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# Deep Learning Models for Accurate Diagnosis and Detection of Bone Pathologies: A Comprehensive Analysis and Research Challenges



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**Abstract:** The presence of bone disease has been observed to have a substantial influence on an individual's overall health. There are conventional techniques to detect as well as diagnose them but they often suffer limitations in the form of misdiagnosis because of manual error as well as maximum time consumption. Therefore, it is of utmost importance to accurately and proficiently identify it by integrating conventional methods with advanced artificial intelligence techniques. The objective of this study is to conduct a comprehensive analysis of the present state of research concerning the identification and diagnosis of bone disease using machine learning and deep learning. A review is conducted in accordance with the PRISMA guidelines which focus on the examination of scholarly articles published within the timeframe of 2019 to 2024. This review analyzes peer-reviewed literature and research findings to show how machine and deep learning can improve bone disease diagnosis accuracy. It has been found that in the case of osteoporosis, the highest recall, precision, and F1 score is computed by random forest with 93%, 94%, and 93%, respectively while as advanced CNN technique computed 98% accuracy for osteoporosis and 98.4% accuracy, 95% sensitivity as well as 97% specificity for osteonecrosis. Likewise, for bone tumor and osteoarthritis, AlexNet achieved 98% and 98.90% accuracy, respectively. The study introduces a novel approach to the diagnosis of bone diseases by emphasizing the usage of advanced learning techniques over conventional methods. Additionally, the paper highlights the significance of analyzing the clinical or imaging data and extracting features to improve image quality and provide a pathway toward more accurate and efficient diagnosis of bone diseases. By delving into these techniques, the paper offers valuable insights into enhancing diagnostic capabilities for bone diseases, which ultimately leads to improved patient care and treatment outcomes.

## Introduction

Bone is a dynamic and metabolically active tissue composed primarily of calcium and collagen. It possesses the unique ability to grow and remodel throughout an individual's lifetime. The framework, commonly referred to as the skeleton, plays a crucial role in safeguarding and providing structural support to the internal organs and the overall body (Wawrzyniak et al., 2022). It has been observed that certain diseases or issues, such as environmental factors, genetics, diet, and infection, can have an impact on the flexibility and strength of bones. These factors can give rise to various bone diseases, which include osteoarthritis, fractures, osteomalacia, osteoporosis, etc (Figure 1) and the manifestation of these diseases can be identified through symptoms such as swelling, tenderness, and pain (Santhakumar, 2023).

In addition, it is worth noting that in the majority of severe cases, the diseases affecting the bones result in limited mobility and increased weakness, which eventually results in fractures (Campagne, 2022). An individual affected with bone disease or bone cancer experiences a multitude of physiological alterations such

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as swelling, weight loss, pain, fever, anaemia, and tenderness (Sampath et al., 2024). Therefore, it is of utmost significance to promptly identify these symptoms in their initial stages in order to facilitate early diagnosis and deliver timely and suitable treatment to the patient.

the likelihood of misdiagnosis and improve patient outcomes. Moreover, AI enables predictive analytics that allows healthcare providers to analyze the risk of developing bone diseases on the basis of patient data such as gender, age, lifestyle factors, and medical history. This

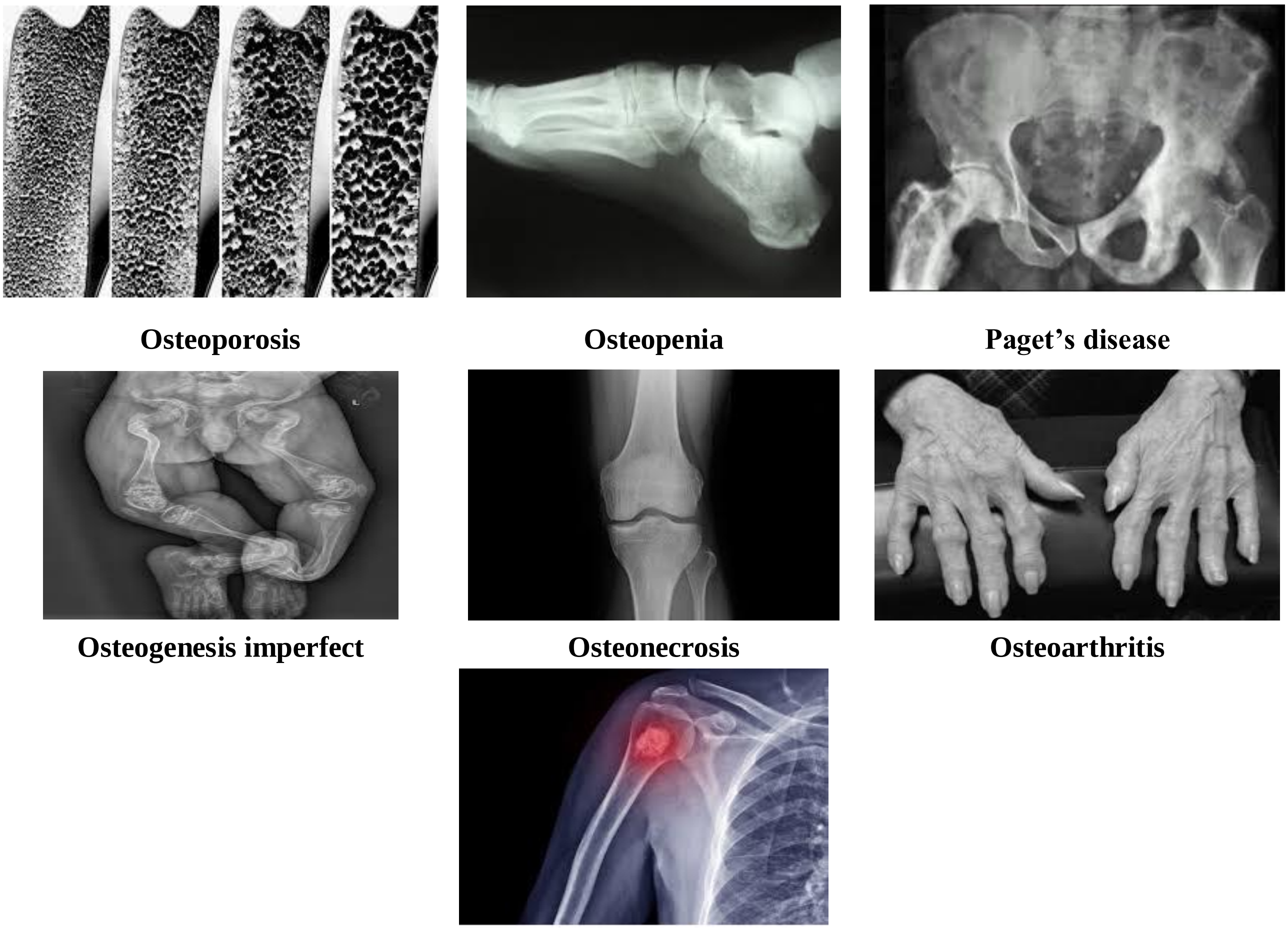


**Figure 1. Different types of bone diseases (Machine Learning Datasets).**

There are various traditional techniques to diagnose bone diseases, such as bone scans like DEXA scans, which provide valuable information on bone density but may not capture subtle changes in bone structure. Imaging modalities like MRI and CT scans offer detailed images of bones and surrounding tissues but are time-consuming, expensive, and may involve radiation exposure, especially in the case of CT scans (Ahmad et al., 2023). In contrast, AI technologies offer promising results in the field of detecting and classifying bone diseases. One of the most significant benefits is the ability of AI algorithms for analyzing medical images precisely and efficiently in order to surpass the human capabilities (Singh et al., 2024). Apart from this, AI-based machines and deep learning techniques are able to identify subtle abnormalities in bone structure and help in the early detection of diseases such as osteoarthritis, osteoporosis, bone tumors, etc. (Pan et al., 2024). Furthermore, AI algorithms are also useful in assisting radiologists to interpret images more accurately to reduce

predictive capability facilitates proactive interventions and personalized treatment plans to enhance the quality of care for patients that are diagnosed with bone diseases (Changela et al., 2023).

