CHAPTER 6

ASSESSMENT OF BONE MINERAL HEALTH OF HUMANS BASED ON X-RAY IMAGES USING DEDUCTIVE INFERENCE

6.1 INTRODUCTION

Deduction logical reasoning derives the consequences of the assumed and a sound proof mechanism. This chapter concentrates on the deductive inference in a classification problem. Reduced bone mass of humans is a useful indicator of increased fracture risk and early mortality. Moreover, bones become weak due to ageing, smoking habits, drinking habits, long term use of steroid drugs and Vitamin D deficiency. Women are more prone to reduced bone mass after menopause. Hence, for all these reasons, study of bone mineral health is very essential and this chapter proposes an alternative way of analyzing bone mineral health with the help X-ray images of patients based on deduction.

Bones are rigid organs that constitute the endoskeleton of vertebrates. They support and protect many organs of the body, store minerals, produce red and white blood cells. Bones have complex internal and external structure, come in different shapes, hard and strong in nature but lightweight and serve multiple functions. Bones together with muscles, ligaments and joints help in movement of various body parts. Bone is made up of bone matrix. It is composed primarily of inorganic hydroxyapatite and organic collagen. Bone is formed by the hardening of this matrix around
entrapped cells. Remodeling is the process of resorption followed by replacement with little change in shape and occurs throughout a person's life. The purpose of remodeling is to regulate calcium homeostasis, repair micro-damaged bones and to shape the skeleton during growth.

Bone mineral density (BMD) is a measure of the amount of hydroxyapatite (Hap) and mineral salts per unit area in the bone that is used as an indicator of the bone’s health. The mineral content in a bone sample is evaluated by direct evaluation through the atomic absorption spectroscopy and inductively coupled plasma method or by indirect method, which consists of single or dual X-ray diffraction and computer tomography to obtain the bone mineral density. The indirect method measurement is painless, non-invasive and involves low radiation exposure over the spine or hip region. By using direct methods, it is possible to obtain quantitative information regarding the bone mineral components, whereas in indirect methods, the information is closely related to the optical absorption of the bone tissues. Nowadays, BMD is measured by dual-energy X-ray absorptiometry (DXA). The DXA system uses double X-ray intensities in order to obtain two images, one of which is taken at high energy, whereas the second one is taken at low energy. The difference between the two is normally used to calculate the BMD by means of a calibration function of the system itself.

The average density of the bone is around 1000 to 1200 mg/cm². The density varies for age, race and gender. Bone density tests measure two conditions, osteopenia and osteoporosis. BMD would be greater than or equal to 833 mg/cm² for normal people. Osteopenia is a condition where BMD is lower than normal, like between 648 mg/cm² and 833 mg/cm² (Bone Physiology 2013). With further bone loss, osteopenia leads to osteoporosis, a disease of the bones, where BMD is still reduced (less than 648 mg/cm²), bone microarchitecture deteriorates and the amount and variety of proteins in bone are
altered. Poor bone density relates to higher probability of fracture. Bones become weak and can break from a minor fall or even from simple actions like sneezing. People over the age of 50, people with smoking habits, drinking habits, long term use of steroid drugs and Vitamin D deficiency are more susceptible for having less bone density. Women are more susceptible to get osteoporosis due to the reasons:

- Women tend to have thinner, smaller bones than men
- Estrogen, a hormone that protects bones, decreases sharply when women reach menopause, which can cause bone loss.

Fractures are the most dangerous aspect of osteoporosis. Acute and chronic pain is often attributed to fractures from osteoporosis and can lead to further disability and early mortality. Reduced bone mass is therefore a useful predictor of increased fracture risk. Normal and Osteoporotic conditions of a bone are shown in Figure 6.1.

![Figure 6.1 Normal and Osteoporotic Conditions of Bone](image)

BMD values vary depending on race, age, gender and other health conditions. DXA is the most widely used and most thoroughly studied bone
density measurement technology. But it is quite an expensive method in developing countries like India. Moreover, it requires frequent calibration to work properly. Hence, this chapter explores the possibility of developing an affordable and reliable system to study bone health based on X-rays using deductive inference.

