Fuzzy Inference System for Osteoporosis Detection

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***Abstract*— The goal of this paper is to propose a fuzzy inference framework for diagnosis of osteoporosis disease in the field of medical imaging. The idea behind such a framework is to assist the physician to detect, control and treat various forms of osteoporosis in better way. The degree of disease is computed by fuzzy expert system and conventional X-ray image processing technique and a final decision is taken by combining both the results. Primary advantage of proposed algorithm is: (a) The fuzzy expert system performs as an expert to diagnosis and (b) The X-ray imaging system calculates bone density. The use of different membership functions and extensive number of rules; in addition to the fuzzy edge directed image interpolation (FEDI) technique helps design an efficient osteoporosis detection framework. The extensive experiments conducted on 20 patients have demonstrated that the proposed algorithm can replace the existing, expensive and not readily available bone density calculation techniques in this field.**

Keywords— fuzzy logic; image interpolation; membership functions; Osteoporosis; rules.

I. INTRODUCTION

Osteoporosis, a progressive bone degrading disease often called 'silent disease' is affecting men and women all around the world regardless of ethnic group, race and age [1-3]. The degradation of bone mass and bone strength that cause osteoporosis is higher on people over 60 years old, than younger ones. But there is a chance of mild osteoporosis termed as osteopenia [3] which affect younger people as well. According to World Health Organization (WHO), osteoporosis has been operationally defined on the basis of bone mineral density (BMD) assessment [4], which describes a threshold called T-score. T-score equal to or less than 2.5 standard deviations below young adults are recognized as osteoporosis; a T-score between 1 and 2.5 indicates osteopenia (low bone mass); and T-score greater than 1 indicates the absence of disease or being normal. Osteoporosis develops for different reasons. To choose an appropriate treatment, it is necessary to diagnose the disease properly by checking bone density. Some of the common bone density measuring scanning methods are: Ultrasound, X-ray, DEXA, QCT, MRI etc. But the gold standard for bone density measurement proposed by WHO is 'Dual Energy X-ray Absorptiometry' abbreviated as DXA or DEXA [5-7]. However, detection of osteoporosis or osteopenia using DEXA scan is quite expensive and not easily available. In addition, it is not suitable for monitoring bone density changes [8] easily. So it is necessary to find an alternate way to detect osteopenia which reduces the possibility of osteoporosis by combining the idea of clinical risk factors in fuzzy inference along with BMD calculation.

The recent trends in artificial intelligence (AI) help design systems to treat and diagnose various diseases in medical application. The ability of designing systems, that simulate ideas, ability and behavior of human as an expert can be made through AI. Researchers have come up with different approaches to identify osteoporosis and future fracture risk using artificial neural network [9], genetic algorithm, support vector machine [10], fuzzy neural network etc.,.

An expert identifies certain disease based on some predefined symptoms or facts. While consulting experts, patients need to answer few questions (e.g. is there pain?) as inputs and instead of yes/no, they use words like mild, severe, and very severe. It is difficult to deal with these kinds of words (referred to as 'linguistic variables') rather than numbers while designing an expert system. In addition, there exists some vagueness in the input to the system. So it is necessary to have a tool that handles vagueness as well as linguistic terms in such a manner that, it is able to identify a specific disease. In this paper, we are proposing to use the idea of fuzzy logic to design an expert system that can diagnose osteoporosis because of its ability to conceive vague data and human knowledge to make an appropriate tool. Fuzzy inference systems are characterized by fuzzy set theory which is an extension of classical set theory [11-12]. Three major steps are involved in fuzzy expert system design: Fuzzification, Inference and De-fuzzification.

The ability to map human knowledge and behavior to an expert system with simple designing techniques makes fuzzy inference a versatile tool for medical diagnosis and identification [13-14]. Researchers use fuzzy rule based system for medical diagnosis such as liver disorders [15], hypertension [16], heart disease, cancer etc. Furthermore, fuzzy logic systems are introduced for diagnosis of osteoporosis disease. An intelligent medical diagnostic system accessible online, was proposed [17] as an initial screening for osteoporosis which make use of fuzzy inference as well as neural network technology. A fuzzy relational database management system (FRDMS) is generated in [18] that can be applied for osteoporosis patients. In [19] Binaghi et al. had proposed fuzzy expert system for diagnosis of postmenopausal osteoporosis. Twenty machine learning techniques were assessed to identify osteoporotic or non-osteoporotic persons in [20]. But all these approaches require database to work perfectly.

