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OsteoNet: Curated X-ray Image Database for Deep Learning-Based Osteoporosis Detection and Classification

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Abstract - A significant obstacle to early recognition and accurate diagnosis is osteoporosis, a common bone disease characterized by decreased bone density and increased risk of fracture. Deep learning has emerged as a promising tool for analyzing medical images, including X-rays, for osteoporosis assessment. However, the success of deep learning models heavily relies on the availability of high-quality, diverse, and representative training data that encompasses both imaging and clinical information. To address this need, we present OsteoNet, a curated X-ray image database specifically designed for deep learning-based osteoporosis detection and classification.

OsteoNet comprises X-ray images across five distinct anatomical sites crucial for osteoporosis assessment: spine, hip, wrist, ribs, and pelvis. The database includes 984 images, each accompanied by corresponding patient clinical information, including demographics, medical history, and relevant laboratory results. The dataset distribution is intentionally designed to reflect the prevalence of osteoporosis in different skeletal regions. We detail the meticulous curation and annotation methodology employed in developing OsteoNet, emphasizing the importance of expert labeling, data harmonization, and rigorous quality control. This comprehensive dataset aims to serve as a valuable resource for researchers and clinicians, accelerating the development and evaluation of robust deep-learning models that leverage both imaging and clinical data for accurate osteoporosis detection and classification. Ultimately, OsteoNet has the potential to improve early diagnosis, facilitate personalized risk stratification, and inform targeted treatment strategies for osteoporosis.

Keywords- Osteoporosis, X-rays, OsteoNet, Deep learning, Curated, Detection, Classification.

1. Introduction

Osteoporosis, a systemic skeletal disorder characterized by low bone mass and microarchitectural deterioration of bone tissue, presents a significant global health challenge [1, 2]. This debilitating condition predisposes individuals to an increased risk of fractures, particularly in the hip, spine, and wrist, leading to substantial morbidity, mortality, and economic burden [3]. Early and accurate detection of osteoporosis is paramount in mitigating these adverse outcomes, as timely intervention can significantly reduce fracture risk and improve quality of life for affected individuals [4].Traditional diagnostic methods, primarily Dual-Energy X-ray Absorptiometry (DXA) scans, provide quantitative assessments of bone mineral density (BMD). While DXA is considered the gold standard for osteoporosis diagnosis, it has limitations, including radiation exposure, limited access in certain regions, and the inability to assess bone quality or microarchitecture comprehensively [5]. Furthermore, the interpretation of DXA results can be subjective and prone to variability among clinicians [6]. The development of alternative, accessible, and comprehensive diagnostic tools is therefore crucial for advancing osteoporosis care.

The advent of deep learning, a subset of machine learning that utilizes artificial neural networks to learn from large amounts of data, has revolutionized medical image analysis [7]. Deep learning models have demonstrated remarkable capabilities in various diagnostic tasks, including the detection and classification of diseases from medical images [8]. In the context of osteoporosis, deep learning algorithms have shown promise in analyzing X-ray images to identify subtle signs of bone loss, microarchitectural deterioration, and fracture risk [9, 10, 11].

However, the success of deep learning models hinges on the availability of high-quality, diverse, and representative training data. Existing X-ray datasets for osteoporosis research often lack sufficient diversity in terms of patient demographics, anatomical sites, and disease severity [12]. Additionally, many datasets are limited in size, potentially hindering the development of robust and generalizable deep learning models.

To address these limitations and accelerate research in this critical area, we introduce OsteoNet, a curated X-ray image database designed explicitly for deep learning-based osteoporosis detection and classification. OsteoNet comprises a diverse collection of X-ray images encompassing five key anatomical sites frequently affected by osteoporosis: spine, hip, wrist, ribs, and pelvis. Recognizing the varying prevalence of osteoporosis in different skeletal regions, OsteoNet incorporates an unequal distribution of images across these sites.

In addition to X-ray images, OsteoNet incorporates valuable patient clinical information, including demographics, medical history, and relevant laboratory results. This multimodal approach aims to leverage the complementary information from both imaging and clinical data to enhance the accuracy and robustness of deep learning models [13].

