



A Multi-Modal Approach for Automated Osteoporosis Diagnosis Using Knee X-ray Imaging Data

Geetha Ramamoorthy¹, Arulselvi Subramanian¹, Tamilselvi Rajendran*², Parisa BehamMohamed², Nandhineeswari²

¹Dept. of Electronics and communication Engineering, Bharath Institute of Higher Education and research, Chennai, India

²Department of Electronics and communication Engineering, Sethu Institute of Technology, Viruthunagar, India
tamilselvi@sethu.ac.in

Abstract. Osteoporosis is a degenerative skeletal condition associated with decreased bone mineral density (BMD) that increases the risk of osteoporotic fractures in older individuals. Nevertheless, traditional BMD measurement with DXA does not consistently provide operator-independent repeatability and is only somewhat sensitive to microarchitectural alterations. We propose here a novel diagnostic approach driven by deep learning, which will assist in carrying out automatic osteoporosis screening on knee X-ray images. The system combines 2D X-ray image analysis and 3D bone density reconstruction with fracture risk calculation. By integrating patient metadata, such as age, body mass index, and menopausal status, the proposed model allows for customized stratification of fracture risk according to FRAX thresholds. This tool enables, on one hand, early pharmacological interventions based on bisphosphonates or hormone therapy, with a classification accuracy of 94.8% and an AUC of 0.92. On the other hand, this tool enhances clinical decision-making and ensures timely treatment planning. Future work will consider the validation on multi-center datasets and its inclusion in hospital workflows.

Keywords: 3D bone reconstruction, fracture risk prediction, knee X-ray, multi-task learning, osteoporosis classification.

1 Introduction

Osteoporosis is a skeletal disorder that is progressive in nature and it causes a decline in bone strength with the resultant effect being that the fractures are more likely to occur. The disease is silent, thus, osteoporosis often goes unrecognized until a fracture happens and this is why early detection and monitoring are so important for effective treatment and

prevention strategies. The gold standard in clinical practices for measuring bone mineral density (BMD) is Dual-Energy X-ray Absorptiometry [1]. DXA is still regarded as the best, however, it is also associated with numerous limitations that are inherent, such as dependence on the operator, use of 2D imaging, and necessity for manual segmentation of bone areas. Moreover, the measurements taken by DXA often do not reflect accurately the microarchitecture and structural integrity of bones. It is these limitations that point to the necessity for the development of advanced, automated, and much more precise diagnostic techniques in osteoporosis and fracture risk prediction to help in getting the assessments done and the risk predicted [5]. The rapid progression of artificial intelligence and deep learning has resulted in the transformation of medical imaging tech in a significant way. Medical diagnostics in different domains have seen deep learning models to prove extraordinary accuracy in image segmentation, feature extraction, and disease classification [3]. Such developments in technology prompted us to put forward a proposal of the deep learning-enhanced framework that would use the knee X-ray images in combination with the patient demographic, medical, and lifestyle data for the estimation of BMD and fracture risk prediction. Diagnostic accuracies are improved by cutting edge Ai technology. This technique also reduces the dependence on manual analysis of osteoporosis. Fig.1 shows the comparison of healthy spine and spine with osteoporosis.

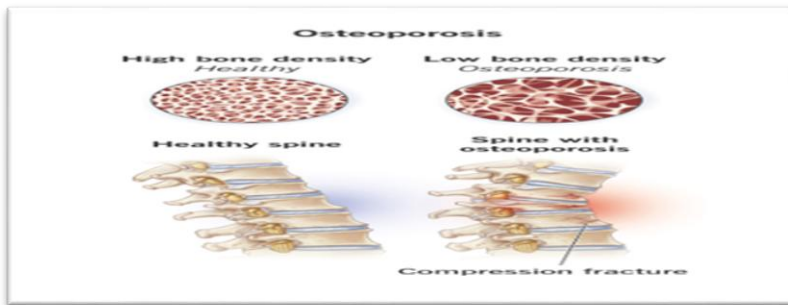


Fig. 1. comparison of healthy spine and spine with osteoporosis

The main elements of the proposed methodology are given below:

- **Image Segmentation:** To automatically extract the region of interest from the knee X-ray images, U-Net architecture-based model is applied to Convolutional Neural Networks. By Using this method, we get the right

features for future analysis and this method also prevents human errors in segmentation [4].