In this article, fuzzy inference frame work is introduced in the same way how an expert would diagnose osteoporosis or osteopenia disease. Initially, all the symptoms that cause osteoporosis/ osteopenia are defined in terms of membership functions that describe fuzzy sets in the frame work. The degree of disease is calculated from another set of membership functions with the help of fuzzy inference rules. Finally a decision is made with the help of fuzzy inference technique and knowledge base system. In addition, some image processing/enhancement techniques are included on X-ray images instead of DEXA for susceptible or all patients. The primary advantage of proposed work is that, the degree of disease is confirmed only after examining both the conditions. In addition, the acceptance for vague inputs (such as varying degrees of symptoms) and absence of databases to predict an appropriate degree of disease make it more reliable.

The rest of the paper is organized as follows. Section II would discuss various symptoms that cause osteoporosis. The proposed method to diagnose osteoporosis using fuzzy expert system and X-ray imaging technique is presented in Section III and IV respectively. Finally the experimental results in Section V and the conclusion in Section VI are presented.

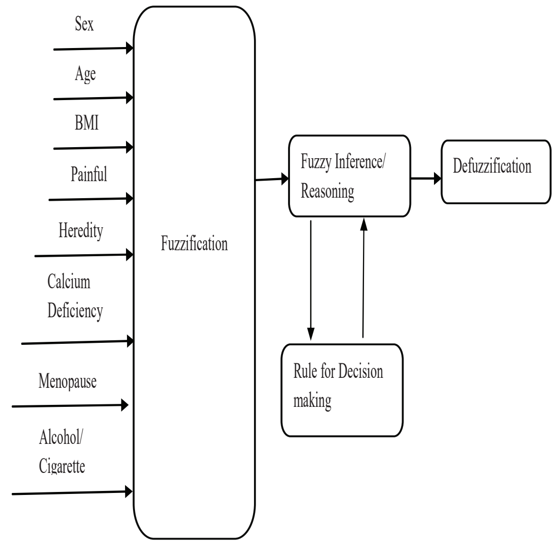


Fig. 1. Proposed framework

II. SYMPTOMS OF OSTEOPOROSIS/OSTEOPENIA

Osteoporosis is a disease characterized by loss of bone tissues that cause it to become brittle and fractured. Bone loss can start at a younger age and advance slowly or due to deficiency of calcium. Osteoporosis can only cause symptoms when there is a fracture. Wrist, spine, hip and other part of skeleton particularly in the pelvis and humerus or upper arm fractures are the most common. All these fractures usually occur only for older aged patients. Generally speaking, the risk of osteoporosis and fracture depends on bone health. Some of the common risk factors of osteoporosis are: sex, age, heredity, race, body size, losing height and stooped posture. As per [1-3] osteoporosis is more common in women than in men. The reason for this gender gap is the low bone density of women compared to men. For men or women, the older you are, the weaker the bone gets. About 50% of people in their 80s have osteoporosis [21]. Studies show that genetic factors can be strong predictors of bone mass, bone density and bone size that cause osteoporosis. Race is also considered as a risk factor.

