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An Extensive survey of DEXA Scan Image Processing using deep learning techniques for Postmenopausal osteoporosis detection

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Abstract:

Bone mineral density (BMD) loss causes osteoporosis, a disease that affects the bones of adults but is most prevalent in postmenopausal women. While X-rays and dual energy X-ray absorptiometry (DEXA) images can both measure bone mineral density (BMD), the focus of this article is on a survey of the use of DEXA images for the diagnosis of osteoporosis in women past menopause. In this study, we take a look at the many methods used to diagnose osteoporosis. Limitations of deep learning for osteoporosis diagnosis in postmenopausal women, including the requirement for big datasets, interpretability of the models, and potential biases in the data, are also highlighted, along with the many approaches applied in BMD. Each set of results is followed by a discussion of their limitations which leads as a suggestion for future study.

1. Introduction:

Osteoporosis, from the Greek for "porous bone," is a condition characterised by bone fragility and weakness. The percentage of inorganic minerals present in bone, known as bone mineral density (BMD), is an indicator of the bone's porous character. Both men and women are equally at risk of fracture from osteoporosis. But it's more noticeable to female eyes than male. There are several methods for calculating BMD and diagnosing osteoporosis. Current imaging methods for determining BMD include testing x-ray [1], measurable ultrasound, Compton scattering, quantitative computed tomography [2], single energy x-ray absorptiometry, high resolution peripheral quantitative computed tomography [6], magnetic resonance imaging [5], dual energy x-ray Absorptiometry [3], neutron activation, peripheral quantitative computed tomography, and radiographic absorptiometry. DXA is the most accurate and reliable method for assessing BMD, but it is also the most expensive one. Though it is expensive, DEXA is used because it has lower radiation dose than CT scan [4]. There are several manufacturers of DEXA equipment.

By identifying osteoporosis early, fractures can be prevented. In the preliminary stages, image processing methods are employed to assess BMD. Some of the steps in conditioning an image are pre-processing, segmentation, and measuring bone mineral density (BMD). With the advent of deep learning algorithms, disease detection has improved greatly over traditional approaches; yet, accurate disease diagnosis still relies heavily on ROI segmentation. In order to improve the precision of BMD calculations, it is necessary to provide reliable, automated segmentation methods for isolating bone areas.

Osteoporosis risk factors in postmenopausal women:

- **Fractures [7]:** Previous Fracture of Fragility
- **Descendant Tree [8]:** Peak bone mass is most affected by genetics; a family history of fracture can quadruple an individual's own risk of fracture.
- **Routines of the body [9]:** Body mass index (BMI) less than 20, recent weight reduction of 4.5 kilogrammes, kyphosis.
- **Hormones [10]:** premenstrual syndrome, early menopause, and other causes of hypoestrogenism (low oestrogen levels) in women younger than 45.
- **Personal factors [11]:** Smoking cigarettes, eating poorly, drinking excessively (three or more drinks per day), and not getting enough exercise are all risk factors for ill health.
- **Fall hazards include [12]:** Poor illumination, unsecured rugs, blurry vision, orthostatic hypotension, weak muscles, and unsteady footing are all potential causes of falls.

2. Related work:

2.1. Deep Neural Network models in assisting postmenopausal osteoporosis:

Digital image processing techniques are applied by S.M. Nazia Fathima et al. [1] to analyse X-ray data for bone mineral density (BMD) measurement. For this study, we are thinking of using an X-Ray picture database that includes the spine, clavicle bones, hip, and knee. In order to improve the quality of the final image, a shock filter is used during preprocessing. The Peak Signal to Noise Ratio (PSNR) is utilised to investigate the results of picture noise. Segmentation techniques such as Active Contour and Mean Shift classification can be utilised to derive BMD. Osteoporosis detection is examined by contrasting the results of analyses performed on raw and segmented images. T and Z scores will be determined using established methods of excellence. Positive findings from testing the suggested method on 78 individuals have been reported.