Thus, given the aforementioned facts, the primary objective of this paper is to provide a comprehensive summary and analysis of the research conducted by researchers in the field of using machine and deep learning techniques for the detection and diagnosis of diverse bone diseases. The ultimate goal is to draw specific implications based on the findings of these studies.

## Research contribution

The main *contribution* of the study is mentioned as following:

- Extensive background information on bone disease, which includes its types, traditional treatment techniques, limitations, and how AI can address these limitations, has been provided.

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- A systematic review of relevant research papers has been conducted using the PRISMA criteria, and several research questions have been formulated. Apart from this, a comprehensive survey as well as analysis of researchers' contributions to the use of machine and deep learning techniques for detecting and classifying bone diseases has been done, which also include the challenges they face.
- At the end, the answers to the research questions have been framed by understanding the impact as well as the role of AI techniques in the realm of detecting as well as classifying bone diseases.

## Research questions

In addition, the study also covered a few research questions that are discussed in the Discussion section:

***RQ 1:*** **What is the optimal approach for integrating clinical data, such as patient demographics and medical history, with imaging data to improve the accuracy of AI-based bone disease detection systems?**

***RQ 2:*** **How do variations in imaging techniques, such as resolution, noise levels, imaging modalities, etc impact the performance of AI-based bone disease detection models?**

***RQ 3:*** **What are the most effective feature extraction methods for representing bone characteristics in medical images to improve the classification of bone disease detection model?**

***RQ 4:*** **What are the future research directions and potential applications of AI techniques in the field of bone disease detection and diagnosis?**

## Review Methodology

This review has been done according to the PRISMA (Preferred reporting items for systematic Reviews and Meta-Analyses) guidelines, as shown in Figure 2, to minimize the bias process and provide a transparent as well as systematic approach to conducting reviews.

A comprehensive search was conducted manually between 2019 and 2024 in five distinct publication databases, namely Google Scholar (https://scholar.google.co.in), ScienceDirect (https://www.sciencedirect.com), PubMed (http://www.ncbi.nlm.nih.gov/pubmed), Springer (https://www.springer.com/in), and Scopus (https://www.scopus.com) with the aim of identifying the relevant papers in order to ensure the thoroughness of the review. The publication has been queried using the keywords "bone cancer", "osteoporosis", "Paget's disease", "Osteopenia", "machine learning", "Osteoarthritis", "artificial Intelligence", "Osteogenesis imperfect", and "deep learning", as well as numerous keyword combinations.

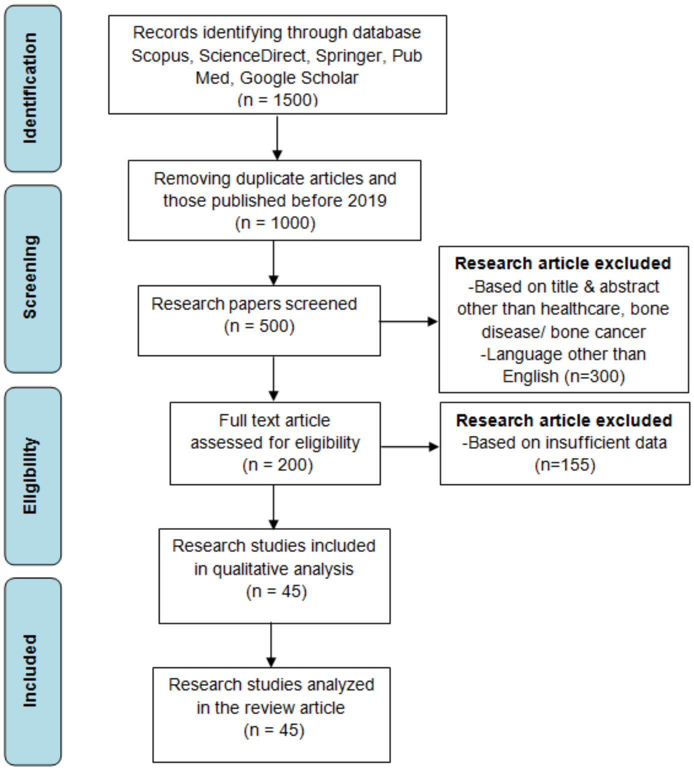


**Figure 2. PRISMA criteria.**

The method of selecting research articles is determined by a set of inclusion and exclusion criteria, which involves four distinct phases: *identification,* when documents are identified by visiting multiple repositories, *Screening* is the process of transparently selecting papers by examining the decisions made at various phases of the systematic review. *Eligibility* refers to the process of evaluating all full-length articles, while *Included* refers to the total number of papers accepted for the article. PRISMA improves the quality of reporting for systematic reviews, meta-analyses, and peer-reviewed publications are referred to understand current research on machine and deep learning techniques for detecting bone diseases (Koul et al., 2023).

## Background

Shim et al. (2020) worked on data obtained from postmenopausal Korean women and aimed to develop machine learning-based model that could effectively predict osteoporosis in them. The researchers applied various machine learning algorithms such as gradient boosting machine, support vector machine, K nearest neighbor, decision tree, logistic regression, random forest, as well as artificial neural network and their performances were later examined using metrics like accuracy, specificity, AUCROC, and sensitivity. The objective behind their research was to provide valuable tools to primary care providers to benefit individuals with the early detection as well as management of osteoporosis. Kerketta et al. (2021) presented a novel approach for developing a well structured as well as accurate machine learning technique to diagnose osteoporosis at its early stage. They combined microwave measurements with machine learning techniques to calculate bone mineral loss for identifying different stages of progression as well as the onset of osteoporosis. As per the researchers, their innovative approach had the capability to improve the outcomes of the patient by enabling early detection and timely treatment of osteoporosis. Tu et al. (2024) identified a high risk of osteoporosis in individuals by using machine learning predictive model. They used German Disease Analyzer database and analyzed the chronic disease as well as demographic records of 10k patients. Ten machine learning techniques were trained as well as tested with the stacker model, which had the combination of AdaBoost classifier, Logistic Regression, along with the Gradient Boosting Classifier. Their applied models analyses the features and were trained with some of the influential variables such as gender, age, lipid disorder, COPD and cancer. Later, on examining their performance, it was observed that the stacker model obtained the best values as compared to the rest techniques, which thereby offered the potential for improved prevention and treatment strategies for osteoporosis. Ramesh and Santhi (2024) worked on the diagnosis of osteopenia and osteoporosis by using a sequential deep-learning technique. They used training as well as testing dataset and focused on increasing the precision by reducing false positive rates in order to improve the performance of their proposed model. Their study emphasized the importance of deep learning techniques to handle large datasets efficiently, although at a higher cost due to complexity of modeling the data.