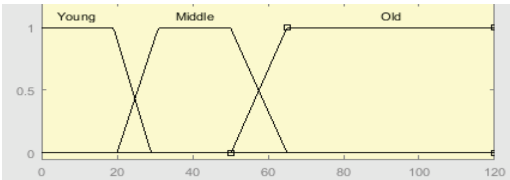
In addition to age, sex and heredity, we have considered calcium deficiency, height, weight, body mass index (BMI), pain in prescribed body parts, years since menopause and consumption of cigarette/alcohol. In addition, the amount of physical stress that an individual may experience a day is also considered to diagnose osteopenia. As discussed in [3] osteoporosis is diagnosed upon bone density which depends on amount of calcium content in the bones. So it is necessary to maintain a steady level of calcium in the body to get rid off osteoporosis or osteopenia. It also gives us a chance to distinguish osteoporosis/osteopenia from the calcium deficient diet. However, another index, referred as BMI, can be easily obtained from individual's height and weight & it indicates the body fat and weight. Obviously body weight is measure of bone density, such that low body weight or low BMI indicates underweight and risk of osteoporosis. But this index can't be considered directly as a strong measure of BMD. Pain or swelling in the wrist, spine, hip or other parts of skeleton can also be considered as risk factors of osteoporosis/ osteopenia. Women after menopause or early menopause are at higher risk of osteoporosis because of estrogen hormone variation in their body. Consumption of alcohol and smoking degrades bone density as the bone degrading osteoclasts are accelerated by alcohol and smoking that disrupts calcium absorption. All these factors are considered to diagnose osteoporosis/ osteopenia.

III. OSTEOPORORSIS DIAGNOSIS: FUZZY EXPERT SYSTEM

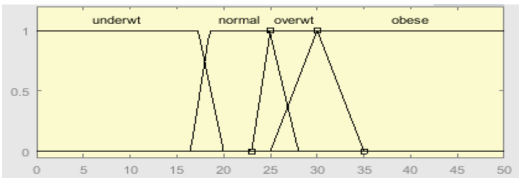
The first step to design an expert system is; fuzzification of risk factors that cause the disease. Fuzzification is a process of mapping all real world items in to fuzzy world using different types of curve that shows degree of belongingness called 'membership functions' [11-13]. The varying degree of belongingness is represented by vagueness in their boundaries. As an expert predicts the disease after examining risk factors, a final decision is made by defuzzification unit with the help of fuzzy reasoning and rules. Fuzzy reasoning is a technique that helps deduce the final goal from a set of facts or premises. Knowledge from an expert is termed as rules in the system. The primary steps in osteoporosis diagnosis system are; (a) Fuzzification of risk factors; (b) Acquiring knowledge from experts and studies to form rules that makes final decision in the fuzzy domain with fuzzy inference technique; (c) Defuzzification process that helps us get back values from fuzzy world to real world. This arrangement is shown in Fig.1.

A. *Fuzzification of Risk factors*

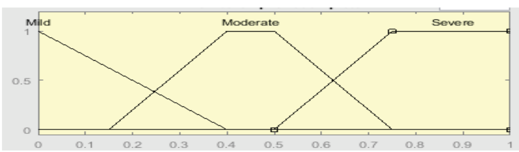
As discussed, fuzzy inference system is characterized by membership functions. A membership function is a curve that shows degree of belongingness of each element in the range of zero to one. The process of fuzzification converts risk factors in to combination of fuzzy sets. The shape of curve varies upon requirement and we usually deal with triangular and trapezoidal type membership functions as shown below.



