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Osteoporosis Diagnosis through Visual Segmentation and Classification: Extensive Review

[1]Mr. Ch. Sekhar, [2]Ms. A. Sharmila, [3]Mr. Ch. Narayana, [4]Mr. A. Rutwick, [5] Mr. B. Srinu, [6]Mr. D. Pramod Kumar, [7]Mr. B. Snehith

[1]Department of Computer Science and Engineering, GMRIT Rajam, India sekharch.gmrit@gmail.com

[2]20341a0508@gmrit.edu.in, [3]20341a0538@gmrit.edu.in, [4]20341a0502@gmrit.edu.in, [5]20341a0532@gmrit.edu.in, [6]20341a0544@gmrit.edu.in, [7]20341a0520@gmrit.edu.in

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ABSTRACT—

Osteoporosis, a prevalent and progressive bone disorder, is characterized by diminished bone density and quality, resulting in heightened fragility and susceptibility to fractures. Various factors such as age, gender, hormonal fluctuations, and genetics contribute to the development of osteoporosis. Given its widespread prevalence, accurate and timely diagnosis is essential, prompting the exploration of advanced diagnostic methodologies. This survey aims to review and analyze the utilization of advanced technologies in bone health assessment, with a focus on image segmentation and deep learning models. Specifically, Convolutional Neural Networks (CNNs) are employed for feature extraction, followed by the application of transfer learning algorithms such as VGG-19, U-Net, and RESNET. The integration of pre-trained models and transfer learning techniques enhances the models' capability to discern variations in osteoporosis severity. Evaluation metrics including F1-score, recall, and confusion matrix are utilized to assess the performance of the reviewed approaches.

Keywords— Osteoporosis, Transformers, CNN, Transfer Learning, X-ray images, Diagnosis.

I. INTRODUCTION

Osteoporosis, an increasingly common and advancing bone ailment, presents a notable public health challenge owing to its link to diminished bone density and compromised bone integrity. The consequence of this condition is an increased susceptibility to fractures, underscoring the urgent need for accurate and timely diagnostic interventions.

The multifaceted nature of osteoporosis development involves a complex interplay of factors such as age, gender, hormonal fluctuations, and genetic predispositions. Given its widespread impact, the assessment of bone health demands sophisticated diagnostic tools capable of providing nuanced insights into the severity of osteoporosis.

This research project endeavors to address the critical need for advanced technologies in bone health assessment by leveraging state-of-the-art methodologies. In this endeavor, we strive to harness the power of advanced deep learning techniques, including Transformers and Convolutional Neural Networks (CNNs), to analyze digital knee X-ray images with intricate visual segmentation. The focus on knee X-ray images stems from the recognized relevance of knee joint health as an indicator of overall bone strength and resilience. The main goal of this project is to retrieve essential data concerning the severity of osteoporosis from digital knee X-ray images through the integration of cutting- edge technologies.

Transformers, known for their prowess in handling sequential and spatial data, will be employed for precise segmentation tasks, enabling the isolation of relevant features indicative of bone health. Additionally, deep learning models, such as CNNs, will be utilized for feature extraction, enhancing the model's ability to discern subtle variations in bone density and quality. To further augment the effectiveness of deep learning models and transfer learning techniques., including VGG-19, U-Net, and RESNET, will be integrated. Leveraging pre-trained models and transfer learning techniques is expected to enhance the models' capacity to recognize and interpret variations in osteoporosis severity across diverse datasets

This project holds the promise of advancing the field of bone health assessment by amalgamating cutting-edge technologies in image analysis and deep learning. The proposed methodology seeks To enhance the precision and effectiveness of osteoporosis diagnosis, ultimately contributing to more effective interventions and improved patient outcomes.

II. LITERATURE STUDY

Peng et al. (2023) performed research to explore the possibility of using models rooted in deep learning on CT scans for osteoporosis screening. They collected a dataset of 1219 cases from different CT scanners, incorporating diverse examination technique such as low-dose CT scans for screening lung cancer and routine CT of different body regions. The study utilized a VB-Net structure for automatic segmentation of trabecular bone in CT scan images, followed by DenseNet for establishing classification and regression models for predicting osteoporosis and bone density respectively. The study highlighted the advantages of using deep learning models to precisely forecast bone density measurements and classify bone density into three categories based on opportunistic CT scans. However, it did not address potential biases and limitations associated with utilizing data from diverse medical institutions and CT devices. Results showed promising performance with mean AUC values of 0.999 for training set, 0.970 for test set, and 0.933 for independent test set. Future directions include validating the models on larger and more diverse datasets, integrating them into clinical decision support systems, and conducting prospective studies for real-time prediction during CT scans. [1]