Pan et al. (2024) developed and evaluated a deep-learning model using chest CT images for opportunistic osteoporosis screening. The dataset included 1048 health check subjects, segmented into training, tuning, and test sets. Subjects were categorized into normal, osteopenia, and osteoporosis groups based on quantitative CT measurements. A segmentation model was constructed to compare with manual labeling using the dice similarity coefficient (DSC). Two classification models were developed: one using fusion features of lumbar vertebral bodies 1 and 2, and the other using features from lumbar 1 alone. Receiver operating characteristic curves assessed diagnostic efficacy, and the Delong test compared areas under the curve. Küçükçiloğlu et al. (2024) used computed tomography and magnetic resonance imaging data and developed diagnostic models using deep learning techniques for the prediction of bone mineral loss of the lumbar vertebrae. They used the data of patients who underwent both CT / MRI as well as lumbar dual-energy X-ray absorptiometry examinations. Multimodal as well as unimodal convolutional neural networks with dual blocks were proposed for predicting osteoporosis and were later compared with the six existing pre-trained deep learning techniques. Hung et al. (2022) developed an AI-based machine-learning model for predicting the outcomes of drug interactions in osteoporosis and Paget's disease treatment. They used a Drug-Drug Interaction (DDI) dataset obtained from the DrugBank database, focusing on medications used for these conditions. Various chemical features were extracted from the simplified molecular-input line-entry system (SMILES) of defined drug pairs exhibiting interactions. Machine-learning algorithms were then employed to learn from these extracted features, facilitating the prediction of drug interaction outcomes. Sampath et al. (2024) employed CNN along with image processing techniques to perform the binary classification of cancerous and normal bone images. Median filtering was used to process the CT scan medical images and canny edge detection. K means clustering was applied for segmenting and identifying regions having tumor pertaining to various types of bone cancer, such as osteochondroma, enchondroma, and parosteal osteosarcoma. Later multiple CNN models were applied and examined to classify the segmented image data as normal or cancerous. Kanimozhi et al. (2024) stated the need for diagnosis of bone cancer accurately as well as efficiently. For this, they used various techniques to extract the features such as NGDTM, GLRLM, as well as GLCM for optimizing the classification performance of deep learning techniques like multilayer perceptron, radial bias function, recurrent neural network, and convolutional neural network. In addition to this, the researchers also addressed the challenges of classifying bone cancer subtypes and stages, as well as emphasize the importance of feature extraction and deep learning in achieving precise results. von Schacky et al. (2022) aimed to develop machine learning models for differentiating between benign and malignant bone lesions as well as validate their performance with the results obtained by radiologists. They worked on the histopathology data obtained from 880 patients whose average age falls in the rage range of 33.1 years. Out of 880, 213 were diagnosed with malignant and the remaining 667 with benign. Data was split into 70% for training, 15% of validation (15%), and the rest 15% for internal testing. Apart from this, they also used the data of an additional 96 patients, which was collected from another institution for external testing. Machine learning models were trained with the demographic data and radiomic features, while as external testing involved assessment by radiologists and radiology residents who specialized in musculoskeletal tumor imaging. Noguchi et al. (2022) developed a deep learning based algorithm to automatically detect bone metastases on CT scans, which were collected from the years 2009 to 2019. The model was trained with positive scans and negative scans showing bone with and without metastases, respectively, along with an additional set of 50 positive and 50 negative scans, which were collected for validation and testing. The performance of the DLA model for the clinical data was examined through an observer study that involved board-certified radiologists. Georgeanu et al. (2022) explored the use of Deep Learning Algorithms to diagnose malignant bone tumors by using MRI medical imaging modalities. Dataset of 39 MRI scans had been used, which were taken from 23 patients having benign and malignant tumors. ResNet50 was trained and examined on the basis of precision, accuracy, area under the curve, and recall. During experimentation, it was found that the model obtained the highest accuracy as well as recall rates for both T1, with 97% accuracy and 95.65% recall and T2 with 95% accuracy and 95.52% recall. Zaki et al. (2021) proposed fuzzy logic methods to improve the edge detection in the images of osteogenesis imperfecta (OI) images as it was crucial for bone modeling as well as analyzing fracture risk. They stated that to process noisy OI images, fuzzy logic was useful to handle imprecise data as well as ambiguity. Additionally, the researchers also mentioned that in the future, fuzzy logic techniques for detecting edges could be beneficial for improving the accuracy of models for detecting fractures in the bone. Li et al. (2024) worked on the diagnosis of fetal skeletal dysplasia by assessing the efficacy of molecular testing and prenatal ultrasound. The data were collected from pregnant women with fetal SD at a clinic between May 2019 and December 2021. Results from 40 pregnant women revealed that 82.5% exhibited short limb deformity, with other malformations including central nervous system (25.0%), facial (17.50%), cardiac (15%), and urinary system (12.5%). Genetic testing yielded a positive rate of 70.0%, predominantly identifying single-gene disorders (92.8%) attributed to mutations in genes such as FGFR3, COL1A1, COL1A2, EVC2, FLNB, LBR, and TRPV4. The most prevalent SD subtypes were osteogenesis imperfecta (OI), thanatophoric dysplasia (TD) and achondroplasia (ACH). Gestational age at initial diagnosis varied significantly among TD, OI, and ACH subtypes, with no notable difference in femoral shortening between the groups. Additionally, a portion of OI cases (5 out of 12) had a family history.

Shen et al. (2023) aimed to develop an MRI-based deep learning system for detecting early osteonecrosis of the femoral head and assess its feasibility in a clinical setting. The researchers worked on the MRI images of hips, which had been collected from Jan 2019 to 2022 and focused exclusively on those MRI images that were diagnosed with ONFH disease at its early stage. Advanced CNN model was trained and its parameters were optimized to obtain the optimal accuracy, specificity, and sensitivity. In addition to this, they also compared the performance of their model with the results obtained by the orthopedic surgeons to validate its efficacy. A fully automatic deep learning model was developed by Wang et al. (2021) collected the data from MRI images of 298 patients from Jan 2016 to Dec 2019 who were diagnosed with osteonecrosis of the femoral head. Out of 298, 110 patients were in the early stage of this disease and the rest were at one stage higher. The researchers split their dataset into 70:30 ratio and delineated 3640 segments as the ground truth definition. Later, the performance of the model to diagnose this disease was evaluated using ROC curve, which includes Hausdroff distance and AUC. Additionally, differences between the ground truth and predicted definitions were computed and analyzed using Bland–Altman plot as well as Pearson correlation. Abdullah & Rajasekaran (2022) worked on localizing as well as diagnosing the severity of knee osteoarthritis accurately using deep learning techniques. Data from more than 50 years of patients had been taken from where 3172 digital x-ray images of anterior–posterior view knee joints were used and applied to FasterRCNN for the localization of joint space width in the knee and ResNet50 model for extracting features. Besides this, AlexNet technique was also used to classify the severity of knee osteoarthritis and examined for various metrics. Raza et al. (2024) used radiographic images and applied feature extraction as well as machine learning algorithms to accurately diagnose and classify different stages of knee osteoarthritis (KOA) stages from radiographic images. They worked on the dataset of 3154 X-ray images of the knee and used histogram-oriented

