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A comparative study on detection of osteoporosis using deep learning methods: A review

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Abstract

Osteoporosis is a silent bone disease characterized by low bone mass and loss of bone tissue that may lead to weak and fragile bones and decreases in bone strength which increases the risk of fractures. It is more common in women rather than men. DEXA that is Dual Energy X-ray Absorptiometry is a model to diagnose osteoporosis although its low-availability, expensive, and high radiation exposure. The CAD (Computer-Aided Diagnosis) has enhanced the analysis to a higher level. The advanced learning paradigm that is Deep-Learn, Machine-Learn and Artificial Intelligence has exposed a turning point in the medical field which leads to accurate diagnosis of osteoporosis. The review is based on various anatomical sites such as lumbar spine, hip, forearm, calcaneus, and dental are assisted and examined based on validation, pre-trained networks, and accuracy. The combination of clinical data and images are fed to deep learning models specifically CNN-Convolutional Neural Network, RNN-Recurrent Neural Network may result in completely automatic detection and diagnosis of osteoporosis.

Keywords: Artificial intelligence, classification, deep learning, feature extraction, machine learning, osteoporosis

1. Introduction

Osteoporosis means porous bone, identified as a disease categorized as a micro architectural deterioration of bone tissue and low bone mass which leads to brittleness bone, increases the risk fractures of the wrist, hip, and spine [1]. In Indian women Osteoporosis is a major public health issue, expected over the age of 50 years, postmenopausal relates to bone metabolism which increases the rates of fractures. The bones of the spine affected by osteoporosis of vertebrae which in turn leads to hunched or stooped posture. The fracture rate can be reduced by the intake of calcium and vitamin D [2]. The decreasing bone-mass with age in men and women as shown in Fig 1.

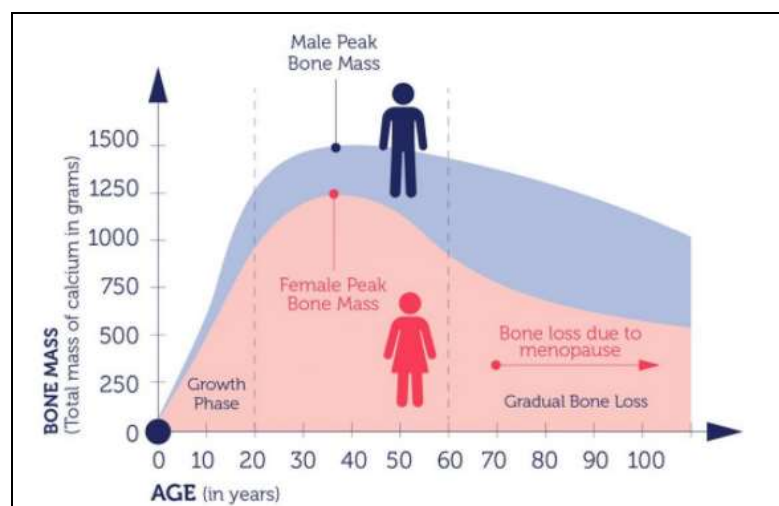


Fig 1: Decreasing bone-mass with age in men and women [28]

Artificial Intelligence (AI) has the potential of a machine to mimic human behaviour intelligence—is perched to transform the medical practice [3]. AI is a compatible technology, designed to develop the human performances of medical researchers, physicians, and nurses. In medicine, AI is not to substitute the doctor but to intensify medical expertise. In recent times, AI is a hot issue of the 4th industrial revolt. The approaches of AI tool trained to diagnose the patients with fracture which leads to the risk of osteoporosis precede the radiologist traditionally examine the report. The fig. 2 shows the stages of the Intelligent System.

Machine learning (ML) is a cluster of artificial intelligence that creates healthcare smarter and tool for medical research like diagnostic imaging, treatment optimization, genetic tests, and electro diagnosis. The mainstay task of ML is classifier and prediction. Its role is applied in the field of medicine, which helps to diagnose and treat patients. Depending on the prediction utilization of ML is developed to assess the T-score of the lumbar spine and categorize the healthy vertebra and osteoporotic vertebrae by the usage of Hounsfield units (HU) of lumbar computed-tomography (CT) [4].

