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How Osteoporosis Looks Like in CT Scan Images: An Alternative Osteoporosis Assessment

Maya Genisa[1]*, Johari Yap Abdullah[2], Bazli Bin MD Yusoff[2], Aryenti[3], Juniarti[4]

[1] Department of Biomedical Sciences, School of Postgraduate Studies, YARSI University, Jakarta, Indonesia
[2] School of Dental, Universiti Sains Malaysia (USM), Kota Bharu, Malaysia
[3] Faculty of Medicine, YARSI University, Jakarta, Indonesia
[4] YARSI University, Jakarta, Indonesia

Corresponding Author Email: maya.genisa@yarsi.ac.id

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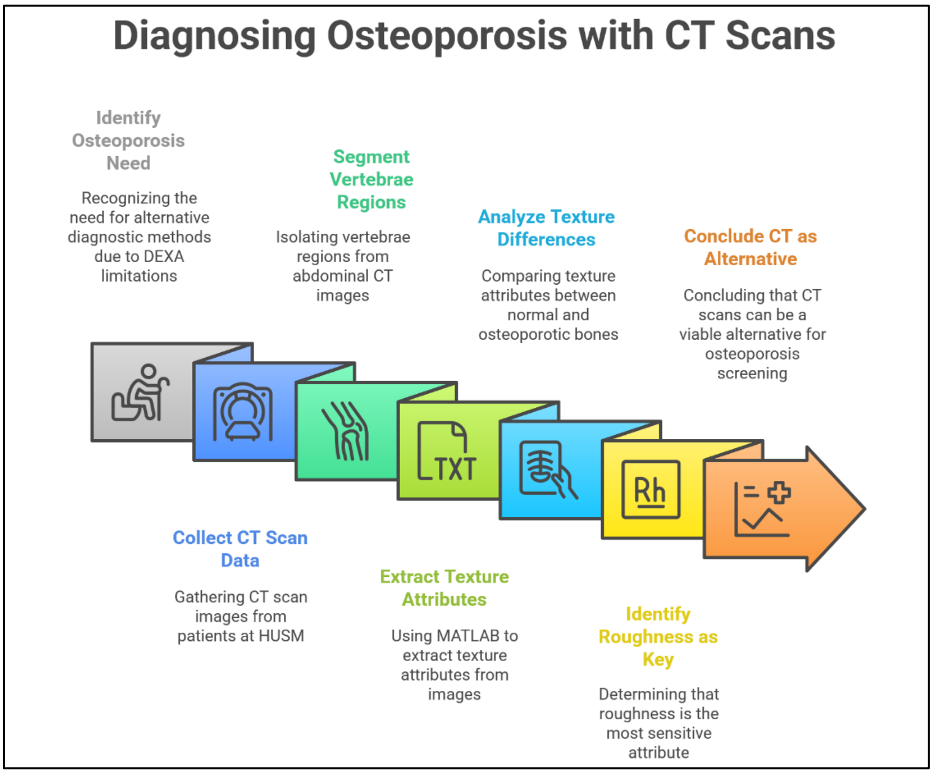
ABSTRACT

Osteoporosis is a silent degenerative disease that commonly affects the elderly, leading to decreased bone density and increased risk of fractures. Dual-Energy X-ray Absorptiometry (DEXA) is the standard tool for assessing Bone Mineral Density (BMD), but its limited availability and high cost in many healthcare facilities, especially in developing countries like Indonesia, necessitate alternative diagnostic methods. This study aims to assess the potential use of Computed Tomography (CT) scan images as a substitute for DEXA in detecting osteoporosis. The objective is to analyze bone texture attributes from CT images to differentiate between normal and osteoporotic bone structures. The method involved collecting CT scan data from patients at Hospital Universiti Sains Malaysia (HUSM). The vertebrae regions were segmented from the abdominal CT images using image processing techniques to isolate bone tissue. Four image-derived texture attributes—Roughness, Contrast, Greyscale, and Phase—were then extracted using MATLAB-based analysis. The results showed that osteoporotic bones had higher values in Roughness and Contrast, and lower values in Greyscale and Phase compared to normal bones. Among these, Roughness was identified as the most sensitive attribute in detecting changes associated with osteoporosis. These findings indicate that CT scan images, when analyzed through proper segmentation and texture evaluation, have the potential to serve as a viable alternative for osteoporosis screening, particularly in settings where DEXA is unavailable.

