RESEARCH ARTICLE

Strut analysis for osteoporosis detection model using dental panoramic radiography

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Objectives: The aim of this study was to identify variables that can be used for osteoporosis detection using strut analysis, fractal dimension (FD) and the gray level co-occurrence matrix (GLCM) using multiple regions of interest and to develop an osteoporosis detection model based on panoramic radiography.

Methods: A total of 454 panoramic radiographs from oral examinations in our dental hospital from 2012 to 2015 were randomly selected, equally distributed among osteoporotic and non-osteoporotic patients ($n = 227$ in each group). The radiographs were classified by bone mineral density (T-score). After 3 marrow regions and the endosteal margin area were selected, strut features, FD and GLCM were analysed using a customized image processing program. Image upsampling was used to obtain the optimal binarization for calculating strut features and FD. The independent-samples *t*-test was used to assess statistical differences between the 2 groups. A decision tree and support vector machine were used to create and verify an osteoporosis detection model.

Results: The endosteal margin area showed statistically significant differences in FD, GLCM and strut variables between the osteoporotic and non-osteoporotic patients, whereas the medullary portions showed few distinguishing features. The sensitivity, specificity, and accuracy of the strut variables in the endosteal margin area were 97.1%, 95.7 and 96.25 using the decision tree and 97.2%, 97.1 and 96.9% using support vector machine, and these were the best results obtained among the 3 methods. Strut variables with FD and/or GLCM did not increase the diagnostic accuracy.

Conclusion: The analysis of strut features in the endosteal margin area showed potential for the development of an osteoporosis detection model based on panoramic radiography. *Dentomaxillofacial Radiology* (2017) **46**, 20170006. doi: [10.1259/dmfr.20170006](https://doi.org/10.1259/dmfr.20170006)

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Introduction

Osteoporosis is characterized by low bone mass and micro-architectural deterioration.¹ This disease is

referred to as a silent bone disorder associated with fragility fractures, since a significant number of osteoporotic cases go undiagnosed until the first bone fracture.² With the rapid aging of the worldwide population, the prediction and early diagnosis of osteoporosis have become important health care issues.^{3,4}

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The current principal method for diagnosing osteoporosis is bone mineral density, which is usually measured by dual energy X-ray absorptiometry.⁵ Panoramic radiography can provide a valuable screening opportunity and its cost is included in routine dental care. The inferior cortex is the most commonly studied region of interest (ROI) for osteoporosis detection in panoramic radiography. The mandibular cortical index (MCI) has generally been accepted as a useful tool for osteoporosis screening using this ROI.⁶ However, the MCI has the limitation of a lack of complete reproducibility, which is associated with visual assessments in general.⁷

For objective mathematical analysis, texture analysis techniques such as fractal dimension (FD)^{8–12} and the gray level co-occurrence matrix (GLCM)^{8,13} have been used. However, studies of these methods have provided conflicting results, most likely because they did not sufficiently focus on ROI selection and the parameter adjustment for optimal binarization. The marrow and the inferior cortex, which have been used in most studies, might show confusing features in osteoporotic patients. Many studies have used the density correction using Gaussian blur introduced by White and Rudolph¹⁴ for calculating the FD. However, most studies have used the same blurring parameters despite having different image resolutions.^{15–17}

Strut analysis is a quantitative morphologic method that has been widely used to quantify the structural elements of various objects in the medical field, including trabecular pattern analysis.^{18–20} In dentistry, many studies have used this method to screen for osteoporosis detection in periapical radiography.^{5,14,21} Strut analysis has not yet been applied to multiple ROIs in panoramic radiography.²²

The purposes of this study were (1) to identify variables that can be used for osteoporosis detection via strut analysis, FD and GLCM in multiple ROIs of panoramic radiography with appropriate parameter adjustment and (2) to develop an osteoporosis detection model using a decision tree and support vector machine (SVM).

Methods and Materials

Ethics statement

This study was approved by the Institutional Review Board of our Dental Hospital (approval number: [2-2016-0028]). This study had a non-interventional retrospective design and all data were analysed anonymously. The IRB of our Dental Hospital waived the need for individual informed consent.

