Introduction

Osteoporosis is an abnormality characterised by reduction in quality and density of bone, which eventually leads to a frail skeleton and frequent fracture risks. It has been noticed that women of 45 years and above affected by osteoporosis spend more time in hospital than women affected by other disorders such as diabetes, myocardial infarction and breast cancer [1]. In the past 10 years, the greatest challenge faced by the community and healthcare authorities in terms of public health concerns is that the world population is increasing as regards ageing people. Global epidemiological records show that osteoporotic fractures in Asia have topped the list. Despite ample documentation proving such as diabetes, myocardial infarction and breast cancer [1].

Diagnosis of osteoporosis by extraction of trabecular features from hip radiographs using support vector machine: An investigation panorama

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Osteoporosis
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ABSTRACT

Background: Lifespan and its quality can be improved by early diagnosis of osteoporosis. Analysis of trabecular boundness on digital hip radiographs could be useful for identifying subjects with low bone mineral density (BMD) or osteoporosis. The main aim of our study was to evaluate the ability of a kernel-based support vector machine (SVM) with respect to diagnosis and add to knowledge about the trabecular features of digital hip radiographs for identifying subjects with low BMD.

Method: In this paper we present an SVM kernel classifier-based computer-aided diagnosis (CAD) system for osteoporotic risk detection using digital hip radiographs. Initially, the original radiograph was intensified, then trabecular features such as boundness, orientation, solidity of spur and delta were evaluated and radial bias function (RBF) based discrimination was manifested. The next step was the evaluation of the diagnostic capability of the proposed method in order to spot subjects with low BMD at the femoral neck in 50 (50.7 ± 14.3 years) South Indian women with no previous history of osteoporotic fracture. Out of 50 subjects, 28 were used to train the classifier and the other 22 were used for testing.

Results: The proposed system has achieved the highest classification accuracy documented so far by means of a fivefold cross-validation analysis with mean accuracy of 90% (95% confidence interval (CI): 82 to 98%); sensitivity and positive predictive value (PPV) were 90% (95% CI: 82 to 98%) and 89% (95% CI: 81 to 97%), respectively. Pearson's correlation was observed at the level of p < 0.001, between extracted image trabecular features with age and BMDs measured by dual energy x-ray absorptiometry (DXA). Extracted image features also demonstrated significant differences between high and low BMD groups at the level of p < 0.001.

Conclusion: Our findings suggest that the proposed CAD system with SVM would be useful for spotting women vulnerable to osteoporotic risk.

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1. Introduction

that the risk and manifestation of osteoporosis differ significantly among populations, the actual number of Asian Indian fractures remains unknown [2]. Decreased-trauma or fragility fracture is the main output of osteoporosis; hip fracture is the main consequence, because it induces many abnormalities such as chronic pain, low quality of life, premature death and disability. Once a hip fracture is manifested, about 20% of people are dead within a year, another 20% need care for a longer period of time and one-third are unable to return to their previous jobs. People who survive the fracture lead a low-profile life. Fracture treatment is a costly affair and in the near future even higher socioeconomic groups will be unable to bear the cost. The main reason for measuring bone density in all high-risk post-menopausal women remains ambiguous in many countries [3]. Asia is the continent in which diagnosis and treatment of osteoporosis has been deferred, even in people who come under the high risk category because of existing fractures. This situation is worse in backward rural areas, where the incidences of hip fractures are often treated at home without...
prompt surgical aid in hospitals [3] because of the high cost of DXA usage as well as its difficult accessibility. It is effectively a pipe dream in rural backward regions. Bone mineral density (BMD) alone cannot be the sole criterion for categorising people affected by osteoporotic fractures. Variables other than BMD should also be considered in the detection of future fracture risk [4,5]. The general statistics affirm that a decreased rate of BMD is directly proportional to the chances of osteoporotic fracture occurrence. Nonetheless, low fracture thresholds are seen in subjects over 50 who could have been diagnosed with the initial stage of osteoporosis as per WHO standards [6]. One striking factor that has been noticed is the presence of fractures in women who were not diagnosed as osteoporotic in about half of all cases [7,8]. It has been demonstrated that BMD cannot be the sole criterion for proving the fragile bone abnormality in women affected by fractures because of the overlapping nature of BMD measurements between control and fracture groups [9]. The mechanical properties of trabecular bone have been greatly influenced by bone parameters other than BMD [10,11]. Out of these, trabecular bone micro-architecture can operationally define osteoporosis [12]. Trabecular micro-architectural moderation (trabecular plate loss) has a greater role in decreased bone strength than trabecular thinning [13]. The present study aims to devise a low-cost investigational tool from simple x-ray images in order to diagnose osteoporotic risk or low BMD.