Wani and Arora (2023) introduced a novel approach aimed at diagnosing osteoporosis in knee X-rays through transfer learning with convolutional neural networks (CNNs). Their study presented a meticulously validated dataset comprising 381 knee X-ray images, medically confirmed via T-scores extracted from the Quantitative Ultrasound System. Leveraging deep learning techniques, particularly transfer learning utilizing CNN architectures like AlexNet, VggNet- 16, ResNet, and VggNet-19, the authors devised a cost- effective and widely accessible diagnostic system for early osteoporosis detection using X-ray imaging. However, a notable limitation of their work pertains to the relatively modest dataset size, potentially affecting the generalizability and robustness of their proposed approach. Despite this constraint, the classifiers demonstrated promising performance, with the pretrained AlexNet architecture achieving an accuracy of 91.1% on their dataset. Looking ahead, the authors identified future avenues for research, including further optimization of their proposed modified U- Net architecture, exploration of additional attention mechanisms, and expansion of the methodology to encompass more diverse datasets for improved robustness and applicability. [2]

Kumar, Goswami, and Batra (2023) aimed to devise a cost- effective diagnostic technology for the early detection of osteoporosis by categorizing knee X-ray images into normal, osteopenia, and osteoporosis categories. Their study utilized a dataset comprising X-rays from 240 subjects, with varying bone density conditions: 37 normal, 154 osteopenia, and 49 osteoporotic cases. The model under consideration employed three pre-trained CNN architectures: Inception v3, Xception, and ResNet 18, with pre-processing techniques such as normalization and data augmentation. Normalization was implemented to adjust pixel values to a standardized scale. to a range from 0 to 1. The fuzzy rank-based ensemble model showcased a distinct advantage in accurately diagnosing osteoporosis in knee radiographs through CNNs. However, the approach's limitations were noted, including its reliance on transfer learning and CNNs, which may necessitate substantial annotated data for training and might not fully encapsulate the intricacies of osteoporosis diagnosis across diverse populations and imaging conditions. Nonetheless, the ensemble model demonstrated promising results, achieving a classification accuracy of 93.5%, with impressive AUC values of 98.1 for normal, 97.9 for osteopenia, and 97.3 for osteoporosis. Looking ahead, the authors proposed future directions encompassing the refinement of deep learning models, expansion to other imaging modalities, and clinical validation of the automated osteoporosis screening method. [3]

Nazia Fathima and colleagues (2020) sought to devise and proposed a modified U-Net architecture incorporating an attention unit to achieve precise segmentation of bone areas from X-ray and DEXA images, with a specific focus on osteoporosis diagnosis. Their study utilized two datasets: the DEXSIT database, comprising 126 DEXA scan images from 42 subjects, and the XSITRAY database, containing 78 X-ray images from 78 subjects. The proposed methodology involved a revised U-net architecture incorporating an attention unit and side layers for bone region segmentation in both types of images. Additionally, the study introduced a mathematical model for estimating bone mineral density (BMD) from the delineated bone area and calculating the T-score based on the estimated BMD. The advantage of their approach lies in presenting a novel method utilizing an adapted U-Net structure featuring an attention block and auxiliary layers for segmenting osteoporosis in medical images. However, limitations of the study included the small dataset size for training CNN models and the absence of comparison with other existing knee osteoporosis detection methods. Despite these limitations, the proposed method acquires promising results with an accuracy rate of 88% across both datasets and Dice scores of 0.94 and 0.92 for DEXSIT and XSITRAY, respectively. For future improvements, the authors suggested increasing the quantity of validation and training images to enhance the proposed method's performance. [4]

Fang et al. (2021) aimed to evaluate the utilization of deep learning in individuals diagnosed with primary osteoporosis, specifically focusing on developing a fully automatic method convolutional neural networks (DCNN) for segmenting vertebral bodies and calculating bone mineral density (BMD) in CT images. Their dataset comprised 1449 patients who underwent spinal or abdominal CT scans, collected from three different CT vendors. The proposed methodology involved utilizing a fully convolutional neural network (U- Net) for automated vertebral body segmentation alongside a convolutional neural network (DenseNet-121)for BMD calculation. Noteworthy advantages of their methods included fully automated identification of osteoporosis and BMD, accurate segmentation results exhibiting high correlation with manual segmentation, and strong agreement with BMD values derived from quantitative computed tomography (QCT). However, the study had limitations, including its retrospective nature, which might introduce selection bias, and the utilization of a specific dataset from three different CT vendors, potentially limiting generalizability. Despite these limitations, the results of the study demonstrated that the automated segmentation using deep learning methods exhibited strong correlation with manual segmentation for the four lumbar vertebral bodies (L1-L4), yielding minimum average dice coefficients ranging from 0.782 to 0.823 across different testing sets. [5]