Subjects

A total of 454 panoramic radiographs (227 from non-osteoporotic patients and 227 from osteoporotic patients, using random sampling) with T-scores taken for oral examinations in Yonsei University Dental

Table 1 Differences in mean values of age and bone mineral density between osteoporotic and normal patients

	Osteoporosis (n = 227)	Normal (n = 227)	P value
Male (n) (%)	34 (15.0)	61 (26.9)	0.002 ^a
Female (n) (%)	193 (85.0)	166 (73.1)	
Age	64.44 (12.96)	57.49 (11.93)	<0.001 ^b
BMD			
L1 - L4 (g/cm ²)	-1.60 (2.20)	0.08 (0.99)	<0.001 ^b
Femur neck (g/cm ²)	-1.40 (1.88)	-0.13 (0.70)	<0.001 ^b
Trochanter (g/cm ²)	-0.89 (1.43)	0.42 (0.84)	<0.001 ^b
Total hip (g/cm ²)	-0.97 (1.49)	0.45 (0.77)	<0.001 ^b
Wards (g/cm)	-1.90 (2.43)	-0.39 (0.99)	<0.001 ^b

BMD, bone mineral density.

The given values are means, and values between brackets indicate the standard deviation.

Age refers to the age of subjects at the time of the radiographic imaging.

BMD was tested within 6 month from the date of the radiographic imaging.

^aObtained from X² test.

^bObtained from independent *t*-test.

Hospital from 2012 to 2015 were used for the analysis. Patients with a T-score below -2.5 for at least 1 site among the lumbar spine vertebrae 1–4, the femur neck, trochanter, total hip, and Ward's triangle and with having no sites above -1.0 were defined as having osteoporosis. Patients with a T-score above -1.0 at all of these locations were defined as normal. Panoramic radiographs within 6 months from the T-score test were included, and patients taking drugs to treat osteoporosis were excluded from the study. Basic demographic information and T-scores are presented in Table 1. A Cranex 3+ Ceph panoramic apparatus (Soredex Co, Helsinki, Finland) was used with voltage settings of 67–71 kV at 10 mA (exposure time, 19.5 s). Images were read using a FCR XG5000 cassette reader (Fuji film Co, Tokyo, Japan) at 170 dpi. The images were stored in the Digital Images in Communication and Medicine 3.0 file format (512 × 512 pixels) and transferred to MATLAB R2016a (MathWorks, Natick, MA). All images were normalized in the range from 0.0 (black) to 1.0 (white). An experienced oral and maxillofacial radiologist then selected images using a calibrated 21.3-inch colour monitor. Images without blurring, motion artefacts, surgical defects, or overlapping hyoid bone were selected.

Customized analysis program: Using MIJ version 1.3.9 (Biomedical Imaging Group), which is a Java package for exchanging images between MATLAB and ImageJ (version 1.6; National Institutes of Health, Bethesda, MD), we made a customized computer program. Obtaining the ROIs and feature analysis were performed in MATLAB. Intermediate image processing was performed in ImageJ, which has been used by most other studies in this field (Figure 1).

Figure 1 Flowchart of image processing and feature analysis. The process inside the rectangular box represents image processing using ImageJ. The black area represents the image processing procedure and line arrow represents feature analysis. Obtaining the ROIs and feature analysis were performed using MATLAB. ROIs, regions of interest.

All images were anonymized and 4 ROIs were selected by 1 observer who was trained for 2 weeks (Figure 2). The second measurement was performed by the same observer 2 weeks after the first measurement, using the same 20 images. ROIs were selected from the side of the bilateral region with less noise and fewer overlapping structures. ROIs 1–3 were selected in the medullary

Figure 2 A total of 4 regions of interest (ROIs) were selected in the panoramic radiography: the centre of the condylar head (ROI 1), centre of the ramus (ROI 2), and area below and between 2 molars (ROI 3). The endosteal margin area (ROI 4) was selected horizontally from the intersection point of the oblique line and ramus to the midpoint between the image center and the intersection point.

portion with a fixed square dimension (5×5 mm), and corresponded to the centre of the condylar head (ROI 1) without any degenerative disorder, the centre of the ramus (ROI 2), and the area below and between the 2 molars (ROI 3) without periapical radiolucency or sclerosis. If a molar was missing, the centre area horizontally 2 cm medial from the intersection point of the oblique line and ramus was selected. For ROI 4, after an observer defined several points along the endosteal margin (horizontally from the intersection point to the midpoint between the image centre and the intersection point), a curved ROI containing margins 3 mm above and below the curves connecting the selected points was stretched automatically in a rectangular shape. The final ROI height was then refined manually to avoid coming into contact with the inferior margin of the cortex (Figure 3).