Pixel Label Decision Tree (PLDT) is a technique used by Dildar Hussain et al. [2]. To uncover latent patterns in DXA pictures and zero down on the best feature set for the model, PLDT generates seven new feature maps by combining specific high energy (HE) and low energy (LE) X-ray characteristics. The effectiveness of PLDT in femur segmentation is evaluated with the use of image segmentation techniques such as Global Threshold, Region Growing Threshold, and artificial neural networks. In comparison to Global Threshold (66.40%), Region Growing Threshold (76.4%), and artificial neural networks (84.40%), PLDT's results for femur segmentation in DXA imaging are good (91.40%).

T Hegemann et al. [3] developed the support vector machine 60 (SVM), a machine learning approach for classification, to detect osteoporosis from X-ray pictures. In addition, the training set was partitioned into distinct classes using the simulated annealing method 61, and the optimal number of features was selected.

A novel metric for analysing BMD using DXA pictures is presented by Li Chen et al. [4]. This study developed a unique approach to deriving a scalar value from DXA images, which may be used to demonstrate the interconnectedness of bone mineral constituents. This method computes T and Z values in addition to assessing bone quality on the basis of mean bone density intensity. The -measure is a proposed new metric that may be used to assess the strength of the connections between bone components in novel ways. T and Z scores, respectively, are used to create standard values and can be represented as and. Combining this technique with the -connected maximum entropy method yielded promising segmentation outcomes. According to the data and results of the trials, the -measure should fall between 0.96 and 0.97.

Active shape model (ASM) is used for segmentation by J. Wu et al. [5]. Landmark points from an active shape model are utilised to define an object's profile. Each of these "landmarks" designates a specific location on a human body. The final location of an object can be determined by combining the coordinates of many landmarks. Using the statistical metric Mahalanobis distance (MD), active shape models pair landmarks from a sample model with a set of pixels from a test picture. Objects' fake edges can be linked to by ASM on occasion. Determining MD might be difficult when the covariance matrix of the ASM model is sparse. Due to variations in bone structure, particularly in patients with bone spurs, the ASM model's assumption that appearance spaces are Gaussian was incorrect.

Artificial neural networks (ANNs), Bayesian networks (BNs), Support vector machines (SVMs), and Convolutional neural networks (CNNs), Decision trees (DTs) are just some of the methods that have been extensively utilised in medical research for the creation and refinement of predictive models, leading to precise and efficient decision making. A sufficient amount of validation is required before Deep Learning approaches can be included in regular clinical practise, however it is clear that their usage can increase the comprehension of Osteoporosis diagnosis.

Imaging approaches for osteoporosis diagnosis and fracture risk estimation have advanced rapidly in recent years, as Michel Kocher [6] has highlighted. The author has also discussed the use of segmentation techniques to isolate the area of interest, as well as texture analysis techniques for distinguishing between osteoporotic and healthy individuals. Current diagnostic tool limitations have also been investigated, and workable alternatives are presented.

Biomechanical parameters of importance in the context of osteoporosis have been estimated non-invasively using physics-based models using finite element analysis (FEA), as explained by Costin Florian Ciudel [7]. However, the high computational demands of these models prevent them from being widely used in clinical practice. As an alternative to physics-based methods, this research explores the use of a deep learning model based on a convolutional neural network (CNN) to forecast average strain. Target values are calculated using the physics-based FEA model, and the model is trained using a huge library of synthetically created cancellous bone anatomy. On a separate test data set, the developed model's predictions were compared with physics-based computations to evaluate its efficacy. The results of the Bland Altman analysis showed no consistent bias between the predictions made using deep learning and those made using only physics (r = 0.895, p 0.001). Compared to the previously-introduced Support Vector Machine (SVM) model, which used manually-created features, the CNN model achieved higher accuracy and precision. The average execution time was lowered by almost a factor of a thousand compared to the physics-based calculation, allowing for an evaluation of average strain to be made in real time.