Key Messages:

- Computed Tomography (CT)-based textural analysis emerges as a viable and accessible alternative to the gold-standard DEXA for opportunistic osteoporosis screening, addressing the critical issue of limited availability and high cost of DEXA scanners in many healthcare environments.
- Osteoporotic bone can be quantitatively differentiated from healthy bone on CT images through specific textural attributes, with increased 'Roughness' and 'Contrast' and decreased 'Greyscale' and 'Phase' values serving as key indicators; 'Roughness' was identified as the most sensitive attribute for detecting degenerative bone changes

GRAPHICAL ABSTRACT



INTRODUCTION

Indonesia currently is preparing a strategy to face the conditions aging population. Where one of the consequences is the proportional elderly population in Indonesia is increasing over time. Statistical data shows that there has been an increase elderly population from 4.5% in 1971 to 10.7% in 2020 and is projected to increasing to 19.9% in 2045 (1). Apart from that, the increment of elderly population will also become a second demographic bonus, where the productive age will increase but on the other hand, it demands adequate support facilities for the elderly, including health services. One of the main problems in the health of the elderly is degenerative disease like decreasing of their bone quality and quantity which is referred as osteoporosis.

Osteoporosis is a degenerative disease of the bones caused by decreased bone quality and density and it is found mainly in elderly (2). With reduced bone quality and density in cases of osteoporosis, bones will become more fragile and have a higher risk of fracture. Bone fracture cases, some of them have fatal consequences such as paralysis and or even death following severe complications. Osteoporosis is usually detected based on examination of DEXA (Dual-Energy X-Ray Absorptiometry) for evaluation of BMD (3). Unfortunately, the availability of DEXA is scarce in hospitals or clinics in Indonesia, with operational cost relatively expensive. There is a need to develop an alternative technique that is cheaper and has many facilities available both in clinics and hospitals. This is important to anticipate the high prevalence of the disease in Indonesia. Osteoporosis or bone loss is a degenerative disease that is categorized as a silent disease that can affect anyone and it is especially common in older people aged between 50-80 years. The level of risk of people with osteoporosis in Indonesia is quite high, namely one out of every 4 women in Indonesia has a risk of osteoporosis in that age range (4), and the risk level for women is 4 times higher than the risk for men in the same age range. Osteoporosis is characterized by a decrease in bone density due to a decrease in the mineral content in the bones accompanied by a decrease in bone strength, where this situation triggers a high risk of bones becoming easily broken (5).

The diagnosis of osteoporosis is usually carried out by measuring the patient's BMD (Bone Mineral Density) obtained from DEXA/DXA. The screening of BMD is important to obtain an early diagnosis and to avoid fractures (6).

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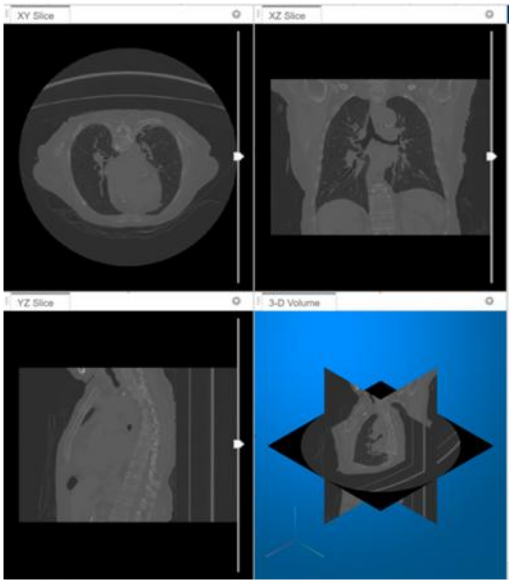
There is other possibility of using other radiological modalities/alternatives other than DEXA to diagnose osteoporosis. One of the potentials is the use of CT-scan modality as an alternative technology that can be used as a tool to diagnose osteoporosis (7). The opportunistic screening for evaluation of BMD based on CT scan is feasible but still need to be integrated with clinical assessment and validation (8). CT- scan images with Hounsfield Unit(HU) less than 160 can be used as indicator of osteoporosis (9). The potential of using imaging technique based on CT scan image has been tested by Genisa et.al (10). In their experiment, they generate some images attribute derived directly from CT-Scan data.

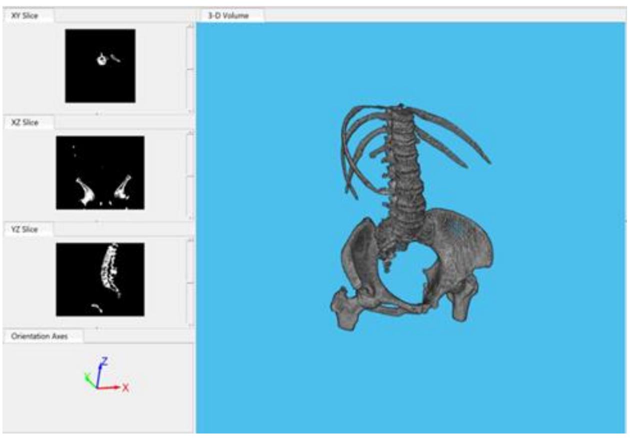
This study aims to evaluate the feasibility of using CT scan images as an alternative method for osteoporosis assessment by identifying and comparing image-derived attributes from segmented bone structures in normal and osteoporotic conditions.

