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**Research Article**

# An Extensive Survey of Deep Learning Models for Osteoporosis Detection

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**ABSTRACT**

Osteoporosis is a condition characterized by low bone mass and structural deterioration of bone tissue and is increasingly becoming a crucial health concern, especially among the older population. The condition also affects the skeletal system in later life. Recognition of pre-disease states during early osteoporosis management plays a critical role in preventing osteoporosis development. The present study is a comprehensive investigation concerning the establishment and assessment of osteoporosis detection deep learning models developed with data obtained from individuals over fifty years. The investigation aimed to develop and compare predictive models engineered for the purpose to classify normal and osteoporosis users. To determine the performance of the newly developed deep learning models, this study compared the profound learning methods to prediction models. The data were collected from community-dwelling participants at a medical center in Taiwan who enrolled in a health check-up program. Various images were collected to extract the features. These modalities included in the prediction model were obtained from chest CT and CT radiomics, while the extracted features from dental radiographic images were also utilized to classify osteoporosis using deep convolutional neural network models. The results of this test prove that deep learning models could significantly increase the efficiency of osteoporosis determination. Such comparative analysis validates certain deep learning concepts, such as DenseNet121 in distinguishing normal and osteoporosis user sets with a high accuracy rate. Concerning these new machine learning concepts, new insights possible persons on a greater vein at risk may be classified for preventive measures.

**Keywords:** Osteoporosis detection, Deep learning models, Radiographic imaging

## INTRODUCTION

Osteoporosis is a common skeletal disorder characterized by low bone mass and poor bone structure, which presents a majorpublic health issue worldwide, particularly among older persons. Osteoporosis is associated with an elevated morbidity and mortality risk due to fractures, with the vertebral, hip, and wrist as the primary sites. Given the demographic impact of worldwide life expectancy, osteoporosis prevalence will escalate; hence, early detection, preventive, and therapeutic strategies are essential. In the past, the diagnosis of osteoporosis was belated due to the lack of imaging techniques that could discriminate normal bones from fragile ones, with dual-energy x-ray absorptiometry and quantitative computed tomography putting forward after preliminary discovery. These platforms are costly, not readily accessible to, and expose individuals to radiation. Machine and deep learning have the potential to mitigate several of these and other problems. Machine learning, artificial neural networks , support vector systems , random forests , nearest neighbor algorithms , and logical prediction models may anticipate osteoporosis risk and classify individuals based on their bone health. The algorithms can examine considerable clinical and imaging data to id features or indications that osteoporosis may apply an impact patient-specific measures. Deep learning applications are a technique subset that have the advantage of high accuracy. Researchers can apply convoluted neural nets and other such strategies to medical images such as CT, X-ray, and dental radiographs to identify complicated information within them using this method. The most advanced surveys of deep learning techniques for osteoporosis detection in adults aged above fifty involve a detailed analysis of the technology's accuracy in contrasting conventional measurements. We utilized information collected from imaging checks executed on individuals from Taiwan's health exam programs. It is an extensive group, as certain persons possess extensive features and submit to various scanning ops and BMD testing. The acquisition of these strong machine learning and deep learning technologies in osteoporosis discovery and operation offers tremendous potential. It is feasible to foster early discovery to increase the negative influence of the disorder and increase preventive activities for high-risk citizens via the powerful capabilities of AI and data. The advanced paper will aid in the promotion of technological responses aimed at the betterment of bone disorders. Fig. 1 illustrates a conventional deep learning structural model.

