Prediction of Osteoporosis Using Artificial Intelligence Techniques: A Review

Sachin Kumar Chawla and Deepti Malhotra

Abstract Osteoporosis is a condition that goes unnoticed until it causes fragility fractures. Reduced bone mass density (BMD) raises the risk of osteoporotic fractures. Currently, osteoporosis is detected using traditional procedures such as DXA scans or FEA testing, which need a lot of computer resources. However, early diagnosis of osteoporosis, on the other hand, allows for the detection and prevention of fractures. The radiologist was able to successfully segment the region of interest in medical imaging to improve disease diagnosis using automated segmentation, which is not possible with traditional methods that rely on manual segmentation. With more advancement in technology, various AI learning techniques have been introduced which tends to generate results efficiently in less time. Keeping this essence, some researchers have developed AI-based diagnostic models based on biomarkers for effective osteoporosis prediction. This article seeks to thoroughly investigate efforts on automated diagnostic systems using artificial intelligence techniques based on quantitative parameters (biomarkers) for early osteoporosis prediction considering the data from 2016–2021. Based on the existing studies, this article highlights the open issues existing in the literature that needs to be addressed and also presented an outline of the proposed work based on knee X-ray and AI techniques which will be implemented in the future and could be an aid to the clinicians.

Keywords PR · Panoramic radiography · DXA · Dual X-ray absorptiometry · ANN · Artificial neural network · RF · Random forest · LR · Logistic regression · FEA · Finite element analysis · SVM · Support vector machine · KNN · k-nearest neighbor · CV · Cross-validation · ML · Machine learning · MLR · Multivariate linear regression · DT · Decision tree · CNN · Convolutional neural network · CT · Computed tomography · BMD · Bone mineral density · LBP · Local binary pattern · PPV · Positive predictive value · FRAX · Fracture risk assessment tool ·

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DB · Database · AUROC · Area under the receiver operator characteristic · FEDI · Fuzzy edge detection algorithm · OA · Osteoarthritis

1 Introduction

Over 200 million people worldwide, mostly the elderly, suffer from osteoporosis, a metabolic bone disease [1–5]. Reduced bone density increases bone fragility and fractures susceptibility; spinal compression fractures are the most common types. According to the World Health Organization, osteoporosis is defined as having a bone mineral density that is 2.5 standard deviations or more below the mean for a young, healthy adult T-score (DXA measure 2.5) [6–9].

Because not all physicians have access to this technology, it may not be feasible to routinely test the general population using DXA, even if early detection can reduce the risk of future morbidity and mortality from fracture-related consequences. To accurately screen patients and decrease over-diagnosis and misdiagnosis, extensive study has been done on when and how to utilize DXA and how to avoid giving patients a false sense of security [10–14]. Osteoporosis is commonly diagnosed in clinical settings using a battery of clinical tests, while some of the treatments can be pricey and a few of the tests might generate erroneous results as a consequence of anthropogenic or other chemical flaws [15–20].

As a result, we need an expert system that can scan medical records in a variety of formats and deliver accurate, dependable results without fatigue or error [21]. With the growing trend of technology, AI techniques have evolved in medical diagnosis and found to be a promising solution to improving health care [22]. Many CAD systems based on demographic parameters (Age, gender, eating habits, and life style) and vision-based modalities (MRIs, DXA, and CT scans) have recently been developed in the field of osteoporosis with better accuracy [23–25]. However, such systems are not deployed in clinical practices. This may be due to high-cost involvement or difficult data acquisition procedure [13]. Keeping this essence in mind, the researchers are attempting to develop a cost-effective system using AI techniques and X-ray images which could be convenient and can be used in real time and yield better results with greater accuracy (Fig. 1).

2 Literature Review

This section provides a brief insight into the existing osteoporosis detection techniques introduced by the various researchers covering the period 2016–2021.

- **Gao et al.** [1] provided a systematic study to show how using medical images and AI techniques to diagnose osteoporosis has been developed. Using the Quality Assessment of Diagnostic Accuracy Studies (QUADAS-2) methodology, the