METHODS

Data selection has been performed to collect the CT scan images that consist of normal and osteoporosis patients from Hospital Universiti Sains Malaysia (HUSM). Data in DICOM were processed for segmentation. Segmentation was performed to get the targeted bone by removing all other tissues. Thresholds and manual segmentation were conducted during the segmentation process. Figure 1 shows the original and segmented bone from CT scan image to keep only the bone part.



(a)



(b)

Figure 1. Example of CT-Scan Images (a), and Its Segmented Bone Part Only (b)

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Pelvic bone is the one of the highest risk of fracture when people have an osteoporosis. The fracture can be triggered by just falling from a standing position or daily activities. Pelvic bone has high fragility hence need to be more careful from the accident that can trigger the fracture (11). The fracture of pelvic is painful especially when patient is moving or walking. The incidence of pelvic fracture is quite high and need long term clinical treatment (12).

The evaluation of targeted bone was specific to the pelvic and lower back (lumbar spine) bone. Various images attribute was generated on the selected area for the evaluation. Those image attributes were: Root Mean Square (RMS), Roughness, Contrast, and Phase attributes. The quantification of the strength of each attribute were calculated by summation of the attributes normalized by number of pixels on the selected area of interest.

$$Attribute\ Index = \frac{1}{N}\sum_{i=1}^{N} A_i \qquad (1)$$

Where the N is number of pixel and Ai is the attribute value on each pixel inside the area of interest.

Greyscale attribute or RMS attribute is the square root of total square of HU on each pixel inside the region of interest (ROI) as expressed in equation (2).

$$RMS\ Attribute = \sqrt{\frac{1}{N}\sum_{i=1}^{N} HU_i^2} \qquad (2)$$

Where HU is the greyscale or HU value of the pixel and N is the number of pixels inside the ROI.

Roughness attributes is defined as a subtraction of the HU value of each pixel with their mean value in the ROI. The formula for the calculation is shown in equation (3).

$$RI = HU_i - \frac{1}{N}\sum_{i=1}^{N} HU_i \qquad (3)$$

Where HUi is the HU value of each pixel and N is number of pixels inside the ROI.

Contrast attribute is calculated as first derivative of the envelope of rate changes of HU spatially. This attribute showed the strength of the X-ray energy absorption on each pixel. The formula for the Contrast attribute is expressed in equation (4).

$$Contrast\ Attribute = \left[\frac{\sum_{k=-K}^{+K}\left(\left[\frac{\partial HU_{jk}}{\partial x}\right]^2 + \left[\frac{\partial HU_{jk}}{\partial y}\right]^2\right)}{\sum_{k=-K}^{+K}\sum_{j=1}^{j} HU_{jk}^2}\right]^{1/2} \qquad (4)$$

Where the HU is the value of greyscale (HU) on each pixel, x and y is the position of the pixel in two-dimension (2D) images.

Phase attributes is calculated by transforming the image into complex image through Hilbert transform function. In complex form, each pixel will have a real and imaginary part of HU value. The Phase attribute is taken from arcus tangent of real and imaginary part ratio as expressed in equation (5).

$$Phase\ Attribute = arc\ Tan\left(\frac{H\{hu(x,y)\}}{hu(x,y)}\right) \qquad (5)$$

Where the H is Hilbert transform and hu is the HU value on each pixels inside ROI, and x and y are spatial coordinate of the pixel. The strength of each attribute is indicated by the Index value calculated by equation (1).

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RESULTS

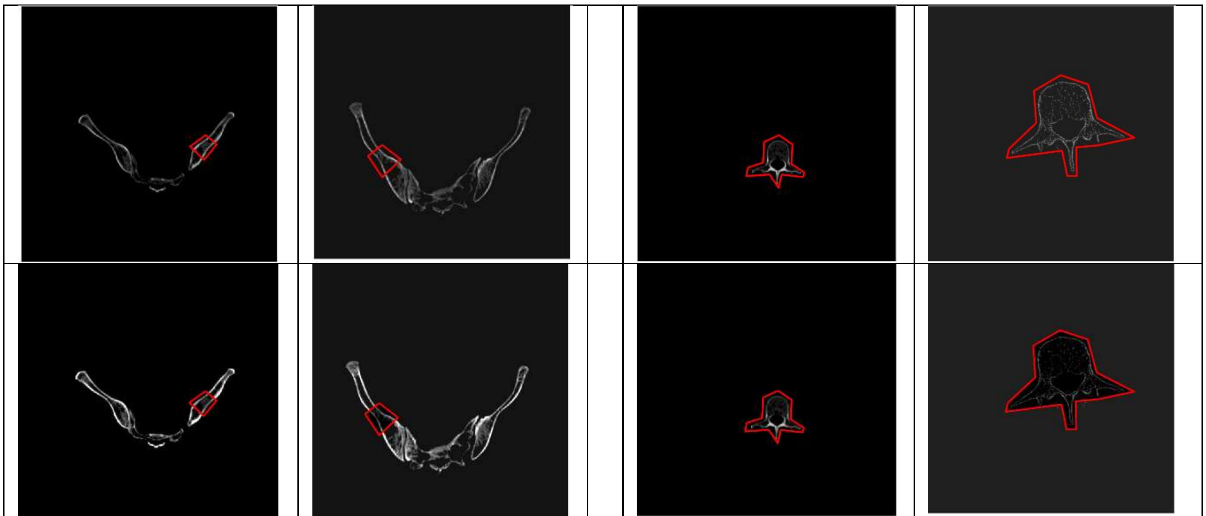
Four image attributes have been tested on the data sets consist of normal and osteoporosis bone on the pelvic and lumbar spine bone. The categories of normal and osteoporosis bone is determined by a specialist in HUSM. The ROI was signed by the redline on each figure as the area of the assessment.