**Table 1. Analysis of the previous work.**

| Author's Name | Dataset | Bone disease | Techniques | Outcomes | Challenges |
|---|---|---|---|---|---|
| Shim et al. (2020) | Data of 1792 patients collected from Korean National Health | Osteoporosis | LR | Acc = 75.8%<br>Sens =0.60<br>AUC = 72.6%<br>Spec = 0.85 | Ambiguity during survey, Difficulty in generalizing for different population |
| | | | KNN | Acc = 72.9%<br>Spec = 0.78<br>AUC = 71.2%<br>Sens =0.65 | |
| | | | DT | AUC = 68.4%<br>Sens =0.54<br>Acc = 72.0%<br>Spec = 0.83 | |
| | | | RF | AUC = 72.7%<br>Acc = 76.3%<br>Sens =0.59<br>Spec = 0.87 | |
| | | | GBM | AUC = 65.2%<br>Acc = 63.3%<br>Sens =0.73<br>Spec = 0.58 | |
| | | | SVM | Acc = 74.3%<br>AUC = 72.4%<br>Sens =0.65<br>Spec = 0.80 | |
| | | | ANN | Acc = 72.4%<br>Spec = 0.68<br>Sens =0.80<br>AUC = 74.1% | |
| Kerketta et al. (2021) | Real time dataset of bone density | Osteoporosis | KNN | Precision = 90%<br>Recall = 87%<br>F1 score = 87%<br>Support = 99% | Lack of interpretability |
| | | | Decision Tree | Precision = 89%<br>Recall = 89%<br>F1 score = 89%<br>Support =99% | |
| | | | Random Forest | Precision = 94%<br>Recall = 93%<br>F1 score = 93%<br>Support = 94% | |
| Tu et al. (2024) | 10k records from German Disease Analyzer database | Osteoporosis | Logistic Regression | AUCROC = 75.3% | The model couldn't work for unseen data, Limited information in the dataset |
| Ramesh & Santhi (2024) | 5401 features from public dataset | Osteoporosis, Ostropenia | Sequential Deep Neural Network | Accuracy = 82%<br>Precision = 87.11%<br>Sensitivity = 80.14%<br>Specificity = 86.14% | Limited dataset |
| Pan et al. (2024) | Real time data of 1048 patients | Osteoporosis, Ostropenia, Normal | CNN Model 1 | AUC =0.98,0.952,0.99 | Lack in external validation because of hardware constraints |
| | | | CNN Model 2 | AUC = 0.978, 0.940, 0.983 | |
| Küçükçiloğlu et al. (2024) | 120 MRI images | Osteoporosis | Proposed CNN model | Accuracy = 96.54% | Trained the model with small number of samples |
| | 100 CT scan images | | | Accuracy = 98.84% | |
| Hung et al. (2022) | DrugBank database | Osteoporosis, Paget's disease | Stacked ensemble model | Accuracy = 74% | Optimization of model is required to enhance the performance |
| Sampath et al. (2024) | 1141 CT scan images | Bone tumor | AlexNet | Accuracy = 98% | Limited dataset |
| Kanimozhi et al. (2024) | MRI dataset | Bone cancer | GLCM+LBP +DL | Accuracy = 94% | The model needs to be fine tuned |

| | | | | | |
|---|---|---|---|---|---|
| von Schacky et al. (2022) | 880 X-ray images | Bone tumor | ANN | Accuracy = 80% Sensitivity = 75% AUC = 0.79 | Only able to classify binary class of bone cancer i.e. benign and malignant |
| Noguchi et al. (2022) | 1838 CT images | Bone metastases | 3D ResNet | Sensitivity = 82.7% | Limited information in the data |
| Georgeanu et al. (2022) | 39 MRI T1 and T2 weighted Images | Bone cancer | ResNet50 | Accuracy = 95% | Small size of the dataset |
| Shen et al. (2023) | 11061 bone images | Osteonecrosis | Advanced CNN | AUCROC = 98% Accuracy = 98.4% Sensitivity = 97.6% Specificity = 98.6% | High computational cost, overfitting |
| Wang et al. (2021) | MRI data of 298 patients | Osteonecrosis | CNN | AUC= 0.97 Sensitivity = 0.95 Specificity = 0.97 | Misclassification, model needs to be optimized |
| Abdullah & Rajasekaran (2022) | 3172 Knee images | Osteoarthritis | AlexNet | Accuracy = 98.90% | Lack of generalizability |
| Raza et al. (2024) | 3154 Knee x-ray images | Osteoarthritis | XGBoost classifier | Accuracy = 98% | Not reliable, misclassification |

gradients merged with linear discriminant analysis and min-max scaling technique for preparing data and extracting features. Six machine learning classifiers, such as SVM, random forest, Gaussian naïve Bayes, KNN, XgBoost, and decision tree, were applied and examined after fine-tuning their performances were fine-tuned with GridsearchCV optimizer. Additionally, an ensemble model was constructed to further enhance accuracy and mitigate overfitting risks for already high-accuracy models.

Apart from this, the researchers' work has been thoroughly analyzed and compared based on specific factors, as stated in Table 1.

## Research gaps

Research in the field of bone diseases, particularly osteoporosis, osteoarthritis, bone tumors, and osteonecrosis, has seen significant advancements with the integration of machine learning and deep learning techniques. However, despite these advancements, several research gaps persist.

Firstly, while various machine learning algorithms such as logistic regression, k-nearest neighbors, decision trees, random forests, support vector machines and artificial neural networks have been applied to diagnose osteoporosis with relatively high accuracies, challenges related to ambiguity during surveying and difficulty in generalizing across different populations remain due to limited dataset (Shim et al., 2020). Additionally, interpretability issues plague some models, hindering their clinical adoption (Kerketta et al., 2021). Moreover, the efficacy of these models on unseen data and the limited information available in some datasets present obstacles to their practical utility (Tu et al., 2024; Ramesh and Santhi, 2024; Pan et al., 2024; Küçükçiloğlu et al., 2024; Hung et al., 2022). Similarly, in the context of bone tumors and bone cancer classification, research gaps persist in the form of limited datasets (Sampath et al., 2024; Kanimozhi et al., 2024; von Schacky et al., 2022), leading to challenges in model fine-tuning and generalization. Additionally, the inability of some models to classify beyond binary classes of bone cancer, such as benign and malignant, further underscores the need for more comprehensive datasets and models capable of handling multiclass classification tasks (von Schacky et al., 2022). Moreover, despite achieving good results in detecting and classifying osteonecrosis using advanced convolutional neural networks (CNNs), the researchers also faced certain challenges, such as overfitting, high computational costs, misclassification, and the need for model optimization persist (Shen et al., 2023; Wang et al., 2021). Furthermore, in the domain of osteoarthritis,

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challenges related to generalizability and reliability, as well as potential misclassification issues, highlight the need for further research to address these limitations (Abdullah et al., 2022; Raza et al., 2024).

## Result and Discussion

**RQ1: What is the optimal approach for integrating clinical data, such as patient demographics and medical history, with imaging data to improve the accuracy of AI-based bone disease detection systems?**

To integrate imaging data with clinical data like medical history, demographics of patients etc, promptly escalates the accuracy of AI-based systems to detect bone diseases. There are various approaches that can be used for performing this task such as the first one is *Feature Fusion* where the concatenation techniques are used to combine the features extracted from the imaging data with the features selected from the medical history of patients. This helps the AI model to consider both patient as well image-based information during the learning process and improves the prediction accuracy. The second one is *Multi-Modal Learning*, which uses multi-input neural network that allows the models to integrate the information collected from multiple modalities, such as structured clinical data and medical images, to process it effectively (Prasad et al., 2024). The third one is *Data Augmentation*, where augmentation is performed on image data with specific information about the patients, such as their gender, medical history etc, for creating a large size dataset to train the AI model and improve the generalizability. The next one is *Attention Mechanisms*, which focuses on the relevant information obtained from imaging as well as clinical data by analyzing the importance of different modalities as well as features in the context of input data (Shorten and Khoshgoftaar, 2019). Further comes, *Transfer Learning* where the models are trained by the large bulk of clinical as well as imaging data in order to leverage their prediction accuracy. Apart from this, these models are also fine-tuned using various optimizers such as ADAM, RMSprop, and SGD to optimize the performance of the applied models. One more optimal approach is *integrating domain knowledge*, which identifies the clinically relevant features of bone diseases, defines appropriate feature transformations, and interprets the prediction of model in the context of medical practice guidelines (Mondal et al., 2023; Kumar et al., 2024).