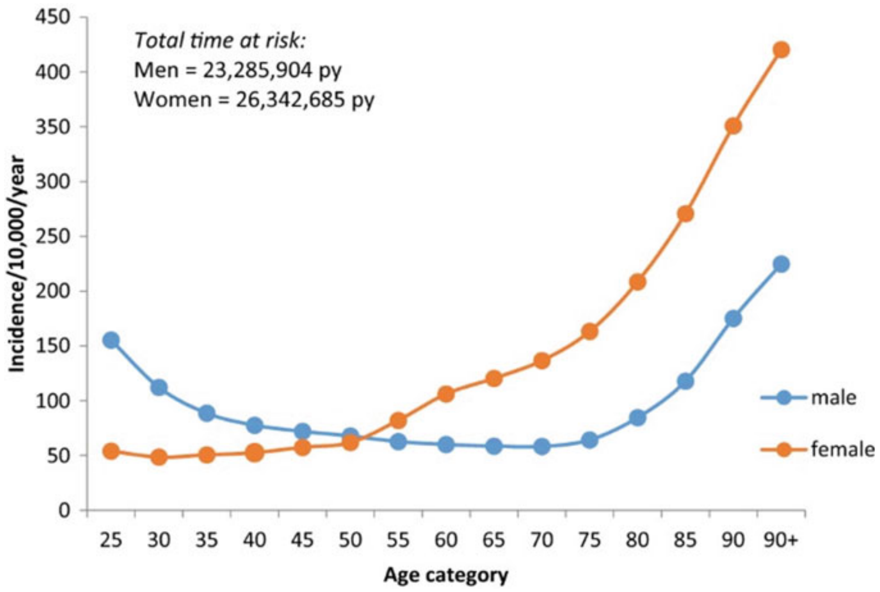

Fig. 1 Annual prevalence rate of osteoporosis worldwide

included studies' bias and quality were evaluated. They had an accuracy of 95 percent.

- **Ho et al.** [2] Dual-energy X-ray absorptiometry is the old standard in this discipline and has been recommended as the primary method for determining bone mineral density (BMD), which is an indicator of osteoporosis (DXA). It is recommended to utilize standard radiography for osteoporosis screening as opposed to diagnosis. They had an accuracy of 88 percent.
- **Fang et al.** [3] developed a fully automatic method for bone mineral density (BMD) computation in CT images using a deep convolutional neural network and outlined a plan for using deep learning for individuals with primary osteoporosis (DCNN). They were 82 percent accurate on average.
- **Shim et al.** [4] proposed Ml algorithms are highly accurate at predicting the risk of osteoporosis. It could assist primary care professionals in identifying which female patients should get a bone densitometry examination if they are at high risk of osteoporosis. They had an accuracy of ANN 0.742%, SVM 0.724%, and KNN 0.712%.
- **Yamamoto et al.** [5] built a model using convolutional neural networks (CNNs) based on hip radiographs to diagnose osteoporosis at an early stage. They had an accuracy of 93 percent.
- **Yasaka et al.** [6] propounded a method that is based upon unenhanced abdominal computed tomography (CT) images. A deep learning method can calculate the lumbar vertebrae's bone mineral density (BMD). They had an accuracy of 97 percent.

- **Kalmet et al.** [7] Compared to doctors and orthopedists, CNN performed better. They had an accuracy of 99%.
- **Park et al.** [8] The major purpose of this research is to help doctors make an accurate diagnosis of colorectal cancer. With an accuracy of 94.39 percent, one fully linked layer and 43 convolutional layers make up our recommended CNN design.
- **La Rosa** [9] developed a robotized computer-aided diagnostic strategy that incorporates a variety of previously offered standardizations, like MLR and ICA highlight extraction, for the detection of OA. The recommended CAD has higher categorization rates than those found in past investigations. The multivariate linear regression (MLR) technique was used to analyze 1024 X-ray pictures of people with osteoarthritis.
- **Ferizi et al.** [10] Deep learning algorithms were applied to analyze MRI images of knee bones using the 3D MRI datasets SK10, dataset OAI Imorphics, and dataset OAI ZIP. The 3D CNN and SSM models were used in this analysis. The SK110, OAI Imporphics, and OAI ZIb 3D MRI dataset's accuracy for these models was 75.73 percent, 90.4 percent, and 98.5 percent, respectively.
- **Rehman et al.** [11] In this study, deep learning methods were used to X-ray pictures of osteoarthritis patients. KNN and SVM algorithms were used SVM. KNN was found to be 100% accurate and SVM to be 79% accurate for normal images, whereas KNN was found to be 100% accurate and SVM was found to be 100% accurate for aberrant images.
- **Jaiswal et al.** [12] X-ray images are used to analyze osteoarthritis in the knee using deep learning techniques. The authors described a novel method for noninterventional detection and analysis of knee OA using X-rays. It might make the process of finding a treatment for knee pain more efficient. With a separate testing set, their approach yields the best multi-class grouping results: a normal multiclass accuracy of 66.71 percent, a radiographical OA accuracy of 0.93, a quadratic weighted Kappa of 0.83, and an MSE of 0.48. This could be compared to how people typically think. The study included 3000 patients from the osteoarthritis initiative dataset.
- **Reshmalakshmi and Sasikumar** [13] The purpose of this study is to use MRI imaging of knee bones to diagnose knee bone disorders. This technique made use of online MRI datasets. This work employs the scale space local binary pattern feature extraction method. The accuracy of the research was 96.1 percent.
- **Antony et al.** [14] In this work, MR images of the knee joint were used to identify cartilage lesions, such as cartilage softening, fibrillation, fissuring, focal defect broad thinning due to cartilage degeneration, and acute cartilage damage. They had achieved 87.9% accuracy.
- **Liu et al.** [15] The results of total knee arthroplasty (TKA) using patient-specific instruments (PSIs), which are described in this study, are comparable to those of TKA using conventional equipment in terms of post-operative radiography results. They had a 95% accuracy rate.
- **Ebsim et al.** [16] This research describes a strategy for integrating different detection techniques to find femur and radius fractures. To detect fractures,

these algorithms extract several types of characteristics. They were 82.6 percent accurate.