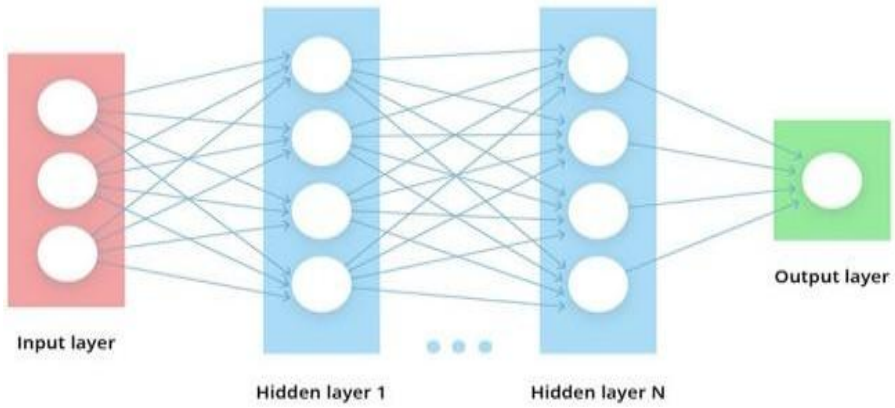


Figure 1: A Deep Learning Model's Typical Structure

Osteoporosis is a devastating silent skeletal disease associated with low bone mass and structural damage that impose a huge epidemiologic burden worldwide, especially among the geriatric population. Early diagnosis of osteoporosis is vital in fracture prevention and decreasing related mortality and morbidity. However, the most common tools for the diagnosis of this condition, such as dual-energy X-ray absorptiometry and quantitative computed tomography , are limited by the lack of accessibility, cost, and radiation dose; therefore, better diagnostic tools are needed. Over the past decade, deep learning technologies have shown increasing promise in re-engineering artificial intelligence, machine learning, and medical imaging and have proven powerful in accurately and reliably recognizing various pathologic patterns in many conditions, including osteoporosis. Deep learning facilitates large-scale medical imaging analysis of X-rays, computed tomography (CT) scans, anddental radiographs to define concealed differences in bone density and structure and assist in the prediction of osteoporosis.

Deep learning allows for efficient large-scale analysis of existing clinical imaging via the ability of the described algorithms toaccurately find hidden patterns and regularities in the model, leading to more efficient diagnosis and well-timed management. Such systems have many benefits, including enhanced sensitivity and specificity, less expensive equipment, automation, and accelerated image analysis. Combined with patient characteristics, deep learning may facilitate precise osteoporosis diagnosis and prerequisite reports to develop a personalized treatment plan. Thus, this introduction discusses the unprecedented innovations that deep learning is facilitating in osteoporosis diagnostics using advanced imaging and artificial intelligence. Thereview identifies how deep learning models, specifically CNNs, identify medical image patterns to predict osteoporosis development to show the varied capabilities inherent in deep learning models for clinical bone health discovery.

## LITERATURE SURVEY

The subsequent development and validation of advanced machine learning models for the early detection of osteoporosis across diverse populations have shown promising possibilities, utilizing multimodal data integration for the improvement of predictive accuracy. For example, it has been proven that the combination of image features with patient variables, as in the case of hip radiographs and clinical data, leads to the significant improvement of osteoporosis identification accuracy, demonstrating the additional synergistic effects of patient variables on the image analysis Similarly, a multi-layer perceptron neural network model of a prediction of osteoporosis by physical characteristics and activity factors in adult women has demonstrated relatively good performance, indicating the possibility of screening in resource-limited settings. The research of texture features from trabecular bone lumbar vertebrae L1-L4 using neural network model integration has also resulted in high classification accuracy, showed to be superior to DXA diagnosis Machine learning algorithms, including XGBoost, were employed for prediction of osteoporosis in type 2 diabetes mellitus and osteopenia patients, and the results have indicated the most valuable risk factors and have led to the creation of high-accuracy classifier. Moreover, a classifier using multiscale fractal, lacunarity, and entropy distributions of radiographs was also demonstrated to have high generalization capability. In a different study, a hierarchical model has been designed for opportunistic screening for osteoporosis with the other medical indication, which does not require DXA due to a high-grade expensive. Machine learning algorithms were employed for the prediction of osteoporosis risk in Vietnamese women, who have shown the main significant risk factors as features including age, height, and weight. The last models of osteoporosis screening revealed high efficiency as deep learning analysis architecture for detection of osteoporosis by dental radiographs and chest CT radiographs. It should be noted that the last model of osteoporosis diagnosis was uncompetitive compared to the majority of tested applications. This tendency is mostly due to innovative data science approaches and models development.