6.2 RELATED WORK

DXA is recognized as the acceptable method to measure BMD. DXA scans can have errors between 5 and 8% due to calibration, positioning and other factors. X-rays are cheaper and many researchers have shown that there exists relationship between plain radiographic patterns and three-dimensional trabecular architecture. Moreover, the BMD values calculated depend on race, age and other health conditions and not a constant for all people throughout the world. Figure 6.2 gives the trabecular bone of hip.
Luo et al (1999) have shown that the plain radiograph contains architectural information directly related to the underlying 3D structure based on the study of human calcaneal trabecular bone. Veenland (1999) has assessed the suitability of different texture analysis methods for use in radiographs and also to select texture features that are able to quantify the changes in the radiographic trabecular pattern occurring in osteoporosis.

Chappard et al (2001) showed that texture analysis by Euclidean and fractal methods provided significant differences in the two bones of a rat model submitted for disuse induced by Clostridium botulinum Toxin and found that such analysis on radiographs appears able to detect architectural differences in the trabecular architecture even when bone loss has not reached a value sufficient enough to induce changes appreciable by DXA. Again, Chappard et al (2005) have shown that the trabecular characteristics were found to be highly correlated with texture parameters describing the X-ray image and suggested that the texture analysis of X-ray films might be a suitable approach to investigate the disorganization of bone in osteoporosis. X-ray films constitute a 2D projection of the trabecular architecture, the resulting image is texture and this may be an indicator of disease etiology.

Guggenbuhl et al (2006) in their study found a good correlation between texture analysis of X-ray radiographs and 3-D bone micro architecture assessed by micro-CT of human iliac bone. Jimenez et al (2011) have determined the parameter equation that defines the ratio of the pixels in radiographs and BMD and demonstrated the methodology on Wistar rats' femur bones on a calibrated system.

All this suggest that the study of bone mineral health by direct means is tedious and harmful to the human body and so an indirect measure by the DXA is an accepted methodology. With the technology yet to reach the common masses being hindered by cost and the BMD values available are
only for the white race, the study of bone mineral health with the help of X-ray images is a boon to the developing nations.

6.3 PROPOSED METHODOLOGY

Researchers have investigated the relationship between bone health and bone X-ray images through various experiments. This study is based on deductive inference: If bone health is related to the DXA scan of the person, and the DXA scan can be related to the single X-ray scan, then bone health can be related to the single X-ray scan.

The following methodology is proposed:

- Image filters and H-domes image slicing is applied to enhance X-ray images in preprocessing,
- Texture and fractal dimension are computed in feature extraction
- Information gain based feature subset selection, and
- Supervised learning algorithm to classify patients to have bone mineral health to be Normal (Normal mineral density), Medium (osteopenia condition) and Low (osteoporosis condition).

Extraction of essential features is a necessary step in a supervised learning process so as to differentiate the classes appropriately. The X-ray bone image undergoes preprocessing, feature extraction and classification phases.
6.3.1 Preprocessing of X-ray Images

Raw X-ray images possess low frequency noise due to X-ray diffusion in soft tissues and high frequency noise due to X-ray acquisition and imaging characteristics. Chappard et al (2001), (2005) have applied a median filter to eliminate low frequency noise and a "top hat" filter to eliminate high frequency noise to increase the contrast of the bony structures within the image. Guggenbuhl et al (2006) binarized the images by applying automatic thresholding based on the histogram frequency distribution of grey levels. Abidi et al (2003) applied a series of common enhancement algorithms like linear regression, gamma intensity adjustment, logarithmic intensity adjustment, histogram equalization, edge and morphological operations etc. on X-ray images of luggage scenes and compared the results; They also proposed a new method to determine the optimal number of clusters or thresholds when segmenting X-ray images consisting of low density threat weapons. They used image hashing via intensity slicing such that objects of different intensity values are more visible. Intensity slicing can be done by equal interval image slicing, cumulative image slicing and H-domes image slicing. In this chapter, H-domes image slicing for intensity slicing of image hashing for the bone X-ray images is proposed.

The raw X-ray image is subjected to Wiener filter to reduce noise. The background effects are removed by top hat and bottom hat filters which also have the benefit of adding a significant degree of smoothing to the spectrum. H-domes image slicing is further applied to remove small grains. Figure 6.3 represents a sample original pelvis image of a patient and Figure 6.4 represents the enhanced image.
6.3.2 Feature Extraction