- **Deniz et al** [17] This study's objective was to assess conventional radiography and MRI for early diagnosis and classification of OVFs and to measure the rate of misdiagnosis of OVFs. They were 81 percent accurate.
- **Reshmalakshmi and Sasikumar** [18] This study's goal is to demonstrate a deep convolutional neural network-based automatic proximal femur segmentation technique CNN. They had a 95% accuracy rate.
- **Gornale et al.** [19] To determine if quantitative susceptibility mapping (QSM) accurately measures postmenopausal women's osteoporosis. They had a 86 percent accuracy.
- **Schotanus et al.** [20] By integrating the results of the traditional X-ray image processing method with the fuzzy expert system used to calculate the degree of osteoporosis, a conclusion is made. To indicate the likelihood of osteopenia, the authors in this study display the percentage reduction in bone density. Furthermore, it is determined that the ratio of trabecular to total bone energy is 0.7985, indicating a loss of bone density of 7.985 percent.
- **Chen et al.** [21] This work uses DCCN to automatically assess the degree of knee osteoarthritis from radiographs. When adjusted for regression loss, the network's multi-class grade 0–4 classification accuracy in this study is 59.55 percent.
- **Hordri et al.** [22] In this study, authors have segmented a knee X-ray picture using the active contour algorithm before using several feature extraction methods. Using the random forest classifier, the retrieved features revealed an accuracy rate of 87.92 percent.

3 Comparative Analysis

The study on various osteoporosis detection methods based on a variety of deep learning and machine learning technologies offered by various researchers is summarized in this section.

Table1 summarizes a comparative analysis of various existing AI prediction techniques for osteoporosis detection. From this table, it was observed that researchers have employed various datasets depending on various modalities (MRI, CT scans, and X-ray), but these models cannot be generalized as it employs a small sample size. In the case of MRI and CT scans, the data acquisition is tedious and more expensive, and it sometimes requires patients to be still which causes more difficulty for the affected subjects. On contrary, an X-ray is a more convenient method for detecting osteoporosis in clinical settings. Keeping this essence, most of the researchers have worked on X-ray imaging data for osteoporosis prediction.

From Fig. 2, it has been observed that out of all ML or DL techniques, the DCCN classifier yields the best accuracy independent of the modalities. The rationale behind the adoption of such a model is that it can learn to perform actions from text, auditory,

Table 1 Comparative analysis of existing AI prediction techniques for osteoporosis detection

Author	Objectives	Data	Input data amount	Methods	Trained data	Main results
Gao et al. [1] (2021)	Employing artificial intelligence to analyze medical photos to detect osteoporosis	X-ray CT	3186 patients metanalysis	DCNN, CNN	Training samples set 940 In which 610 adverse cases and 330 decent ones	95%
Ho et al. [2] (2021)	Using a deep learning neural network, plain X-ray radiography is used to predict bone mineral density	X-ray	3472 pairs of pelvis X-ray images	CNN	2800 (male = 609, female = 2191) pelvis X-ray 5027 unilateral femur images (male = 1115, female = 3912)	0.88%
Fang et al. [3] (2020)	Screening for osteoporosis in multi-detector CT imaging making use of deep convolutional neural networks	CT	(244 images, 16.8%), osteopenia (605 images, 41.8%), and normal (600 images, 41.4%)	DCNN model	Set 1 463 images, set 2 200 images, and set 3 200 images	0.823, 0.786, 0.782

(continued)

Table 1 (continued)

Author	Objectives	Data	Input data amount	Methods	Trained data	Main results
Shim et al. [4] (2020)	Use of machine learning techniques to predict osteoporosis risk in postmenopausal women	X-ray MRI CT	1792 34% Osteoporosis	ANN, SVM, KNN	76% fivefold CV_24%	ANN 0.742%, SVM 0.724%, KNN 0.712%
Yamamoto et al. [5] (2020)	Hip radiographs and patient clinical covariates are used in deep learning for osteoporosis classification	X-ray	1131 (53% Osteoporosis)	ResNet-18, ResNet-34, Google-Net, Effective-Net b3, Effective-Net b4	80% 10% 10%	AUROC 0.937%
Yasaka et al. [6] (2020)	Deep learning is used to forecast bone mineral density from CT tomography using a convolutional neural network	CT	2045 (% not stated)	CNN(4 layers)	81% 9% 10% (external validation)	0.96%
Kalmet et al. [7] (2020)	A narrative overview of deep learning in fracture detection	X-ray	1,891 69 percent fracture images	ResNet-152	90 percent trained 10 percent testing	1%, compassion 0.99%, specificity 0.97%
Park et al. [8] (2020)	Using optimized CNN, adenocarcinoma recognition in endoscopy images	Colonoscopy images dataset	49,458 images	CNN	49,048 images	94.3%