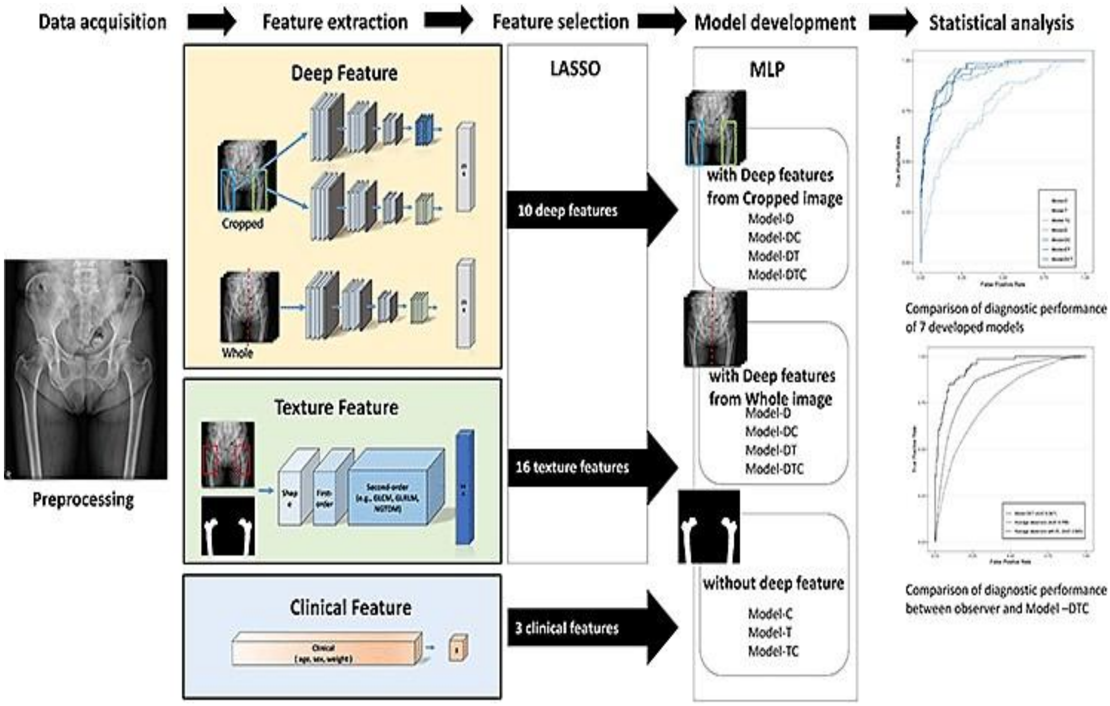


Figure 2: Deep Learning Phases Osteoporosis detection

| Author et al. | Paper Objective | Technique | Merits orDemerits | Dataset | Device Data Used | MetricsUsed |
|---|---|---|---|---|---|---|
| Wang et al. | Machine learning models for osteoporosis screening | ANN, SVM,RF, KNN, LoR | Merits: Outperformed traditional OSTA model, Achieved AUROC of 0.781- 0.843. Demerits:Not specified | Data from health checkupprograms in Taiwan | DXA | AUROC |
| Inui et al. | Predicting low BMD without using DXA | Logistic regression, Decision tree, Randomforest, | Merits: High accuracy (up to 0.834), High AUC (up to 0.961). | 2541 females' medical records | Medical records, Blood tests | Accuracy,AUC |
| | | Gradient boosting, LightGBM | Demerits: FRAX's limitations noted | | | |
| Wang et al. | Chest CT deep learning model for opportunistic osteoporosis screening | Deep learning-based segmentation, ResNet-101 | Merits: High AUCscores (up to 0.980), Model based on lumbar 1 vertebra reduces scan length and radiation dose. Demerits: Limited external validation | 1048 physical examination subjects' chestCT images | CT | AUC, DSC |