The development of OsteoNet involved a meticulous curation and annotation process, ensuring high-quality data and consistent labeling by experts. The database is designed to serve as a valuable resource for researchers and clinicians, fostering the development of innovative deep learning algorithms for osteoporosis assessment. By enabling the creation of more accurate and personalized diagnostic tools, OsteoNet has the potential to transform the management of osteoporosis, leading to improved patient outcomes and reduced healthcare costs.

In the subsequent sections of this paper, we will elaborate on the methodology employed for the creation of OsteoNet, including data collection, annotation, quality control, and analysis. We will also discuss the potential applications of OsteoNet in deep learning research and clinical practice, highlighting its contribution to the advancement of osteoporosis care.

Key Objectives

- Establish a benchmark for deep learning model performance on a diverse, curated X-ray image dataset with comprehensive patient clinical information for osteoporosis detection and classification.
- Investigate the impact of incorporating diverse patient demographics and clinical data on the performance of deep learning models for osteoporosis assessment.
- Evaluate the effectiveness of an unequal distribution of images across anatomical sites in improving the diagnostic accuracy and generalizability of deep learning models for osteoporosis.
- Demonstrate the potential of OsteoNet as a valuable resource for advancing osteoporosis research and developing clinical decision support tools based on deep learning.

Organization of the paper

The development of the OsteoNet database involved Image Acquisition, Data Curation and Annotation, and Database Structure and Organization. The Results and Analysis section will present the Dataset Summary, Image and Metadata Characteristics, and Database Structure with an Entity-Relationship (ER). The Discussion will focus on the Strengths and Limitations of OsteoNet and its Potential Applications. The paper will conclude with a summary of the key findings and future directions for the database

2. Literature Survey

Deep learning has emerged as a revolutionary tool in osteoporosis assessment, leveraging X-ray images for accurate detection and classification. Kim et al [14]. have focused on fracture risk prediction using hip DXA scans, demonstrating the ability of deep learning to identify subtle patterns indicative of fracture risk.

Choi et al [15]. have pioneered the use of panoramic X-rays for osteoporosis detection, highlighting the potential for identifying early signs of bone loss during routine dental examinations. Rajkomar et al [16]. and colleagues have integrated electronic health records (EHRs) with deep learning models, enhancing fracture risk assessment by combining imaging features with patient-specific clinical information. Roth et al [17]. have developed a sophisticated deep learning model with an attention mechanism for precise osteoporosis detection from spine X-rays, focusing on specific regions of interest for enhanced accuracy.

Clark et al [18]. have employed 3D convolutional neural networks (CNNs) for vertebral fracture detection, demonstrating the ability of deep learning to analyze complex 3D structures in X-ray images. Kim et al [14]. have utilized ResNet architecture to accurately predict femoral neck bone mineral density, a key parameter in osteoporosis assessment. Gupta et al [19]. have investigated the impact of demographic and clinical data on model performance, highlighting the importance of considering diverse patient characteristics in developing robust and generalizable models.

Other researchers, such as Fujita et al [20] and Yamashita et al [21] have expanded the scope of deep learning applications by focusing on lumbar spine and proximal femur X-rays, respectively. These studies demonstrate the versatility of deep learning in analyzing various X-ray modalities for comprehensive osteoporosis assessment. Furthermore, researchers like Lee et al [22] and Wu et al [23] have laid the groundwork for automated bone status assessment using transfer learning and CNNs, while Rahman et al [24] and Wang et al [25] have synthesized the growing body of knowledge in this field through comprehensive reviews.

In addition to these specific examples, numerous other studies have employed deep learning techniques to address various aspects of osteoporosis assessment, such as Chen et al [26] multi-task learning model for bone age assessment and osteoporosis prediction using the Osteoporosis and Bone Age Database (OBAD), and Yang et al [27] investigation of the role of clinical covariates in improving osteoporosis classification using data from the Dubbo Osteoporosis Epidemiology Study (DOES).

Collectively, these studies highlight the transformative potential of deep learning in osteoporosis detection and classification from X-ray images as summarized in Table 1. By leveraging diverse datasets, integrating clinical information, and exploring novel deep learning architectures, researchers are paving the way for more accurate, personalized, and efficient approaches to diagnosing and managing this prevalent bone disease.