2. Materials and methods

2.1. Selection of study population

Our study is a sincere attempt to initiate a novel approach to abnormalities related to osteoporosis within the framework of public health. A free osteoporotic camp was organised by the end of the year 2010, with the consent of our SRM Hospital and Medical Research Centre, SRM University, Chennai, India. Each and every participant who attended the camp provided written voluntary consent by signing the relevant document. The protocol detailed in the present study was examined and certified by the institutional ethics personnel of the healthcare department. Fifty South Indian pre- and post-menopausal women with a mean age of 50.7 ± 14.3 years participated in the study. Subjects with disorders such as rheumatoid arthritis, endocrine abnormalities like thyroid disease, Paget’s diseases, hypo- and hyperthyroidism, bone integrity and associated malignancy, diabetes, pregnancy, chronic liver and severe trauma-induced fractures were excluded from the study. None of the studied population had a previous history of osteoporotic fracture.

2.2. Imaging techniques

A digital x-ray machine (Multiphos, Siemens, Germany) at 45 to 80 kV, 2 mA was used by a single experienced x-ray imaging technologist to acquire a standard digital radiograph of the right femur region was internally rotated by 15°. A standard narrow fan beam scanner with multi-view image reconstruction (DPX Prodigy DXA Scanner, GE Lunar Corporation, Madison, WI, USA) was used for right-side femur DXA scans. BMD quantifications at the sites neck (N-BMD), Ward’s region (W-BMD), trochanter (Tr-BMD), shaft (S-BMD) and total proximal femur (T-BMD) were evaluated by the software provided by the manufacturer. The WHO benchmark for osteoporotic diagnosis was adopted in this study. The study population was sub-divided into two groups on the basis of calculated T-score values of measured total femur BMD values as follows: (1) normal (n=23, mean ± SD age = 44.0 ± 11.0 years); those with T-score ≥ −1; and (2) at risk of osteoporosis (n=27, age = 53.7 ± 13.8 years); those with T-score < −1 SD.

2.3. Radiographic image processing

Each radiograph was first rotated and the femoral shaft axis was standardised to obtain a uniform alignment of the images. Then the region of interest (ROI) measuring 128 x 128 pixels was placed and manually cropped by a trained operator at the clinically significant area on the neck region of each radiograph. The detailed flow of the proposed system with a marked ROI on a sample radiograph is outlined in Fig. 1.

2.3.1. Normalisation

The intensity of the digital x-ray image, acquired from various subjects, generally varied; the grey level varied over large distances as a result of radiological artefacts and the fat tissue projection on the radiograph corresponded to the low frequency noise of the image. Hence, the technique proposed by Geraets and colleagues was used to eliminate the low frequency noise of the image when the trabecular component of the image was taken into account [14]. Then the intensity normalisation, incorporating the histogram specification technique detailed by Debashis and colleagues [15], was used in order to obtain the desired histogram by maximising a measure that represented increase in information (trabecular structure enhancement) and decrease in ambiguity, which are contradictory indicators of contrast enhancement (histogram equalisation). This approach was independently applied to each individual 3 x 3 sub-block in order to obtain normalised ROI (I_0).
The next phase involved the application of a thinning algorithm to the binary image \((IB)\) obtained by Eq. (3). Parallel thinning with two sub-iteration algorithms [16,17] was utilised in order to extract the skeleton of the trabecular structure by reducing the thickness of each line of patterns to single pixel width.