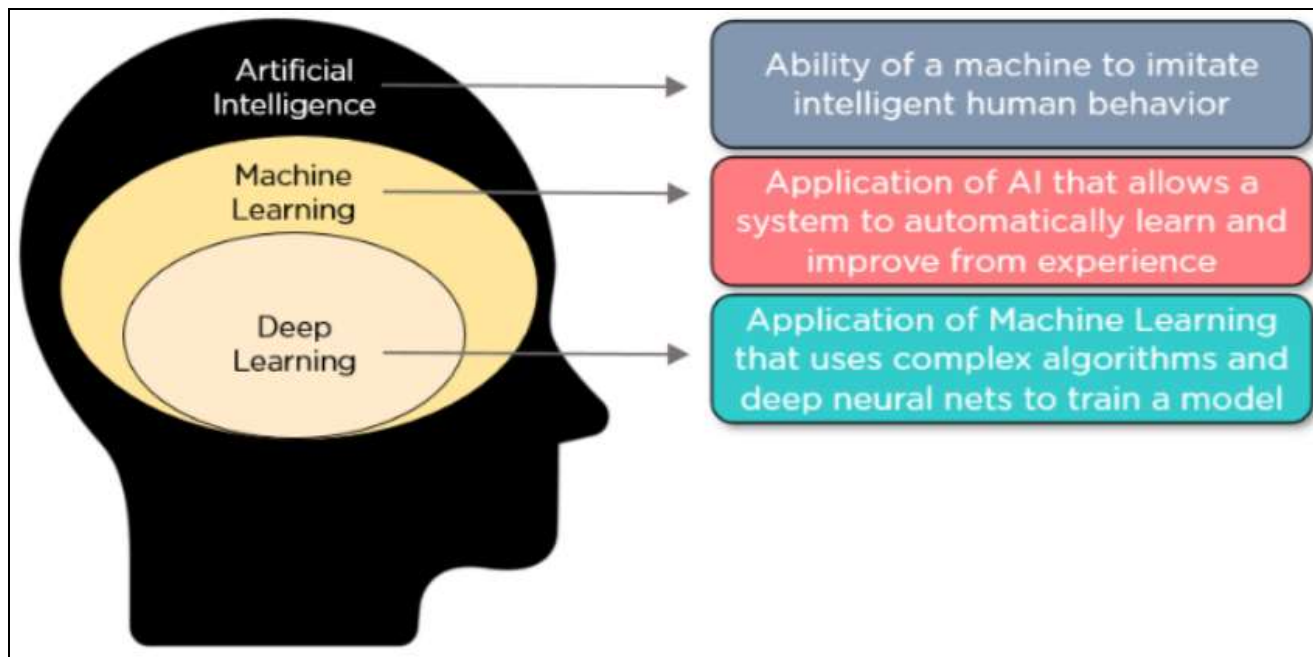


Fig 2: Intelligent System (Artificial Intelligence, Machine learning and Deep learning) [29]

ML has ample scope in medical use will be stable and incessant which is essential for a doctor to gain the fundamental idea of ML. The major categories of ML are supervised and unsupervised learning. In Supervised learning (SL) the datasets are labelled and trained to predict the output from the input data and in unsupervised learning, the datasets are not labelled and be trained to inherit itself from the existing data [5]. The logistic and linear regression is a part of the SL algorithm which is used as a predictive paradigm. The Linear regression (LR) patterns show to predict the linear relationship between two variables (dependent and independent) and this pattern correlates the independent (sex, age, and HU of lumbar CT) and dependent (T-score) variables and logistic regression (LoR). is a type of binary regression where dependent variable has only two (“0” and “1”) values i.e., output is classified as the controlled and osteoporotic spine .To design a model in the medical field, it is essential to

comprehend the fundamental concept of ML and AI and to improve accuracy.

The methodology used in deep learning use architecture of the neural network, the “deep” indicates an increase in numeral hidden layers hence the models are named as a deep neural network (DNN). Conventional the approach in neural network (NN) have two-three hidden layers but DNN has innumerable as 150. DNN uses large labelled datasets while NN doesn’t require manual attribute extraction as it learns directly the features from the data [7]. The current trend in DNN is the Convolutional neural network (ConvNet or CNN). It directly extracts the features from image because CNN does convolution between input data and learned features and uses two dimensional (2-D) Convolutional layers which makes architecture processing compatible with 2-D image data. The automatic extraction of features improves accuracy.