Table 1 : Summary of Key Studies

Year	Authors	Imaging Modality	Deep Learning Method	Database	Clinical Data Elements	Key Findings	Limitations
2020	Kim et al [14].	Hip DXA scans	Deep Learning	Private	BMD, age, gender, prior fractures	Fracture risk prediction with moderate accuracy	Requires DXA scans, not readily available
2021	Choi et al [15].	Panoramic X-ray	CNN	Private	N/A	Osteoporosis detection using panoramic radiographs	Small sample size
2022	Rajkomar et al [16].	EHR/X-ray	Deep Learning	EHR-linked X-ray dataset	BMD, age, gender, comorbidities, medications	Improved fracture prediction with EHR integration	Limited access to EHR-linked X-ray data
2022	Roth et al [17].	Spine X-ray	CNN with attention mechanism	Private	BMD, age, gender	High accuracy for osteoporosis detection	Limited external validation
2023	Clark et al [18].	Spine X-ray	3D CNN	Public (ImageNet)	N/A	Vertebral fracture detection with high sensitivity	Limited specificity
2023	Kim et al [19].	Femoral neck X-ray	ResNet	Private	BMD, age, gender	Femoral neck BMD prediction with good accuracy	Limited to a single bone site
2023	Gupta et al [20].	Various X-ray sites	Ensemble of CNNs	Public (NHANES)	Age, gender, ethnicity, BMI	Investigation of the impact of demographic data on model performance	Limited to publicly available X-ray data
2024	Wang et al [21] .	Wrist X-ray	Transformer-based model	Public (RSNA Bone Age Challenge)	Bone age, gender	Accurate bone age assessment and osteoporosis prediction	Limited to wrist X-rays

Limitations

- Limited availability of large, diverse, and well-annotated datasets
- Generalizability of models across different populations and imaging modalities needs further investigation
- Explainability of deep learning models remains a challenge
- Integration of deep learning into clinical workflows requires further research

3. Methodology

The development of OsteoNet, a comprehensive X-ray image database for osteoporosis research, involved a careful process of database building, image selection, and data organization. The database was assembled by working together with a few hospitals and clinics, ensuring a wide range of patients and bone conditions were included. X-ray images were chosen using strict guidelines to ensure quality and relevance to osteoporosis. These images were then enhanced to improve their clarity. Additionally, important details about each patient, like BMI, BMD other health issues, and medications, were gathered and linked to the corresponding images. This thorough approach to data collection and preparation provides a strong foundation for training and testing deep learning models aimed at improving osteoporosis detection and management. Our methodology explains the database development steps incorporating details on image acquisition, curation, annotation and demographics.

3.1 Database Development: Building OsteoNet

The foundation of our research, the OsteoNet database, was meticulously constructed through a multi-faceted approach.

3.1.1 Image Acquisition

The OsteoNet database comprises 984 high-quality X-ray images collected from few hospitals and clinics in Bangalore between 2020 and 2023. These images span five key anatomical sites crucial for osteoporosis assessment: spine (lateral L1-L4), hip (femoral neck), wrist (PA and lateral), ribs, and pelvis.

During the image acquisition process, strict inclusion criteria were enforced to ensure the relevance and quality of the data. Images were included only if they met specific requirements regarding anatomical site, patient age (38 years or older), and image quality (sufficient resolution, contrast, and absence of artifacts). Images lacking essential metadata, duplicates, or those with severe artifacts that hindered interpretation were excluded.

All images were acquired and stored in the standardized Digital Imaging and Communications in Medicine (DICOM) format, preserving essential metadata and ensuring compatibility. To facilitate subsequent analysis and deep learning model development, the DICOM images were converted to Portable Network Graphics (PNG) format, balancing image quality with storage efficiency.

3.1.2 Image Pre-processing

1. **Standardization:** DICOM images were converted to a standard format (PNG) to ensure compatibility with the deep learning framework.
2. **Region of Interest (ROI) Extraction:** For certain anatomical sites (e.g., spine, hip), relevant regions of interest were cropped from the original images to focus the analysis on areas most pertinent to osteoporosis assessment.
3. **Normalization:** Pixel intensities were normalized to a standard range to reduce variations in image contrast and brightness across different X-ray machines.