Figure 1 shows the sequence of image processing and analysis. After localizing the ROIs, the GLCM was calculated first. The image was then enlarged to 400% with bicubic interpolation (upsampling, Figure 4a) and processed following the method introduced by White and Rudolph.¹⁴ The image was blurred with a Gaussian filter (with a sigma of 35 and a filter size of 33), and density correction was performed by subtracting the blurred image from the original one. A gray value of 128 was

Figure 3 Regions of interest (ROIs) 4 (the endosteal margin area) was obtained by a customized program using the 5 steps below. (a) ROI containing endosteal margin area. (b) User defined points (black circles) along the endosteal margin. (c) Smooth spline curves (dotted curve) connecting the user-defined points and curved ROI 3 mm above (white curve) and below (white curve) the spline curves. (d) Stretched rectangular ROI. (e) Redefined ROI to avoid coming into contact with the inferior border; the dotted white line represents the redefined ROI. (f) Final ROI with upper and lower boundaries trimmed.

then added at each pixel location and the binarization and skeletonization process was performed. Fractal and strut analysis were performed using these binary images. The same radiologist who selected images determined the upsampling ratio (400%) that showed the optimal binarization results in a preliminary test. The effect of the upsampling is shown in Figure 4. Compared to the binarization result of a 400% upsampled image (Figure 4c),

the result of the original image (Figure 4b) has unseparated clusters of binary structures, while the result of the 1600% upsampled image (Figure 4d) still has large-scale variations that can be susceptible to noise.

Gray level co-occurrence matrix: The GLCM is a way of analysing texture features using a second-order statistic that can be used to describe the spatial distribution

Figure 4 Image processing results according to different upsampling (enlargement with interpolation) ratio with Gaussian filter (35 sigma and 33 filter size). When resampled to 400%, the binary and skeletonized images showed optimal results. (c), (d) were resized to 400% after the image processing for comparison (a) Original image (5×5 mm, left) and 400% upsampled image (right); (b) Binary and skeletonized images (original image); (c) Binary and skeletonized images (400% upsampled); (d) Binary and skeletonized images (1600% upsampled).

of the gray levels in an image.²³ In this study, contrast, correlation, energy, and homogeneity were used from each original ROI with 1 distance ($d = 1$).

Fractal dimension: FD provides a statistical index of complexity comparing how the detail in a pattern changes with the scale at which it is measured.^{10,13} In this study, FD was calculated using skeletonized images with the box-counting method.¹¹

Strut analysis

The strut analysis method involved several steps. The area of high density and the length of the periphery were analysed using a binary image. The high-density region was defined as being represented by white pixels in the binary image. The periphery corresponded to the outer margin of the high-density region. Skeletonization of the binary image was performed for analysing structural elements, which consisted of a node (crossing point), terminus (free end), and strut (connection between 2 other elements). All features were expressed as a proportion of the related length, area, or perimeter to facilitate direct comparisons (Table 2).

Classification method for osteoporosis detection: A decision tree²⁴ and SVM¹³ were employed to create a classification model for osteoporosis detection based on panoramic radiography. The decision tree is a non-parametric supervised learning method to create a classification model by learning simple decision rules. X^2 automatic interaction detection was used for the decision tree algorithm in R (the PARTY package). The main goal of the SVM classifier is to output an optimal boundary (hyperplane) that categorizes the data sets. This study adopted the Gaussian radial basis function kernel in R (KERNLAB package), since it was found to show the highest performance. The regularization

parameter, $C = 1$, was used with the termination criterion of 0.001 to optimize the kernel.

Statistical analysis

The paired sample *t*-test was used to assess intraobserver reliability in ROI selection.

We compared the FD, GLCM, and the strut variables of the 2 groups using the independent-samples *t*-test. A 10-fold cross validation was performed to validate the accuracy of the decision tree and SVM models. All statistical tests were conducted using R statistical software version 3.3.1 (R Development Core Team, Cambridge, MA). The tests were two-sided and $p < 0.05$ was considered the cut-off for statistical significance.