By applying the aforementioned few optimal approaches to integrate clinical data with imaging data, AI-based bone disease detection systems can achieve reliability as well as higher accuracy in order to improve patient outcomes and healthcare decision-making.

**RQ2: How do variations in imaging techniques, such as resolution, noise levels, imaging modalities, etc impact the performance of AI-based bone disease detection models?**

There can be a significant impact of variation in imaging techniques, which includes noise levels, resolution, as well as imaging modalities on the performance of AI-based system to detect as well as classify disease of the bone. Table 2 presents the influence of these factors on the performance of models (Link and Kazakia, 2020; Yavanamandha et al., 2023; Srivastava and Tripathi, 2023; Kaur et al., 2022; Gautam et al., 2022):

**Table 2. Factors responsible for affecting the performance of models.**

| Factors | Reason |
|---|---|
| **Resolution** | If the image is of higher resolution, it provides more detailed information related to the structure of bone, while as the images with lower resolution contain less information, which ultimately will lead to the reduction in the detection accuracy of abnormalities in the bone. |
| **Noise Levels** | The noise levels in the image can degrade its quality as well as create some distortions to hinder the ability of the model in extracting the relevant features. |
| **Imaging Modalities** | To capture different aspects of bone anatomy as well as pathology, imaging modalities like CT scans, X-rays, MRI, as well as ultrasound play an important role. These modalities, albeit have their own limitations or strengths in terms of contrast, specificity, sensitivity etc, but it would be wrong to say that these models using one modality may generalize well for the unseen dataset. |
| **Data Augmentation** | To improve the robustness as well as generalization ability of the models for real time dataset, it is important to train them with different images which represent various acquisition techniques, |

| | |
|---|---|
| | such as adjusting image resolution, adding noise, or applying transformations to imitate different imaging modalities. |
| **Model Adaptation** | To adapt variations in the imaging techniques for different clinical settings, AI based techniques should be fine-tuned by optimizing their hyper parameters in order better to suit the characteristics of the target imaging modality. |

**RQ3: What are the most effective feature extraction methods for representing bone characteristics in medical images to improve the classification of the bone disease detection model?**

The choice of feature extraction methods for representing bone characteristics in medical images plays a crucial role in enhancing the performance of AI-based detection models. Several effective feature extraction techniques have been utilized in the field of medical imaging. Below mentioned are some of the commonly used methods:

## Histogram of Oriented Gradients (HOG)

It is a popular technique to extract the features by computing histograms of gradient orientations in localized regions of an image. In the case of detecting bone disease, HOG can capture shape as well as texture information of bone structures (Figure 3), which are important characteristics to distinguish between healthy and diseased regions (Shrivastava and Nag, 2024). Below are the equations that are mathematically expressed for the HOG technique:

Let's take Sobel operator to compute the image gradients $G_x$ and $G_y$ as shown in eq (i):

$$G_x = \frac{\delta I}{\delta x}, G_y = \frac{\delta I}{\delta y} \qquad \text{................ (i)}$$

where $I$ refers to the intensity values of the image. Next, eq (ii) is used to calculate the magnitude $M$ and orientation $\theta$ of the gradients:

$$M = \sqrt{{G_x}^2 + {G_y}^2}, \quad \theta = \arctan(\frac{G_y}{G_x}) \qquad \text{.......(ii)}$$

Later, the image is then divided into small cells and within each cell, a histogram of gradient orientations is computed. Let $hist(i)$ represent the histogram bin corresponding to the $i-th$ orientation range, which is computed by eq (iii).

$$hist(i) = \sum p\epsilon cell\ \omega_p \text{ x } M_p \qquad \text{........ (iii)}$$

where $M_p$ refers to the magnitude of the gradient at pixel p, and $\omega_p$ is the weight of pixel p. After computing the histograms for all cells, neighboring cells' histograms $hist_{norm}(i)$ are combined through block normalization, as shown in eq (iv).

$$hist_{norm}(i) = \frac{hist(i)}{\sqrt{\sum_i (hist(i))^2 + \in}} \qquad \text{...... (iv)}$$

Finally, Further, the normalized histogram of all cells are concatenated to form the final HOG descriptor $H$ (eq (v)), which later results in a high-dimensional feature vector that effectively represents the local texture and shape characteristics of the image.

$$H = [hist_{norm}(1), hist_{norm}(2), \dots\dots, hist_{norm}(n)] \qquad \text{.....(v)}$$

This feature vector $H$ can be then used for various tasks such as detection, classification, or segmentation of objects.

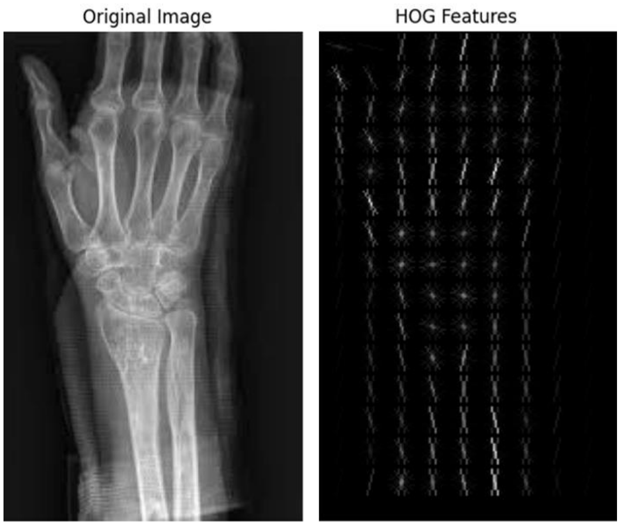


**Figure 3. Bone image after applying HOG features**

## Local Binary Patterns (LBP)

It is a texture descriptor that is used to encode the local patterns of pixel intensities in an image (Figure 4). It has the property of effectively capturing the textural properties of bone tissues after analyzing the coordinate arrangement of intensity values (Khojastepour et al., 2019). To calculate the LBP value at a specific pixel ($xc$ , $yc$) in an image, the following eq (vi) is as follows:

$$LBP_{P,R}\ (x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c) \text{ x } 2^p \qquad \text{(vi)}$$

Where, $LBP_{P,R}\ (x_c, y_c)$ refers to the LBP value at the pixel $(x_c, y_c)$, P belongs to the number of neighboring pixels considered in the computation, R is the radius from the center pixel, $g_c$ and $g_p$ is the intensity value of the center as well as neighboring pixel respectively, and s(x) is a function defined by eq (vii):

$$f(x) = \begin{cases} 1, & if\ x \geq 0 \\ 0, & otherwise \end{cases} \qquad \text{(vii)}$$


**Figure 4. Bone image after applying LBP features**

### Gray-Level Co-occurrence Matrix (GLCM)

It is used for computing the statistical measures of pixel intensity relationships within a specified neighborhood in an image. Features derived from GLCM, such as contrast, energy, entropy, and homogeneity (Figure 5), provide valuable information about the spatial distribution and texture patterns of bone tissues, which can aid in discriminating between different bone conditions (Htun et al., 2023). The GLCM is typically represented as a matrix $P(i,j)$, where $i$ and $j$ represent the intensity values of two neighboring pixels in the image. The mathematical equation for computing it is shown eq(viii):

$$P(i,j;d,\theta) = \frac{1}{N_d}\sum_{x=1}^{N_x}\sum_{y=1}^{N_y} \delta(I(x,y) = i, I(x+\Delta x, y+\Delta y) = j) \qquad \text{(viii)}$$

Here, $P(i,j;d,\theta)$ is the GLCM at displacement d and angle $\theta$, $N_d$ is the total number of displacements for angle $\theta$, $N_x$ and $N_y$ are the dimensions of the image, $\delta$ is the Kronecker delta function, $I(x,y)$ is the intensity value of the pixel at coordinates (x,y) in the image, $\Delta x$ and $\Delta y$ are the displacements along the x and y axes, respectively.