(a) Age description

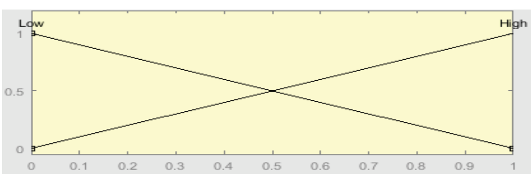


(b) Measure of BMI

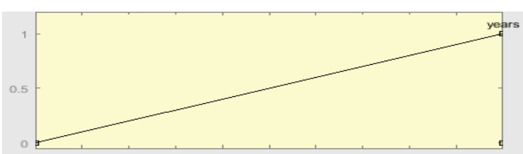


(c) Amount of Pain

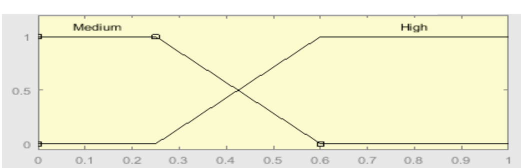
(d) Calcium deficiency: Diet



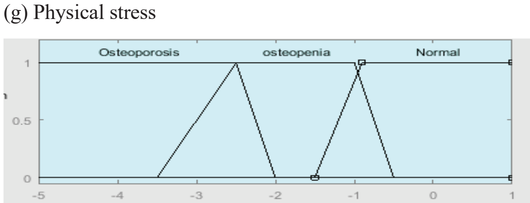
(e) Consumption of Alcohol/Cigarette



(f) Years since Menopause



(g) Physical stress



(h) Osteoporosis prediction

Fig.2. Membership functions of risk factors and osteoporosis prediction

Table 1: Risk factors: Fuzzy sets and its Range

Risk factor	Fuzzy set	Range
Age (in years)	Young Middle Old	0-30years 20-65years 50-120years
Sex	Man /Woman	0/1
Heredity	No /Yes	0/1
BMI (in kg/m^2)	Underweight Normal Overweight Obese	<18.5 18.5-24.9 25-29.9 >30
Painful	Mild Moderate Severe	0-0.4 0.15-0.75 0.5-1
Calcium deficiency: Diet	Low Moderate Good	0-0.4 0.15-0.75 0.5-1
Year since Menopause	Years	0-50 years
Alcohol/ Cigarette	Low High	0-1 1-0
Physical stress	Medium High	0-0.6 0.25-1
Condition	Normal Osteopenia Osteoporosis	1/-1.5 -0.5/-3.5 -2/-5

$$trimf\ (x,[a,b,c]) = \max\left(\min\left(\frac{x-a}{b-a},\frac{c-x}{c-b}\right),0\right)$$

$$trapmf\ (x,[a,b,c,d]) = \max\left(\min\left(\frac{x-a}{b-a},1,\frac{d-x}{d-c}\right),0\right) \qquad (1)$$

where, x is the coordinate that represent risk factors and parameters *a, b, c, d* determine the x coordinates of the corners of membership function. Hence to design an expert system all symptoms and decision are represented in the form of membership functions as shown in Fig.2. The fuzzy sets and its range for each risk factor are described in Table1. For example, consider risk factor 'age' which is decomposed in to three fuzzy sets as Young, Middle and Old based on ages in years. More clearly, an individual of age 20 comes under Young group with membership function '1' (from the Fig 2(a)) and age of 28 comes under Middle group since the degree of belongingness (y-axis) of 28 is more in Middle compared to Young. Other than sex and heredity, all other factors are defined in fuzzy domain with varying degree of membership grade (vagueness). Sex and heredity is defined in crisp domain with membership function either zero or one. The degree of osteoporosis is determined by three fuzzy sets in Fig. 2(h).

B. *Description on Fuzzy Rules and Inference*

Modeling of fuzzy rule base system is performed with symbolic relation expressed by rules. Interpretability of rules decides the accuracy of system. Rules are selected among the possible combination of fuzzy sets that describes risk factors of osteoporosis. Selected rules for proposed articles are gathered from studies and experts. The simplest form of fuzzy rule base system is *if* x *then* y, where x is known as antecedent and y as consequent. More antecedents and consequents can be connected using connectives. For ease of representation, we have shown only four rules among forty five that depict the degree of osteoporosis.

Rule 1: *if* Age is Old *and* Sex is Female *and* Heredity is Yes *and* BMI is Normal *and* Pain is Severe *and* Diet is Moderate *and* Year since menopause is ten years *and* Alcohol/Cigarette consumption is Low *and* Physical stress is Medium; *then* the condition is Osteoporosis.

Rule 2: *if* Age is Middle *and* Sex is Female *and* Heredity is No *and* BMI is Normal *and* Pain is Mild *and* Diet is Moderate *and* Year since menopause is zero years *and* Alcohol/Cigarette consumption is Low *and* Physical stress is Medium; *then* the Condition is Osteopenia.

Rule 3: *if* Age is Young *and* Sex is Male *and* Heredity is No *and* BMI is Normal *and* Pain is Mild *and* Diet is Moderate *and* Year since menopause is zero *and* Alcohol/Cigarette consumption is High *and* Physical stress is Medium; *then* the Condition is Normal.