Results

All bone mineral density values and the sex and age distribution were significantly different in osteoporotic and non-osteoporotic patients (Table 1). No significant differences were found in intraobserver reliability (0.051–0.942) of 95% of the variables in the 4 ROIs.

Table 2 presents summary statistics regarding the strut and textural features of the 4 ROIs. The endosteal margin area (ROI 4) showed significant differences for 16 of the 19 features it contained, whereas only 7 variables showed statistical significance in the other 3 ROIs. In ROI 4, the features related to the terminus showed a reduction in osteoporotic patients, whereas features related to the strut length and node exhibited an elevation. This result is correlated to the skeletal structures of osteoporotic patients, which showed longer and more connected struts than were observed in the non-osteoporotic group (Figure 5).

Table 2 Mean and standard deviation for textural features of osteoporotic and normal patients

	ROI 1			ROI 2			ROI 3			ROI 4		
	Osteoporosis (Mean $\pm$ SD)	Normal (Mean $\pm$ SD)	<i>p</i> value	Osteoporosis (Mean $\pm$ SD)	Normal (Mean $\pm$ SD)	<i>p</i> value	Osteoporosis (Mean $\pm$ SD)	Normal (Mean $\pm$ SD)	<i>p</i> value	Osteoporosis (Mean $\pm$ SD)	Normal (Mean $\pm$ SD)	<i>p</i> value
FD	1.275 $\pm$ 0.071	1.271 $\pm$ 0.063	0.460	1.289 $\pm$ 0.075	1.29 $\pm$ 0.071	0.820	1.217 $\pm$ 0.067	1.225 $\pm$ 0.070	0.187	1.049 $\pm$ 0.004	1.065 $\pm$ 0.008	<0.001 ^a
Strut												
HDA	0.491 $\pm$ 0.020	0.490 $\pm$ 0.017	0.366	0.483 $\pm$ 0.019	0.482 $\pm$ 0.020	0.499	0.483 $\pm$ 0.019	0.482 $\pm$ 0.018	0.656	0.463 $\pm$ 0.009	0.468 $\pm$ 0.012	<0.001 ^a
/total area												
Periphery	0.018 $\pm$ 0.002	0.018 $\pm$ 0.002	0.148	0.019 $\pm$ 0.002	0.019 $\pm$ 0.002	0.696	0.017 $\pm$ 0.002	0.018 $\pm$ 0.002	0.023 ^a	0.006 $\pm$ 0.000	0.007 $\pm$ 0.000	<0.001 ^a
/total area												
Periphery/HDA	0.037 $\pm$ 0.004	0.038 $\pm$ 0.003	0.136	0.040 $\pm$ 0.005	0.040 $\pm$ 0.004	0.575	0.036 $\pm$ 0.004	0.037 $\pm$ 0.004	0.031 ^a	0.013 $\pm$ 0.001	0.014 $\pm$ 0.001	<0.001 ^a
TSL/HDA	0.020 $\pm$ 0.002	0.020 $\pm$ 0.001	0.940	0.021 $\pm$ 0.002	0.021 $\pm$ 0.001	0.864	0.019 $\pm$ 0.002	0.019 $\pm$ 0.002	0.054	0.006 $\pm$ 0.000	0.007 $\pm$ 0.000	<0.001 ^a
TSL/total area	0.010 $\pm$ 0.001	0.010 $\pm$ 0.001	0.628	0.010 $\pm$ 0.001	0.010 $\pm$ 0.001	0.907	0.009 $\pm$ 0.001	0.009 $\pm$ 0.001	0.095	0.003 $\pm$ 0.000	0.003 $\pm$ 0.000	<0.001 ^a