(continued)

Table 1 (continued)

Author	Objectives	Data	Input data amount	Methods	Trained data	Main results
La Rosa [9] (2019)	A decision support tool for the early identification of knee OA utilizing X-ray imaging and machine learning was developed using data from the OA initiative	X-ray	1024 images	MLR	Train data 80% Tested data 20%	AUROC 82.9%
Ferizi et al. [10] (2019)	Automated knee bone and cartilage segmentation for osteoarthritis initiative using statistical shape knowledge and convolutional neural networks	MRI	3D MRI datasets SKI10 dataset-OAI Imorphics dataset OAI ZIB	3D CNNs, SSMs	3D MRI datasets SKI10 Dataset OAI Imorphics, dataset OAI ZIB	75.8%, 90.4%, 98.4%
Rehman et al. [11] (2019)	Identification of knee osteoarthritis using texture analysis	X-ray	X-ray images of OA patients	KNN SVM	Train data 70% Tested data 30%	Normal: KNN = 99%, SVM = 79% Abnormal: KNN = 98%, SVM = 97%
Jaiswal et al. [12] (2018)	A deep learning-based automatic diagnosis of knee osteoarthritis from plain radiographs	X-ray	The osteoarthritis dataset contains 3000 participants	CNN	Trained data 70% Tested data 30%	Auroc = 66.71%, ROC curve = 0.93%, Auroc = 0.93%, MSE = 0.48%

(continued)

Table 1 (continued)

Author	Objectives	Data	Input data amount	Methods	Trained data	Main results
Reshmalakshmi and Sasikumar [13] (2018)	A framework based on SSLBP for feature extraction in knee MRI scans to identify bones	MRI	Online MRI dataset	LBP SVM	Trained data 90% Tested data 10%	96.1% 88.26%
Antony et al. [14] (2018)	Deep learning approach for knee MR image evaluation	MRI	17,395 images	CNN	16,075 images trained 1320 images testing	87.9%
Liu et al. [15] (2018)	Total knee arthroplasty with positive alignment using MRI-based patient-specific tools	MRI	841 knee images	PSI	70% trained 30% testing	89.1%
Ebsim et al. [16] (2018)	Using Optimized CNN, adenocarcinoma recognition in endoscopy images	Colonoscopy images dataset	49,458 images	CNN	49,048 images	94.39%
Deniz et al. [17] (2018)	The use of MRI in determining the kind of osteoporotic vertebral fractures and their impact on diagnosis	MRI	173 patients images dataset	AO spine classifier	70% trained 30% testing	81%
Reshmalakshmi and Sasikumar [18] (2018)	DCCN for proximal femur segmentation from MR images	MRI	44 patients images dataset	DCCN	70% trained 30% testing	95%

(continued)

Table 1 (continued)

Author	Objectives	Data	Input data amount	Methods	Trained data	Main results
Gornale et al. [19] (2018)	An additional and accurate indicator of osteoporosis in postmenopausal women is bone susceptibility mapping with MRI	MRI	QCT images dataset	CNN	70% trained 30% testing	87%
Schotanus et al. [20] (2016)	Osteoporosis detection using fuzzy inference	X-ray	20 patients images	FEDI	20 patients images	79%
Chen et al. [21] (2016)	DCCN for determining the severity of radiographic osteoarthritis in the knee	X-ray	8892 images of knee joints	DCCN	7030 images	95%
Hordri et al. [22] (2016)	Image from a knee X-ray was used to identify osteoarthritis	X-ray	200 knee images	Random forest classifier	40% trained 60% testing	87.92%

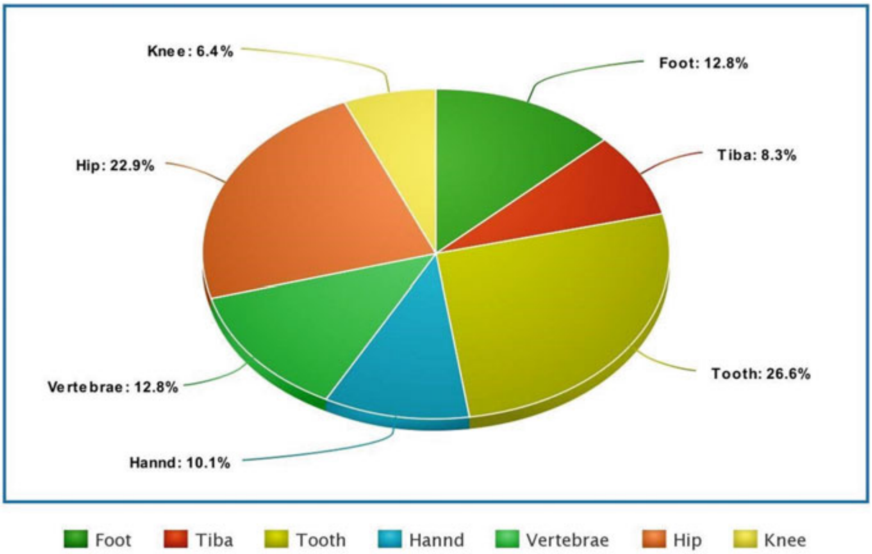

Fig. 2 Performance % accuracy of existing AI techniques for early osteoporosis detection

or visual input and can do so with astounding accuracy—in certain cases, even better than human performance.