Tang et al. (2021) introduced a novel diagnostic method for osteoporosis screening, utilizing a convolutional neural network (CNN) applied to diagnostic computed tomography (CT) slices. Their objective was to propose a method that leverages CNNs to analyze 2D CT slices and extract features for Qualitative detection of bone mineral density facilitates the segmentation of the region of interest (ROI), allowing for precise delineation for further analysis. The study tested their proposed model, MS-Net, on a dataset comprising 756 images from the test dataset. While the advantage of their approach lies in improving the accuracy of osteoporosis diagnosis through CNN-based methods, a notable limitation is the absence of comparison with existing methods or benchmarks in the field of osteoporosis and osteopenia diagnosis. Nonetheless, their model, BMDC-Net, achieved an efficiency of 76.65% and an AUC of 0.9167, demonstrating promising results. Looking ahead, the authors suggested future work focusing on developing a model to establish a relation between 3D CT images and clinical BMD diagnosis results, thereby expanding the scope of their research. [6]

Ramesh and Santhi (2022) aimed to develop a hierarchical classification approach for diagnosing osteoporosis and osteopenia employing a sequential deep learning algorithm. Their research utilized two publicly accessible datasets, the Femoral and Spine datasets, each containing 5401 entries with 10 features per record, for testing and evaluation. The proposed model employed the Sequential Deep Convolutional Neural Network (SDCNN) algorithm for training and testing, comparing its performance with alternative deep learning classification methods including Long Short-term Memory (LSTM), Convolutional Neural

Networks (CNN), Recurrent Neural Networks (RNN), Multi- layer Perceptron Neural Networks (MLP), and Deep Belief Neural Networks (DBN). While the advantage of their research lies in discussing the use of deep learning algorithms such as GANs, VAEs, and CNNs in unsupervised learning, highlighting their versatility and applicability across various domains, a notable limitation is the absence of discussion regarding the computational resources required for training and deploying the proposed technique, potentially impacting its real-world applicability. Looking ahead, the authors suggested exploring deep learning's interpretability further to enhance understanding of the algorithm's decision-making process and improve trust in its results, thereby opening avenues for future research. [7]

Yasaka et al. (2020) aimed to investigate the use of deep learning, specifically a convolutional neural network (CNN), for estimating bone mineral density (BMD) from unenhanced abdominal CT images. Their dataset comprised unenhanced abdominal CT images of the lumbar vertebrae alongside corresponding BMD measurements obtained from dual-energy X-ray absorptiometry (DXA) scans. The study involved developing and training a CNN to estimate BMD from these CT images. Noteworthy advantages of their approach included the application of deep learning, particularly CNNs, for BMD estimation from unenhanced abdominal CT images. However, a limitation of the study was identified, emphasizing the need for future prospective studies to consolidate results and assess the automated identification of osteoporotic fractures using CNNs on CT images. Despite this limitation, the CNN model demonstrated high performance in diagnosing osteoporosis, evidenced by area under the receiver operating characteristic curve (AUC) values of 0.965 and 0.970 for internal and external validation datasets, respectively. Looking ahead, the authors highlighted the importance of future studies in consolidating results and further exploring the potential of CNNs in automatic detection of osteoporotic fractures using CT images. [8]

Liu et al. (2022) presented a hierarchical model leveraging machine learning to screen for osteoporosis, incorporating demographic characteristics, clinical data, and CT images. Their retrospective dataset comprised 2210 individuals, with 2188 undergoing routine laboratory tests and 268 undergoing CT scans. Methodologically, the study employed statistical analysis, feature selection, and classification techniques, including Mann–Whitney U tests, Chi-square tests, Pearson correlation tests, and Kruskal–Wallis H-tests. Notably, the hierarchical model showcased advantages in osteoporosis detection by integrating clinical data and CT images while eliminating irrelevant and redundant features through rigorous statistical analysis. However, a limitation of the study was noted as the lack of external validation using an independent dataset. Moving forward, the authors suggested future research to focus on validating the proposed model with a separate dataset to evaluate its generalizability and robustness.