Rule 4: *if* Age is Young *and* Sex is Female *and* Heredity is Yes *and* BMI is Overweight *and* Pain is Moderate *and* Diet is Moderate *and* Year since menopause is zero years *and* Alcohol/Cigarette consumption is Low *and* Physical stress is Medium; *then* the Condition is Osteopenia.

These types of rules are known as knowledge base and when a fact is arrived, decision is carried out by inference unit with the help of rules. Performance of the system relies on a number of predefined rules. Fuzzy inference is a technique that deduces a goal from a set of facts or premises. Facts are the fuzzy rules derived from knowledge base system. The two prominent types of inference techniques are Mamdani and Sugeno. We preferred Mamdani method as it is simple and easy to handle in the absence of database.

IV. Osteopororsis Diagnosis: X-ray Imaging Technique

Image processing is gaining importance in the field of biomedical engineering. Several imaging techniques have been developed to facilitate earlier detection and diagnosis of osteoporosis. Complications related to osteoporosis, such as fractures or compression can be detected easily with these imaging techniques. But all these methods seem to be

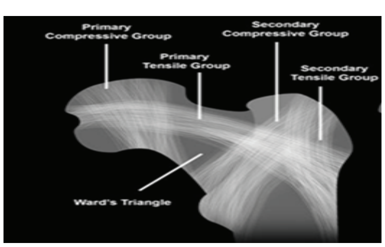


Fig.3. Normal Femur bone with ROI

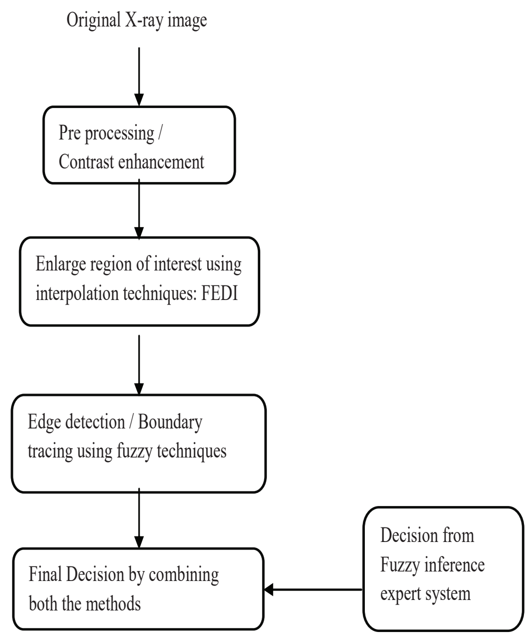


Fig.4. Femur bone Enhancement steps

expensive and not easily available everywhere. In addition, limitations of bone density tests make these methods less unswerving. Despite the advent of newer and accurate quantitative techniques such as QCT and DEXA, osteoporosis is still most commonly diagnosed using conventional radiography [23]. Bone injury or fracture due to osteoporosis can be identified with readily available conventional X-ray imaging technique. This section describes the role of image processing in diagnosing osteoporosis from X-ray images rather than DEXA or QCT.

The bone density decreases as the degree of disease increases and BMD is not the only parameter to diagnose osteoporosis. Hence, our work is proposing analysis of the region of interest by enhancing the resolution of trabecular bone pattern. It is possible to diagnose osteoporosis by analyzing trabecular and cortical bone energy. The common osteoporotic fracture areas of wrist, hip and spine have relatively high ‘trabecular to cortical’ bone ratio. As shown in Fig.3, part of femur bone is selected to describe the role of image processing based osteoporosis detection. In addition to subjective analysis, some image parameters are calculated to ensure bone density.