Figure 3 depicts the % usage rate of various medical descriptions for analysis of osteoporosis. From this figure, it has been observed that there is extensive research on X-ray image data for early osteoporosis prediction due to its ease of availability and less cost in comparison to other modalities (MRI and CT scans).

4 Open Gaps and Challenges

This section proffers the existing gaps and challenges in the field of early osteoporosis prediction.

1. **Insufficient Standardized Dataset** Specifically for images of the knee joint, there aren't many available standardized sample datasets. The generalizability of the model may be constrained by the fact that researchers have created their datasets under controlled conditions. Hence, there is a dire need to create open-source datasets that will be beneficial for the research community in building a robust model for early osteoporosis prediction [17–20, 22].
2. **Sample Size in Osteoporosis Prediction Models** In the case of X-ray images, an open-source dataset is available on multiple sites, but there is a huge amount of heterogeneity in data which in turn affects the performance of the model. To overcome heterogeneity, transfer learning techniques could be employed.

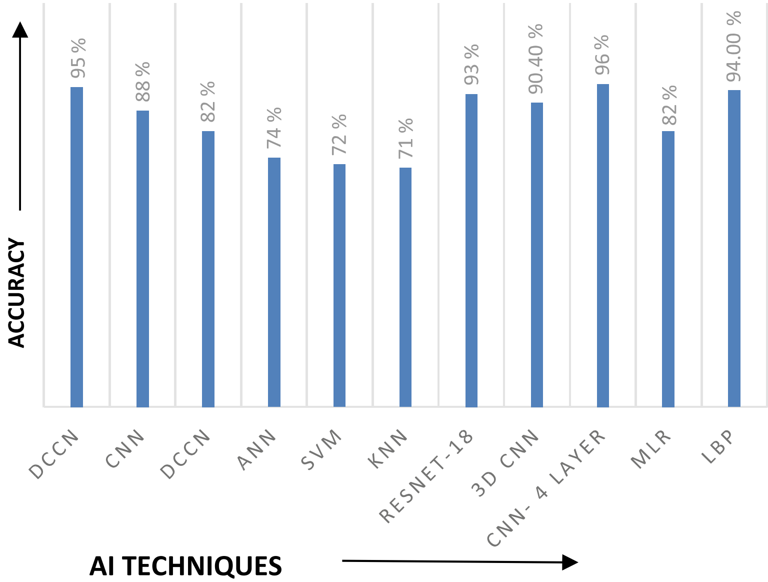

Fig. 3 %age utilization ratio of data modalities in early osteoporosis prediction

3. **High Computational Cost** Diagnosis of osteoporosis is a challenging task as the current traditional medical diagnostic systems, such as (DXA, FEA, and FRAX), are not widely available and, among other limitations, are expensive for low economics[1, 3, 4].
4. **Delayed Diagnostic Rate** Conventional methods for diagnosing osteoporosis involves manual segmentation which is time-consuming and more prone to human errors**.** With the advent of artificial intelligence, the radiologist was able to successfully segment the region of interest in medical imaging to improve disease diagnosis, which could not be possible with traditional methods that rely on manual segmentation. [4, 9, 23, 24].
5. **Lack of Interpretability** The long-term goal of the computational model is to present a methodology that is more transparent and reliable, specifically in the context of appropriately classifying osteoporosis patients. In the real world, health practitioners are apprehensive to utilize AI techniques. Hence, a model should be more transparent and robust to ease osteoporosis diagnosis in clinical settings.
6. **Severity Estimation** Most of the studies have only focused on classifying osteoporosis and did not consider the severity of the disorder or its subtypes. [6, 9, 13].

5 Proposed Intelligent Osteoporosis Classifier

From the exhaustive literature, it has been observed that various researchers have developed X-ray imaging data and intelligent systems used for osteoporosis detection, but no study has been conducted to classify osteoporosis subclasses. Hence, there is a need to develop an efficient framework that has the potential capability to classify osteoporosis and its subclasses. Figure 4 shows the percentage usage of various body regions in detecting early osteoporosis. From this figure; we observed that knee regions have very less work down in this field due to the less dataset availability and heterogeneity in the osteoporosis dataset. Our proposed framework is based on knee X-ray images. Keeping this essence in mind, this study proposes an intelligent osteoporosis classifier based on knee X-ray imaging data. We proposed a deep learning model that can have the potential capability to classify osteoporosis and its subclasses. Data collection, data preprocessing, prediction model, and results are among the main elements (Fig. 5).