Materka & Strzelecki (1998) have discussed that image texture is a rich source of visual information and that feature extraction, texture discrimination, texture classification and shape reconstruction are the major issues in texture analysis; Results from the feature extraction stage are used for texture discrimination, texture classification or object shape determination. Also, to be noted is that analysis of fractal dimension can additionally enrich diagnostic knowledge about bone microarchitecture. Chappard et al (2001), (2005), Guggenbuhl et al (2006) have used run-length distribution, "skyscraper" fractal analysis, "blanket" fractal analysis and statistical analysis in their experiments to establish the correlation between texture analysis and bone mineral content, between texture analysis and histomorphometry and between texture analysis and bone micro-CT. In this chapter, it is proposed to use the run-length distribution, fractal dimension, and statistical parameters as features.
A feature vector is created for each X-ray image based on global qualities like average gray level, average contrast, smoothness, moments, uniformity and entropy, gray level run length statistics like Short Run Emphasis (SRE), Gray Level Run Emphasis (GRE), Gray Level Non-uniformity (GLN), Run Percentage (RP), Run length non-uniformity (RLN), and fractal dimension, gray level co-occurrence matrix (GLCM) characteristics like contrast, correlation, energy and homogeneity.

6.3.3 Verification

The features so extracted are applied to a set of standard classification algorithms available in WEKA. Many classification algorithms are available, but the algorithms used are Multi-layer perceptron (MLP), Decision Table (DT) and AdaBoost. The choice of these algorithms is based on the characteristics possessed by them. A 3-fold cross-validation was applied to all the algorithms.
6.4 RESULTS AND DISCUSSION

PSG Hospitals is a 810 bedded, tertiary care hospital with qualified and experienced faculty and state of the art infrastructure, affiliated to PSG Institute of Medical Sciences & Research, Coimbatore, India (2013). The hospital houses various specialties like Medicine, Surgery, Obstetrics & Gynecology, Paediatrics, Orthopaedics, Radiology and Emergency Medicine. The hospital has been recognized for implementation of various social welfare schemes and is an internationally acclaimed centre to conduct various clinical trials.

6.4.1 Data Set Used

Experiments are conducted on the spine and pelvis X-ray images of patients between the ages of 10 and 90, collected over a period of time. Experiments are conducted on 104 pelvis and 162 spine images of the patients of PSG Hospitals.

Each of the images was subjected to image filters and H-Domes image slicing and was divided to 4 sections. Global qualities like (average gray level, average contrast, smoothness, 3rd moment, uniformity and entropy), gray level run length statistics like (Short Run Emphasis (SRE), Gray Level Run Emphasis (GRE), Gray Level Non-uniformity (GLN), Run Percentage (RP), Run length non-uniformity (RLN), and fractal dimension), and gray level co-occurrence matrix (GLCM) characteristics like (contrast, correlation, energy and homogeneity) combined with fractal dimension are extracted for each section. A total of 16 features per section which makes it to 64 combined with age and gender gives a total of 66 features. The class used to identify the mineral content is Normal (healthy bone), medium (osteopenia), low (osteoporosis). Four doctors identified the class attribute separately based on the X-ray image and the class type was decided based on
the majority voting by them. There was 25% of tie in the class type in such a process and lower the class attribute was decided.

The average age of the patients under study was 46.18. There are 135 females and 131 males.

**6.4.2 Performance Analysis**

Features are extracted after the images are pre-processed for enhancement and supplied to the classification algorithms with 3 fold cross-validation. True positive rate (TPR), False positive rate (FPR), precision (PRE), recall (REC), F-measure (F_M), ROC and accuracy results are tabulated in Table 6.1 for 3 classes.

Same set of classification algorithms are also applied taking it as a 2 class problem (normal and abnormal bone health). Table 6.2 infers the fact that abnormality in the bone health is being identified better by the system, but delineation into osteopenia and osteoporosis is not that evident.

Experiments are separately conducted for female patients alone on the same three classifiers for a two class problem as in Table 6.3. It can be noted that the accuracy is increased and for all the three cases DTs seem to be giving a higher accuracy.

**6.5 CONCLUSION**

The methodology described in this chapter has extended the idea and relationship established by various researchers between bone mineral health and X-ray radiography images. DXA equipment from different manufacturers might not give identical results, because of differences in calibration and bone edge detection algorithms. Moreover, the BMD values specified by WHO is based on white women (Bone Physiology 2013) and as a
result, the BMD values calculated for other countries or on other race for the same age cannot have this as the reference.