Quantitative Comparison

The quantitative comparison is conducted to see the difference on the applied attributes between normal and osteoporosis bone conditions. The differences are referring to the attribute index generated on each attributes. The index is normalized to the scale from 1 to 100.

1. RMS or Greyscale Attribute

RMS or Greyscale attributes are calculated by equation (2) and the strength of this attribute indicate by the Index number calculated by equation (1). The RMS attribute and its index number applied on the pelvic and lumbar spine are shown in Figure 2. RMS attributes indicate the average of the HU inside the ROI. There is a relationship between BMD and HU of CT scan image, a high bone density (BMD) is correlated with high HU in CT scan images and vice versa (13). However, the linearity between bone density and HU is still doubted (14). As shown in Figure 2, the normal bone either in pelvic or lumbar spine gives a higher RMS index compared to osteoporosis bone. Application of this attribute can be applied by selecting the suspected area. However, the threshold of the RMS Index as indication of normal or osteoporosis still need further testing on more data before can applied as a clinical diagnosis. Once the solid testing on various data samples, possible to determine the RMS number as a threshold to identify either the bone in normal condition or osteoporosis. In term of visualization, there are no more significant difference between original image and RMS attribute. There is not much different between osteoporosis and normal bone.



RMS Index=52	*RMS Index=48*	*RMS Index=74*	*RMS Index=26*

Figure 2. Comparison Between Original CT Scan (Upper) And RMS Attribute (Lower) At Condition From Left To The Right: Normal Pelvic Bone, Osteoporosis Pelvic Bone, Normal Lumbar Spine Bone, And Osteoporosis Lumbar Spine.

2. Roughness Attribute

The concept of roughness attribute is coming from the surface where if medium is smooth the roughness will be less. However, the roughness attribute is based on the density variation read from HU of CT image. If bone has homogenous density everywhere then in term of density, bone become smooth. If bone has a high-density variation, the value of HU will roughly change or the roughness will be high. Example of the roughness concept on the CT scan images is shown in Figure 3. Normal bone looks smoother/solid compared to osteoporosis bone.

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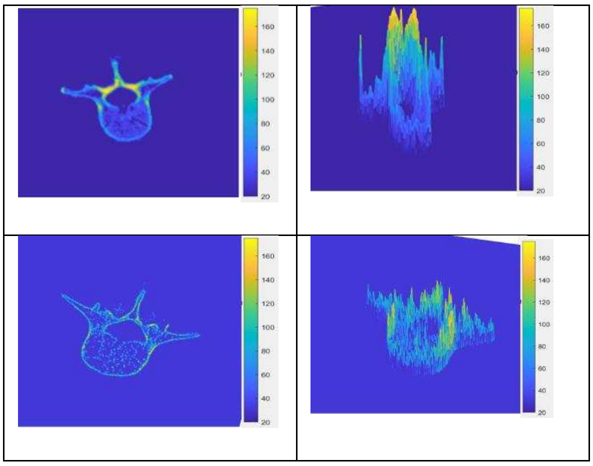

Figure 3. HU of Lumbar Spine Plotted In Coloured 3D View With Different Angle View: Normal Bone (Upper), And Osteoporosis Bone (Lower).

Application of roughness attribute on data set consists of normal and osteoporosis bone are shown in Figure 4. There is consistency of roughness attribute from normal to osteoporosis bone conditions either in pelvic or lower spine bone. The roughness index is lower in normal bone and higher in osteoporosis bone. The index number also shows a significant different from normal to osteoporosis condition.