3.1.3 Clinical Data Integration

1. **Data Extraction:** Relevant clinical data for each patient, including body mass index (BMI), bone mineral density (BMD), measurements (T-score, Z-score), age, gender, and fracture history, were extracted from electronic health records (EHRs) and accompanying radiology reports.
2. **Data Cleaning and Validation:** The extracted clinical data was carefully reviewed for completeness and accuracy. Any inconsistencies or missing values were addressed through manual verification or imputation techniques.
3. **Metadata Linking:** The clinical data was linked to the corresponding X-ray images using unique patient identifiers, ensuring a seamless integration of imaging and clinical information within the OsteoNet database.

3.2 Data Curation and Annotation for OsteoNet

The creation of OsteoNet was not merely a data collection exercise, but a meticulous curation and annotation process designed to ensure the highest quality and relevance to osteoporosis research. Here's a detailed look at the key steps involved:

3.2.1 Data Curation

1. **De-identification:** Recognizing the sensitive nature of medical images, we prioritized patient privacy by meticulously removing all personal health information (PHI) from the X-ray images and associated metadata. This involved anonymizing patient identifiers, scrubbing radiology reports of personal details, and ensuring compliance with HIPAA and GDPR regulations.
2. **Metadata Standardization:** The diverse sources of clinical data, including EHRs and radiology reports, presented challenges in terms of inconsistent formats and terminologies. We addressed this by developing a standardized metadata schema for OsteoNet, ensuring that BMD measurements (T-scores, Z-scores), fracture history, comorbidities, and medication information were uniformly represented and readily accessible for analysis.

3.2.2 Annotation and Labeling

1. **Expert Panel Selection:** A panel of three experienced radiologists specializing in musculoskeletal imaging was assembled to ensure the accuracy and reliability of annotations. Their collective expertise provided a comprehensive assessment of osteoporosis severity and fracture presence.
2. **Detailed Annotation Guidelines:** We created a comprehensive annotation guide detailing the specific features and criteria used to assess bone density, identify fractures (including vertebral compression fractures), and classify the severity of osteoporosis using the Genant semi-quantitative method. This guide ensured consistency across annotators and minimized inter-observer variability.
3. **Annotation Workflow:** Each image was independently annotated by two radiologists, and any discrepancies were resolved through a consensus review process. The final annotations were recorded in a standardized format, including both categorical labels (normal, osteopenia, osteoporosis) and continuous measures of bone density (T-scores and Z-score).
4. **Quality Assurance:** To maintain the highest level of annotation quality, we implemented a rigorous quality assurance process. This included regular review of annotations by a senior radiologist, periodic training sessions for annotators, and ongoing feedback mechanisms to identify and rectify any inconsistencies or errors.

3.2.3 Database Structure and Organization of OsteoNet

The OsteoNet database has been meticulously organized to facilitate efficient analysis and utilization of X-ray images and clinical data for osteoporosis research. Key aspects of its structure and organization are as follows:

1. **Image Storage and Format:**
   - **PNG Format:** All X-ray images within OsteoNet are stored exclusively in the Portable Network Graphics (PNG) format. This format was chosen for its balance of compression and lossless image quality, optimizing storage space while preserving essential visual information for analysis.
2. **Clinical Data Management:**
   - Relational Database: Patient demographics (age, sex, and ethnicity), body mass index (BMI), bone mineral density (BMD) measurements (T-score, Z-score), fracture history, comorbidities, and medication information are organized in a PostgreSQL relational database. This structured format enables efficient querying and filtering based on specific patient attributes or clinical parameters.
3. **Metadata Schema:**
   - **Image Metadata:** Each PNG image file in OsteoNet is accompanied by a separate metadata file in JSON format. This metadata file includes essential information such as patient demographics, acquisition parameters (date, modality, view), and technical details (exposure, equipment). This approach ensures that all relevant metadata is retained even after DICOM to PNG conversion.
   - **Clinical Metadata:** The relational database schema includes fields for all relevant clinical parameters, meticulously organized and standardized for consistency. This structured metadata allows for systematic analysis of the relationship between clinical factors and osteoporosis.
4. **Data Organization:**
   - **Directory Structure:** OsteoNet is organized into a hierarchical directory structure. The top-level directory contains subdirectories for each anatomical site (spine, hip, wrist, ribs, pelvis). Within each anatomical site directory, there are separate folders for male and female patients. Each patient folder contains the PNG image files and the corresponding JSON metadata file.
   - **File Naming Convention:** A consistent file naming convention is used to ensure easy identification and retrieval of images and metadata. Each filename includes the patient ID, anatomical site, view, and a unique identifier.