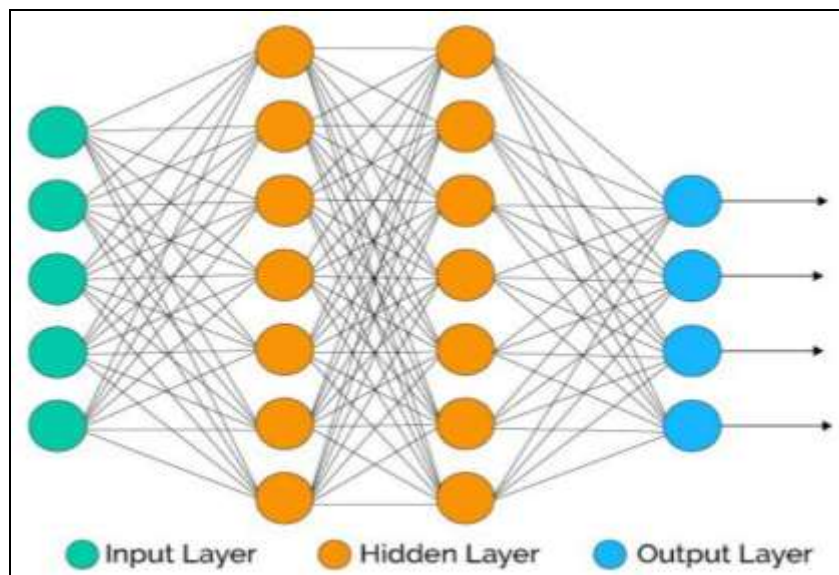


Fig 3: Deep learning [30]

From Fig. 3. The 1st layer is hidden layer for edge detection, the next layer is detecting a combination of edges followed by identifying features and combining all these layers, at last, output layer is identifying the combination of features that recognizes the object.

Deep learning (DL) is a specific form of machine learning (ML). The workflow of ML begins with the related features where it extracts manually from images and these features are used to generate a model which classify objects within the image, while deep learning (DL) extracts significant feature automatically from images and it performs “End-to-End” (E2E) learning- where model fetches raw data and automates the classification. In DL if the range of data increases, granular learning converges and improves accuracy whereas in ML training data should be specific otherwise the model reaches over fitting.

2. Materials and Methods

2.1 The Channel of a Diagnostic Technique to Detect Osteoporosis

The quantitative diagnostic imaging-modality tools follow general channels to detect Osteoporosis which are divided

into 5- stages: 1) Acquisition of image 2) Pre-Processing 3) Segmentation method i.e. sub-image (ROI), 4) Extraction of feature, and 5) Classification (as shown in Fig. 4). In stage-1, Images are acquired (1) using dedicated imaging modalities and while capturing the image degradation occurs, therefore pre-processing of the image is done and in stage 2 the quality of the image can be improved by suppressing surplus deformation or image-feature enhancement is done by preprocessing method indicates transforming the raw-data prior fed to deep learning or the machine learning method [8]. The ROI-bone image segmentation depends either on manually, semi-automatic, or complete automate segmentation of the method is applied in the 3rd stage. In the 4th stage, numerous feature-extraction techniques are considered to extort noteworthy features is taken from segmentation of ROI –bone image (cortical and trabecular bone character) features are used to diagnose non-osteoporotic or osteoporotic. The stage-5 works on classifiers based on scores (Z and T) are computed from standard reference-values or use of ML-technique for classifying the control and osteoporotic subject.