Proposed work flow of X-ray image processing is shown in Fig.4. As biomedical images are affected by large amount of noise, the first step is to design a median filter. The ability of fuzzy logic system to deal with vague and imprecise data, we propose fuzzy inference based median filtering [13] for image preprocessing or noise removal. Secondly, to enhance visualization of bone region in the X-ray image, contrast of preprocessed image is improved by modifying the method proposed in [22]. Any bone fractures or hard porous on the bone can be identified by edge detection approach. Fuzzy inference based edge detection method [12] is employed to

Table 2: Details of Patients

Risk factors	Age (in years)	Sex	Heredity	BMI (in kg/m^2)	Painful	Calcium deficiency: Diet	Year since Menopause	Alcohol/ Cigarette	Physical stress
Patient 1	76	Female	No	28.5	Severe	Moderate	21	Low	High
Patient 2	54	Female	No	22.7	Medium	Moderate	2	Low	Medium
Patient 3	38	Female	Yes	21.3	Medium	Low	0	Low	Medium
Patient 4	23	Female	No	19.5	Mild	high	0	Low	Medium
Patient 5	66	Male	No	21.9	Medium	Moderate	0	Low	Medium
Patient 6	57	Female	No	22.2	Mild	high	10	Low	Medium
Patient 7	50	Male	No	19	Medium	Moderate	0	Low	Medium
Patient 8	76	Female	No	12.3	Severe	high	30	Low	Medium
Patient 9	85	Female	No	20.8	Severe	high	35	Low	Medium
Patient 10	60	Female	Yes	17.9	Medium	Moderate	8	Low	High
Patient 11	72	Male	No	20.4	Severe	Moderate	0	High	High
Patient 12	70	Female	Yes	23.8	Severe	high	22	Low	Medium
Patient 13	78	Female	Yes	19.8	Medium	Moderate	25	Low	Medium
Patient 14	68	Male	Yes	19.2	Severe	Moderate	0	High	Medium
Patient 15	55	Male	No	23.7	Mild	Low	0	High	High
Patient 16	28	Female	No	22	Mild	Low	0	Low	Medium
Patient 17	30	Male	Yes	22.5	Mild	Moderate	0	Low	Medium
Patient 18	40	Male	No	23	Mild	Moderate	0	High	High
Patient 19	31	Female	Yes	18.4	Medium	Low	0	Low	High
Patient 20	18	Male	Yes	19.6	Mild	Moderate	0	Low	Medium

identify edge pixels in the image and boundaries are identified using active contour evaluation. In addition, some image characteristics (area, energy, mean, correlation etc.) can be evaluated for detailed analysis on image pixels. To diagnose the internal bone pattern, it is necessary to identify edges and boundaries of image. Distinct and textured appearance of trabecular bone is obtained as a result of resolution enhancement process followed by edge detection process. This enhanced trabecular bone pattern improves visualization of bone internal pattern and thus osteoporosis detection. Finally, to understand the degree of bone degradation or porous bone rate, high resolution trabecular and cortical bone patterns are evaluated. In order to improve image resolution, a region of interest is upscaled several times using fuzzy edge directed image interpolation technique called FEDI. The FEDI approach is based on eight image gradients and edge orientation of image pixels. Enhanced trabecular and cortical bone pattern and measures helps identify the degree of porous and bone density respectively. For an osteoporotic patient, trabecular bone tries to extend till cortical bone with relatively high bone porous rate. Porous bone is characterized by bone mass and bone structural deterioration.

V. Experimental Results

Diagnosis of osteoporosis using fuzzy expert system and X-ray imaging technique performs as an expert and later identifies the characteristics of inner bone pattern. The experiments were carried out for 20 patients residing in the southern part of India. Details of 20 patients are listed in Table 2. Initially, to evaluate the performance of fuzzy expert system, details of Patient3 are given as facts to fuzzy inference system. Based on the strength of symptoms, different membership functions are activated and a final decision is drawn. Fig.5 shows the degree of each symptoms and final decision obtained from fuzzy inference system. From this fuzzy framework (in Fig.5) it is clear that the degree of disease obtained is -2, which means Patient3 has osteopenia. So once fuzzy rules are designed accurately, it is possible to identify even osteopenia using fuzzy expert system. The degree of disease is calculated from the degree of membership functions of symptoms and listed rules. A particular value (-2) that shows the degree of disease is calculated using fuzzy centroid method. Hence, fuzzy expert system is capable of evaluating degree of osteoporosis with expert knowledge.