2.3.3. Trabecular feature extraction

The next vital phase was to evaluate the trabecular boundness by analysing the topology of the trabecular network following skeletal extraction \((IB)\). The trabecular network describes the typology of the various connections between the bifurcation point and the connecting segments (trabecular strut and ridge ending point); the crossing point and isolated point represent an interruption in the trabecular network. Using the properties of the crossing number (CN) (shown in Eq. (4)), the present pixel \((p)\) can then be classified as a ridge ending, bifurcation or other point.

\[
p = \begin{cases} 
\text{Isolated point,} & \text{if } X_{CN} = 0 \\
\text{Ridge ending point,} & 1 \leq X_{CN} \leq 2 \\
\text{Bifurcation point,} & X_{CN} = 3 \\
\text{Crossing point,} & \text{Otherwise}
\end{cases}
\]  

(4)

where

\[
X_{CN}(p) = \frac{1}{8} \sum_{i=1}^{8} |X_{i+1} - X_i|, \quad X_9 = X_1
\]  

(5)

The concept of CN (Eq. (5)) is widely used for extracting these finer points in a skeleton. The practical measure of connectivity as proposed by Rutovitz [18] was the conversion number from a white point to a black point and vice versa when the points of eight neighbours traversed counterclockwise as shown in Fig. 2. The following image features were extracted from the processed image \(I_b\).

1. Trabecular bone area (TBA)

The trabecular bone mass was assessed by the trabecular bone area. The amount of trabecular bone is determined by TBA calculated from the binary image \((I_b)\). The total number of white pixels with black as the neighbour has been referred to as TBA.

2. Euler number \((EN)\)

The binarised image is used to calculate the \(EN\) in order to determine the trabecular structure connectivity. The \(EN\) is defined as the difference between the total number of skeletons in the image and the number of holes in those skeletons.

3. Orientation

Orientation is defined as the angle between the major axis of the skeleton that has the same second moments around the region and the horizontal \((X)\) axis [19]. If \(\theta\) is the angle between major axis and horizontal axis \(X\), as demonstrated in Fig. 3, then

\[
\tan 2\theta = \frac{2 \sum_{i=1}^{n} (X_i - X)(Y_i - Y)}{\sum_{i=1}^{n} [(X_i - X)^2 + (Y_i - Y)^2]}
\]  

(6)

4. Eccentricity

Eccentricity \((ECC)\) is estimated by the following equation:

\[
ECC = \sqrt{\frac{L_a^2 - L_b^2}{L_a}}
\]  

(7)

where \(L_a\) and \(L_b\) are the lengths of major and minor axes, respectively.
5. Convex area of the polygon
The convex polygon area consisting of a skeleton is given by

\[
\text{Convex area} = \frac{1}{2} \sum_{i=1}^{N} \left[ x_{i} \times y_{i+1} - x_{i+1} \times y_{i} \right] = \frac{1}{2} \sum_{i=1}^{N} \left[ x_{i} \times y_{i+1} + x_{i+1} \times y_{i} - x_{i+1} \times y_{i+1} - x_{i} \times y_{i} \right]
\]

(8)

The ‘determinant’ is displayed below and consists of the coordinates \((x_{1}, y_{1}), (x_{2}, y_{2}), (x_{3}, y_{3}), \ldots (x_{n}, y_{n})\) of a convex polygon. The coordinates, starting and ending at the same point, should be arranged counterclockwise around the polygon.

6. Number of regions (Ns)
\(N\) is nothing but the candidate segmentation, followed by the total number of segments. A higher number of segments is present in images possessing a trabecular region. The quantification in pixels is called segment length (SL).

7. Number of sensitive regions (Ns)
Segment number, where segment length is more than five, is considered as \(N_s\).

8. Solidity
Solidity can be defined as the ratio of the skeletal area and convex hull area, i.e.

\[
\text{Solidity} = \frac{\text{Filled area}}{\text{Convex area}}
\]

(9)

9. Extent
Extent is nothing but the pixel concentration in the bounding box which is also existent in the region and it can be computed using the following formula

\[
\text{Extent} = \frac{\text{Area}}{\text{Area of bounding box}}
\]

(10)

10. Spur count (SC)
This is the number which specifies ridge points, terminating in a particular region.

\[
\text{SC} = \sum_{p=1}^{N_s} \text{XCN}(p) = 1 \text{ or } \text{XCN}(p) = 2
\]

(11)

11. Delta count (DC)
This is the region which consists of bifurcation points.

\[
\text{DC} = \sum_{p=1}^{N_s} \text{XCN}(p) = 3
\]

(12)

where \(p\) is the centroid pixel in the current window and \(N_s\) is the total number of windows in the skeletal region.