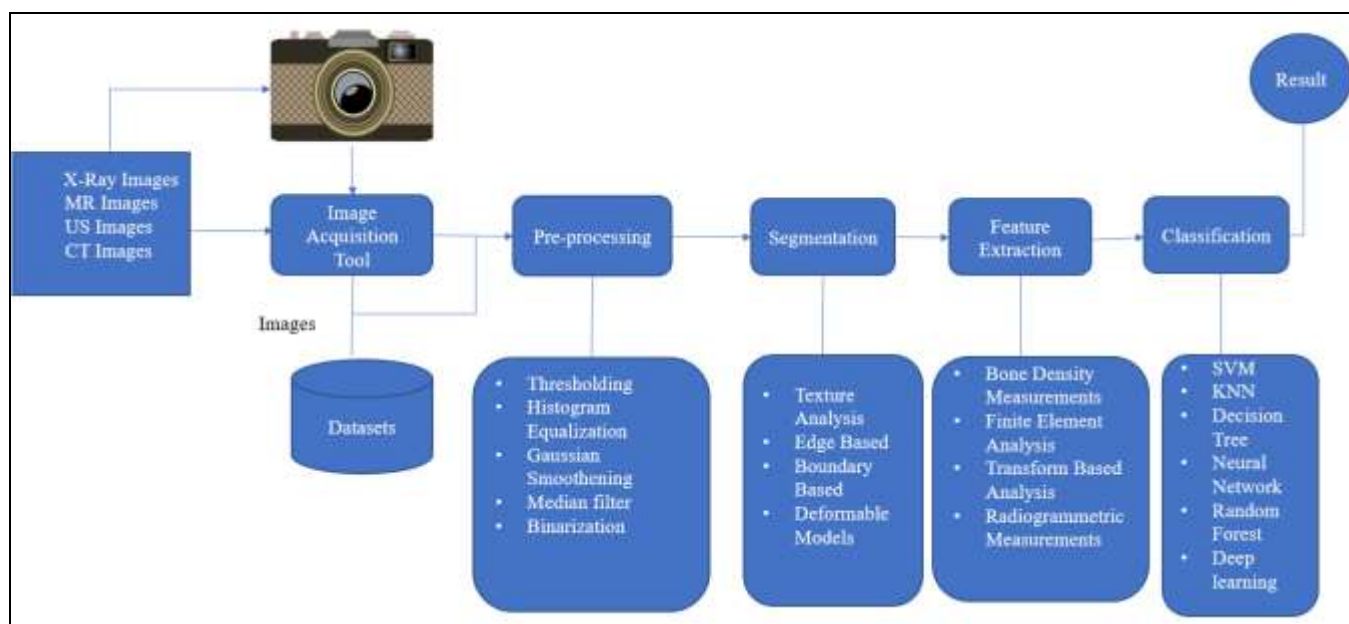


Fig 4: Channel to detect Osteoporosis [31]

2.2 Quantitative Imaging Modalities to Diagnose Osteoporosis

The numerous Image Acquisition Tools (IAT) [8, 9] used in the medical field for detecting osteoporosis and fracture-risk prediction as shown in Fig. 5 and Table -I.

The fine-tuning and transfer learning showed better performance of deep Convolutional neural network (DCNN) for Osteoporosis screening in Dental Panoramic Radiographs (DPRs) images and by applying the mapping technique of Gradient-weighted activation class depends on features of image in right border also lower left of mandibular showed differences. The 4 groups used in DCNN Model - three-Convolutional layer (CNN3), Visual Geometry Group (VGG-16), the transfer learning (VGG-16_TF) and fine-tuning by the transfer learning model(VGG-16_TF_FT) [11] accord better

accuracy [10]. These outcomes were used for screening an automatic osteoporotic patient with less training datasets. The hand radiograph (HR) classification showed Osteoporosis on the 2nd Metacarpal cortical-percentage. Segmentation was used to identify which specific pixels belong to the second metacarpal PA (Poster Anterior) x-ray images using Fully Convolutional Network-8(FCN-8) CNN with accuracy (94.8%). The LeNet Convolutional Neural Network (LeNet-CNN) used to classify Laterality with accuracy (99.62%), Specificity (100%) and Sensitivity (99.3%). The overall accuracy is shown in [11]. The formation of the CNN series showed an accurate classification of an osteoporotic and control subject. In addition to this, CNN can generate accurate image adaptation rely on vertical and laterality alignment.