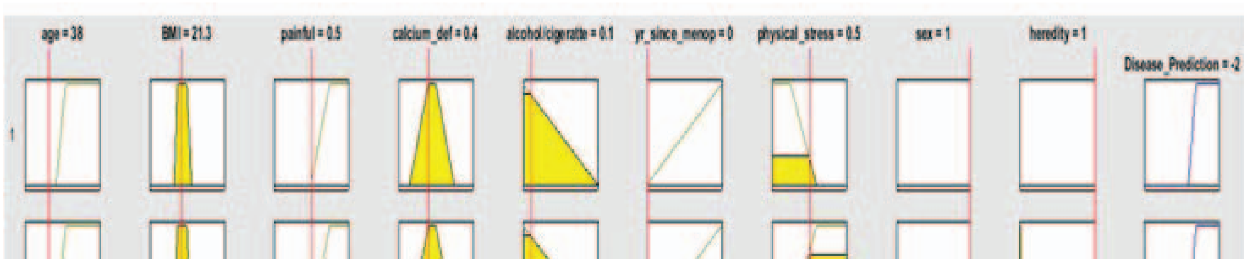


Fig.5. Fuzzy expert system to predict the degree of disease from set of membership functions and rules. The degree of osteoporosis is shown as -2 which mean patient has osteopenia.

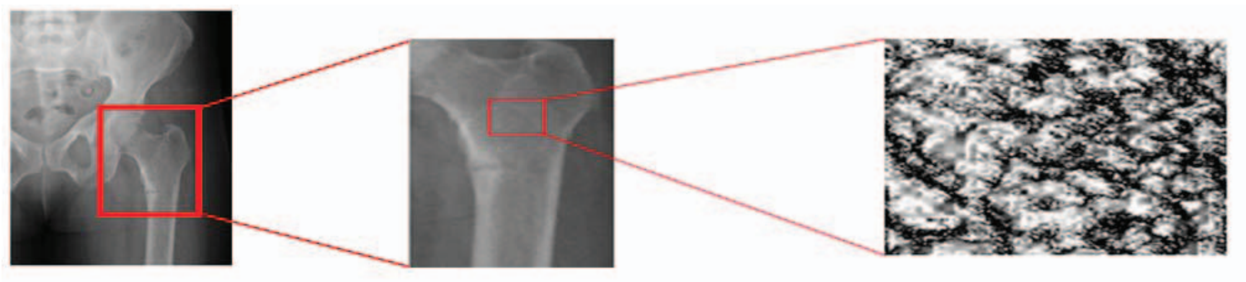


Fig.6 (a) Region of interest is enhanced several times to analyze the trabecular pattern.

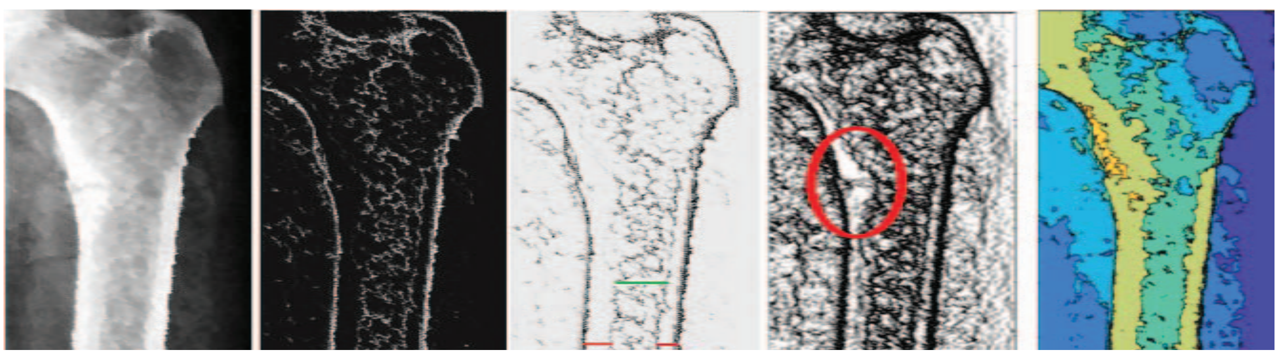


Fig.6 (b) Proposed imaging technique. From left to right: Resolution enhanced region of interest, Application of edge detection method, Inverted edge showing trabecular (green line) and cortical (red line) bone width, Disparity in trabecular bone structure showing chances of osteopenia, Active contour region helps to calculate trabecular (yellowish green) to cortical (bluish green) bone width.