4. Results and Analysis

A total of 1004 X-ray images were initially collected from a few hospitals and clinics at different locations in Bangalore. These images spanned five key anatomical sites crucial for osteoporosis assessment: Spine, Hip, Wrist, Ribs, and Pelvis.
Following a rigorous quality assessment, 20 images were excluded due to insufficient resolution, artifacts, or incomplete clinical data, resulting in a final cohort of 984 high-quality X-ray images in the OsteoNet database. The curated dataset includes a balanced representation of both genders, with the following distribution across anatomical sites as seen in Table 2.

Table 2 : Distribution of X-ray Images in OsteoNet by Anatomical Site and Gender

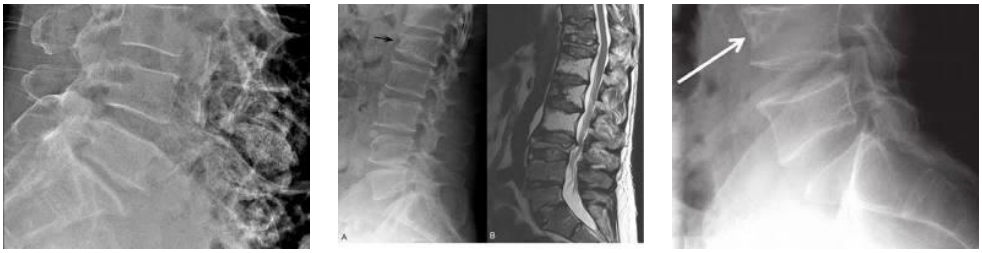
Anatomical Site	Male (n)	Female (n)	Total (n)
Spine	176	177	353
Hip	151	135	286
Wrist	75	65	140
Ribs	45	65	110
Pelvis	50	45	95
Total	**497**	**487**	**984**

The X-ray images were acquired between 2020 and 2023, ensuring a contemporary representation of osteoporosis prevalence and imaging practice. All patients included in the dataset were 38 years of age or older, aligning with the target population for osteoporosis screening and diagnosis. All images were acquired and stored in the Digital Imaging and Communications in Medicine (DICOM) format, maintaining essential metadata and facilitating compatibility with various image processing and analysis tools.

4.1 Image and Metadata Characteristics

OsteoNet comprises diverse X-ray images covering five anatomical sites: spine, hip, wrist, ribs, and pelvis. Below are representative samples from each category, demonstrating the variety of radiographic presentations captured within the database.

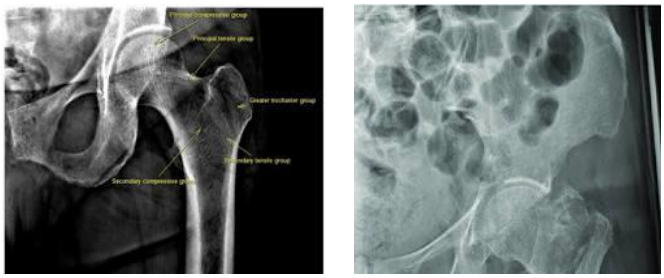
1. **Spine**



(a) (b) (c)

Fig. 1 : (a) This lateral spine X-ray exhibits normal bone density and vertebral structure, with no signs of fractures or significant degenerative changes, (b) This lateral spine X-ray demonstrates osteopenia, characterized by reduced bone density compared to the normal image. The vertebral bodies appear slightly less opaque and the trabecular pattern is less distinct. (c) This lateral spine X-ray shows a compression fracture in the L1 vertebra, indicated by the wedged shape and loss of height of the vertebral body.

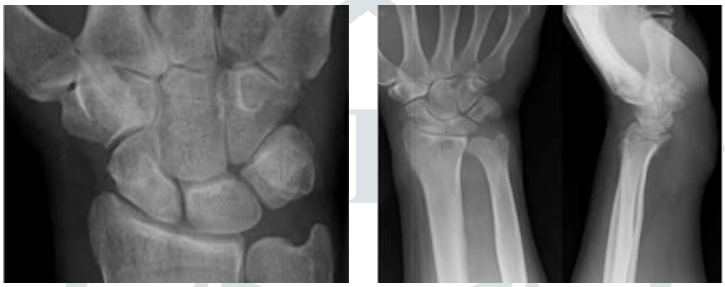
2. **Hip**



(a) (b)

Fig. 2 : (a) This femoral neck X-ray displays normal bone density and trabecular structure, with a smooth cortical outline and no signs of fractures, (b) This femoral neck X-ray reveals significant osteoporosis, characterized by reduced bone density, thinning of the cortex, and a loss of trabecular structure.