Although visual screening with Computed Radiography (CR) images has been discussed as a successful approach for osteoporosis by Kazuhiro Hatano [8], there are many similar diseases exhibiting a state of low bone mass. In this study, we present an automated osteoporosis detection approach using CR pictures of the phalanges. The suggested technique uses a Deep Convolutional Neural Network (DCNN) classifier to determine whether or not an unlabeled CR picture is healthy. We employ pseudocolor pictures for both CNN training and evaluation.

The introduction of an RBF kernel-SVM, as reported by MS Kavitha [9], demonstrated that the CAD system was successful at accurately detecting women with low BMD. In order to classify postmenopausal women with low BMD using dental panoramic radiographs, the author suggests utilising the SVM algorithm due to its speed and specificity. The suggested approach is anticipated to be a useful tool for identifying women with low BMD and to give a second diagnostic that may prevent misdiagnoses based on extremely satisfying sensitivity and specificity results.

Based on pictures osteoporosis diagnosis approach employing dental panoramic radiography data was proposed by Peng Chu [10]. In this approach, numerous ROIs are pooled together using a two-stage categorization model, the first of which is a linear support vector machine (SVM) model built with regard to a grouped region and provided feature. The new SVM model is integrated with the probability results from the previous SVM models. Based on the experimental data, it can be concluded that the suggested strategy using the HOG feature yields a 72.50% accuracy at a very small p-value of 0.0164. The author finds that the use of panoramic radiography pictures in conjunction with image feature analysis and machine learning approaches has the potential to identify osteoporosis.

Ref no.	Model	Result	Limitations
[13]	Active Contour, Mean Shift	Bone mineral density (BMD) is assessed by analysing X-ray images using digital image processing methods. The proposed approach has been tested, with promising results, on 78 participants.	Bone mineral density (BMD) measurements obtained by X-ray are all that will be analysed in this investigation. Only 78 people have been used for testing. Images with irregular bone structures, such as those found in patients with bone spurs, might present a challenge for the segmentation algorithms being applied. The study did not evaluate its findings in relation to other methods currently used to assess bone mineral density.
[14]	Pixel Label Decision Tree	When applied to DXA images, the Pixel Label Decision Tree (PLDT) approach successfully segments the femur at a rate of 91.40 percent.	Segmentation of femurs in DXA imaging is the only topic of this investigation. Global Threshold, Region Growing Threshold, and ANNs are the only other methods we have to compare our findings against. Only femur segmentation is considered in the model's evaluation at this time.
[15]	Support Vector Machine	A classification method based on the machine learning technique of support vector machine 60 (SVM) is developed for identifying osteoporosis in X-ray images.	The success of this work is dependent on the use of simulated annealing to determine the ideal number of features and to divide the training set into discrete classes. Patients with unusual bone architecture may not respond positively to the SVM for diagnosing osteoporosis. There was no evaluation of the study's findings in relation to other osteoporosis diagnosis methods.
[16]	DXA images	A novel metric for analysing BMD using DXA pictures is presented. This method computes T and Z values in addition to assessing bone quality on the basis of mean bone density intensity. The -measure should fall between 0.96 and 0.97.	In this paper, a unique measure for evaluating BMD using DXA scans. T and Z values are calculated using this procedure, and bone quality is evaluated using the average bone density intensity. The value of the -measurement must be between 0.96 and 0.97.
[17]	Active Shape Model	The process of segmentation employs an Active Shape Model (ASM).	When the model's covariance matrix is sparse, ASM may struggle to calculate the Mahalanobis distance. Patients with bone spurs or other unusual bone abnormalities may not benefit from ASM. The study did not evaluate its findings in relation to other picture segmentation methods.
[18]	Segmentation, texture analysis	The use of imaging techniques for identifying osteoporosis and calculating fracture risk has progressed dramatically in recent years.	The author discussed the shortcomings of existing diagnostic tools and offered viable replacements. There was no mention of the disadvantages of the proposed solutions.
[19]	Convolutional Neural Network	The use of a convolutional neural network (CNN) based deep learning model for strain prediction is investigated. The CNN model improved accuracy and precision over the previously released Support Vector Machine (SVM) model, which relied on human-created features.	The study's effectiveness rests on the employment of a convolutional neural network-based deep learning model for average strain forecasting. Biomechanical parameter estimates within the context of osteoporosis utilising physics-based models are the scope of this investigation. No evaluation of the study's findings against other methods of estimating biomechanical parameters was performed.
[20]	Deep Convolutional Neural Network (DCNN)	Screening by sight using CR pictures method that works for treating osteoporosis	Only effective for osteoporosis; won't help with other bone diseases.
[21]	Support Vector Machine (SVM)	Women with low BMD can be identified using an SVM algorithm.	Low bone mineral density (BMD) in postmenopausal women alone.
[22]	Linear Support Vector Machine	The accuracy of an SVM model for osteoporosis using the HOG	Confining ourselves to panoramic X-ray images and HOG feature analysis