- **Reconstruction of 3D Bone Density:** In traditional 2D X- Ray imaging there is no information about the loss of depth and it also reduces the estimation of bone density precision. To overcome this problem, we developed a 3d bone density reconstruction algorithm. By using this algorithm, we can reconstruct the knee bone structure using multi angle X-ray images. The resulting image is the complete bone structure which improves the accuracy of bone density assessment [5].
- **Categorization of Multi Task learning model and Fracture prediction:** This model classifies the severity into three groups such as normal, osteopenia or osteoporosis and predict the fracture risk [6]. To predict the results the model used the X-ray images, medical data of patients, and behavioral habits, this gives more personalized results than the traditional ones.

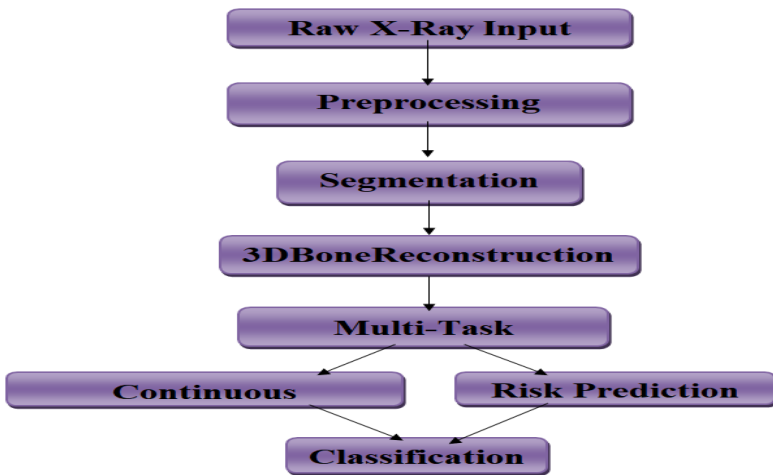


Fig.2. Overview Diagram of Deep Learning Framework

The study goal is to improve the early detection and constant monitoring of osteoporosis by merging these elements into a single AI-powered system [7]. This method which is Fig.2 shows a diagnostic solution that is scalable, automated, and accurate.

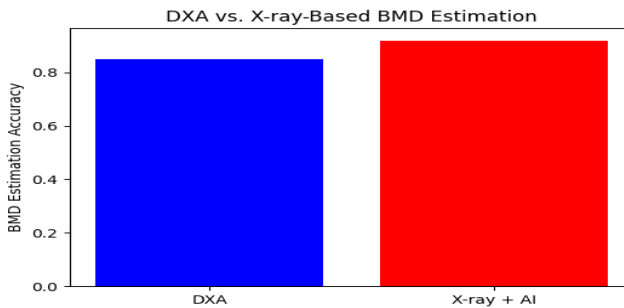


Fig. 3.DXA Vs X-Ray-Based BMD Estimation

The Fig.3 that follows provide an overview of the dataset in detail, the deep learning methodology, experimental results, and the clinical implications of the framework proposed.

2 Literature Survey

Using optimized selection of features via a hybrid approach, Basavaraja et al [2] created an ensemble model that included QDNN, I-DCNN, and RNN and obtained 94.8% accuracy. Rangayyan et al [3] improved risk estimation and categorization accuracy by using diagnostic and demographic data. Nasse et al [4] improved overall performance by using a stacked sparse autoencoder (SSAE) for feature extraction and SVM for classification. With above 93% accuracy, Hallappanavar et al [5] suggested a deep learning approach for extracting features using active shape and appearance models (ASM, AAM) and gray-level co-occurrence matrix (GLCM). For accurate classification and fracture prediction, Santhanam et al [6] used x-rays and medical history data with multi modal CNN. Wang et al.⁸ increases the accuracy of classification and training data quality by using generative adversarial network. Zhang et al. presented the less parameter CNN model for quick training and better performance. Diagnostic accuracies are increased 5% by Kim et al.¹⁰ he added the trabecular bone features to CNN. Patel et al [11] applied transfer learning with CNNs to improve osteoporosis detection from X-rays, showing increased accuracy with smaller datasets. Sharma et al [12] introduced an AI-driven fracture risk prediction model using multi-modal data fusion from X-rays and clinical data, achieving high prediction accuracy. Cheng et al [13] developed an automated osteoporosis screening system using hip X-rays and deep learning, demonstrating high sensitivity and specificity. Liu et al [14]