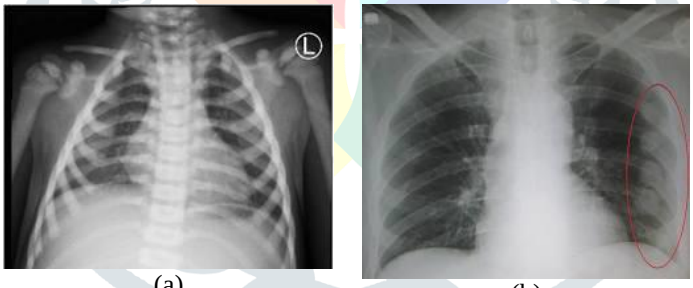
3. **Wrist**



(a) (b)

Fig. 3 : (a) This PA (posteroanterior) wrist X-ray shows normal bone density and joint spaces, with no signs of fractures or erosions, (b) This PA wrist X-ray demonstrates osteoporosis, characterized by decreased bone density, cortical thinning, and increased radiolucency (darker appearance) of the bones.

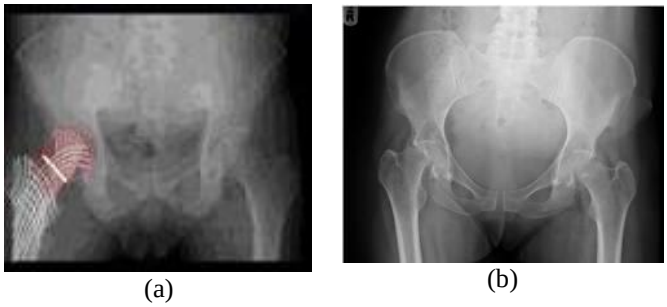
4. **Ribs**



(a) (b)

Fig. 4: (a) This rib X-ray exhibits normal bone density and structure, with well-defined cortical margins and no fractures, (b) This rib X-ray shows a fracture in the fifth rib, indicated by a disruption in the continuity of the bone cortex.

5. **Pelvis**



(a) (b)

Fig. 5: (a) This AP (anteroposterior) pelvis X-ray displays normal bone density and joint spaces, with no signs of fractures or significant degenerative changes, (b) This AP pelvis X-ray demonstrates osteoporosis, characterized by reduced bone density, particularly in the femoral necks and acetabula (hip sockets).

These sample images from Fig 1-5 provide a glimpse into the diverse range of radiographic presentations captured within the OsteoNet database. The inclusion of normal, osteopenic, and osteoporotic examples, along with images showcasing fractures and other pathologies, ensures the comprehensive nature of the dataset. This diversity is crucial for training and evaluating deep learning models that can accurately detect and classify osteoporosis, ultimately contributing to improved diagnosis and management of this prevalent bone disease