5.1 Dataset Description

Data collection is the most important aspect of the diagnosis system, and selecting an appropriate sample for machine learning trials is crucial. This dataset will be taken from the Kaggle repository and contains knee X-ray data on knee joints (1656 images). The severity of the offense includes images from a variety of categories. The images descriptions are as follows:

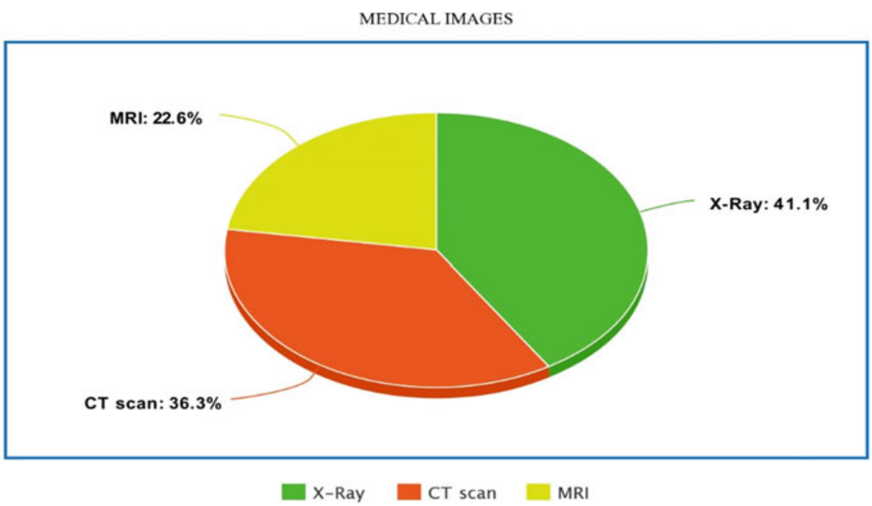

Fig. 4 %age usage of various body regions in detecting early osteoporosis

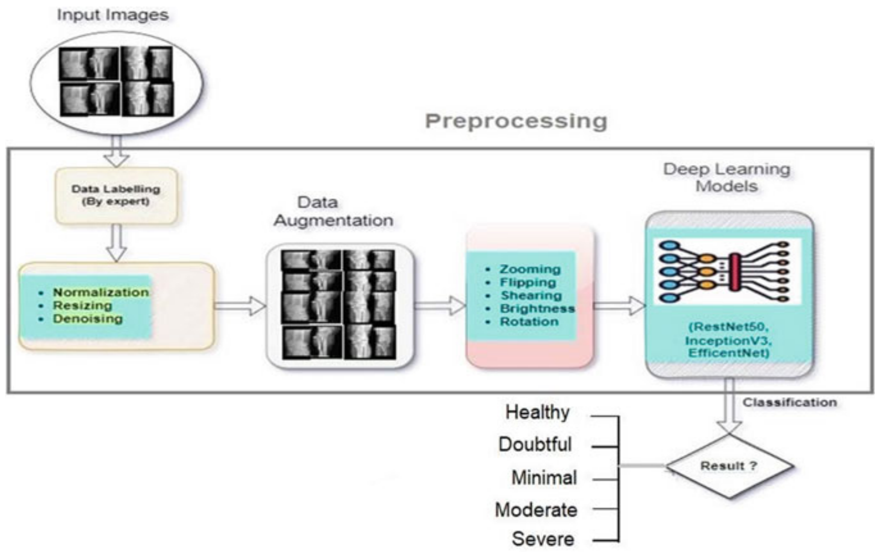

Fig. 5 Intelligent osteoporosis classifier

CLASSES	NO. OF IMAGES
Class (0) Healthy	639
Class (1) Doubtful	296
Class (2) Minimal	447
Class (3) Moderate	223
Class (4) Severe	51

5.2 Data Preprocessing

After data collection, preprocessing of the dataset will be employed to improve the images. The obtained images may be improved so that the data might aid in the early detection of osteoporosis cases in various stages. We will resize each input image while maintaining the aspect ratio in the initial preprocessing stage to lower the training expenses. Additionally, to balance the dataset, we will perform up-sampling and down-sampling. During the up-sampling procedure, areas are randomly cropped to increase minority classes. Flipping and 90o rotation are commonly used to balance the samples of the various classes, improve the dataset, and prevent overfilling. To satisfy the cardinality of the smallest class, more instances of majority classes can be removed throughout the down-sampling process. Each image in the generated distributions is mean normalized to remove feature bias and minimize training before being flipped and rotated.