| | | | | | | |
|---|---|---|---|---|---|---|
| Hidjah et al. | Deep Convolutional Neural Network for osteoporosis detection using dental radiographic images | Deep Convolutional Neural Network | Merits: High validation and testing accuracy (98.10%, 92.50%). Demerits: Notspecified | Dental periapical radiographs of postmenopausal Javanese women | Dental radiographic images | Accuracy |
| Fasihi et al. | AI for evaluating, predicting, and classifying osteoporosis risk factors | Decision tree, RF, KNN, SVM, GB, AB, ANN | Merits: High AUROC (up to0.99), Recommends sports programs.Demerits: Data only from three hospitals, Exclusion of alcohol consumption index | 1224 men and women's clinical data from hospitalsin Tehran | Clinical data | AUROC |
| Liu et al. | SVM classifier for osteoporosis diagnosis based on radiographic features | SVM | Merits: High accuracy and sensitivity. Demerits: Notspecified | 104 lumbar spine L4 and 174 calcaneus radiographs | Radiographic images | Accuracy, Sensitivity |
| yaningrumet al. | Trabecular bone segmentationfor osteoporosis detection | Machine learning, K-means, Multilayer perceptron | Merits: Highaccuracy (90.48%), specificity, and sensitivity. Demerits: Not specified | 120 regions of interest on periapical radiographs | Periapical radiographs | Accuracy, Specificity, Sensitivity |
| hmukh etal. | Predicting osteoporosis and fractures using genetic risk scores | Gradient boosting machine-learning | Merits: Differential effectof wGRS on risk. Demerits: Limited predictive capacity | 409633 UK Biobank participants | Genetic data | AUC |
| Bui et al. | Prediction models for osteoporosisrisk in Vietnamese women | Machine learning algorithms | External validationnot conducted | Vietnamese population | Clinical and demographic data | AUC, Brier score, Precision, Recall, F1-score |
| Wu and Park | Predicting osteoporosis risk using machine learning with cohort data | Machine learning, XGBoost | Merits: High AUCand accuracy, Includes genetic factors. Demerits: Weak correlation between fracture incidence and predicted osteoporosis risk, Lower accuracy for women | Ansan/Anseong cohort and HEXA cohort | Demographic, biochemical, genetic | AUC, Accuracy |
| Mohammed and George | Osteoporosis detection using DEXA scan images with deep learning | p learning,CNN | Merits: High accuracy (98%),Improved with preprocessing. Demerits: Not specified | "Osteoporosis DEXA scans images" dataset from Pakistan | DEXA | Accuracy |

| | | | | | | |
|---|---|---|---|---|---|---|
| Patil et al. | Deep learning for osteoporosis detection in lumbar vertebrae | Neural network, PHOG | Merits: High classification accuracy (99.34%), High sensitivity. Demerits: Notspecified | X-ray imagesand DXA reports of patients | X-ray, DXA | Accuracy, Sensitivity, ROC AUC |
| Sukegawa | Deep learning for osteoporosis classification from dental panoramic radiographs | CNN, Ensemblemodel | Merits: High accuracy and AUC, Improved with ensemble model and patientcovariates. Demerits: Notspecified | Dental panoramic radiographs collected from a general hospital | Dental panoramic radiographs | ccuracy,AUC |
| Zhang et al. | Joint learning framework for osteoporosis diagnosis combining segmentation and classification | Deep learning, Segmentation, Classification | Merits: High overall accuracy(93.3%), High AUC scores. Demerits: Annotation of lesion areas is time-consuming, Existing diagnosis methods are costly | Self-builtdataset | CT | ccuracy,AUC |
| Yaqin et al. | DCNN for osteoporosis detection in patients with rheumatoid arthritis | Deep convolutional neural network | Merits: High accuracy in detection, Comprehensivenursing intervention improves outcomes. Demerits: Notspecified | 90 patients with osteoporosis | X-ray | Accuracy, Sensitivity, False-negative rate |

There are some common gaps in the majority of studies when it comes to the comprehensive risk factors and real-world applicability of the existing proposed models and particularly concerning the diverse populations and various types of data sources. Although many studies have shown high accuracy and utility in predicting or diagnosing osteoporosis using machine learning and deep learning techniques, the following common gaps can be highlighted.

***Lack of external validation:*** Some models were validated using a single dataset or within a specific population and were not externally validated across different demographic and geographic populations. Consequently, the generalizability and applicability of these models to broader populations has been put into question and not responded, which can be exemplified by the studies by Fasihi et al. and Bui et al. that lacked external validation. Comprehensive risk factors. Although some studies integrated clinical, demographic, and even genetic data, the gap about the comprehensive combination of these data sources to improve the performance remains. The studies by Deshmukh et al. and Zhang et al. had the purpose to address this gap, but still, the more integrated risks factors, including lifestyle and environmental factors, can be considered. Real-world application and implementation. Consequently, itis clear that despite the high accuracy and performance metrics in many e studies, these models do not address the real-world challenges of implementation. Very seldom do the studies consider aspects such as integration with the existing healthcare IT systems, data privacy and security, and the user-friendly interface development for healthcare professionals. Annotation and preprocessing challenges. As it was noted in the work by Zhang et al. , the process of lesion area annotation and the overall data preprocessing can be quite challenging and time-consuming. Hence, this becomes one of the bottlenecks for developing efficient and knowledgeable diagnostic tools, and the automated or semi-automated technique was not considered.