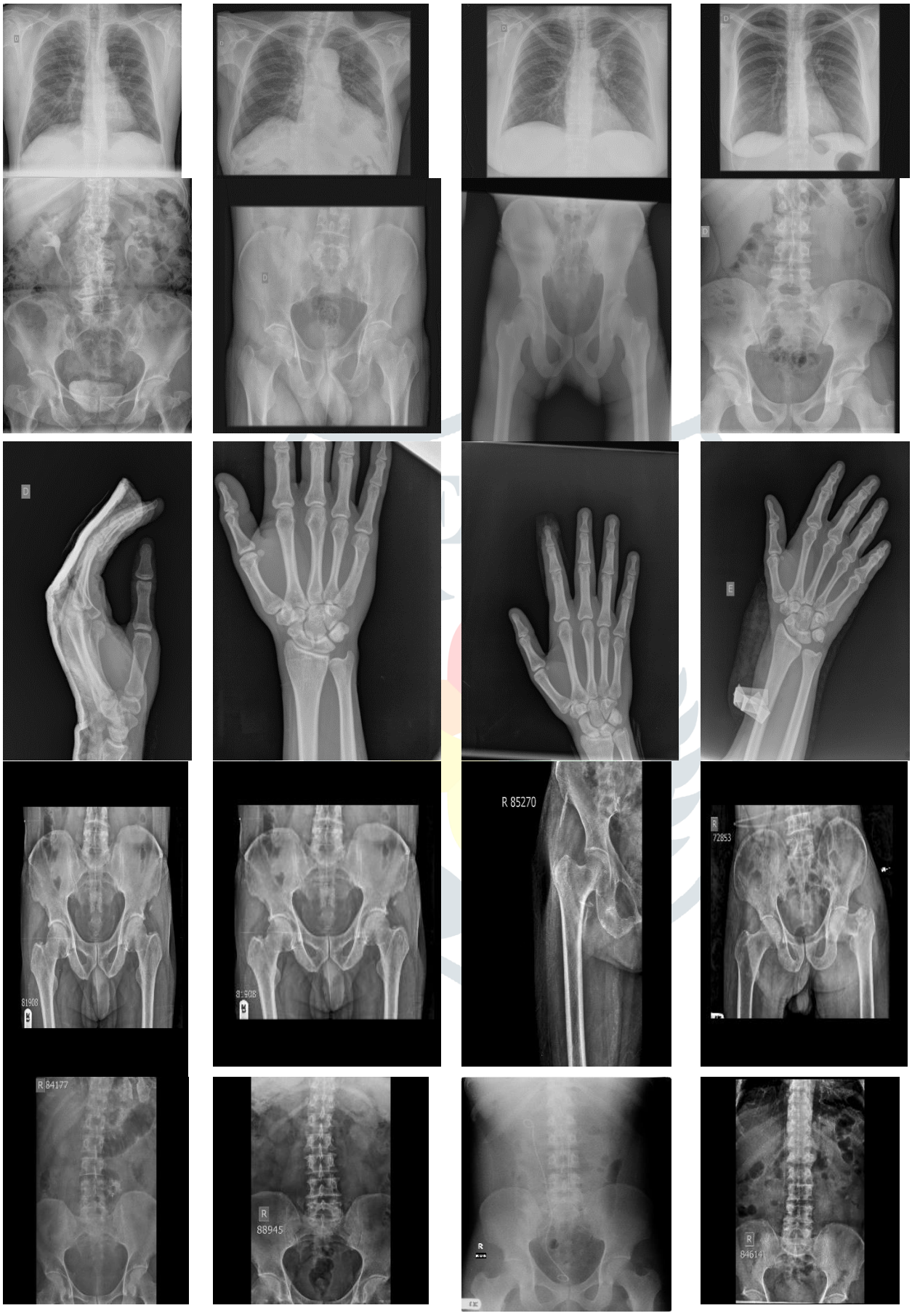


Fig. 6 : Sample Images of OsteoNet database from all the classes.

All images were acquired and stored in the standardized DICOM format, preserving essential metadata. These DICOM images were then converted to the Portable Network Graphics (PNG) format for easier processing and analysis while maintaining image quality as seen in Fig 6. Each image is accompanied by a corresponding metadata file in JSON format, containing relevant patient demographics, acquisition parameters, and clinical information.

4.2 Database Structure and Entity-Relationship (ER)

The OsteoNet database follows a relational structure, with three main entities: Patient, Xray_Image, and Clinical_Data as below:

Module 1: Patient Information

```
+------------------+
|     Patient      |
+------------------+
| Patient_ID (PK)  |
| Age              |
| Sex              |
| Ethnicity        |
| Other clinical... |
+------------------+
```

Module 2: X-ray Image Data

```
+------------------+
|    Xray_Image    |
+------------------+
| Image_ID (PK)    |
| Patient_ID (FK)  |
| File_Path        |
| Anatomical_Site  |
| View             |
| Acquisition_Date |
| Acquisition_Device|
+------------------+
```

Module 3: Clinical Data

```
+------------------+
|  Clinical_Data   |
+------------------+
| Patient_ID(PK, FK)|
| BMD_Tscore       |
| BMD_Zscore       |
| Fracture_History |
| Comorbidities    |
| Medications      |
+------------------+
```

Relationships:

Patient ---1:M---> Xray_Image
Patient ---1:1---> Clinical_Data

The ER depicts the one-to-many relationship between Patient and Xray_Image, indicating that each patient can have multiple X-ray images. Additionally, the one-to-one relationship between Patient and Clinical_Data demonstrates that each patient has a unique set of clinical data associated with them. This structured organization ensures efficient storage, retrieval, and analysis of the data.