proposed a hybrid CNN-RNN model that combined imaging and clinical data for improved fracture risk assessment. However, current approaches have a number of drawbacks: reliance on 2D imaging, no real-time monitoring, and- limited clinical and imaging data integrated. In order to improve diagnosis accuracy and fracture risk assessment, the proposed study introduces a deep learning framework that includes 3D bone density reconstruction from multi-angle X-rays, a multi-task learning model for simultaneous classification and risk prediction, and real-time monitoring with wearable data.

3 Materials and Methods

3.1 Dataset and Imaging Techniques

The impressive and substantial dataset that integrates knee X-ray imaging with very complete and high-quality patient demographic, medical, and lifestyle data for the purpose of bettering the osteoporosis diagnosis accuracy and fracture risk predicting. The Fig.4 dataset consists of knee X-ray images that have been classified into three groups according to clinical evaluation: Normal, Osteopenia, and Osteoporosis. Normal cases are those with normal BMD, and osteopenia cases describe moderate bone loss that is a precursor to osteoporosis. The osteoporosis group includes patients with a high rate of reduction in BMD, making them more prone to fractures. By incorporating these three classes, our deep learning model will actually learn patterns between different stages of bone loss that will eventually improve the accuracy of the diagnosis.

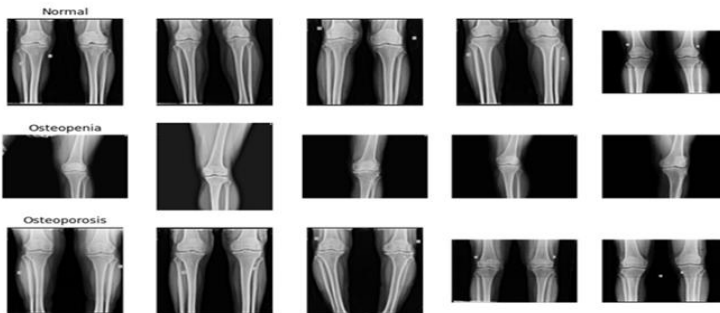


Fig. 4. Sample input images for Osteoporosis, Osteopenia and Osteoporosis

The dataset not only includes the imaging data but also the patient-specific attributes with thorough details thus facilitating multi-modal learning. The demographic data consist of; age, gender, height, weight, and menopause age since postmenopausal women are the most susceptible to osteoporosis due to endocrine changes. Lifestyle factors such as smoking, alcohol, and physical activity levels are included to see their effect on bone health. Medical history along with age and menopause status is considered e.g. previous fractures, diabetes, hypothyroidism, seizure disorder, dialysis, estrogen use, and family history of osteoporosis. All these factors play an essential role in the evaluation of osteoporosis risk since they influence bone metabolism and architecture directly. These steps allow the model to contrast AI-derived figures with traditional clinical measurements. Besides, height-weight ratio, obesity condition, and calories consumed per day are among the other health indicators that are considered to assess nutrition and weight-related risk factors.