	(SVM)	feature is 72.50 percent.	

2.2. Deep Neural based image analysis of postmenopausal osteoporosis using different scan techniques:

Zhao et al. (2021) employed a deep learning-based method to examine CT scans and make predictions about osteoporosis in postmenopausal women. The authors tested the accuracy of their trained CNN using a dataset consisting of CT scans from 250 postmenopausal women. With an AUC of 0.90, the research concluded that their approach was very accurate and sensitive in predicting osteoporosis. This suggests that deep learning-based techniques might give accurate and reliable diagnosis of osteoporosis using CT scans, since the CNN-based strategy performed similarly to the standard DXA-based method. However, only 250 postmenopausal women were included in the data set, so the study cannot be considered statistically significant. To judge the results' applicability, more research with bigger samples is required.

Bone mineral density (BMD) in postmenopausal women was predicted using an MRI image analysis method developed by Kazi et al. (2020) that relied on deep learning. The authors tested the efficacy of a CNN they trained using a dataset consisting of 100 3D MRI scans of postmenopausal women and their BMD predictions. With a correlation coefficient of 0.89, the study found that their projected BMD values were very consistent with the observed BMD values. This suggests that deep learning-based techniques, such as CNN, might be used to reliably predict BMD using MRI, since their performance was equivalent to that of standard DXA-based assessment of BMD. However, only 100 women past menopause were included in the study's data set, so its generalizability is limited. To judge the results' applicability, more research with bigger samples is required.

For the purpose of predicting osteoporosis in postmenopausal women, Li et al. (2021) analysed ultrasound pictures using a deep learning-based technique. The authors investigated the accuracy of their CNN's prediction of osteoporosis using a dataset containing ultrasound pictures from 200 postmenopausal women. The AUC for predicting osteoporosis using their approach was found to be 0.87, indicating great accuracy and sensitivity. This suggests that deep learning-based techniques might give accurate and reliable diagnosis of osteoporosis using ultrasound pictures, since the CNN-based strategy performed similarly to the conventional DXA-based method. However, only 200 postmenopausal women were included in the data set, so the study cannot be considered statistically significant. To judge the results' applicability, more research with bigger samples is required.

To assess the likelihood of a hip fracture in postmenopausal women, Zhang et al. (2020) used a deep learning-based method to examine CT scans. The authors tested the efficacy of a CNN they trained using a dataset containing CT scans of 460 postmenopausal women who were at risk for hip fractures. With an AUC of 0.82, the research found that their strategy was very accurate and sensitive in predicting the probability of hip fractures. Risk assessment for hip fracture in postmenopausal women may benefit from deep learning-based techniques, since the CNN-based method outperformed the standard DXA-based evaluation of BMD. Only 460 postmenopausal women were included in the data set, so more research with larger samples is needed to draw any firm conclusions about the study's findings.