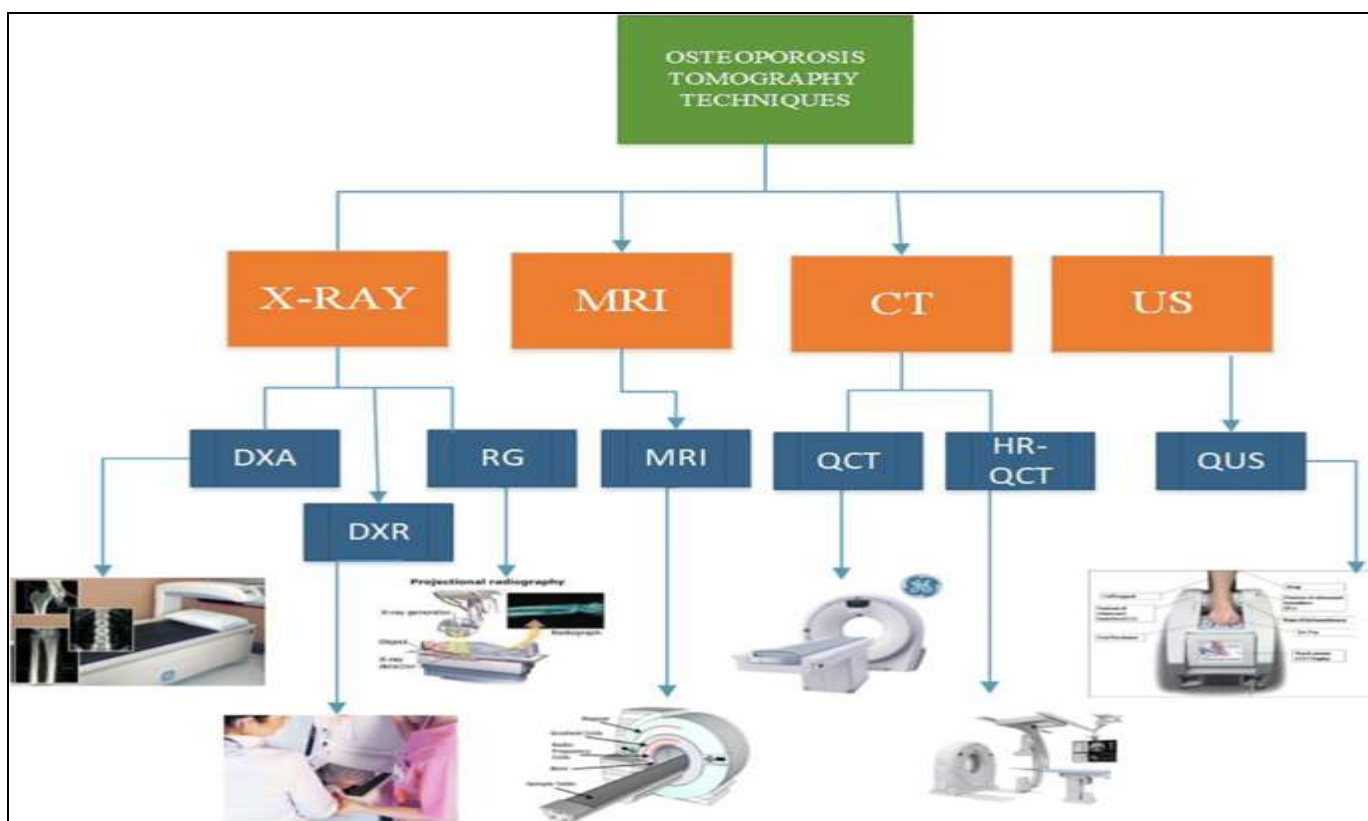


Fig 5: Imaging Modalities to diagnose Osteoporosis [31]

Table I: Performance parameters comparison for Example 1

Sl. No	Image Modality	ROI	Feature Extraction	Advantages	Dis-Advantages
1.	DXA (Dual X-ray Absorptiometry)	<ul style="list-style-type: none"> Whole Body Fore-arm Hip Lumbar Spine 	The ratio of Bone Mineral Content(BMC) to the total area is measured by BMD	<ul style="list-style-type: none"> Radiation Exposure is low Gold Standard Scanning time is low 	<ul style="list-style-type: none"> Unable to define Micro-architecture of bone Very Expensive Equipment availability is very low areal measurement gives different for bone-sizes and values
2.	DXR(Digital X-ray Radiogrammetry)	Meta-carpal bones(Hand-bones)	BMD is extracted from Radiogrammetry along with cortical (porosity)	<ul style="list-style-type: none"> Alternative for low economy(Cost-Effective) No biasing human error Correlation is Good with DXA 	<ul style="list-style-type: none"> Unable to compute Volumetric BMD Texture of Trabecular is not considered
3.	Radiography	Lumbar spine, hip, calcaneum, dental and forearm	<ul style="list-style-type: none"> Texture Analysis(Connectivity, anisotropy) 	<ul style="list-style-type: none"> Commonly available Cost-Effective 	<ul style="list-style-type: none"> Radiation exposure higher It generates 2D images