N:Tm/sq cm	0.076 $\pm$ 0.010	0.075 $\pm$ 0.009	0.437	0.079 $\pm$ 0.011	0.079 $\pm$ 0.011	0.990	0.067 $\pm$ 0.011	0.067 $\pm$ 0.012	0.698	0.007 $\pm$ 0.001	0.008 $\pm$ 0.001	<0.001 ^a
N:Tm/TSL	7.648 $\pm$ 0.913	7.613 $\pm$ 0.872	0.675	7.892 $\pm$ 1.080	7.904 $\pm$ 1.082	0.901	7.420 $\pm$ 1.145	7.338 $\pm$ 1.069	0.432	2.295 $\pm$ 0.209	2.358 $\pm$ 0.332	0.016 ^a
N:Tm/periphery	4.177 $\pm$ 0.554	4.085 $\pm$ 0.482	0.060	4.177 $\pm$ 0.522	4.156 $\pm$ 0.490	0.660	3.858 $\pm$ 0.518	3.796 $\pm$ 0.526	0.212	1.145 $\pm$ 0.105	1.149 $\pm$ 0.153	0.726
N:Tm/HDA	0.154 $\pm$ 0.021	0.153 $\pm$ 0.019	0.632	0.165 $\pm$ 0.026	0.165 $\pm$ 0.024	0.900	0.138 $\pm$ 0.026	0.139 $\pm$ 0.027	0.663	0.015 $\pm$ 0.002	0.016 $\pm$ 0.003	<0.001 ^a
N:Nd/sq cm	0.049 $\pm$ 0.009	0.05 $\pm$ 0.008	0.112	0.051 $\pm$ 0.01	0.051 $\pm$ 0.008	0.534	0.041 $\pm$ 0.008	0.042 $\pm$ 0.010	0.251	0.005 $\pm$ 0.001	0.004 $\pm$ 0.001	<0.001 ^a
N:Nd/TSL	4.896 $\pm$ 0.584	5.046 $\pm$ 0.625	0.009 ^a	5.057 $\pm$ 0.704	5.019 $\pm$ 0.552	0.523	4.498 $\pm$ 0.613	4.528 $\pm$ 0.745	0.650	1.568 $\pm$ 0.127	1.344 $\pm$ 0.207	<0.001 ^a
N:Nd/periphery	2.694 $\pm$ 0.480	2.727 $\pm$ 0.468	0.454	2.707 $\pm$ 0.536	2.663 $\pm$ 0.424	0.331	2.364 $\pm$ 0.433	2.371 $\pm$ 0.530	0.868	0.784 $\pm$ 0.079	0.657 $\pm$ 0.112	<0.001 ^a
N:Nd/HDA	0.099 $\pm$ 0.016	0.102 $\pm$ 0.016	0.061	0.106 $\pm$ 0.019	0.105 $\pm$ 0.015	0.598	0.084 $\pm$ 0.017	0.086 $\pm$ 0.019	0.208	0.010 $\pm$ 0.001	0.009 $\pm$ 0.002	<0.001 ^a
N:Nd/N:Tm	0.649 $\pm$ 0.109	0.673 $\pm$ 0.122	0.029 ^a	0.654 $\pm$ 0.133	0.648 $\pm$ 0.118	0.575	0.620 $\pm$ 0.123	0.629 $\pm$ 0.134	0.465	0.685 $\pm$ 0.045	0.573 $\pm$ 0.065	<0.001 ^a
GLCM												
Contrast	0.226 $\pm$ 0.053	0.228 $\pm$ 0.053	0.759	0.211 $\pm$ 0.061	0.226 $\pm$ 0.062	0.009 ^a	0.228 $\pm$ 0.035	0.229 $\pm$ 0.034	0.768	0.043 $\pm$ 0.008	0.046 $\pm$ 0.010	<0.001 ^a
Correlation	0.944 $\pm$ 0.016	0.942 $\pm$ 0.017	0.395	0.946 $\pm$ 0.020	0.941 $\pm$ 0.019	0.002 ^a	0.944 $\pm$ 0.012	0.943 $\pm$ 0.012	0.784	0.992 $\pm$ 0.002	0.991 $\pm$ 0.002	0.082
Energy	0.104 $\pm$ 0.017	0.103 $\pm$ 0.014	0.705	0.110 $\pm$ 0.019	0.109 $\pm$ 0.022	0.670	0.104 $\pm$ 0.014	0.104 $\pm$ 0.012	0.882	0.141 $\pm$ 0.009	0.141 $\pm$ 0.011	0.799
Homogeneity	0.844 $\pm$ 0.032	0.844 $\pm$ 0.034	0.960	0.856 $\pm$ 0.039	0.847 $\pm$ 0.039	0.016 ^a	0.848 $\pm$ 0.023	0.849 $\pm$ 0.023	0.812	0.972 $\pm$ 0.005	0.971 $\pm$ 0.006	0.049 ^a

FD, fractal dimension; GLCM, gray level co-occurrence matrix. HDA, area of high-density region; N, number; Nd, Nodes; Periphery, the total number of pixels on the outer margin of the high-density region; sq, square; Tm, Termini; TSL, total length of struts.