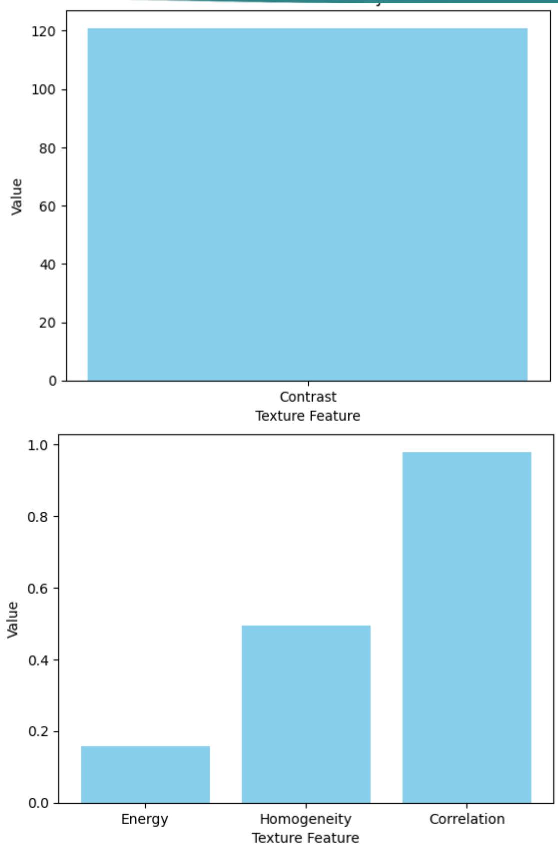


**Figure 5. Texture feature analysis of bone image**

### Convolutional Neural Networks (CNNs)

Advanced deep learning models such as VGG, DenseNet, AlexNet, ResNet etc have the properties of convolutional neural networks, which offers them a powerful ability for detecting and diagnosing bone diseases. CNN architectures have the characteristic of learning the hierarchical features directly from the raw intensities of the pixel automatically and make them well-defined to analyze medical images (Singh and Singh, 2023; Koul et al., 2024). In fact, pre-trained deep learning or transfer learning models can be fine-tuned for extracting features specifically for bone disease detection tasks. This fusion of methodologies enables to extraction of highly discriminative features from bone images and facilitates tasks such as segmentation, classification, and detection of bone diseases with great accuracy and efficiency (Koul et al., 2024). Mathematically, it can expressed as eq(ix)

$$\hat{Y} = softmax(W_{out}.ReLU(W_{fc}.vec(Y) + b_{fc}) + b_{out}) \qquad \text{(ix)}$$

$\hat{Y}$ is the predicted output, $vec(Y)$ represents the falttened output of the last pooling layer, $W_{fc}$ and $b_{fc}$ are the weight matrix and bias term of the fully connected layer respectively, $W_{out}$ and $b_{out}$ are the weight matrix and bias term of the output layer respectively, ReLU is the rectified linear unit activation function applied

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element-wise to the output of the fully connected layer and softmax is used to transform the output into probabilities for classification.

### Wavelet Transform

It decomposes an image into multiple frequency bands, capturing both local and global image features at different scales. Wavelet-based features are effective in capturing multi-scale texture patterns and structural information of bone tissues (Figure 6), making them suitable for detecting subtle abnormalities and variations in medical images (Bagaria et al., 2021). Let $f(x,y)$ represent a 2D image function, where $(x,y)$ are the spatial coordinates. The Continuous Wavelet Transform of the image function $f(x,y)$ with respect to a wavelet function $\psi(a,b)$ is defined as shown in eq(x):

$$W_f(a,b) = \iint f(x,y).\ \psi *_{a,b} (x,y) dx\, dy \qquad \text{(x)}$$

$W_f(a,b)$ is the wavelet transform of $f(x,y)$ at scale $a$ and translation $b$. $\psi *_{a,b} (x,y)$ is the complex conjugate of the wavelet function $\psi(a,b)$ scaled by $a$ and translated by $b$. The integration is performed over all spatial coordinates $(x,y)$. The wavelet function $\psi(a,b)$ is usually chosen to be a scaled and translated version of a mother wavelet function $\psi_0(x,y)$, such as the Morlet wavelet or the Mexican hat wavelet.

### Scale-Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF)

They are keypoint-based feature extraction techniques widely used in computer vision. These methods are designed to detect and describe distinctive local features within an image, allowing for robust matching and recognition tasks invariant to scale, rotation, and illumination changes (Karanam et al., 2022). SIFT identifies key points by analyzing the local intensity extrema across multiple scales using a Difference of Gaussians (DoG) approach (Figure 7), while SURF achieves similar results through the use of integral images and box filters for efficient computation. Once key points are detected, both methods compute descriptors that capture the local texture and structure around each key point, encoding information such as gradient orientations, magnitudes, and spatial distributions (Bansal et al., 2021). In the context of medical imaging, particularly in bone images, SIFT and SURF play crucial roles in detecting anatomical landmarks and key structures, enabling subsequent analysis and classification tasks such as bone disease diagnosis, image registration, and anatomical structure localization. These feature extraction


**Figure 6. Different image variations of bone to detect abnormality.**

methods provide robustness to variations in image appearance and facilitate the identification of important regions for further analysis and interpretation in medical imaging applications (Sharma et al., 2021).

**Figure 7. Extraction of key points on bone image using SIFT.**

The selection of feature extraction methods depends on various factors, including the complexity of the bone disease detection task, the availability of labeled training data, computational resources, and the interpretability of extracted features. Experimentation and validation on representative datasets are essential to determine the most effective feature extraction techniques for a given application in AI-based bone disease detection.

**RQ4: What are the future research directions and potential applications of AI techniques in the field of bone disease detection and diagnosis?**

In order to revolutionize the clinical practice, there are various research directions that can be considered to evolve the impact of AI based learning techniques for detecting as well as diagnosing bone diseases. Multimodal fusion stands out as a promising avenue as it allows for the integration of different medical imaging like CT, MRI and X-ray to provide comprehensive information on bone health, which in return enhances the diagnostic accuracy of the model by capturing nuanced details which may be missed by the individual imaging modality (Link and Kazakia 2020; Koul et al., 2022). In addition to this, using longitudinal analysis in AI systems could help to monitor disease as well as optimize treatment by analyzing valuable insights to track changes in bone morphology over time. Artificial intelligence techniques can also be used to personalize medicine by leveraging patient data in order to tailor them to treatment plans. Moreover, automatic screening and decision support systems powered with AI capabilities help in early identification as well as detection of risk in developing bone disease along with the assistance to healthcare providers by offering predictive analytics and real-time insights (Saha and Yadav, 2023). As AI technologies continue to advance, hence, efforts to enhance model transparency and interpretability are essential for fostering trust and acceptance among clinicians and patients. Collaborative initiatives aimed at promoting data sharing, standardization, and benchmarking would further accelerate innovation and drive the widespread adoption of AI-based technologies in bone disease management.