**Comparison and benchmarking against the current standards:** Although some papers include the competition of models against the traditional DXA, there is no detailed benchmarking against the current best practices or standards in osteoporosis screening and diagnosis. For example, the performance of deep learning models on real-world, diverse, and noisy data compared with the gold standard DXA tests was not considered. Cost-effectiveness analysis. Also, no works including the cost-effective modeling connected to real world healthcare institutions were met, and only clinical efficacy is presented, which is not enough for economic healthcare organizations. Longitudinal studies and patient outcomes. Along with these standards implementation, there is a gap in longitudinal studies to measure thepatient outcomes and validate the prediction possibility of these models.

## DEEP LEARNING STUDIES FOR SOLVING OSTEOPOROSIS DETECTION

With rapid advancement in medical imaging and diagnostics, deep learning has changed the landscape, providing new insight into methods for detecting osteoporosis. Deep learning architectures, including Convolutional Neural Networks , Deep Neural Networks , and more complex versions such as ResNet, DenseNet, and VGG, have proved to be very useful when applied to osteoporosis detection. These modelsare able to learn hierarchical features from data to predict bone mineral density loss and fracture risk withhigh accuracy . This paper reviews on the application of these deep learning models to osteoporosis detection; explains some of the mathematical equations used to implement these models.

### *3.1 Convolutional Neural Networks (CNNs)*

CNNs are a type of deep neural networks that are excellent at processing data with a grid-like structure, such as images. A typical CNN architecture used for Osteoporosis detection include convolutional layers, activation functions, pooling layers, and fully connected layers. Other layers include: conv = input: convolution The conv layer connects input and is used by nn . Its filter has the shape of the convolutional weights. The biases are defined using a convolution configuration option. batchnorm_2d =input: batchnorm_2d output: batchnorm_2d The planar batch normalization layer is fully connected.31. fcc-nonlinearity = input: fcc-nonlinearity A ) converts the input to scalar output using the given synthesisfunction. This name must not be a standard name prefaced with “fcc-.”. conv-tmp = input :conv-tmp The planar Convolutional (CONV) layer treats input as shared weights. It implements the convolution only asa forward. Corresponding to Neural Network Matrices DOC (N), of shape NN.

$$F_{ij}^{(l)} = \sigma\left(\sum_{m=0}^{M-1} \sum_{n=0}^{N-1} W_{mn}^{(l)} \cdot X_{(i+m)(j+n)} + b^{(l)}\right) \qquad (1)$$

Where $W_{mn}^{(l)}$ represents the weights of the convolution kernel and $F_{ij}^{(l)}$ is the feature map at layer $l, X_{(i+m)(j+n)}$ is the input image pixels, $b^{(l)}$ is the bias term, and $\sigma$ is a nonlinear activation function like ReLU.

Pooling Layer: Pooling, which is usually max pooling, used to decrease the spatial dimensions of the input volume to the next layer of convolutions such that the dimension can be defined as w={[w+2p-f]/s+1}* {[h+2p-f]/s+1}*d. It can be mathematically represented as follows,

$$P_{ij} = \max_{a=0}^{A-1} \max_{b=0}^{B-1} F_{(i\cdot s+a)(j\cdot s+b)} \qquad (2)$$

Where $F_{(i\cdot s+a)(j\cdot s+b)}$ are the values of the feature map within the pooling window, $P_{ij}$ is the output of the pooling layer, and $s$ is the stride of the pooling operation.

Advanced Models: ResNet , also referred to as Residual Networks, which differs from other models through the skip connections and residual blo can be given as follows:

$$y = F(x, \{W_i\}) + x \qquad (3)$$

Here, $x$ and $y$ are the input and output vectors of the layers considered. The function $F(x, \{W_i\})$ represents the residual mapping to be learned.

DenseNet, which relies on the concept of densely connected convolutions. That is, any layer is given as an input the output feature maps from all the layer before them. It can be defined as follows:

$$x_l = H_l([x_0, x_1, \dots, x_{l-1}]) \qquad (4)$$

Where $H_l$ is a composite function of operations (BN, ReLU, Conv, etc.), $[x_0, x_1, \dots, x_{l-1}]$ represents the concatenation of the feature maps produced in layers 0 to $l-1$.