^a*p* < 0.05

Normal

Osteoporosis

Figure 5 Original and skeletonized images show the pattern difference between normal and osteoporotic patients. The skeletonized images of osteoporotic patients show unorganized and porous structures than found in the normal group. All images were processed after 400% upsampling. (a) Original image; (b) skeletonized image.

Table 3 shows the performance of 3 feature sets using the decision tree and SVM by the 10-fold cross-validation method. For the individual features, the sensitivity, specificity, and accuracy of the strut variables in the endosteal margin were 97.1%, 95.7 and 96.2%

Table 3 Comparison of diagnostic values for decision tree and SVM by 10-fold cross validation in ROI 4

Classification methods	10-fold cross validation		
	Sensitivity (%)	Specificity (%)	Accuracy (%)
Decision tree			
FD	87.4	95.9	91.6
Strut	97.1	95.7	96.2
GLCM	10.0	97.4	53.9
All variable	94.6	97.8	96.0
SVM			
FD	89.5	95.5	92.3
Strut	97.2	97.1	96.9
GLCM	48.6	64.9	56.8
All variable	98.1	96.2	96.4

FD, fractal dimension; GLCM, gray level co-occurrence matrix; SVM, super vector machine.

using the decision tree and 97.2%, 97.1 and 96.9% using SVM; these were the best results obtained among the 3 methods that we evaluated. FD also showed high accuracy (91.6–92.3%), whereas GLCM showed low accuracy (53.9–56.8%). Combining the strut variables with FD and/or GLCM did not increase the accuracy.

Figure 6 shows the decision tree model using strut variables composed of 5 decision nodes containing, number of node per number of termini (N.Nd/N.Tm), total strut length per total area (TSL/total area) and N.Nd/TSL of the endosteal margin area, which exhibited an accuracy of 96.2% using 10-fold cross validation.

Discussion

Reduced bone mass of the jaw is a consequence of osteoporosis in the oral and maxillofacial region.^{25–27} For years, many studies have tried to detect this change in panoramic radiography included in routine dental care. In order to measure the bone quality of the jaws, Lekholm and Zarb proposed a classification (D1 to D4) according to the morphology and distribution of cortical and trabecular bones,²⁸ which was later classified

by computed tomography number. The inferior cortex has been mainly studied for osteoporosis detection using panoramic radiography via mandibular cortical width and the MCI.^{29,30} However, MCW did not show the ability to detect osteoporosis in some studies and the MCI has the limitation of lacking complete reproducibility, which is associated with visual assessments in general.⁷ This study tried to supplement this subjective aspect of the MCI by analysing objective features.

All ROIs of this study were chosen in the posterior mandible, because the anterior part may produce inaccurate results due to the overlapping cervical vertebrae. Additionally, the posterior region is less likely to be blurred than the anterior region because the focal trough is thicker and thus less affected by the patient's position.³¹ Panoramic radiography is not a standard projection technique, so ghost images and differences in the thickness of the object inside the focal trough can influence the gray value of the image and image processing result. We used density correction as a way of reducing these large-scale variations.¹⁴ However, severe variations could not be overcome by this process, and such variation could be a reason why few meaningful results were obtained in the medullary ROIs, which may have been influenced by the ghost images of the opposite ramus (ROI 1 and 2) and the thickness of the cortical layers (ROI 3), respectively.