12. Solidity of spur (SS)
The SS is the ratio of spur counts multiplied by the orientation angle tangential to the trabecular region.

\[
\text{SS} = \frac{1}{N_s} \sum_{i=1}^{N_s} \left[ \text{SC}(i) \times \text{solidity}(i) \right] \times \text{orientation}(i)
\]

(13)

13. Solidity of delta (SD)
The SD is the ratio of delta counts multiplied by the orientation angle tangential to the trabecular region.

\[
\text{SD} = \frac{1}{N_s} \sum_{i=1}^{N_s} \left[ \text{DC}(i) \times \text{solidity}(i) \right] \times \text{orientation}(i)
\]

(14)

14. Confidence level (CL)

\[
\text{CL} = \begin{cases} 
\text{High}(0.9), & \text{if } N_s < 2 \\
\text{Low}(0.1), & \text{otherwise}
\end{cases}
\]

(15)

15. Trabecular boundness (bound)

\[
\text{Boundness} = \frac{1}{N_s} \sum_{i=1}^{N_s} \left[ \left( \frac{\text{DC}(i) \times \text{solidity}(i)}{\text{SC}(i)} \right) + \text{CL}(i) \times \text{orientation}(i) \right]
\]

(16)

2.4. Feature selection
Not all features may be of beneficiary threshold in the classification process; some rather disrupt it [20], so it is essential to identify which features complement the process and which hinder it. A full cross-validation of every possible combination of features can be done on a small feature set or with limitless computing power. It was estimated that it would take more than 3 years to cross-validate a leave-one-out method for every combination of five or more of the 15 features. Although fold cross-validation would be faster, it is likely to suffer bias [21]. A series of heuristics tests can be utilised for feature relevance for more rapid estimation. The efficiency of each of the 15 features is assessed by two non-variable statistical tests; the first test is the Wilcoxon rank sum test, which examines the differential significance of normal and at-risk median values; the second is the ANOVA test, which examines the differential significance of variance values between normal and at-risk groups.

2.5. Classification
A kernel-based SVM was adopted to check the enforcement of the present diagnosis system in order to attain high accuracy [22–24]. The SVM has not been used previously for women with low BMD on the basis of femur x-ray images, although it has been successfully used for medical imaging in various studies. We opted to make use of RBF as the kernel function as it was evidenced to be successful in the training procedure. Investigation of the training samples showed it was possible to actuate the RBF parameter and weighting factors. We excavated a data analysis scheme written in MATLAB, which makes use of existing SVM tools for MATLAB that were used by Scholkopf [25] to perform classification. The South Indian women in the at-risk category were detected by means of sensitivities, specificities, positive predictive values (PPV), negative predictive values (NPV) and accuracy values.
2.6. Performance evaluation

In practice, examination can be carried out on every classifier for sensitivity and specificity comparison, along with overall efficiency and positive and negative prediction levels. The confusion matrix was consequently designed to take into account the trade-off between the actual and classifier-generated outputs. True positive (TP) is defined as the phenomenon whereby the subject can be predicted to possess osteoporotic proneness when actually at osteoporotic risk. True negative (TN) is the mechanism whereby the subject is projected as a healthy person and has sound health in reality. Similarly, false positive (FP) is the situation of incorrect osteoporotic risk prediction when the subject is healthy in reality. False negative (FN) is a condition which is yet another illusion of healthy prediction, when in reality the person is prone to osteoporotic risk.