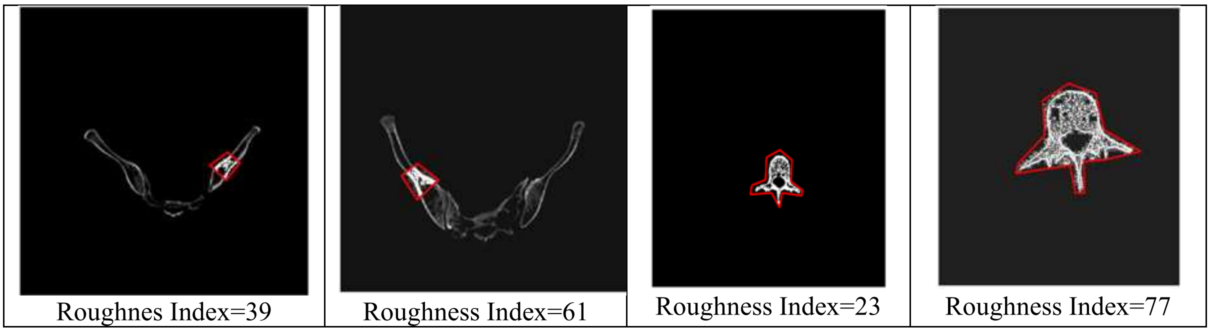

Figure 4. Roughness Attribute And Its Index Of A) Normal Pelvic Bone, B) Osteoporosis Pelvic Bone, (C) Normal Lower Spine Bone, And (D) Osteoporosis Lower Spine Bone.

3. Contrast Attribute

The contrast attribute shows how the strength of HU changes from one to another pixel. If there is a significant HU difference between adjacent pixel, the contrast will be high. It is expected that if bone has homogenous density, HU value will be more constant. It means that the contrast index on the normal bone is expected to have lower value compared to osteoporosis one. The application of this attribute on the pelvic and lower spine bone for normal and osteoporosis conditions is shown in Figure 5. Also, there is consistency of the Contrast Index from normal to osteoporosis conditions. In the normal bone, the Contrast Indexes are lower compared to osteoporosis conditions, either in pelvic or lower spine bone. However, the difference between normal and osteoporosis is not high as roughness attribute.

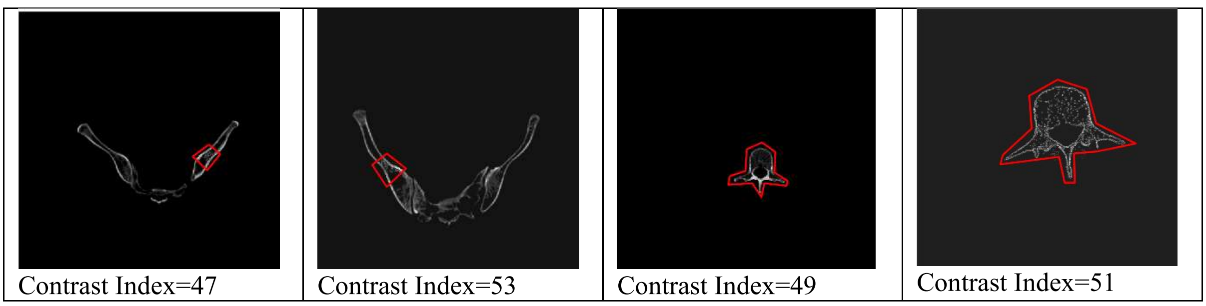

Figure 5. Contrast Attribute And Its Index At: A) Normal Pelvic Bone, (B) Osteoporosis Pelvic Bone, (C) Normal Lower Spine Bone, And (D) Osteoporosis Lower Spine Bone.

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4. Phase Attribute

In time series case, the phase attribute is related to the structure of material, the number of layering can be recognized easily through this attribute. In other word, it is assumed that if the material structure is denser, the phase index of this material will be higher. Normal bone has a denser structure compared to osteoporosis as illustrated in Figure 6 (15). In that model, the normal bone model has ticker bone material compared to osteoporosis model. Phase attribute applied on that model and the result is shown in Figure 6 (b) for both normal and osteoporosis model. The Phase Index shows that the normal bone model has higher value compared to osteoporosis bone model.

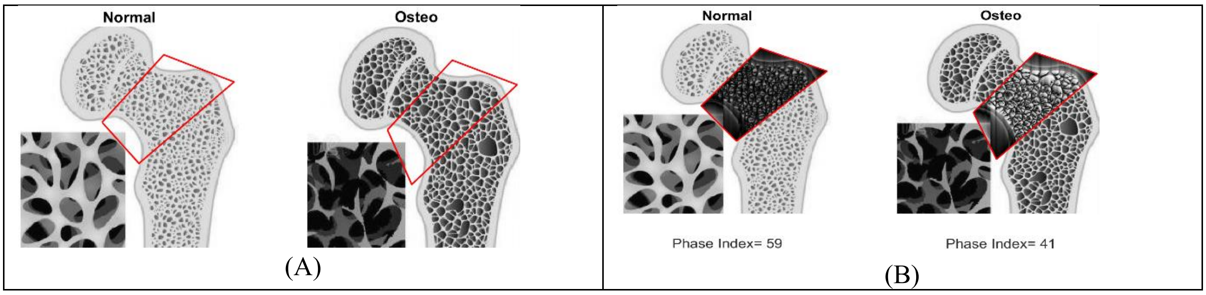

Figure 6. Phase Attribute on Bone Model. (A) Original Image Bone Model, and (B) Phase Attribute and Its Index for Normal and Osteoporosis Bone.