Based on studies of the erosive changes of the mandibular endosteal margin in osteoporotic patients,^{29,30} the endosteal margin area (ROI 4) was newly defined to include both the inferior cortex and superior marrow area, unlike previous studies that analysed each region separately. This study found that almost all the strut features in this ROI showed statistically significant differences between osteoporotic and non-osteoporotic patients. FD has been reported to be useful in detecting osteoporosis in panoramic radiography,^{16,32} whereas

other studies have reported different results.^{11,33} FD showed the second highest result (91.6–92.3%) in this study, which was similar to the accuracy value of 91.2% reported by Kavitha *et al*.¹³ GLCM features showed the poorest performance in this study (53.9–56.8%) which was lower than the accuracy of 83.5% reported in the same previous study.¹³ However, their results are not directly comparable to ours due to differences in the ROI and the number of GLCM variables.

The decision tree and SVM of strut variables in ROI 4 showed the highest diagnostic accuracy (96.2 and 96.9%), which is slightly higher than the 93.0% accuracy reported in the recent study of Kavitha *et al*.¹³ This high diagnostic values show that the strut variables have strong potential for building a model for osteoporosis detection based on panoramic radiography. The decision tree model (Figure 6) showed that the node-terminus ratio decreased and the strut length increased in osteoporotic patients. In non-osteoporotic patients, there was a sharp margin separating the cortical and marrow area, each filled with multiple independent structures. On the contrary, the endosteal margin of osteoporotic patients underwent heavy formation of residue and holes, described by the C3 category of the MCI, which broke the integrity of the 2 areas down into unorganized and porous structures (Figure 5). This osteoporotic change was well captured in the strut analysis as a relative increase in strut length and a decrease in the node-terminus ratio.

The high diagnostic accuracy of strut features in the endosteal margin area can be explained by several factors. First, we compared two distinct groups, without including patients with osteopenia. It may have been difficult to find significant variables if the ambiguous features of osteopenia had been included. Second, the endosteal margin area was located at the bottom of the mandible and was not affected by ghost images.

Figure 6 Decision tree algorithm identifying osteoporotic and normal patients. The decision tree was composed of N.Nd/N.Tm, TSL/total area and N.Nd/TSL of the endosteal margin area, and exhibited an accuracy of 96.2% for screening osteoporosis. Classification results were represented using boxes and the wrong results were coloured with gray. N, number; Tm, termini; Nd, nodes; TSL, total length of struts.

Third, a larger sample size than previous studies may have contributed to a high accuracy, from a statistical perspective.

Image upsampling for optimal density correction may have been another reason for the high accuracy. Blurring, which is usually set by the sigma of the Gaussian filter, is required to remove large-scale variations (low-frequency noise), such as overlapping soft tissue. The kernel size increases as the sigma increases. We found that a sigma value of 35 blurred the original image too much and resulted in unseparated clusters. Because (1) fine-tuning the binarization using the original image was not possible by decreasing the sigma owing to the low pixel resolution and 2) even the smallest 3×3 filter already covered substantial amounts of the original images (29 pixels $\times$ 29 pixels in the square ROI), we enlarged the image for reducing image blur and fine application of the filter. The sigma and the kernel size of the Gaussian filter were fixed at 35 and 33, respectively, which have been used by most papers, for comparison. Image enlargement without interpolation decreases the spatial resolution, which limits the effective sigma size. Interpolation enables fine-tuning of the sigma and binarization results by increasing the spatial resolution of the enlarged image. In addition, we considered popular interpolation and blurring methods for optimal binarization. Bicubic interpolation was adopted because the accuracy of the bilinear and nearest-neighbor methods was limited and may be inadequate for interpolating high frequencies within the image.³⁴ We used the Gaussian filter for extracting low-frequency noise because the median and average filter allowed a great deal of high frequencies.³⁵

The major limitation of this study is that patients with osteopenia were not included. Therefore, a big data study including osteopenia is needed to verify our model for clinical purposes. Furthermore, exploring the endosteal margin area in cone-beam computed tomography images with a three-dimensional version of our index would also be an interesting project.

Conclusion

This study demonstrated that the endosteal margin area was an effective ROI that showed statistically significant differences in FD, GLCM and strut variables between osteoporotic and non-osteoporotic patients, whereas the medullary portions of panoramic radiography showed few distinguishing features. We also found that the strut variables showed the highest sensitivity, specificity and accuracy using the decision tree and SVM. Our findings suggest that the strut method in the endosteal margin area has strong potential for the development of an osteoporosis detection model based on panoramic radiography.

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