Despite this limitation, the hierarchical model demonstrated promising results, particularly with area under the ROC curve values of 0.818, 0.838, and 0.962 for its three layers, indicating superior performance in distinguishing individuals with osteoporosis from those with normal BMD. [9]

Sukegawa et al. (2022) intended to investigate the utilization of deep learning and neural networks for predicting osteoporosis and classifying dental implant systems using panoramic radiographs. Their dataset consisted of 902 panoramic radiographs, with osteoporosis diagnosis performed using DXA, alongside clinical and radiographic data such as BMD and T-score. The study employed deep learning models including ResNet and EfficientNet for osteoporosis classification from dental panoramic radiographs. Notably, the benefit of their approach lies in accurately classifying osteoporosis using CNNs from dental panoramic radiographs, with an ensemble model incorporating patient covariates to improve classification accuracy. However, several limitations were identified, including the need for increased data via collaborative research across multiple centers to improve the accuracy and generalizability of CNN-based classification diagnoses. The study achieved an osteoporosis discrimination accuracy of 83.2% and 90.0% for ResNet and EfficientNet, respectively, with precision values of 74.3% and 71.6% for ResNet and EfficientNet, and recall values of 88.4% and 71.6%, respectively. Looking ahead, the authors emphasized the necessity for further research to identify various convolutional neural networks appropriate for aggregating image quality and patient covariates thereby highlighting potential avenues for future investigation. [10]

III. METHODOLOGY

1. As show Fig. 1, we begin by using the Labelled Knee x-ray Dataset is our input. In this dataset which is having the chest x-ray images.

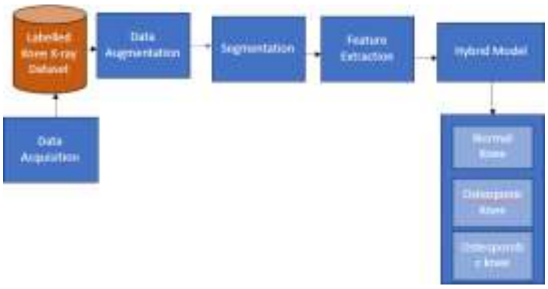

Fig 1: Flow Diagram of the work process

2. Because of the restricted quantity of images within the annotated knee X-ray dataset, data augmentation is being implemented to enlarge the dataset and enhance model effectiveness.
3. Next, we train the dataset using a deep learning model, and we apply the trained model to the segmentation process, resulting in the generation of mask images.
4. These mask images will be given as input to the models and then the output will be classified as three labels. They are Osteoponic, Osteoporosis and a healthy bone

3.1 Convolutional Neural network

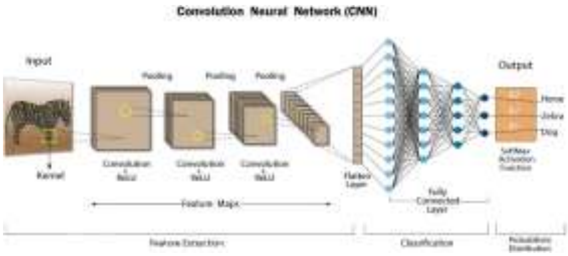

Fig 2: Flow Diagram of CNN

Convolutional Neural Networks (CNNs) revolutionize deep learning for visual tasks. The architecture comprises convolutional layers for feature extraction, using learnable filters (kernels) to detect patterns in input data. Mathematically, the convolution operation involves sliding filters across the input, computing 2-D outputs through the dot product of kernel weights and input patches. This process creates an output volume, essential for diverse feature recognition. Pooling layers, like max pooling, down sample feature maps, enhancing robustness and reducing complexity. Fully connected layers consolidate features for classification or regression, connecting neurons densely. During training, backpropagation optimizes weights to minimize prediction errors. The architecture concludes with activation functions, such as softmax for classification. CNNs excel in tasks like image recognition, owing to their ability to hierarchically learn and extract relevant features from visual data.

3.2 VGG-19

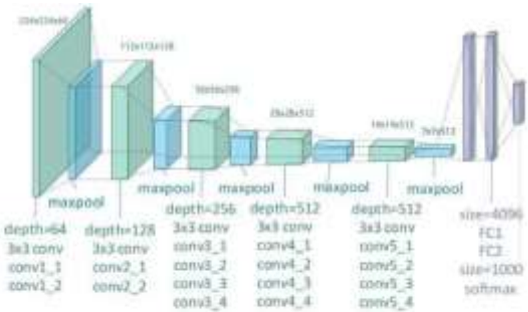

Fig 3: Flow Diagram VGG-19

a convolutional neural network architecture renowned for its depth and effectiveness in image recognition tasks. Methodologically, we scrutinize the architectural nuances of VGG-19, dissecting its sequential arrangement of the convolutional and pooling layers. Through a comprehensive examination of parameter distribution and computational efficiency, we uncover insights into the network's inner workings. Additionally, we explore the implications of VGG-19's depth on its expressive power and feature representation capabilities. Leveraging transfer learning techniques, we investigate the adaptability of pre-trained VGG-19 models for downstream tasks with limited data. Our empirical evaluations on benchmark datasets, including ImageNet, showcase the classification prowess, robustness, and generalization capacity of VGG-19. By unraveling the intricacies of VGG-19, this study contributes to a deeper understanding of convolutional neural networks and provides valuable insights for further advancements in deep learning research and application development.