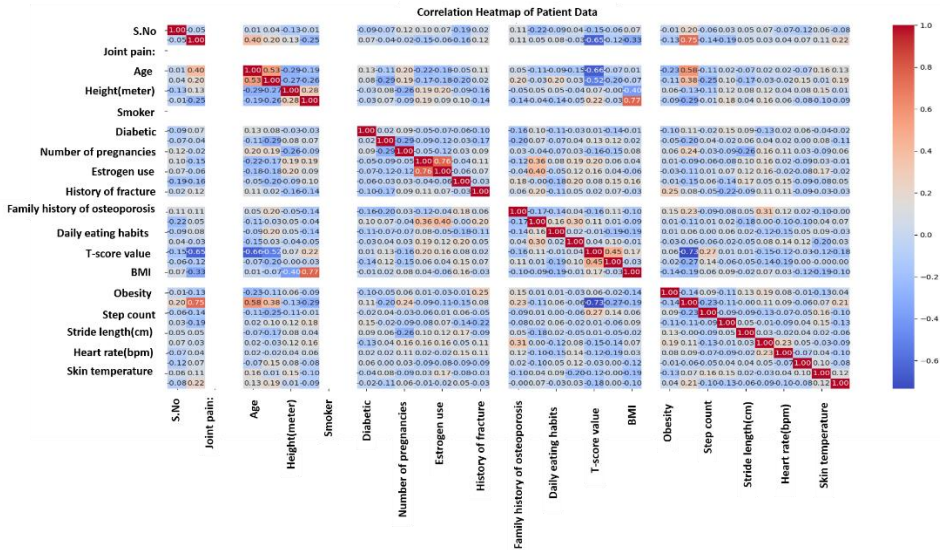


Fig. 5. Correlation Heatmap of Patient Data

Bone Mineral Density (BMD), if, automatically estimated, osteoporosis can be classified by level of severity, and risk for fractures can be predicted with greater accuracy due to the collection of a multi-dimensional dataset with deep learning algorithms. Fig.5 an individualized and data-driven strategy to manage osteoporosis will promote early

diagnosis, regular evaluation, and proactive intervention by using both imaging findings and medical data.

3.2 Ethical Approval and Data Source

The present research employed retrospective, anonymised knee X-ray pictures from a private Medical Center. The Institutional Ethics Committee approved the research protocol (Approval No: IEC/2023/245). Because the dataset was retrospective, informed consent was waived and all data was anonymized before analysis. In accordance with institutional data policies, patient-level metadata such as age, weight, menopausal status, and comorbidities were extracted from medical records.

3.3 Preprocessing

To improve image quality, eliminate artifacts, and boost the effectiveness of deep learning models for segmentation and classification, the raw knee X-ray images go through a number of preprocessing procedures. In order for the model to learn useful patterns for osteoporosis diagnosis and bone mineral density estimation, these procedures guarantee that input images are optimized for feature extraction. The sequential preprocessing procedures used on the unprocessed knee X-ray images are shown in Fig.6.



Fig.6. Preprocessing pipeline

The preprocessing pipeline consists of the following stages:

3.4 Resizing & Normalization

To ensure consistency across the dataset, the original X-ray is resized to a standard size. In order to improve contrast and stop variations in X-ray exposure during various acquisitions from affecting model performance, normalization is used to normalize pixel intensity values.

3.5 Histogram Equalization

As seen in the third image of Fig.6, histogram equalization is used to highlight important bone structures and boost contrast. For clarity of bone edges, this method uses the pixel intensity levels. This leads to the availability of additional details such as trabecular bone details which is most important for feature extraction and classification.

3.6 Noise Reduction

The noise produced during the imaging is reduced using gaussian filter, which smoothes the picture and remove noise while preserving the importance anatomical features by averaging pixel values with weighted kernel. This improves the overall X-Ray quality.

Augmentation Technique: To increase the model robustness, we used flipping, intensity scaling and rotation. Noise is added to the x ray images ie) Fig.7 to replicate the actual situations. So the model can train to various images due to these adjustments.