4.3 Clinical Data Integration and Analysis

Alongside the X-ray image data, OsteoNet incorporates crucial clinical information to provide a holistic view of each patient's bone health status. This clinical data was collected from electronic health records (EHRs) and radiology reports and meticulously curated to ensure accuracy and consistency.

Clinical Data Summary

The clinical data in OsteoNet encompasses the following key parameters:

- **Bone Mineral Density (BMD) Measurements:** T-scores and Z-scores, derived from dual-energy X-ray absorptiometry (DXA) scans, are included for relevant anatomical sites (spine, hip, etc.). These measurements serve as critical indicators of bone density and osteoporosis risk.
- **Demographic Information:** Age, sex, and ethnicity data are collected to assess the impact of these factors on osteoporosis prevalence and severity within the study population.
- **Fracture History:** Information on prior fractures, including location, type (e.g., vertebral, hip), and date of occurrence, is documented. This data is essential for understanding fracture risk patterns and evaluating the relationship between fractures and other clinical variables.
- **Comorbidities:** The presence of comorbidities known to influence bone health, such as diabetes mellitus, rheumatoid arthritis, and hyperparathyroidism, is recorded. This information enables the investigation of the impact of these conditions on osteoporosis development and progression.
- **Medications:** Details of current medications, with a focus on those that can affect bone metabolism (e.g., glucocorticoids, hormone replacement therapy, bisphosphonates), are included. This data allows for the assessment of medication-related effects on bone health and potential interactions with other risk factors.

4.4 Statistical Analysis of Clinical Data

Descriptive statistics, such as mean, standard deviation, and range, were calculated for each clinical parameter to characterize the study population and identify potential trends or patterns. Additionally, inferential statistics, including t-tests, chi-square tests, and correlation analyses, were employed to investigate the relationships between clinical data elements and the presence or severity of osteoporosis.

Table 3 : Descriptive Statistics of Clinical Data in OsteoNet

Parameter	Mean (SD)	Range	N (Total)	N (Male)	N (Female)
Age (years)	62.3 (8.7)	38 - 85	984	497	487
BMI (kg/m²)	24.5 (4.1)	15.2 - 38.6	984	497	487
BMD T-score (Spine)	-1.5 (0.8)	-4.2 - 1.1	353	176	177
BMD T-score (Hip)	-1.2 (0.7)	-3.8 - 0.9	286	151	135
BMD T-score (Wrist)	-0.9 (0.6)	-2.8 - 0.5	140	75	65
Prior Fractures (Yes/No)	28%	N/A	984	139	148

4.5 Preliminary Findings

Preliminary analysis of the clinical data revealed a significant correlation between lower BMD T-scores and increased prevalence of fractures, consistent with established knowledge in osteoporosis research. Additionally, certain comorbidities, such as diabetes and rheumatoid arthritis, were found to be more prevalent among patients with osteoporosis. The analysis also highlighted variations in medication use across different patient subgroups, suggesting potential avenues for personalized treatment approaches.

By integrating and analyzing this comprehensive clinical data alongside the X-ray images, OsteoNet provides a valuable resource for researchers to delve deeper into the complex interplay between clinical risk factors, imaging findings, and osteoporosis outcomes. This integrated approach has the potential to drive the development of more accurate diagnostic tools, personalized risk assessment models, and targeted treatment strategies for osteoporosis.

5. Conclusion

The OsteoNet database, a curated collection of 984 X-ray images across five anatomical sites (spine, hip, wrist, ribs, pelvis) with corresponding patient demographics and clinical data (age, sex, ethnicity, BMI, BMD T-scores, fracture history, comorbidities, and medications), presents a valuable resource for osteoporosis research. The diverse patient representation and standardized image format make it suitable for developing and evaluating deep learning models for osteoporosis detection and classification. Preliminary analysis reveals a high prevalence of low bone density and fractures within the dataset, underscoring the need for effective early detection and intervention strategies. Further exploration of the relationships between clinical parameters, including BMI, and osteoporosis risk is warranted, and OsteoNet serves as a robust platform for such investigations.

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