VGG, which stands for Visual Geometry Group, is one of the simplest model architectures. The essential concept behind the network is 3×3 convolutional layers. The convolutional layers are repeated in the network to increase the network’s depth. The fully connected layers are already formulated for the basic CNN architecture. These models are trained using backpropagation, where the gradient of the loss function with respect to the network’s weights is computed. The gradients with respect to weights W of the network can be expressed as:

$$\frac{\partial L}{\partial W} = \frac{\partial L}{\partial y} \frac{\partial y}{\partial F} \frac{\partial F}{\partial W} \qquad (5)$$

Where the output of the network is given as y; there is a function modeled by the network denoted by F. The computed gradients are then used to update the weights in a direction that will minimize this loss. In most cases, optimization algorithms like SGD and Adam are used to minimize this loss. Hence, CNN-based models are augmented with the deep learning model's architectural innovations to study medical imaging systems, which will serve a vital role in the accurate and early detection of osteoporosis.

## DATASET

***Osteoarthritis Initiative (OAI):*** This dataset provides valuable insights into joint health and can indirectly contribute to osteoporosis research, especially in identifying biomechanical markers related to bone health.

***The MrOS Study & The SOF:*** These gender-specific studies are crucial for understanding sex differencesin bone density loss and fracture risk, providing a rich basis for developing targeted osteoporosis detectionmodels.

***NHANES Bone Densitometry Dataset:*** This provides a diverse demographic scope, making it ideal for studying population-wide bone health trends and developing models that can be generalized across different populations.

***UK Biobank Imaging Study:*** With its vast repository of imaging data, researchers can leverage this datasetto identify subtle indicators of osteoporosis alongside other health conditions.

***The Korean Osteoporosis Study (K-OST) & Public Domain Dataset for Osteoporosis Detection:*** These are instrumental in creating models that account for ethnic variations in bone density and osteoporosis prevalence.

***Hospital-Based Clinical Dataset:*** These datasets are pivotal for developing highly specialized models thatcan integrate clinical and imaging data for comprehensive osteoporosis detection and patient managementstrategies.

| Dataset Name | Description | Size/Content | Imaging Technique | Usage |
|---|---|---|---|---|
| Osteoarthritis Initiative (OAI) | A multi-center, longitudinal, prospective observational study | ıousands of knee MRIand X-ray images | MRI, X-ray | Used to study knee osteoarthritis, but has applications in studying changes related to osteoporosis |
| The MrOS (Osteoporotic Fractures in Men)Study | Focused on the determinants of fracture in older men | Clinical and demographic data, DXAscans | DXA | Studies bone density, structure, and risk factors associated with osteoporotic fractures |
| The Study of Osteoporotic Fractures (SOF) | A study primarily focused on womenaged 65 and older | cal data, X-ray, andDXA scans | X-ray, DXA | Focuses on risk factorsfor osteoporosis and |
| | | | | elated fractures among elderly women |
| NHANES Bone Densitometry Dataset | Part of the National Health and Nutrition Examination Survey | Bone mineral density measurements for various populations | DXA | Provides a cross-sectional dataset for evaluating bone health in the U.S. population |
| iobank ImagingStudy | A large-scale population-basedstudy | Full body MRI scans, including spine images | MRI | While not solely focused on osteoporosis, it includesrelevant imaging data for bone health research |
| The Korean Osteoporosis Study(K-OST) | Specifically tailoredfor the Korean population | Bone density measurements, clinical information | A, QuantitativeCT | Aims to identify genetic and environmental factors affecting bone health in Koreans |
| Public Domain Dataset for Osteoporosis Detection in DEXA Scans | A curated dataset from various publicsources | DEXA scan images labeled for osteoporosis status | DXA | Utilized for developing machine learning models for automatic osteoporosis detection |

| | | | | |
|---|---|---|---|---|
| Hospital-BasedClinical Dataset | Compiled from patient records inspecific hospitals | X-ray and CT images, some datasets include clinical data | X-ray, CT | Often used for localized studies, focusing on algorithm development and validation |

Each dataset contributes uniquely to the field, enabling the development of sophisticated models that can predict osteoporosis with high accuracy, potentially transforming the screening and management of this widespread condition.