Postmenopausal women's fracture risk was predicted using DXA image analysis and a deep learning-based technique by Barbu et al. (2020). They used DXA scans of 208 postmenopausal women to train a convolutional neural network (CNN) and then assessed the model's ability to predict fracture risk. The authors claimed that their approach had an AUC of 0.88 for predicting fracture risk, indicating great accuracy and sensitivity. According to their findings, using CNNs to predict fracture risk was more accurate than using DXA to quantify BMD. The results imply that deep learning-based methods may be able to deliver more accurate risk assessment for bone fractures in women past menopause. The study included just 208 postmenopausal women in its data collection, which is considered a small sample size. Therefore, in order to assess the generalizability of the results, additional studies with larger sample sizes are required.

Collectively, these researches show the promise of deep learning-based methods for analysing various medical images and estimating the likelihood of osteoporosis and fractures in women past menopause. While these methods have shown some encouraging results, more research with larger samples is required to determine their generalizability and clinical utility. The possibility for bias in the datasets used for training and the requirement for extensive validation and testing before these methods can be employed in clinical practise are only two of the constraints of these approaches that must be taken into account.

Ref no.	Method	Results	Limitations
[23]	Deep learning-based approach on CT images to predict osteoporosis in postmenopausal women	The AUC for predicting osteoporosis using their approach was 0.90, indicating high accuracy and sensitivity. This suggests that deep learning-based techniques might give accurate and reliable diagnosis of osteoporosis using CT scans, since the CNN-based strategy performed similarly to the standard DXA-based method.	Only 250 women who had already gone through menopause were included in the study.
[24]	Deep learning-based approach on MRI images to predict bone mineral density (BMD) in postmenopausal women	Their estimated BMD values were quite close to the true BMD values; the correlation coefficient was 0.89. This suggests that deep learning-based techniques, such as CNN, might be used to reliably predict BMD using MRI, since their performance was equivalent to that of standard DXA-based assessment of BMD.	Only 100 women past menopause were included in the data set for this study.
[25]	Deep learning-based approach on ultrasound images to predict osteoporosis in postmenopausal women	The AUC for predicting osteoporosis using their approach was 0.87, indicating high accuracy and sensitivity. This suggests that deep learning-based techniques might give accurate and reliable diagnosis of osteoporosis using ultrasound pictures, since the CNN-based strategy performed similarly to the conventional DXA-based method.	Only 200 women past menopause were included in the study's data set, which is considered a small sample size.
[26]	Deep learning-based approach on CT images to predict the risk of hip fracture in postmenopausal women	The AUC for predicting the likelihood of a hip fracture using their approach was 0.82, indicating high accuracy and sensitivity. Risk assessment for hip fracture in postmenopausal women may benefit from deep learning-based techniques, since the CNN-based method outperformed the standard DXA-based evaluation of BMD.	Only 460 women past menopause were included in the study's data set, which is considered a small sample size.
[27]	Deep learning-based approach on DXA images to predict the risk of fracture in postmenopausal women	The AUC for predicting fracture risk using their approach was 0.88, indicating high accuracy and sensitivity. This suggests that deep learning-based techniques may give better risk assessment for fractures in postmenopausal women, since the CNN-based methodology outperformed the usual DXA-based evaluation of BMD.	The sample size was modest, with only 208 postmenopausal women used in the analysis.

3. Conclusion:

In conclusion, osteoporosis is still a major health issue, especially for women past menopause. Diagnosing and treating osteoporosis relies heavily on the identification of the disease by DEXA imaging. Early results from using deep learning methods to image processing to enhance osteoporosis detection in postmenopausal women are encouraging. However, obstacles remain, such as a lack of interpretability in the models and the requirement for massive datasets. Therefore, more study is required to overcome these obstacles and verify the clinical usefulness of these methods. These drawbacks notwithstanding, deep learning for osteoporosis detection has promising future applications, such as early diagnosis and individualised therapy. To better diagnose and treat osteoporosis in postmenopausal women, further study into this area is crucial, as is evidenced by this survey.

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