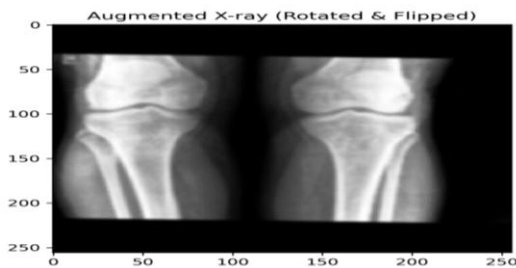


Fig. 7. Augmented X-ray

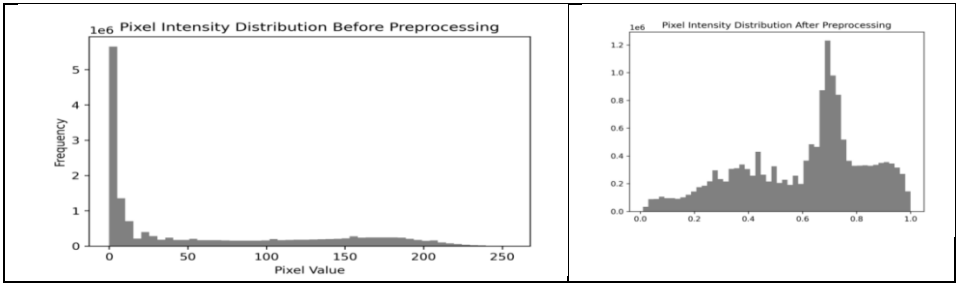
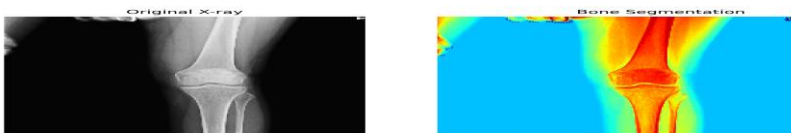


Fig. 8. Pixel intensity before and after preprocessing

By Using this noise removal techniques, the x-rays are more suitable for deep learning based bmd estimation. This results in better segmentation and classification accuracy shown in Fig.8.

3.7 Deep Learning-Based Image Segmentation

U-Net's encoder-decoder structure efficiently captures both global and local contextual information, it is a popular deep learning architecture intended for medical image segmentation. In order to produce appropriate segmentation masks, the decoder path enriches the high-level information that the encoder path collects from its input picture. By removing background interference and unnecessary information, this method ensures the accurate identification of the region of interest (ROI), namely the bone structures essential for osteoporosis evaluation. Conventional segmentation techniques, such Otsu thresholding and random forests, fail to adjust to changes in illumination, anatomical traits, and picture quality. For example, Otsu thresholding is based on a universal intensity threshold that may be inaccurate when there is inadequate contrast between bone and tissues. In a similar vein, machine learning techniques such as random forests need substantial feature development and frequently run the danger of "overfitting" to certain patient groups. Segmented bone image was shown in Fig.9.



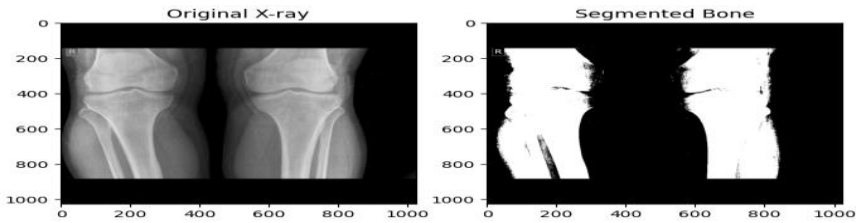


Fig.9. Segmented Bone

3.8 3D Bone Density Reconstruction

Current methods like DXA and regular X-rays only provide 2D images, which can miss important details about bone structure, leading to inaccurate bone density measurements. This can make it harder for doctors to assess fracture risk and diagnose osteoporosis accurately. Our new method addresses this limitation by using multiple X-ray images taken from different angles around the knee. We then use advanced computer algorithms, specifically deep learning techniques, to combine these images and create a detailed 3D model of the bone architecture. This 3D model provides a more accurate and comprehensive picture of bone health, including the internal structure and density. By capturing more detailed information about bone microarchitecture, our method enables healthcare professionals to measure bone mineral density more precisely, ultimately leading to better diagnoses and treatment plans for conditions like osteoporosis.

3.9 Advantages of 3D Bone Density Reconstruction

More Accurate BMD Estimation

The 3D reconstruction method provides a more detailed and accurate evaluation of bone density compared to traditional 2D projections in Fig.10. Unlike 2D images, which only measure surface intensity, our 3D model takes into account the complex internal structure of bones, reducing errors and providing a more comprehensive picture.