3. Results

3.1. Feature selection

The feature extraction techniques detailed in the methodology section (Eqs. (6)–(16)) have been applied to the radiograph of the femoral neck region of interest. Analysis of 15 extracted image features is as follows: Table 1 shows the top five features according to the Wilcoxon test score to be 15, 1, 13, 12 and 3 (boundness, TBA, solidity of delta, solidity of spur and orientation, respectively). In order to obtain Wilcoxon rank coefficients, the data were labelled as ‘0’ and ‘1’ for normal and at-risk groups, respectively. The two lowest ranked features extracted from the table are the delta count (feature 11) and the total number of regions (feature 6), respectively. In both the events, normal and at-risk classes evidenced no significant difference between median values. The calculated Root means squared coefficient of variation (RMS CV) % was 0.12%, 0.16, 1.21, 1.12 and 1.38 for boundness, TBA, solidity of delta, solidity of spur and orientation, respectively. It was found that the features extracted from the processed image were highly reproducible. Table 2 shows the Pearson’s correlation of the top five image features with respect to DXA and demographic features by means of the Wilcoxon rank test. Boundness, TBA, solidity of delta and solidity of spur displayed high co-relational significance of p < 0.001 with respect to FN-BMD, W-BMD, S-BMD and T-BMD and significance of p < 0.05 with respect to age. Orientation demonstrated significance at the level of p < 0.001 for FN-BMD, W-BMD and T-BMD and significance of p < 0.05 with respect to age, BMI and S-BMD. Table 3, which enumerates the test results based on ANOVA, for features 15, 1, 13, 12 and 3 tops the list with the significant level of p < 0.001 among normal and at-risk groups. For feature 6, normal and at-risk groups evidenced no differential significance in dispersion. Henceforth, feature 6 contributes no value to the classification process. Conversely, the dispersion of feature 15 did differ significantly between normal and at-risk groups. The resulting images of the ROI extracted from a normal and at-risk of osteoporotic sample radiograph are shown in Figs. 4 and 5, respectively. Fig. 6 depicts the so-called

<table>
<thead>
<tr>
<th>Features/groups</th>
<th>Normal (n=23)</th>
<th>At-risk (n=27)</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demographic features</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (years)</td>
<td>44.1 ± 11.0</td>
<td>53.7 ± 13.8</td>
<td>0.009**</td>
</tr>
<tr>
<td>Height (cm)</td>
<td>151.5 ± 5.6</td>
<td>148.3 ± 5.6</td>
<td>0.049*</td>
</tr>
<tr>
<td>Weight (kg)</td>
<td>58.7 ± 9.9</td>
<td>50.7 ± 8.3</td>
<td>0.003**</td>
</tr>
<tr>
<td>BMI (kg/m²)</td>
<td>25.6 ± 4.3</td>
<td>23.02 ± 5.3</td>
<td>0.207*</td>
</tr>
<tr>
<td>Extracted image features (feature number)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Boundness (15)</td>
<td>–4.04</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Trabecular bone area (1)</td>
<td>–3.69</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Solidity of delta (13)</td>
<td>–3.67</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Solidity of spur (12)</td>
<td>–3.35</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>Orientation (3)</td>
<td>–3.34</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>Number of sensitive regions (7)</td>
<td>–3.10</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>Spur count (10)</td>
<td>–2.93</td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td>Confidence level (14)</td>
<td>–2.75</td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td>Solidity (8)</td>
<td>–2.72</td>
<td>0.007</td>
<td></td>
</tr>
<tr>
<td>Convex area of the polygon (5)</td>
<td>–2.33</td>
<td>0.020</td>
<td></td>
</tr>
<tr>
<td>Euler number (2)</td>
<td>–2.18</td>
<td>0.029</td>
<td></td>
</tr>
<tr>
<td>Eccentricity (4)</td>
<td>–2.15</td>
<td>0.032</td>
<td></td>
</tr>
<tr>
<td>Extent (9)</td>
<td>–1.54</td>
<td>0.124</td>
<td></td>
</tr>
<tr>
<td>Delta count (11)</td>
<td>–1.29</td>
<td>0.196</td>
<td></td>
</tr>
<tr>
<td>Number of regions (6)</td>
<td>–1.00</td>
<td>0.316</td>
<td></td>
</tr>
</tbody>
</table>

Table 3 Results of ANOVA test for DXA and demographic features as well as top 5 image features assessed using the Wilcoxon rank test.