			<ul style="list-style-type: none"> • Radiogrammetry 	<ul style="list-style-type: none"> • Scanning is easy 	
4.	MRI (Magnetic Resonance Imaging)	Spine, hip and Fore-arm	<ul style="list-style-type: none"> • Compute Histomorphometric features(connectivity and thickness) 	<ul style="list-style-type: none"> • Produce Volumetric measurement • Less radiation exposure • 3D Imaging • Improvement in trabecular bone-micro architecture 	<ul style="list-style-type: none"> • Longer Scan time • Spatial resolution is very low • Very Expensive • Prone to motion artifacts and volume effects
5.	QUS (Quantitative ultrasound)	Tibia,radius,phalanx and calcaneum	Velocity and attenuation(Sound)	<ul style="list-style-type: none"> • No radiation exposure • Cost is low(low economy) • Device is Portable • Non-invasive and simple technique • Sound waves is used to study bone 	<ul style="list-style-type: none"> • Sensitivity and Precision(poor) • accuracy (poor) • Used for specific site • Dissimilar QUS-device measurements undergo minor changes in their measurements
6.	QCT (Quantitative Computed Tomography)	Hip, Lumbar Spine	Volumetric- BMD using system measurement Calibration phantom	<ul style="list-style-type: none"> • Involve 3D-geometric imaging • Analyze the risk-fracture for trabecular and cortical regions • It gives volumetric measurements 	<ul style="list-style-type: none"> • Radiation is higher • whole body scanning has limited access • Scarcity of commercially existing software programming • Artifacts causes variations • WHO – norm do not apply!
7.	pQCT(Peripheral Quantitative Computed Tomography)	Tibia , Distal Radius	Trabecular density and cortical (architecture)	<ul style="list-style-type: none"> • It is suitable for peripheral quantity 	<ul style="list-style-type: none"> • Very Expensive • Radiation dose is high

3. Literature Review

Recurrent Neural Network (RNN) is used to detect and segment Osteoporosis especially the spine and produces image representation of bone density. It has an excellent implementation in the medical-image analysis together with Orthopaedic issues. The practicability of RNN was evaluated and examined using two methods- transfer learning and training from scratch. The analysis reviewed that RNN can utilize image data of DXA gives prediction which differs from the standardized method used in the clinic. The ample potential architectural and with less quantity of data, their factual possibilities are outspread [12]. The study shows that pre-trained RNN provides best fracture risk prediction and reinforces the emphasized advantage of transfer learning i.e., larger datasets and faster training speed. Computer-Assisted Diagnosis (CAD) base DCNN is used to detect Osteoporosis of panoramic x-ray images compared with the diagnosis of Oral and Maxillofacial radiographs. The CAD system was used to examine panoramically-ray images- Multicolumn DCNN (MC-DCNN), (Augment SC-DCNN) Single-Column DCNN by means of Data Augmentation as well as (SC-DCNN) Single-Column DCNN, all these systems were evaluated using Receiver Operating Characteristic (ROC)curve as shown in table1 and these System help to assist dentist for the prior diagnosis of Osteoporosis [13].

The CNN approach [14] was used to automate the condition of bone CT image by decreasing the number of patients. The technique includes Mark Segmentation (MS-net) and Bone Conditions Classification Network (BCC-net) where mark segmentation goal is to place the position and ROI-seg (Region of interest -segmentation), the BCC-net cluster the condition of bone through features. The trained MS network gives marking on input CT (Computed Tomography) image which leads to segmentation and the BCC network finds the probable value of healthy, Osteopenia, and osteoporotic by

segmenting input CT image. The outcome of these network aid radiologists for prelude quality analysis of bone-condition. A Multitask approach used in DNN to pretrained Image-Net for DPR images and enhancing the accuracy to diagnose osteoporosis [15]. The task of Alex-Net is pre-trained on Image-Net used for fine-tuning and input (Patient)classification are profuse partial patches, extraction of DPR images, and the learned features (dental-data) are used for osteoporosis detection. So, Octuplet Siamese Network (OSNet) is the highest feature and 8th trained- ROI DPR-image categorization. The cross-validation is leave-1-out to achieve higher accuracy as shown in Table-1. Artificial neural network (ANN) is a model used to improve the score of OSTA-(Osteoporosis Self-Assessment Tool for Asian's) and was created using female attributes [16] as an input (age, weight) with output femoral neck (T-score). The ROC (Receiver Operating Characteristic) Curve examined by integrating OSTA Score and ANN for screening osteoporosis with improved performance as shown in the table2. Fifteen Classifiers with randomized (200) cross-validation datasets were used. The feature vector of 5 femoral regions(femoral head, greater trochanter, inter-trochanter, neck, and ward) in addition to BMD, fracture risk -assessment tool (FRAX) score, and attributes (age, weight, and height).Out of 15-Classifiers only 3 -classifiers(the linear discriminant, logistic regression, and boosted trees) gave the best results(sensitivity-71% and specificity-83%)for detecting osteoporotic fracture [17]. The MRI and FRAX autonomously showed the best results for recognizing osteoporotic fracture. The bone-quality improvement through mapping of ANN. Addition of Teriparatide composition (T-PD) for not only remodeling BMD (Bone Mineral Density), also BSI (Bone-Strain-Index), TBS (trabecular-bone-score), which strengthens the bone that and minimizes the risk of fracture. The BSI seems to be a sensitivity index of the TPD effect [18]. ANN is a valid tool for