## Conclusion

The paper highlights the importance of artificial intelligence techniques to analyze medical images for improving the detection as well as accurate prediction of bone diseases. It presents the contribution of researchers who have demonstrated the ability to efficiently as well as effectively predict bone disease risk diagnose conditions such as osteoporosis, osteoarthritis etc, using machine learning and deep learning algorithms. Apart from this, the paper also emphasizes on the technique to integrate clinical or medical records, the necessity of using the feature extraction method, the effect of image variation on the classification outcome of AI learning techniques in diagnosing bone diseases as well as mentions about the importance of building trust among patients and healthcare providers. However, in spite of the promising results facilitated by the learning models, certain limitations still persist. A lack of robustness, limited dataset, generalizability, and standardization of models have been found which needs to be improved to ensure its reliability in terms of classification of bone diseases for different populations. In addition to this, there is also a challenge regarding the interpretability of AI techniques, which raises issues related to biased decision-making. In the future, all these limitations can be improved by incorporating large sizes of data with multiple variations so that the model can easily generalize the unseen data and predict the class of bone disease accurately. Besides this, the advanced CNN techniques should be hybridized as well and their parameters should be fine-tuned with optimizers to enhance bone detection and classification, which thereby paves the way for improving the overall quality of life of patients.

## Conflict of Interest

No conflict of interest

## References

Abdullah, S. S., & Rajasekaran, M. P. (2022). Automatic detection and classification of knee osteoarthritis using deep learning approach. *La Radiologia Medica*, *127*(4), 398-406. https://doi.org/10.1007/s11547-022-01476-7

Ahmad, A., Crawford III, C. H., Glassman, S. D., Dimar II, J. R., Gum, J. L., & Carreon, L. Y. (2023). Correlation between bone density measurements on CT or MRI versus DEXA scan: a systematic review. *North American Spine Society Journal (NASSJ)*, *14*, 100204. https://doi.org/10.1016/j.xnsj.2023.100204

Bagaria, R., Wadhwani, S., & Wadhwani, A. K. (2021). A wavelet transform and neural network based segmentation & classification system for bone fracture detection. *Optik*, *236*, 166687. https://doi.org/10.1016/j.ijleo.2021.166687

Bansal, M., Kumar, M., & Kumar, M. (2021). 2D object recognition: a comparative analysis of SIFT, SURF and ORB feature descriptors. *Multimedia Tools and Applications*, *80*(12), 18839-18857.

Campagne, D. (2022). Overview of Fractures. *MSD Manual Consumer Version*. https://www.msdmanuals.com/en-in/home/injuries-and-poisoning/fractures/overview-of-fractures

Changela, A., Kumar, Y., & Koul, A. (2023). Automated System to Diagnose and Detect the Allergy, Common Cold, Flu, and Covid using Machine Learning Approaches. IEEE, In *2023 International Conference on Communication, Security and Artificial Intelligence (ICCSAI)*, pp. 1-6. https://doi.org/10.1109/ICCSAI59793.2023.10421400

Gautam, S., Ahlawat, S., & Mittal, P. (2022). Binary and Multi-class Classification of Brain Tumors using MRI Images. *Int. J. Exp. Res. Rev.*, *29*, 1-9. https://doi.org/10.52756/ijerr.2022.v29.001

Georgeanu, V. A., Mămuleanu, M., Ghiea, S., & Selișteanu, D. (2022). Malignant bone tumors diagnosis using magnetic resonance imaging based on deep learning algorithms. *Medicina*, *58*(5), 636. https://doi.org/10.3390/medicina58050636

Htun, N. T., & Tun, K. M. M. (2023, July). Automatic Detection and Classification of Tibia Bone Fracture from X-ray Images by using Gray Level Co-occurrence Matrix. IEEE, In *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, pp. 1-5. https://doi.org/10.1109/ICCCNT56998.2023.10307328

Hung, T. N. K., Le, N. Q. K., Le, N. H., Van Tuan, L., Nguyen, T. P., Thi, C., & Kang, J. H. (2022). An ai-based prediction model for drug-drug interactions in osteoporosis and Paget's diseases from smiles. *Molecular Informatics*, *41*(6), 2100264. https://doi.org/10.1002/minf.2021002643

Kanimozhi, S., & Chintanpalli, A. (2024). Recent Advancements in Feature Extraction and Classification Based Bone Cancer Detection. http://dx.doi.org/10.2139/ssrn.4689326

Karanam, S. R., Srinivas, Y., & Chakravarty, S. (2022). A systematic approach to diagnosis and categorization of bone fractures in X-Ray imagery. *International Journal of Healthcare Management*, pp. 1-12. https://www.tandfonline.com/doi/pdf/10.1080/20479700.2022.2097765

Kaur, I., Sandhu, A. K., & Kumar, Y. (2022). Utilizing deep transfer learning models and data augmentation to improve image classification. *Mathematical Statistician and Engineering Applications*, *71*(3), 1923-1932. https://doi.org/10.17762/msea.v71i3.1515

Kerketta, S. R., & Ghosh, D. (2021). Detection of onset and progression of osteoporosis using machine learning. *Machine Learning for Healthcare Applications*, pp. 137-149. https://doi.org/10.1002/9781119792611.ch9

Khojastepour, L., Hasani, M., Ghasemi, M., Mehdizadeh, A. R., & Tajeripour, F. (2019). Mandibular trabecular bone analysis using local binary pattern for osteoporosis diagnosis. *Journal of Biomedical Physics & Engineering*, *9*(1), 81. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6409375/

Koul, A., Bawa, R. K., & Kumar, Y. (2022). Artificial intelligence in medical image processing for airway diseases. Cham: Springer International Publishing, In *Connected e-Health: Integrated IoT and cloud computing*, pp. 217-254. https://doi.org/10.1007/s11831-022-09818-4

Koul, A., Bawa, R. K., & Kumar, Y. (2023). Artificial intelligence techniques to predict the airway disorders illness: a systematic review. *Archives of Computational Methods in Engineering*, *30*(2), 831-864. https://doi.org/10.1007/s11831-022-09818-4

Koul, A., Bawa, R. K., & Kumar, Y. (2024). An analysis of deep transfer learning-based approaches for prediction and prognosis of multiple respiratory diseases using pulmonary images. *Archives of Computational Methods in Engineering*, *31*(2), 1023-1049. https://doi.org/10.1007/s11831-023-10006-1

Koul, A., Bawa, R. K., & Kumar, Y. (2024). Enhancing the detection of airway disease by applying deep learning and explainable artificial intelligence. *Multimedia Tools and Applications*, pp. 1-33. https://doi.org/10.1007/s11042-024-18381-y

Küçükçiloğlu, Y., Şekeroğlu, B., Adalı, T., & Şentürk, N. (2024). Prediction of osteoporosis using MRI and CT scans with unimodal and multimodal deep-learning models. *Diagnostic and Interventional Radiology*, *30*(1), 9. https://doi.org/10.4274/dir.2023.232116

Kumar, Y., Garg, P., Moudgil, M. R., Singh, R., Woźniak, M., Shafi, J., & Ijaz, M. F. (2024). Enhancing parasitic organism detection in microscopy images through deep learning and fine-tuned optimizer. *Scientific Reports*, *14*(1), 5753. https://doi.org/10.1038/s41598-024-56323-8