Implementation of phase attribute on CT scan image are provided in Figure 7. As expected of the model, the Phase attribute has a higher value in normal bone compared to osteoporosis bone, either in the pelvic or lumbar spine. The value of Phase Indexes is quite significant difference between normal and osteoporosis bone.

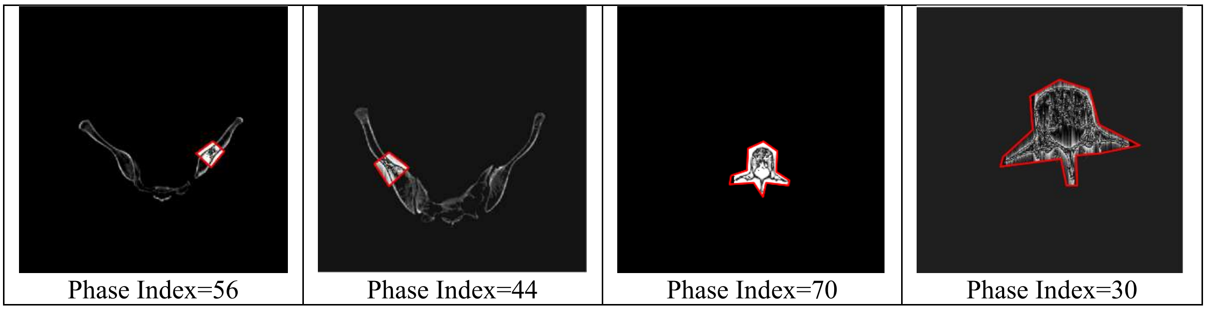

Figure 7. Phase Attribute from Left to The Right: Normal Pelvic, Osteoporosis Pelvic, Normal Lumbar Spine, and Osteoporosis Lumbar Spine Bone and Its Phase Index

The summary of the bone characteristic on the different attributes are shown in Table 1.

Table 1. Summary Of Attribute Characteristic

Attribute Index	Bone Type	Normal	Osteoporosis	Difference	Relative Change (%)
RMS	Pelvic	52	48	4	7.69
	Lumbar Spine	74	26	48	64.86
Roughness	Pelvic	39	61	-22	-56.41
	Lumbar Spine	23	77	-54	-234.78
Contrast	Pelvic	47	53	-6	-12.77
	Lumbar Spine	49	51	-2	-4.08
Phase	Pelvic	56	44	12	21.43
	Lumbar Spine	70	30	40	57.14

Table 1 show that there are two groups of attributes: increase from normal to osteoporosis and decrease from normal to osteoporosis. Roughness and Contrast indicate the attribute index decrease from

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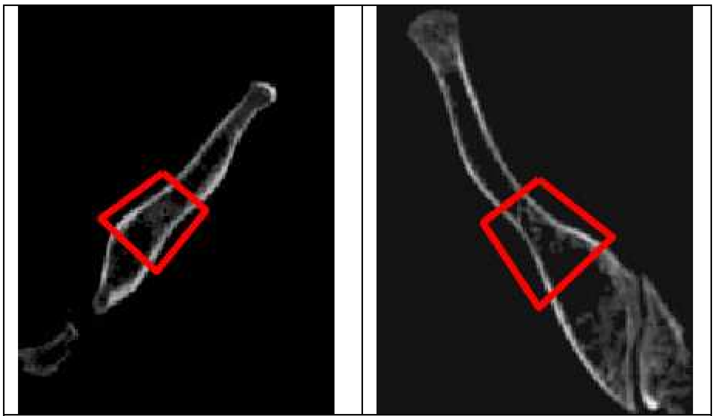
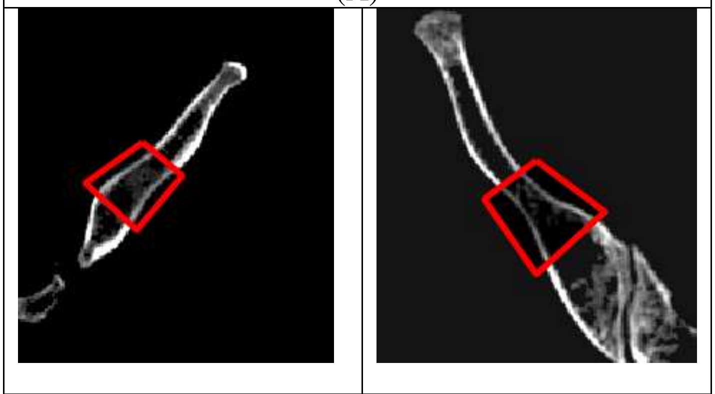
normal to osteoporosis. While Grayscale and Phase attribute are increasing from normal to osteoporosis conditions. Roughness attribute is strongest attribute follow by Phase, RMS, and Contrast.