5.2.1 Data Labeling

In a machine learning model, data labeling is an essential part of the data preprocessing stage. The quality of a dataset can be significantly impacted by any error or inaccuracy made in this procedure. Additionally, a predictive model's overall effectiveness could be ruined and result in misunderstanding. The proposal uses the dataset acquired from the Kaggle repository which further divided the images into 5 classes: Class 0 is Healthy; Class 1 is Doubtful; Class 2 is Minimal; Class 3 is Moderate; Class 4 is Severe.

5.2.2 Normalization

Image normalization is a popular method of modifying the pixel intensity range in image processing. One option is to utilize a function that creates a normalization of the input images.

5.2.3 Resizing

Image resizing is essential to make sure that all of the input images are the same size because their sizes vary. Deep learning models must scale all input photos to the same size before feeding them into the model because they often learn quickly on smaller images and accept inputs of the same size.

5.2.4 Denoising

The procedure of eliminating noise or distortions from an image is known as image denoising. Different types of noise, such as Poisson, Speckle, Gaussian, and Salt & Pepper, may be present in an image. Many vision denoising filters, such as fuzzy-based filters and classical filters, can be used to achieve the purpose of denoising.

5.2.5 Data Augmentation

Data augmentation techniques create several duplicates of a dataset to artificially increase its size. To collect additional data, we only need to make a few minor changes to our old dataset. Minor alterations such as flips or translations, rotations, cropping, scaling, zooming, adding noise, and shearing can be made to increase the size of the dataset.

5.2.6 Results and Prediction

DCNN will be used in the proposed model to identify and categorize images. It makes use of a hierarchical model to construct a network that resembles a funnel before producing a fully connected layer where the output is processed and all neurons are connected. The main advantage of DCNN over the existing techniques is that it automatically extracts key elements without the need for human participation. DCNN would therefore be a great option for spotting osteoporosis in its early phases.

6 Conclusion

After reviewing the existing literature relating to the automated prediction models for early osteoporosis detection, the findings suggest that machine learning and deep learning techniques have been frequently used in osteoporosis diagnostic field. From the exhaustive study, it has been observed that nearly 70% of the studies employed machine learning techniques, and 30% of the studies employed deep learning techniques. However, the work in the field of osteoporosis prediction based on deep learning techniques is very less. The prime focus of this study is to critically access and analyze AI-based models for early osteoporosis prediction using several modalities (X-ray, MRI, CT scans) and AI techniques over the years 2016–2021. After carefully examining the existing gaps and challenges, this paper elucidates some future directions that need to be addressed and proposed an intelligent osteoporosis classifier using X-ray imaging data and a deep convolutional neural network that will be implemented in the future and will pose as a potential aid to research scholars and health practitioners by providing a more precise, effective, and timely diagnosis of osteoporosis.

References

1. Gao L, Jiao T, Feng Q, Wang W (2021) Application of artificial intelligence in diagnosis of osteoporosis using medical images: a systematic review and metaanalysis. Osteoporos Int 32(7):1279–1286. https://doi.org/10.1007/s00198-02105887-6
2. Ho C-S, Chen Y-P, Fan T-Y et al (2021) Application of deep learning neural network in predicting bone mineral density from plain x-ray radiography. Arch Osteoporos 16:153. https://doi.org/10.1007/s11657-021-00985-8
3. Fang Y, Li W, Chen X et al (2021) Opportunistic osteoporosis screening in multi-detector CT images using deep convolutional neural networks. Eur Radiol 31:1831–1842. https://doi.org/10.1007/s00330-020-07312-8
4. Shim J-G, Kim DW, Ryu K-H et al (2020) Application of machine learning approaches for osteoporosis risk prediction in postmenopausal women. Arch Osteoporos 15:169. https://doi.org/10.1007/s11657-020-00802-8