Table 2 Pearson’s correlation (r) between top 5 image features assessed using the Wilcoxon rank test and DXA as well as demographic features.

<table>
<thead>
<tr>
<th>Extracted image features (feature number)</th>
<th>Age (years)</th>
<th>BMI (kg/m²)</th>
<th>N-BMD (g/cm²)</th>
<th>W-BMD (g/cm²)</th>
<th>Tr-BMD (g/cm²)</th>
<th>S-BMD (g/cm²)</th>
<th>T-BMD (g/cm²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boundness (15)</td>
<td>0.345*</td>
<td>0.119</td>
<td>0.665**</td>
<td>0.627**</td>
<td>0.677**</td>
<td>0.462**</td>
<td>0.644**</td>
</tr>
<tr>
<td>Trabecular bone area (1)</td>
<td>0.296*</td>
<td>0.168</td>
<td>0.625**</td>
<td>0.572**</td>
<td>0.655**</td>
<td>0.462**</td>
<td>0.623**</td>
</tr>
<tr>
<td>Solidity of delta (13)</td>
<td>0.295*</td>
<td>0.123</td>
<td>0.618**</td>
<td>0.604**</td>
<td>0.615**</td>
<td>0.489**</td>
<td>0.593**</td>
</tr>
<tr>
<td>Solidity of spur (12)</td>
<td>0.299*</td>
<td>0.244*</td>
<td>0.543**</td>
<td>0.515**</td>
<td>0.574**</td>
<td>0.377**</td>
<td>0.542**</td>
</tr>
<tr>
<td>Orientation (3)</td>
<td>0.285*</td>
<td>0.296*</td>
<td>0.411**</td>
<td>0.391*</td>
<td>0.518*</td>
<td>0.343*</td>
<td>0.473**</td>
</tr>
</tbody>
</table>

Values represented are Pearson’s correlation coefficient (r).

* p < 0.001.
* p < 0.05.
technique’s manifestation as area under the ROC curve (AUC) against the number of features included in the classification. The features were added in the manner specified by the Wilcoxon test scores in Table 1. The performance seems to improve for the first 10 features, but falls slightly after the addition of the last five features. The first 10 features were therefore utilised for all subsequent tests and the last five features were eliminated.

3.2. Performance of SVM classification

The classification of 22 test sets and the processing of 28 training sets were performed by the RBF kernel. In order to train the sets, the classification and labelling of the data, notified to be normal and at-risk group as well as either ‘0’ or ‘1’, respectively, which also corresponded to positive and negative examples for

![Fig. 4. Results: (a) cropped femur neck ROI from digital radiograph of healthy subject (measured T-BMD = 1.087 g/cm²), (b) trabecular enhanced image, (c) binarized image of (b), (d) extracted skeleton, (e) spur points on the skeleton image and (f) delta points on the skeleton image.](image)
SVM training. Table 4 gives information, keeping in view, the fivefold cross-validation as regards the average percentage of 90% (95% CI: 82 to 98%) sensitivity and 87% (95% CI: 78 to 96%) specificity of the diagnostic classification of South Indian women, based on the predictions of the RBF kernel SVM within the framework of T-BMD. The accuracy of the adduced CAD system with SVM for diagnosing South Indian women to be 90% (95% CI: 82 to 98%), PPV and NPV being identified to be 89% (95% CI: 81 to 97%) and 90% (95% CI: 82 to 98%) respectively has been deduced. Table 5 enumerates the factual ROC analysis of SVM results. The AUC is at its peak at 89.1% (95% CI: 86 to 91.2%), the mean value being 86.3% (95% CI: 79.3 to 93.5%). The mean standard error and p value are estimated to be 8.3 and 0.004%, respectively.