investigation in medical applications. ANN is better than logistic regression [LR] for better accuracy as there is a greater number of inputs, discrete parameters, and optimal technique to diagnose osteoporosis. The result of ANN with respect to AUC is more than LR as shown in the table 2 with P-value=0.034^[19]. Fuzzy logic calculations can be used with LR enhanced the best clinical method put into practice. In order to integrate with the information-management system for better analysis. The software package of ANN is an efficient approach for an accurate estimate of segmental and BMD (total) ^[20]. The input attributes: weight, sex, age, BMI, and height beside with segmental reference and BMD (total-values) are fed to ANN (multilayered-input layer) and quantifiable approximation of [BMDlegs, BMDarms, BMDpelvis, BMDspine, and BMDtotal] is generated in the output-layer. ANN model shows a potential approach for evaluating BMD (total-values) and, segmental using statistical values prove the best model to a diagnosis of osteoporosis. To detect Osteoporosis impulse-response test was done on tibial bone using Lab-VIEW. The record of analog-signal was studied in freq-domain (frequency) ^[21]. The vibration generated by natural frequency was a considerable decline in Osteoporosis which shows a reduction in bone strength automatic and mass in bone- minerals. In a recent study, osteoporosis detection was found high-priced and requirement of the virtuoso tool. The method used in this study was easy to use and economically less price. The trend of AI -ML effort linked to the spine include vertebral localization and images of X-ray(discs) ^[22], segmentation of image(ROI), CAD, clinical practice prediction and difficulties, information management the system, bio-mechanics , Retrieving the content of the image, and motion-study. The application of AI in Medical-science secures and authenticates the data and provides the privacy community of real domain appliances. The machine learning model used to evaluate Osteoporosis by HU (Hounsfield units) of surgical on lumbar -CT pairing with QCT-data. MRA (Multiple Regression Algorithm) uses a T-score prediction of 3-independent attributes (sex, age, and HU -Vertebral body on predictable CT) combining with T-score-QCT. The algorithm of logistic regression helped to assist non- osteoporotic vertebra. With the monitoring of machine learning tools Python, the Tensor flow helped the programmer to interface with easier use ^[23]. The Algorithm helps to predict data of QCT of T-scores. The training data sets of this model segregated the lumbar vertebra into 2 classifiers of the non-osteoporotic, osteoporotic spine with better accuracy as

shown in the table 2. In testing-phase, the datasets were 40 vertebrae used to improve the accuracy (92.5%), learning rate(0.0001),(precision, 0.939; recall, 0.969; F1 score, 0.954; area under the curve,0.900).The dynamic method for selection of features, categorization, and detection by using supervised learning methods– Nearest Neighbours (NNs), Support Vector Machines (SVMs) with improved accuracy of 95% as shown in the table 2^[24]. Further yields cost-effective and robust in nature. The 4 attributes were used for prediction of Osteoporosis (height, weight, age, and sex,). To discriminate non-osteoporosis and osteoporosis, 20 ML-Technique were applied depending on the popularity in the biomedical engineering field. The 20 classifiers were validated using 10-fold cross-validation and the results were systematically predicted to avoid further testing. The analyses were standardized and diminished to two attributes (age and weight) which yielded similar results ^[25]. ML classifiers were designed in WEKA (benchmark of ML) are tested using 10-fold cross-validation, training datasets and splitting percentage inclusion and exclusion feature selection. The comparison of the result is done in terms of execution time, classified instances, mean absolute values, and kappa statistics evaluation inclusion and exclusion of feature selection ^[26]. The overall study propose IBK (training and testing set) gives better result exclusion feature- selection, where these techniques [IBK, LMT, J48, JRip, SMO, and bagging] gives an appreciable result of inclusion feature selection. Texture-Characterization of good-quality bone is necessary for Osteoporosis Identification. The Gray Level Co-occurrence Matrix (GLCM), Local Binary Pattern (LBP), Law's, and so on are the standard methods used for texture feature extraction. A collate between deep- features extraction from CNN adjacent conventional features ^[27]. The outcome of this study demonstrates that deep-features have more distinguishing power with respect to classifiers training on them constantly surpass one's training on conventional features.