## PERFORMANCE EVALUATION METRICS

***(a) Accuracy:*** Accuracy is the simplest measure that shows how accurate the model is. Also, it is the ratio of the number ofcorrect predictions to the number of all the observations. It gives an overall idea about the model's accuracy. True Negatives are false predictions of the model and positives and false negatives are all observations. True Positives: The equation of accuracy is as follows in equation.

$$\text{Accuracy} = \frac{\text{True Positives (TP)} + \text{True Negatives (TN)}}{\text{TP} + \text{False Positives (FP)} + \text{False Negatives (FN)+TN}}$$

***(b) Precision:*** Positive Predictive Value is the proportion of appositively predicted observation coroutine to all predicted positive observations; it also describes a quality of the model's positive prediction. The Precision equation is in equation as,

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

***(c) Recall:***. True Positive Rate Sensitivity is the ratio on a given class, how it is capable of identifying all the possible cases. For actually data how the model predicts it correctly, the equation of recall is as follows in equation as

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

***(d) F1-Score:*** It is a harmonic average of both previous matrices when it want to balance both matrices it use this matrix, who's calculating formula is as follow;

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

***(e) AUC-ROC:*** It is a performance measure of the classifying problems at various thresholds settings. ROC is a probability curve, and the AUC represents the separability;

$$\text{AUC-ROC} = \int_{x=0}^{1} TPR(x)dx$$

***(f) Area Under the Precision-Recall curve:*** AUC-PR summarizes a precision-recall curve and is useful when the dataset has a strong Imbalance in AUC, which is as follows in equation as,

$$\text{AUC-PR} = \int_{x=0}^{1} \text{Precision}\ (x)dx$$

***(g) Mean Absolute error:*** MAE; in regression tasks, it determines the average magnitude of errors in a set, is as follows,

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

## CONCLUSION AND FUTURE SCOPE

The application of deep learning in osteoporosis detection has shown potential implications in more accurate, efficient, andearly diagnosis of the widespread bone disease. However, there is still a need for further research and development despite substantial findings made in the area. The conclusion derived from the study findings is as follows: deep learning models, specifically CNNs have achieved better performance in identifying osteoporosis from various imaging modalities, including DXA, X-ray, CT-scans, and MRIs; the models unravel complex patterns and features from medical images that are sometimes impossible for human vision, thus providing an efficient tool for differential diagnosis and predicting the disease; integrating these imaging features with clinical data has helped capture comprehensive patient information . Furthermore, advanced deep learning architectures such as ResNet, DenseNet, and Inception models have further enhanced the accuracy and reliability of osteoporosis detection by utilizing their depth and novel connectivity to address the issues in traditional architecture . Moreover,as the models utilized the metrics based on the confusion matrix and ROC curves, including accuracy, precision, recall, F1 score,and AUC-ROC, it ensured that the diagnostic tool developed is highly performant. Possible future directions in which more investigation is needed include the use of 3D imaging data that gives a more detailed view of bone quality and structure. This can be achieved using 3D CNNs or hybrid model capable of processing volumetric data, which offers more insights into osteoporotic bone density changes. Moreover, validation across populations is valuable as the developed model needs to be versatile and applicable across different settings. For this, future studies can consider cross validation studies across demographics andethnicity backgrounds. Developing real-time, AI-driven diagnostic tools integrated into clinical workflows could be a promising avenue of research. As a result, patient care could be improved due to the possibility of assessing and making decisions on test data during patient visits. In the context of the increasing complexity of deep learning models, the need for explainability is becoming more acute. XAI approaches can promote greater trust from healthcare professionals and, therefore, greater adoption. Osteoporosis treatment response," meaning that besides detection response models can be trained to predict treatment resopne. For example, for a specific patient, they can recommend a treatment plan that would be most effective in this particular case. For this to occur, focus should be on federate learning so that models can be trained across institutions without patient data directly being shared. In addition to that wearables that measure steps and physical activity can integrate and proivide results for doctors . Besides, there is a need for Longitudinal Studies that would require the use of deep learning models to trend changes in bone density over time. This kind of network will help predict osteoporosis onset while the bone loss isn't severely impacting the active lifestyle.

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