Fig. 5. Results: (a) cropped femur neck ROI from digital radiograph of subject at-risk of osteoporosis (measured T-BMD = 0.794 g/cm\(^2\)), (b) trabecular enhanced image, (c) binarized image of (b), (d) extracted skeleton, (e) spur points on the skeleton image and (f) delta points on the skeleton image.
The proposed technique was implemented with MATLAB 7 software with a Windows background (WIN-XP, SP-3) and it took 50 s on an Intel E7500 Core2Duo processor (2.93 GHz) and 2 GB of RAM to calculate the 15 features for each image. The SVM-RBF classifier took an average time of around 8 s per image. The training phase of the SVM-RBF classifier took around 200 s, but this is the only procedure that has to be performed prior to testing the system.

4. Discussion

It has been customary to prescribe DXA scan even for normal subjects, as physicians may suspect them to be at risk of osteoporotic phase. The cost per scan is around 5000 Indian Rupees, which the average Indian can ill afford. Also, the number of DXA machines in South India is limited to fewer than 100. WHO predicted that by the year 2050 India will have the highest number of osteoporotic cases in the world [3]. Marwaha and colleagues and Shatrugna and colleagues observed that 16 to 20% of the studied North Indian post-menopausal women [26,27] exhibited no symptoms of osteoporotic risk factors and our earlier study also showed that 47% of South Indian post-menopausal women had no such symptoms, as confirmed by central DXA [28]. The present study also evidenced that 35% of South Indian post-menopausal women were in a normal phase. There is an immediate need to identify the subjects who are vulnerable to osteoporotic risk, recommend them for osteoporotic screening and identify a screening tool which would work on bulk databases at affordable cost.

The proposed CAD system is advantageous on account of its low cost, the wide availability of x-ray machines and the simple protocol. This device is an attempt to screen low-BMD subjects; owing to its ability to demonstrate 90% (sensitivity) they can be identified properly. Similarly, Kavitha and colleagues reported that the RBF-kernel SVM for mandibular x-ray image for osteoporotic detection exhibited 90% sensitivity and 83% specificity [29]. Our study depicted specificity of 87%, accuracy of 90%, PPV of 89% and NPV of 90%. The early diagnosis of osteoporosis by means of hip radiographic image features achieved an accuracy of 86% by SVM classifier, a value 22% higher than the ANN classifier reported by Istanbullu and colleagues [30]. Similarly, the femur bone fractures from x-ray images were evaluated with different classifiers and high classification accuracy of 82% was reported from a technique which utilised a combinational SVM classifier framework as detailed by Lim and colleagues [31]. Trabecular index based on heel x-ray images achieved 94% accuracy with the SVM classifier detailed by Khaled and colleagues [32]. We managed to utilise our affirmed SVM method with a CAD system and digital hip radiographs to diagnose the South Indian population at risk, easily and quickly. The results reflected the high degree of consistency and reproducibility by means of the SVM kernel adopted in our study. This CAD system has an edge over manual assessment thanks to its automated evaluation system. The present proposed CAD system, by means of image morphological feature extraction, directly evaluates the bones on radiographs, and reduces the measurement errors of the conventional (Singh's index visual scoring) assessment [33].

\[\text{Fig. 6. Performance of the proposed approach, measured by area under the ROC curve (AUC) on image versus different number of image features.}\]

\[\text{Table 4}\]

Performance of the SVM for randomly divided data set (training and independent testing sets) via a stratified 5-fold cross validation.

<table>
<thead>
<tr>
<th>Fold</th>
<th>Size of train data set (n)</th>
<th>Size of test dataset (n)</th>
<th>Classifier output (95% confidence interval)</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Accuracy (%)</th>
<th>PPV (%)</th>
<th>NPV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fold 1</td>
<td>28</td>
<td>10</td>
<td>90 (82–98) 92 (85–99) 91 (84–98) 90 (82–98) 92 (85–99)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fold 2</td>
<td>28</td>
<td>15</td>
<td>93 (86–100) 71 (77–95) 86 (77–95) 88 (79–97) 83 (73–93)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fold 3</td>
<td>28</td>
<td>8</td>
<td>88 (79–97) 93 (86–100) 91 (84–98) 88 (79–97) 93 (86–100)</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Fold 4</td>
<td>28</td>
<td>9</td>
<td>89 (81–97) 92 (85–99) 91 (84–98) 89 (79–97) 92 (85–99)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fold 5</td>
<td>28</td>
<td>13</td>
<td>92 (85–99) 89 (81–97) 91 (84–98) 92 (85–99) 89 (81–97)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>28</td>
<td>13</td>
<td>90 (82–98) 87 (78–96) 90 (82–98) 89 (81–97) 90 (82–98)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

‘n’ indicates number of subjects.

\[\text{Table 5}\]

ROC analysis of the SVM results.