**Table 6.1 Classification measures for 3 classes**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>TPR</th>
<th>FPR</th>
<th>PRE</th>
<th>REC</th>
<th>F_M</th>
<th>ROC</th>
<th>Class</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accuracy</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Classes : Normal(N) / Osteopenia(P) / Osteoporosis(O)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MLP 59.40</td>
<td>0.718</td>
<td>0.289</td>
<td>0.685</td>
<td>0.718</td>
<td>0.701</td>
<td>0.753</td>
<td>N</td>
</tr>
<tr>
<td></td>
<td>0.5</td>
<td>0.304</td>
<td>0.49</td>
<td>0.5</td>
<td>0.495</td>
<td>0.618</td>
<td>O</td>
</tr>
<tr>
<td></td>
<td>0.455</td>
<td>0.072</td>
<td>0.556</td>
<td>0.455</td>
<td>0.5</td>
<td>0.814</td>
<td>P</td>
</tr>
<tr>
<td>DT 56.02</td>
<td>0.685</td>
<td>0.282</td>
<td>0.68</td>
<td>0.685</td>
<td>0.683</td>
<td>0.75</td>
<td>N</td>
</tr>
<tr>
<td></td>
<td>0.5</td>
<td>0.345</td>
<td>0.458</td>
<td>0.5</td>
<td>0.478</td>
<td>0.591</td>
<td>O</td>
</tr>
<tr>
<td></td>
<td>0.341</td>
<td>0.086</td>
<td>0.441</td>
<td>0.341</td>
<td>0.385</td>
<td>0.782</td>
<td>P</td>
</tr>
<tr>
<td>Adaboost 56.39</td>
<td>0.718</td>
<td>0.282</td>
<td>0.69</td>
<td>0.718</td>
<td>0.704</td>
<td>0.727</td>
<td>N</td>
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<tr>
<td></td>
<td>0.622</td>
<td>0.452</td>
<td>0.445</td>
<td>0.622</td>
<td>0.519</td>
<td>0.587</td>
<td>O</td>
</tr>
<tr>
<td></td>
<td>0.0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.738</td>
<td>P</td>
</tr>
</tbody>
</table>

The proposed system is based on the strong correlation between the X-ray images and their underlying micro architecture and the health of the bones. The system weighs on deductive inference and explores through inferential component, the bone mineral health by classification methods. The proposed method seems to identify the health conditions of bone to about 60 %, in case of a 3 class problem and to about 70 % in case of a 2 class problem. When the subjects of study are females, the accuracy appreciably increased to about 80 %.

The proposed system is cheaper, portable, versatile and dependable to study changes in the density of minerals in X-ray images of bones. Similar to DXA, it is a non-contact and non-invasive method. As more radiography
images are added to the data set, the classification algorithms would be able to learn the characteristics of the images pertaining to a particular demography, age and race and able to classify much better.

**Table 6.2 Classification measures for 2 classes**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>TPR</th>
<th>FPR</th>
<th>PRE</th>
<th>REC</th>
<th>F_M</th>
<th>ROC</th>
<th>Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLP 68.05</td>
<td>0.645</td>
<td>0.289</td>
<td>0.661</td>
<td>0.645</td>
<td>0.653</td>
<td>0.737</td>
<td>N</td>
</tr>
<tr>
<td>DT 71.80</td>
<td>0.581</td>
<td>0.162</td>
<td>0.758</td>
<td>0.581</td>
<td>0.658</td>
<td>0.73</td>
<td>N</td>
</tr>
<tr>
<td>Adaboost 72.93</td>
<td>0.661</td>
<td>0.211</td>
<td>0.732</td>
<td>0.661</td>
<td>0.695</td>
<td>0.772</td>
<td>N</td>
</tr>
</tbody>
</table>

**Table 6.3 Classification measures for Females alone**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>TPR</th>
<th>FPR</th>
<th>PRE</th>
<th>REC</th>
<th>F_M</th>
<th>ROC</th>
<th>Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLP 75.94</td>
<td>0.696</td>
<td>0.207</td>
<td>0.64</td>
<td>0.696</td>
<td>0.667</td>
<td>0.785</td>
<td>N</td>
</tr>
<tr>
<td>DT 82.71</td>
<td>0.739</td>
<td>0.126</td>
<td>0.756</td>
<td>0.739</td>
<td>0.747</td>
<td>0.818</td>
<td>N</td>
</tr>
<tr>
<td>Adaboost 78.95</td>
<td>0.63</td>
<td>0.126</td>
<td>0.725</td>
<td>0.63</td>
<td>0.674</td>
<td>0.834</td>
<td>N</td>
</tr>
</tbody>
</table>