Visualization Comparison

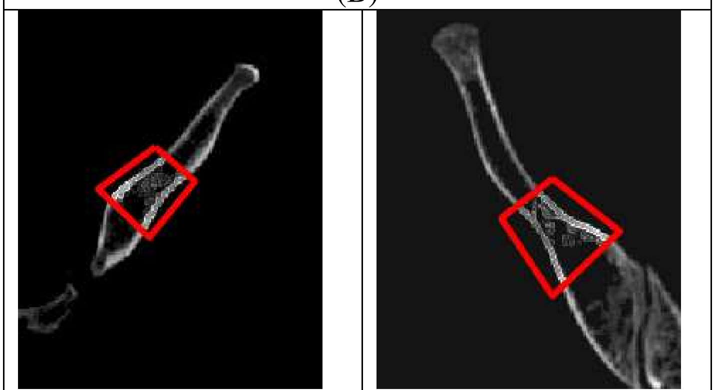
Visualization can help as a quick look indication on the characteristic of bone. To compare the visualization of each attribute, Figure 8 shows the original CT scan compared to each attribute on pelvic bone for normal and osteoporosis condition.



(A)



(B)



(C)

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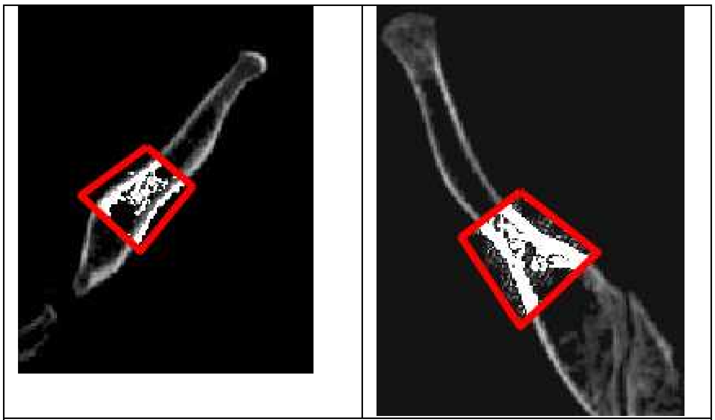
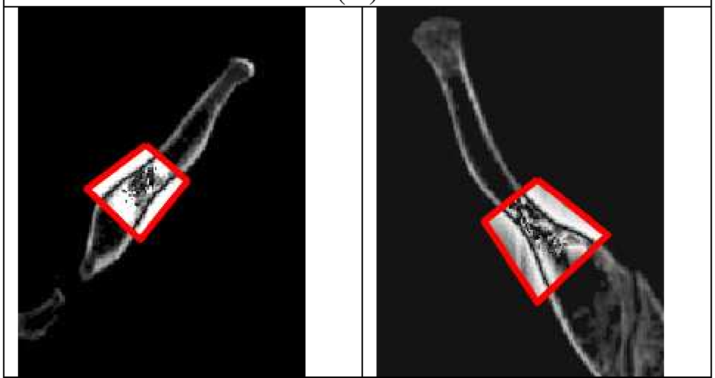


(D)



(f)

Figure 8. Different Visualization of Each Attribute on Pelvic Bone for Normal (Left) and Osteoporosis Bone (Right). (A) Original CT-Image, (B) RMS, (C) Contrast, (D) Roughness, and (E) Phase Attribute.

Roughness and Phase attribute has quite significant changes in terms of visualization compared to the original CT-scan image. It is possible for both attributes become a candidate for a quick look diagnostic of osteoporosis visually. The different between normal and osteoporosis bone conditions is also quite significant different.

DISCUSSION

This study highlights the potential use of CT-scan images as an alternative in assessing bone quality to detect osteoporosis, especially through the analysis of image attributes such as roughness, phase, grayscale, and contrast. The results of the analysis show that the roughness and contrast values are higher in bones of osteoporosis patients compared to normal bones, while the phase and grayscale values tend to be lower. Among the four attributes, roughness appears to be the most sensitive in distinguishing bone conditions. This difference is not only seen quantitatively but also visually in CT-scan segmentation images. These findings indicate that texture analysis in CT images can provide an initial picture of the patient's bone condition, so it can be an initial alternative before DEXA examination is performed.