4. COMPARITIVE ANALYSIS

The comparative analysis reveals a variety of approaches for osteoporosis diagnosis utilizing deep learning methodologies applied to medical imaging data. Peng et al. (2023) demonstrate the feasibility of using deep learning models based on CT scans, employing a VB-Net structure for trabecular bone segmentation and DenseNet for classification and regression models. While their approach yields promising results in accurately predicting bone density values, it overlooks potential biases associated with diverse medical institutions and CT devices. Conversely, Wani and Arora (2023) focus on knee X-ray diagnosis using transfer learning with CNNs, showcasing a cost-effective diagnostic system leveraging pretrained architectures like AlexNet and VGGNet-19. Despite the modest dataset size, their classifiers exhibit strong performance, underscoring the potential of deep learning in early osteoporosis detection through X-ray imaging. However, the limited dataset may impact the generalizability and robustness of their proposed approach, warranting further exploration with larger and more diverse datasets. Moreover, Kumar, Goswami, and Batra (2023) propose a diagnostic technology for knee X-ray classification into normal, osteopenia, and osteoporosis categories, employing pretrained CNN architectures like Inception v3 and Xception.

Model	Accuracy	Precision	AUC(Area Under Curve)	Recall
AlexNet+ Vgg-19	**93.64**	88	0.91	82
MultiLevel Classifier	89	86	0.64	80
BMDC-Net	76.65	80	0.89	78
ResNet50	93.18	78	**0.96**	81

Fig 4: Tabular analysis of accuracy and metrics

Their ensemble model showcases impressive classification accuracy and AUC values, yet reliance on transfer learning and CNNs poses challenges in fully encapsulating the complexities of osteoporosis diagnosis across different populations and imaging conditions. Their ensemble model showcases impressive classification accuracy and AUC values, yet reliance on transfer learning and CNNs poses challenges in fully encapsulating the complexities of osteoporosis diagnosis across different populations and imaging conditions. Despite these limitations, the study underscores the potential of deep learning in automating osteoporosis screening and calls for refinement and validation of models across various imaging modalities and clinical settings.

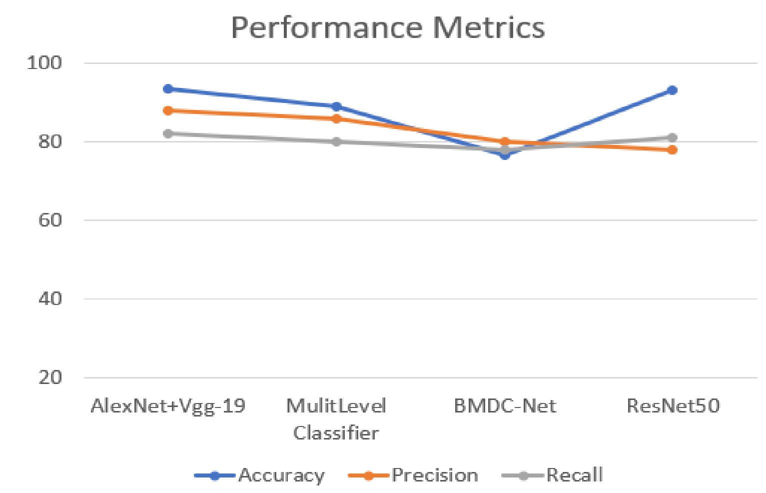

Fig 5: Graphical representation of metrics

These studies collectively highlight the advancements and challenges in deep learning-based osteoporosis diagnosis, underscoring the importance of standardized methodologies, large-scale validation studies, and clinical integration for realizing the full potential of automated diagnostic systems in osteoporosis management and care.

5. CONCLUSION

These studies collectively highlight the advancements and challenges in deep learning-based osteoporosis diagnosis. While deep learning techniques show promise in automating osteoporosis screening and classification, there is a need for standardized methodologies, large-scale validation studies, and clinical integration to ensure their efficacy and reliability across diverse patient populations and imaging modalities. Continued research efforts in this area hold the potential to revolutionize osteoporosis management and improve patient outcomes.

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