4. Results & Discussions

The majority of the Research-work is carried out on osteoporosis detection to circumvent the risk of bone fracture however it is highly affected to trabecular bone i.e., soft and spongy bone rather than compact cortical hard bone. The performance of a system is compared with dissimilar the technique utilized in the current trend are mentioned in Table II.

Table II: Performance Comparison with different methods

Model	Imaging Modality	Human Site	Classification Module/ Pre-Trained Networks	Validation	Accuracy (%)	Auc (%)
CNN ^[10] [VGG16-TR-TF]	X-RAY	DPR (Dental panoramic)	VGG16-TR-TF	5-fold cross	84	85.8
CNN ^[11]	X-RAY	Hand	LeNet- based CNN		93.9	-
RNN ^[12]	MRI	lumbar spine	10-fold cross			
DCNN ^[13] [(SC-DCNN) SC-DCNN (Augment) (MC-DCNN)]	X-RAY	Dental panoramic	-	200 (testing)	98 98.5	97.63 99.91 99.87
CNN ^[14]	CT	lumbar vertebra	BCC- net MS-net	7- fold 2- fold	76.5	91.67
MULTI-TASK SCHEME ^[15]	X-RAY	Dental panoramic	OSNet	Leave-one-out cross-validation	92.59%,	-
ANN ^[16] OSTA-Score	X-RAY & DXA	Femoral Neck	ANN	10-fold cross	78.8 78.3	-
ANN ^[17]	MRI	Femoral Neck	linear discriminant, logistic	23- fold	71	-

			regression, and boosted trees			
ANN [19]	X-RAY	Vertebral	ANN logistic regression	30-osteoporosis 35-non-Osteoporosis 54-Prediction	95.8	95 87.0
ANN [20]	DXA	Arms, legs, spine, pelvis, and total	Demographic Variables (Age, weight, height, lifestyle etc)	200 cross validations	99.78, 99.04, 99.19, 99.89, & 99.9	-
Feed-forward back propagation [21]	CT	tibial bone	ANN	70	-	-
Multiple Regression Algorithm [23]	CT	Lumbar vertebrae	Logistic Regression	Training-158 Testing-40	92.5	90.0
GLCM [24]	X-ray	Calcaneus	SVM, NN	30-fold	95	-
Features of BMD [25]	DXA	Osteoporotic site (hip, spine and arm)	Multilayer perceptron	10-fold	71.51	-
Machine Learning Technique [26]	-	family history, blood calcium, vitamin, and phosphorus.	LMT [logistic model tree]	10-fold	87.14	-
Deep Features [27]	X-ray	Calcaneus	Random Forests	Training-116 Testing-58	79.3103	0.85

5. Conclusion

On boosting follow-up care and identifying personnel with higher risk of fracture requires prompt treatment, coped up with care can enhance the cost-effective management of osteoporosis, dampening downstream costs. However, in the recent medical diagnostic field, DXA is not popularly accessible and it is not cost-effective with several disadvantages and it is not an absolute solution. So, it is necessary to construct a diagnostic system to fulfill the necessities incorporating reliability, ease of availability, cost-effectiveness, and clinical acceptance. In this review study CAD-system vision-based for automatic detection and diagnosis of osteoporosis which inclusion of X-rays, DXA scans, MRIs, and CT-scan of vertebrae were surveyed. The channel to detect Osteoporosis includes acquisition of image, pre-processing, segmenting with respect to ROI, extracting features and lastly the classifiers using machine learning technique. Further, it is observed that texture analyses of trabecular micro architecture using ML based techniques are used to improve the sensitivity, specificity, F1-score and accuracy. The advantage of using ML Technique is self-learning because no further preprocessing is required. However, the standardization of dataset is needed for researchers to assist a universal paradigm. The future directions of research could be concerned to x-ray diagnostic significant tool of low-cost, extensive use and ease of availability. The vision of deep learning model needs large amount of data and the machine in DL learn features automatically from the input data.

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