Secondly, we have suggested X-ray imaging technique to analyze bone structure as well as bone porous pattern to identify depth of osteoporosis. Fig.6 shows result obtained after implementation of different steps in X-ray imaging technique. X-ray of particular patient obtained is preprocessed and region of interest is selected for diagnosis. High resolution trabecular pattern of femur bone as shown in Fig. 6(a) is obtained with the help of FEDI approach. To evaluate porous bone structure, fuzzy edge detection algorithm is used. These tightly packed enhanced image edges reveals that the specimen trabecular bone is not highly affected by low bone density. But disparity in the femur stem pattern showcases the chances of osteopenia (Fig. 6(b) in red circle). In addition to subjective evaluation, trabecular bone width, area, mean correlation, energy and perimeter are calculated using simple MATLAB expressions. The ratio of trabecular to total bone parameter is calculated to identify bone density. Since there is no major discontinuity in image edges, it is clear that there is no major fracture in bone. Furthermore, trabecular and cortical bone analysis shows that, particular patient is not affected by osteoporosis but there is a chance of osteopenia. Measure of bone density can be calculated from trabecular and cortical bone using (2) and by trabecular bone texture analysis. There is significant correlation between BMD and trabecular bone texture parameters [24]. The objective parameters obtained after trabecular texture evaluation is listed in Table 3.

$$Bonedensity = \frac{Trabecular}{Trabecular + Cortical} \qquad (2)$$

Table 3: Objective parameters: % loss in bone density

Parameter	Mean	Correlation	Energy
Bone	0.7892	0.8146	0.9001

Above table shows percentage loss in bone density to reveal the chances of osteopenia. Also the ratio of trabecular to total bone energy is obtained as 0.7985 which means that there is 7.985% loss of bone density. Thus by analyzing trabecular bone structure it is possible to find percentage of bone density loss.

Compared to BMD calculation using DEXA, proposed image processing approach can give more accurate and precise details on bone density. In addition, some studies show that DEXA scanning technique fails to differentiate trabecular and cortical bone structure which have major role in bone density calculation. Moreover conventional X-ray scanning technique which is used as input to the fuzzy inference system is less expensive and more widely available than any other densitometry technique including DEXA. In economic backward countries the cost of DEXA method is three times higher than conventional X-ray technique. Furthermore, considering the socio economic constraints, we are proposing fuzzy expert system to diagnose osteoporosis rather exposing all the patients to harmful radiation. Thus in humanitarian context, proposed fuzzy inference imaging technique suggest a cost effective and easily accessible method and fuzzy expert system suggests harmless osteoporosis detection. This makes proposed method cheaper and accessible to the entire society

VI. Conclusion

An expert system combined with X-ray imaging techniques has been successfully applied in fuzzy domain to diagnose osteoporosis. In this paper, osteoporosis diagnosis is carried out in two different approaches and these two can be combined to design an efficient osteoporosis diagnosis system. Fuzzy expert system is designed as an expert to diagnose osteoporosis and fuzzy X-ray imaging technique is based on bone texture analysis. The expert system identifies the degree of osteoporosis with the help of carefully designed membership functions and rules. Whereas fuzzy X-ray imaging technique, make use of resolution enhancement and edge detection algorithms to analyze trabecular bone texture and thus bone density calculation.

Proposed two-in-one diagnosis system contributes more in the field of medical science to diagnose osteoporosis and osteopenia. While evaluating, both algorithms performs well and the degree of disease is calculated in an efficient manner. These efficient algorithms help early detection of osteoporosis and become momentous contribution for the society of all categories to improve the quality of health care.

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