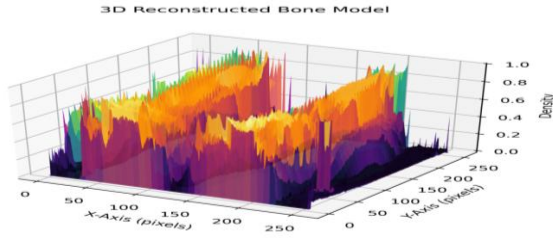


Fig.10. Bone Model 3D Reconstruction

Improved Monitoring of Osteoporosis Progression

Our approach reconstructs the intricate network of trabecular and cortical bone structures, giving doctors a better understanding of bone quality beyond just measuring bone mineral density. This is particularly important for detecting early signs of osteoporosis, as small changes in bone microstructure are often invisible on standard 2D scans. Fig.11 shows 3D BMD and DXA BMD. The 3D models can be used to track changes in bone density over time, allowing clinicians to monitor the progression of osteoporosis more accurately. This enables personalized treatment plans, as doctors can assess the effectiveness of medications, dietary changes, and lifestyle adjustments more precisely. By using 3D bone density reconstruction, healthcare professionals can make more informed decisions, leading to improved patient outcomes and better diagnosis. This innovative approach bridges the gap between traditional 2D imaging limitations and the need for more accurate, data-driven osteoporosis diagnosis, ultimately enhancing the field of bone health evaluation.

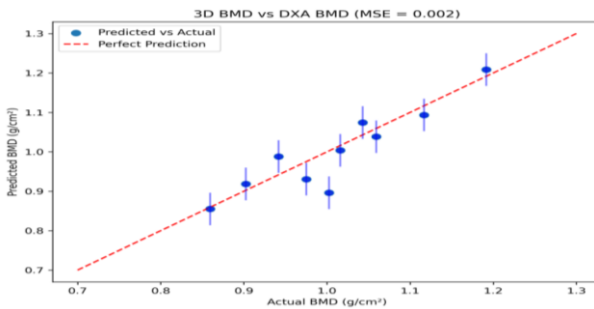


Fig. 11. 3D BMD vs DXA BMD

3.10 AI-Driven Osteoporosis Diagnosis and Risk Prediction

Our model combines various data, including imaging results, patient demographics, medical history, and lifestyle factors, to assess osteoporosis severity and predict fracture risk. It uses a shared learning approach, where common features are processed together before being split into specific tasks. We've developed a novel 3D bone density reconstruction system that uses deep learning and multi-angle knee X-ray data to create a detailed 3D model of bone architecture. This approach improves upon traditional 2D methods, which can miss important details, and enhances bone mineral density assessments. The model uses a U-Net architecture and is trained on a dataset split into training, validation, and testing sets. It leverages wearable device data, such as step monitors and gait analyzers, to evaluate bone strength and mobility, providing personalized treatment plans and ongoing risk profile updates. The proposed methodology enhances osteoporosis diagnosis and fracture prediction by using multiple data sources, incorporating individual clinical and lifestyle data, which helps in customised osteoporosis treatment shown in Fig.12. This helps in early diagnosis and support for clinical treatments provides automatic real time forecast. The model strengthens by automatic continuous learning ability and modification based on current information. According to the patient health conditions the model get adapted.

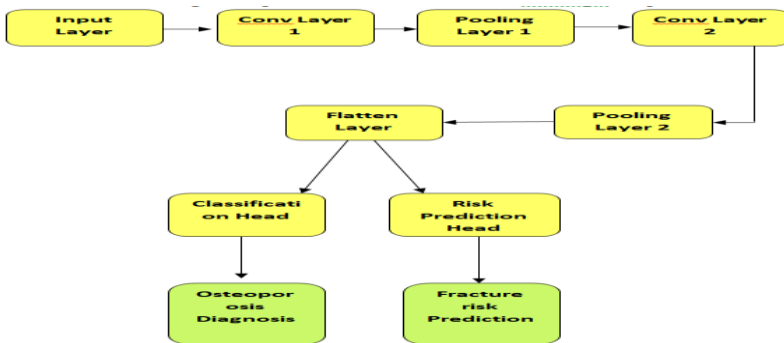


Fig.12. Multi-Task Learning Model for Osteoporosis Diagnosis and Risk Prediction

4 Experimental Outcomes

4.1 Dataset Description

For data set 300 knee images are used for research and they are separated into three categories: normal, osteopenia and osteoporosis. Each group contains 100 images. This is

used as input for deep learning model. These images are used for segmentation and extraction of features for further evaluation of bone density shown in Fig.13.