These findings are in line with the research of Zou et al. (2019), which showed that the Hounsfield Unit (HU) value from CT-scans can be used to identify undiagnosed spinal osteoporosis in patients with lumbar degenerative diseases. However, the approach in this study emphasizes texture analysis rather than relying solely on HU values, providing an additional dimension in the evaluation of bone quality (17).

Furthermore, a study by Lee et al. (2019) showed that texture analysis on head CT images can differentiate between patients with normal bone mineral density and those with osteoporosis. This supports the approach of this study using texture analysis to assess bone quality, expanding the application of this method to various types of CT images (18).

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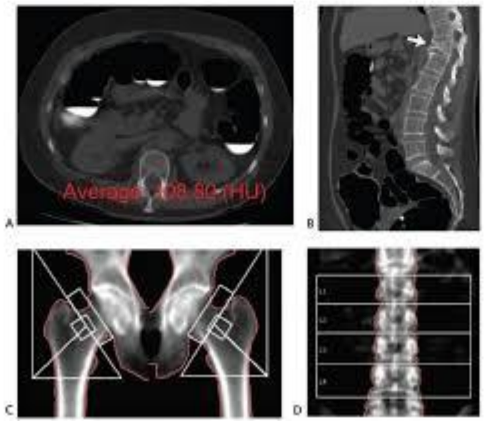

Figure 9. Osteoporosis Detection Based on CT Scan Analysis, (Source: (16))

Figure 10. Texture Analysis from Abdominal CT for Opportunistic Screening, (Source: (17)

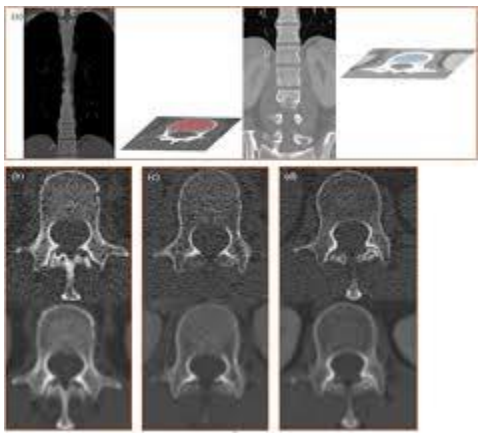

Figure 11. CT Bone Density Assessment with Texture Features, (Source: (18)

In addition, a study by Kim et al. (2023) revealed that morphometric texture analysis using CT Hounsfield Units can be used for indirect osteoporosis screening, offering reliable estimates of Bone Mineral Density (BMD) and Bone Mineral Content (BMC). This approach strengthens the findings of this study that texture analysis on CT images can be an effective tool in early detection of osteoporosis (16).

Thus, this study provides an important contribution to the development of non-invasive methods for osteoporosis detection, especially in areas with limited access to DEXA devices. Texture analysis on CT images may be a promising alternative for osteoporosis screening, allowing for earlier detection and faster intervention. However, further studies with larger data sets and more diverse populations are needed to improve the accuracy and reliability of this method

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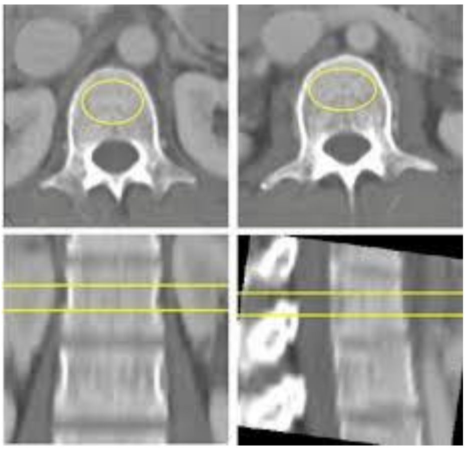

Figure 12. Opportunistic Osteoporosis Screening with Routine CT, (Source: (16,18)

CONCLUSION

Four attributes namely RMS/Greyscale, Contrast, Roughness, and Phase attribute which are derived from imaging technique have been tested to differentiate normal and osteoporosis bone on pelvic and lumbar spine bone. The strength of each attribute is indicated as attribute Index which is normalized by number of pixels inside the ROI. Roughness and Contrast attribute has trend to become lowered on osteoporosis compared to normal, while Phase and Greyscale attribute tend to increase from normal to osteoporosis conditions. Quantitatively, the most sensitive attributes to indicate osteoporosis is Roughness follow by Phase, Greyscale, and Contrast attributes. While in term of visualization the most significant attributes are Roughness and Phase attribute. However, further testing on various bone conditions and different type of bone needs to be conducted before it is become an indicator of osteoporosis based on CT-scan images.

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CONFLICTS OF INTEREST

Declare conflicts of interest or state "The authors declare no conflict of interest."

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