<table>
<thead>
<tr>
<th>Fold</th>
<th>Area under the ROC curve (%)</th>
<th>Standard error (%)</th>
<th>p Value</th>
<th>95% CI (%)</th>
<th>Coordinates of the ROC curve at 0.5 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower bound</td>
<td>Upper bound</td>
<td>Sensitivity</td>
<td>1-Specificity</td>
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<tr>
<td>Fold 1</td>
<td>86.1</td>
<td>8.4</td>
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<td>92.2</td>
<td>15.4</td>
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<tr>
<td>Fold 2</td>
<td>89.1</td>
<td>8.1</td>
<td>0.004</td>
<td>99.2</td>
<td>14.2</td>
</tr>
<tr>
<td>Fold 3</td>
<td>83.4</td>
<td>8.9</td>
<td>0.005</td>
<td>76.9</td>
<td>27.3</td>
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<tr>
<td>Fold 4</td>
<td>81.2</td>
<td>9.1</td>
<td>0.008</td>
<td>72.1</td>
<td>25.2</td>
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<tr>
<td>Fold 5</td>
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<td>7.1</td>
<td>0.000</td>
<td>86.0</td>
<td>12.3</td>
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<tr>
<td>Mean</td>
<td>86.3</td>
<td>8.3</td>
<td>0.004</td>
<td>75.3</td>
<td>18.7</td>
</tr>
</tbody>
</table>
Pulkkinen and colleagues explored the mechanical characteristics of structure-related trabecular features (bone area, trabecular orientation, Euler number and homogeneity index) extracted from digital hip x-ray images and found a significant correlation between DXA features and extracted image features [34]. Likewise, our present study showed a significant correlation between image features (TBA, boundness, solidity of spur, solidity of delta and trabecular orientation) against DXA-measured BMDs and age at the level of p < 0.001. Incremental age is associated with increased osteoporotic risk (decremented BMD) [3]. Eventually, our findings also evidenced the decremented phase with respect to extracted image features against age (as displayed in Table 2) because menopause causes a variation in trabecular architecture as detailed by Ascenzi and colleagues [35]. Our previous study focused on the roughness and waviness of the trabecular pattern of hip radiographs which exhibited statistical significance at the level of p < 0.05 against weight and BMI [28]. The quality of actual trabecular bone can be effectively determined by extracted image 2D features in a gestalt approach and reflects the finding of Steines and colleagues that the 2D trabecular features extracted from digital hip radiographs exhibited a significant correlation with 3D micro components, extracted from micro CT images [36].

The limitations of our study were its confinement to a single ethnic group and the low sample size, which warrant validation with a larger population and a variety of ethnicities.

5. Conclusion

Adequacies of diagnosis attained by the utilisation of an RBF-kernel SVM in the present study showed the accuracy and capability of the proposed CAD system for identifying women at risk of osteoporosis. The accuracy, sensitivity and PPV were 90% (95% CI: 82 to 98%), 90% (95% CI: 82 to 98%) and 89% (95% CI: 81 to 97%), respectively. Consequently, because of its sensitivity, accuracy and PPV outcomes, the proposed methodology is seen as a useful technique for identifying women who are at risk and as a subsidiary diagnostic methodology that will avoid faulty diagnosis. Our methodology is a valuable option for the proposed method because it is cheap, fast and accurate for classification using digital hip radiographs. The extracted image features (boundness, TBA, solidity of delta, solidity of spur and orientation) exhibited a significant correlation with patient age and DXA-measured BMDs at the level of p < 0.001.

Competing interest

All authors declare that they have no competing interests.

Conflict of interest statement

None.

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