Li, L., Jin, X., Liu, S., & Fan, H. (2024). Prenatal ultrasound findings and prenatal diagnosis of fetal skeletal dysplasia. *Journal of Clinical Ultrasound*. https://doi.org/10.1002/jcu.23673

Link, T. M., & Kazakia, G. (2020). Update on imaging-based measurement of bone mineral density and quality. *Current Rheumatology Reports*, *22*, 1-11. https://doi.org/10.1007/s11926-020-00892-w

*Machine Learning Datasets*. https://paperswithcode.com/datasets?q=Fracture%2FNormal%20Shoulder%20Bone%20X-ray%20Images%20on%20MURA

Mondal, S., Nag, A., Barman, A., & Karmakar, M. (2023). Machine Learning-based maternal health risk prediction model for IoMT framework. *Int. J. Exp. Res. Rev.*, *32*, 145-159. https://doi.org/10.52756/ijerr.2023.v32.012

Noguchi, S., Nishio, M., Sakamoto, R., Yakami, M., Fujimoto, K., Emoto, Y., ... & Nakamoto, Y. (2022). Deep learning–based algorithm improved radiologists' performance in bone metastases detection on CT. *European Radiology*, *32*(11), 7976-7987. https://doi.org/10.1007/s00330-022-08741-3

Pan, J., Lin, P. C., Gong, S. C., Wang, Z., Cao, R., Lv, Y., ... & Wang, L. (2024). Effectiveness of opportunistic osteoporosis screening on chest CT using the DCNN model. *BMC Musculoskeletal Disorders*, *25*(1), 176. https://doi.org/10.1186/s12891-024-07297-1

Prasad, R., Musa, F., Ahmad, H., Upadhyay, S., & Sharma, B. (2024). Autism Spectrum Disorder Prediction Using Machine Learning and Design Science. International Journal of Experimental Research and Review, *39*(Spl Volume), 213-228. https://doi.org/10.52756/ijerr.2024.v39spl.017

Ramesh, T., & Santhi, V. (2024). Multi-level classification technique for diagnosing osteoporosis and osteopenia using sequential deep learning algorithm. *International Journal of System Assurance Engineering and Management*, *15*(1), 412-428. https://doi.org/10.1007/s13198-022-01760-9

Raza, A., Phan, T. L., Li, H. C., Hieu, N. V., Nghia, T. T., & Ching, C. T. S. (2024). A Comparative Study of Machine Learning Classifiers for Enhancing Knee Osteoarthritis Diagnosis. *Information*, *15*(4), 183. https://doi.org/10.3390/info15040183

Saha, A., & Yadav, R. (2023). Study on segmentation and prediction of lung cancer based on machine learning approaches. *Int. J. Exp. Res. Rev.*, *30*, 1-14. https://doi.org/10.52756/ijerr.2023.v30.001

Sampath, K., Rajagopal, S., & Chintanpalli, A. (2024). A comparative analysis of CNN-based deep learning architectures for early diagnosis of bone cancer using CT images. *Scientific Reports*, *14*(1), 2144. https://doi.org/10.1038/s41598-024-52719-8

Santhakumar, S. (2023). What to know about bone diseases. https://www.medicalnewstoday.com/articles/bone-diseases

Sharma, A., Mishra, A., Bansal, A., & Bansal, A. (2021). Bone fractured detection using machine learning and digital geometry. Springer Singapore, In *Mobile Radio Communications and 5G Networks: Proceedings of MRCN 2020*, pp. 369-376. https://doi.org/10.1007/978-981-15-7130-5_28

Shen, X., Luo, J., Tang, X., Chen, B., Qin, Y., Zhou, Y., & Xiao, J. (2023). Deep learning approach for diagnosing early osteonecrosis of the femoral head based on magnetic resonance imaging. *The Journal of Arthroplasty*, *38*(10), 2044-2050. https://doi.org/10.1016/j.arth.2022.10.003

Shim, J. G., Kim, D. W., Ryu, K. H., Cho, E. A., Ahn, J. H., Kim, J. I., & Lee, S. H. (2020). Application of machine learning approaches for osteoporosis risk prediction in postmenopausal women. *Archives of Osteoporosis*, *15*, 1-9. https://doi.org/10.1007/s11657-020-00802-8

Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. *Journal of Big Data*, *6*(1), 1-48. https://doi.org/10.1186/s40537-019-0197-0

Shrivastava, A., & Nag, M. K. (2024). Enhancing bone cancer diagnosis through image extraction and machine learning: a state-of-the-art approach. *Surgical Innovation*, *31*(1), 58-70. https://doi.org/10.1177/15533506231220968

Singh, J., Sandhu, J. K., & Kumar, Y. (2024). Metaheuristic-based hyperparameter optimization for multi-disease detection and diagnosis in machine learning. *Service Oriented Computing and Applications*, 1-20. https://doi.org/10.1007/s11761-023-00382-8

Singh, D., & Singh, S. (2023). Precision fault prediction in motor bearings with feature selection and deep learning. *Int. J. Exp. Res. Rev.*, *32*, 398-407. https://doi.org/10.52756/ijerr.2023.v32.035

Srivastava, R., & Tripathi, M. (2023). Systematic Exploration Using Intelligent Computing Techniques for Clinical Diagnosis of Gastrointestinal Disorder: A Review. *Int. J. Exp. Res. Rev.*, *36*, 265-284. https://doi.org/10.52756/ijerr.2023.v36.026

Tu, J. B., Liao, W. J., Liu, W. C., & Gao, X. H. (2024). Using machine learning techniques to predict the risk of osteoporosis based on nationwide chronic disease data. *Scientific Reports*, *14*(1), 1-11. https://doi.org/10.1038/s41598-024-56114-1

von Schacky, C. E., Wilhelm, N. J., Schäfer, V. S., Leonhardt, Y., Jung, M., Jungmann, P. M., ... & Gersing, A. S. (2022). Development and evaluation of machine learning models based on X-ray radiomics for the classification and differentiation of malignant and benign bone tumors. *European radiology*, *32*(9), 6247-6257. https://doi.org/10.1007/s00330-022-08764-w

Wang, P., Liu, X., Xu, J., Li, T., Sun, W., Li, Z., ... & An, Y. (2021). Deep learning for diagnosing osteonecrosis of the femoral head based on magnetic resonance imaging. *Computer Methods and Programs in Biomedicine*, *208*, 106229. https://doi.org/10.1016/j.cmpb.2021.106229

Wawrzyniak, A., & Balawender, K. (2022). Structural and metabolic changes in bone. *Animals*, *12*(15), 1946. https://doi.org/10.3390/ani12151946

Yavanamandha, P., Keerthana, B., Jahnavi, P., Rao, K. V., & Kumar, C. R. (2023). Machine Learning-Based Gesture Recognition for Communication with the Deaf and Dumb. *Int. J. Exp. Res. Rev.*, *34*(Special Vol.), 26-35. https://doi.org/10.52756/ijerr.2023.v34spl.004

Zaki, M. Z. A. A., Som, M. H. M., Yazid, H., Basaruddin, K. S., Basah, S. N., & Ali, M. S. A. M. (2021, October). A Review on Edge Detection on Osteogenesis Imperfecta (OI) Image using Fuzzy Logic. IOP Publishing, In *Journal of Physics: Conference Series*, *2071*(1), 012040. https://doi.org/10.1088/1742-6596/2071/1/012040

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