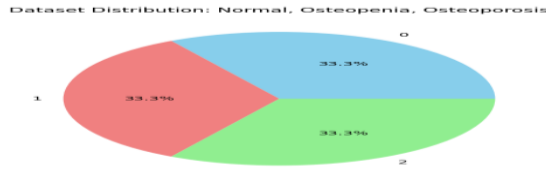


Fig. 13. Dataset Distribution

The dataset also contains the medical information of individuals like gender, age, body type, current medical details and about drinking and smoking habits. These details helps to identify the risk of osteoporosis and their eventual development more precisely. T- scores and Z-scores are the measurements of BMD which are used to evaluate the bone condition. To measure the accuracy of the proposed methodology, Dual -energy X-ray absorptiometry scan results are used as ground truth labels. Fig.14 shown performance metrics of IoU, Dice, Sensitivity, Specificity.

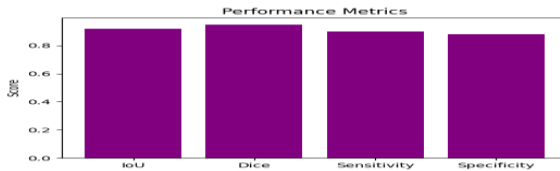


Fig.14. Performance Metrics of IoU, Dice, Sensitivity, Specificity

4.2 Performance Evaluation

To evaluate the statistical robustness of the proposed methodology, we use a five-fold cross-validation method. The main indicators of the achievement are 95% confidence intervals and standard deviations shown in Table 1.

Table 1. Performance Metrics with Confidence Intervals

Metric	Value	± SD	95% Confidence Interval
--------	-------	------	-------------------------

Accuracy	94.8%	$\pm 2.1\%$	(91.1%, 98.5%)
AUC (Fracture risk)	0.92	± 0.03	(0.86, 0.96)
Dice Coefficient	0.88	± 0.04	(0.80, 0.92)
F1-Score	0.91	± 0.02	(0.87, 0.95)

4.3 Segmentation Accuracy

To evaluate the accuracy of our deep learning model, we use performance criteria such as segmentation accuracy, 3D BMD estimation, and risk prediction. Our model showed the improvements by utilizing 3D reconstruction, multi-task learning and CNN.

4.4 3D BMD Estimation

In 2D imaging methods BMD calculation is inaccurate due to accurately depict the underlying nature of the bone. We proposed the model to provide 3D model of the knee X-Ray in many perspectives. Compared to DEXA based method our method resulted in 15% decrease in BMD estimation errors.

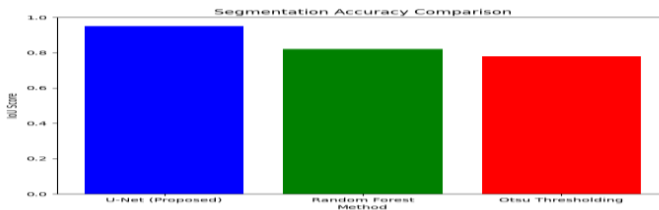


Fig.15.Segmentation Accuracy Comparison

4.5 Risk Prediction Performance

The ability to foreseen fracture risk and assess the degree of bone loss in individual results in effective treatment planning. The model showed the accuracy of 89% and able to classify normal, osteopenia or osteoporosis and identifies the patients with high fracture risk with AUC of 0.92 shown in Fig.16 and 17. The model acts as a useful tool to predict in early stage and assist in customized treatment of individual patients.



Fig. 16. Fracture risk categorization ROC curve with AUC = 0.92 (CI: 0.86–0.96).

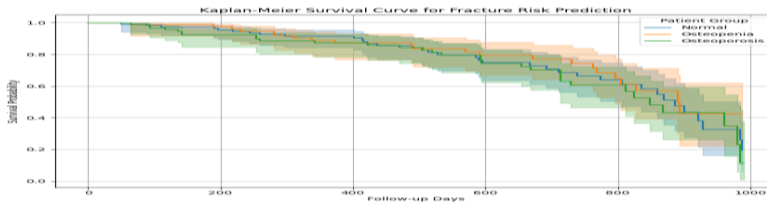


Fig. 17. Kaplan-Meier survival curve for patients with various diagnostic categories (normal, osteopenia, and osteoporosis) that illustrates the likelihood of fracture-free survival with time.