5. Yamamoto N, Sukegawa S, Kitamura A, Goto R, Noda T, Nakano K, Takabatake K, Kawai H, Nagatsuka H, Kawasaki K, Furuki Y, Ozaki T (2020) Deep learning for osteoporosis classification using hip radiographs and patient clinical covariates. Biomolecules 10(11):1534. https://doi.org/10.3390/biom10111534
6. Yasaka K, Akai H, Kunimatsu A et al (2020) Prediction of bone mineral density from computed tomography: application of deep learning with a convolutional neural network. Eur Radiol 30:3549–3557. https://doi.org/10.1007/s00330-02006677-0
7. Kalmet PHS, Sanduleanu S, Primakov S, Wu G, Jochems A, Refaee T, Ibrahim A, Hulst LV, Lambin P, Poeze M (2020) Deep learning in fracture detection: a narrative review. Acta Orthop 91(2):1–6. https://doi.org/10.1080/17453674.2019.1711323
8. Park H-C, Kim Y-J, Lee S-W (2020) Adenocarcinoma recognition in endoscopy images using optimized convolutional neural networks. Appl Sci 10(5):1650. https://doi.org/10.3390/app10051650
9. La Rosa F (2017) A deep learning approach to bone segmentation in CT scans. PhD thesis, The University of Bologna, Bologna, Italy
10. Ferizi U, Besser H, Hysi P, Jacobs J, Rajapakse CS, Chen C, Saha PK, Honig S, Chang G (2018) Artificial intelligence applied to osteoporosis: a performance comparison of machine learning algorithms in predicting fragility fractures from MRI data. J Magn Reson Imaging 49(4):1029–1038. https://doi.org/10.1002/jmri.26280
11. Rehman F, Shah SIA, Riaz M, Naveed; Gilani SO, Faiza R (2019) A region-based deep level set formulation for vertebral bone segmentation of osteoporotic fractures. J Digit Imaging 33:191–203. https://doi.org/10.1007/s10278-019-00216-0
12. Jaiswal AK, Tiwari P, Kumar S, Gupta D, Khanna A, Rodrigues JJPC (2019) Identifying pneumonia in chest x-rays: a deep learning approach. Measurement 145:511–518. https://doi.org/10.1016/j.measurement.2019.05.076
13. Reshmalakshmi C, Sasikumar M (2017) Trabecular bone quality metric from x-ray images for osteoporosis detection. In: 2017 International conference on intelligent computing, instrumentation and control technologies (ICICICT), pp 1694–1697. https://doi.org/10.1109/ICICICT1.2017.8342826
14. Antony J, McGuinness K, O'Connor NE, Moran K (2016) Quantifying radiographic knee osteoarthritis severity using deep convolutional neural networks. In: 2016 23rd International conference on pattern recognition (ICPR), pp 1195–1200. https://doi.org/10.1109/ICPR.2016.7899799
15. Liu F, Zhou Z, Samsonov A, Blankenbaker D, Larison W, Kanarek A, Kijowski R et al (2018) Deep learning approach for evaluating knee MR images: achieving high diagnostic performance for cartilage lesion detection. Radiology 289(1):160–169. https://doi.org/10.1148/radiol.2018172986
16. Ebsim R, Naqvi J, Cootes T (2016) Detection of wrist fractures in x-ray images. In: Clinical image-based procedures. Translational research in medical imaging. CLIP 2016. Lecture notes in computer science, vol 9958. Springer, Cham. https://doi.org/10.1007/978-3-319-46472-5_1
17. Deniz CM, Xiang S, Hallyburton RS et al (2018) Segmentation of the proximal femur from MR images using deep convolutional neural networks. Sci Rep 8:16485
18. Reshmalakshmi C, Sasikumar M (2016) Fuzzy inference system for osteoporosis detection. In: 2016 IEEE Global humanitarian technology conference (GHTC), pp 675–681. https://doi.org/10.1109/GHTC.2016.7857351
19. Gornale SS, Patravali PU, Manza RR (2016) Detection of osteoarthritis using knee x-ray image analyses: a machine vision-based approach. Int J Comput Appl 145(1):0975–8887
20. Schotanus MGM, Thijs E, Heijmans M et al (2018) Favourable alignment outcomes with MRI-based patient-specific instruments in total knee arthroplasty. Knee Surg Sports Traumatol Arthrosc 26:2659–2668. https://doi.org/10.1007/s00167-017-4637-0
21. Chen Y, Guo Y, Zhang X et al (2018) Bone susceptibility mapping with MRI is an alternative and reliable biomarker of osteoporosis in postmenopausal women. Eur Radiol 28:5027–5034. https://doi.org/10.1007/s00330-018-5419-x

22. Hordri NF, Samar A, Yuhaniz SS, Shamsuddin SM (2017) A systematic literature review on features of deep learning in big data analytics. Int J Adv Soft Comput Appl 9(1):32–49
23. Giornalernale SS, Patravali PU, Manza RR (2016) Detection of osteoarthritis using knee X-ray image analyses: a machine vision-based approach. Int J Comput Appl 145:20–26
24. Madani A, Moradi M, Karargyris A, Syeda-Mahmood T (2018) Semi-supervised learning with generative adversarial networks for chest X-ray classification with the ability of data domain adaptation. In: 2018 IEEE 15th International symposium on biomedical imaging (ISBI 2018), pp 1038–1042. https://doi.org/10.1109/ISBI.2018.8363749
25. Sharma AK, Toussaint ND, Elder GJ, Masterson R, Holt SG, Robertson PL, Ebeling PR, Baldock P, Miller RC, Rajapakse CS (2018) Magnetic resonance imaging-based assessment of bone microstructure as a non-invasive alternative to histomorphometry in patients with chronic kidney disease. Bone 114:14–21. https://doi.org/10.1016/j.bone.2018.05.029
26. Marongiu G, Congia S, Verona M, Lombardo M, Podda D, Capone A (2018) The impact of magnetic resonance imaging in the diagnostic and classification process of osteoporotic vertebral fractures. Injury 49(Suppl 3):S26–S31. https://doi.org/10.1016/j.injury.2018.10.006