056170036  0.0  0.0  0.0  0.0  0.0  0.0  0.0
0.0 0.0

      ...  pxl1016  pxl1017  pxl1018  pxl1019  pxl1020
pxl1021 pxl1022 \
  0  ...      0.0   0.0   0.0   0.0   0.0   0.0   0.0
  1  ...      0.0   0.0   0.0   0.0   0.0   0.0   0.0
  2  ...      0.0   0.0   0.0   0.0   0.0   0.0   0.0
  3  ...      0.0   0.0   0.0   0.0   0.0   0.0   0.0
  4  ...      0.0   0.0   0.0   0.0   0.0   0.0   0.0

    pxl1023       cx       cy
  0     0.0 0.418045 0.589474
  1     0.0 0.674436 0.496992
  2     0.0 0.484211 0.505263
  3     0.0 0.511278 0.475188
  4     0.0 0.381955 0.511278

  [5 rows x 1027 columns]
  (3998, 1027)
  New dataframe's shape: (11994, 1027)
  Trainset shape: (11394, 32, 32, 1)
Validateset shape: (600, 32, 32, 1)
```

Figure 7: Dataset Details

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 32, 32, 32)        832
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 32, 32, 32)        25632
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 16, 16, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 16, 16, 64)        18496
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 16, 16, 64)        36928
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 8, 8, 64)          0
_________________________________________________________________
flatten (Flatten)            (None, 4096)              0
_________________________________________________________________
dense (Dense)                (None, 512)               2097664
_________________________________________________________________
dense_1 (Dense)              (None, 64)                32832
_________________________________________________________________
dense_2 (Dense)              (None, 2)                 130
=================================================================
Total params: 2,212,514
Trainable params: 2,212,514
Non-trainable params: 0
Epoch 1/8
179/179 [==============================] - 62s 270ms/step - loss: 0.6457
Epoch 2/8
179/179 [==============================] - 49s 276ms/step - loss: 0.3991
Epoch 3/8
179/179 [==============================] - 48s 267ms/step - loss: 0.1835
Epoch 4/8
179/179 [==============================] - 50s 281ms/step - loss: 0.1080
Epoch 5/8
179/179 [==============================] - 52s 289ms/step - loss: 0.1071
Epoch 6/8
179/179 [==============================] - 51s 286ms/step - loss: 0.1070
Epoch 7/8
179/179 [==============================] - 51s 287ms/step - loss: 0.1070
Epoch 8/8
179/179 [==============================] - 53s 295ms/step - loss: 0.1058
357/357 [==============================] - 8s 20ms/step - loss: 0.1070
Score on trainset: 0.107005275785923
19/19 [==============================] - 0s 18ms/step - loss: 0.1055
Score on validate set: 0.10549381375312805
```

Figure 8: Model & Epoch value



CONCLUSION

For detecting osteoporosis by measuring bone mineral density using DXA scan images, algorithms like k-means clustering and mean-shift are used for segmentation of bone in this methodology and also accuracy of algorithm used is calculated. In addition, a futuristic mathematical approach is presented to accurately detect the osteoporosis state by measuring the T–score values in DXA pictures with a new metric ‘S' derived from Bone Mmineral Density (BMD) data.

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