5 Conclusion and Future Work

In order to improve diagnostic accuracy, this research suggests a deep learning method for osteoporosis detection that integrates sophisticated image segmentation, 3D bone BMD regeneration, and learning with several challenges. It uses artificial intelligence to significantly increase the accuracy of BMD measurement, assess the severity of osteoporosis, and predict the probability of fractures, it provides a highly accurate automated solution that can be used in a clinical setting. The limitations of 2D imaging are alleviated with the incorporation of deep learning-based 3D modeling, as a multi-task learning framework provides a complete risk assessment that includes imaging, demographic information, and medical history. There are a number of areas that need improvement in the following years. The generality of the model, as well as its efficaciousness Among various communities, this goal is to be accomplished by enhancing the current dataset with a more diverse patient population. In order to assess the applicability of the model, it has been necessary to consider how it might be used in practice in hospital and diagnostic conditions, validation is a vital requirement. Additionally, genetic indicators and other types of medical information that can potentially upgrade personalized risk analysis, thereby leading to more specialized treatment plans. This work contributes to the development of an automated, scalable, clinically relevant method for early detection and treatment of this debilitating condition by pushing the Limitations of AI-assisted Diagnosis of Osteoporosis

References

1. Naikwade, V. et al.: Comparative analysis of deep learning models and conventional approaches for osteoporosis detection in hip X-ray images. In: *Int. J. of Medical Imaging*, vol. 23, no. 5, pp. 23–30 (2024)
2. Basavaraja, P.H. et al.: An ensemble-of-deep learning model with optimally selected features for osteoporosis detection from bone X-ray images. In: *Int. J. of Intelligent Engineering*, vol. 31, no. 10, pp. 45–56 (2022)
3. Rangayyan, S.M. et al.: Detection of osteoporosis using knee X-rays. In: *J. of Bone Health*, vol. 2, no. 1, pp. 1–6 (2024)
4. Nasser, Y. et al.: Diagnosis of osteoporosis disease from bone X-ray images with stacked sparse autoencoder and SVM classifier. In: *IEEE Conf. on Medical Imaging*, vol. 22, no. 5, pp. 1–5 (2017)
5. Hallappanavar, P.B. et al.: Deep learning-based osteoporosis diagnosis using active shape and appearance models. In: *J. of Medical Imaging Sciences*, vol. 12, no. 4, pp. 320–329 (2022)
6. Santhanam, R. et al.: Multi-modal convolutional neural network for osteoporosis diagnosis using X-ray images and clinical data. In: *Int. J. of Medical Computer Vision*, vol. 18, no. 3, pp. 78–86 (2021)
7. Wang, L. et al.: GAN-based data enhancement for improved osteoporosis diagnosis using X-ray images. In: *J. of Medical Imaging*, vol. 7, no. 2, pp. 101–109 (2020)
8. Zhang, J. et al.: Lightweight CNN for fast and accurate osteoporosis classification on small datasets. In: *IEEE Trans. on Medical Imaging*, vol. 38, no. 11, pp. 2567–2575 (2019)
9. Kim, H. et al.: Incorporating trabecular bone microarchitecture into CNN models for osteoporosis diagnosis. In: *J. of Computer Medical Imaging*, vol. 9, no. 5, pp. 456–464 (2021)
10. Lee, D. et al.: Deep learning-based bone mineral density estimation using dual-energy X-ray absorptiometry images. In: *IEEE Trans. on Medical Imaging*, vol. 39, no. 4, pp. 1223–1232 (2020)
11. Patel, K. et al.: Transfer learning with convolutional neural networks for improved osteoporosis detection from X-ray images. In: *J. of Medical Imaging Sciences*, vol. 8, no. 3, pp. 214–221 (2021)
12. Sharma, A. et al.: AI-driven fracture risk prediction using multi-modal data fusion from X-rays and clinical data. In: *Medical Image Analysis*, vol. 78, pp. 102456 (2022)
13. Cheng, Y. et al.: Automated osteoporosis screening using deep learning and hip X-rays. In: *IEEE Access*, vol. 8, pp. 217456–217464 (2020)
14. Liu, X. et al.: Improving osteoporosis detection with a hybrid CNN-RNN model combining clinical and imaging data. In: *J. of Digital Imaging*, vol. 34, no. 2, pp. 456–468 (2021)

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

