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Importance of Knee Osteoporosis Diagnosis for Faster Intervention Utilizing Machine Learning

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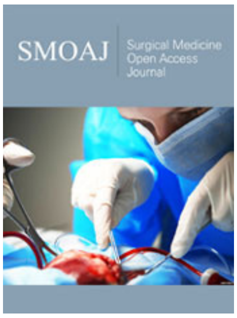

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Abstract

Osteoporosis is a disorder in which the bones deteriorate and become brittle. It is commonly referred to as a "silent disease" since symptoms do not appear until a fracture occurs. Normally, bones create new bone and remove old bone, but osteoporosis upsets this equilibrium, resulting in greater bone loss than bone creation. Osteoporosis symptoms are subtle, yet it frequently leads to fractures, causing pain, disability, and loss of independence. The existing procedures for diagnosing osteoporosis are time-consuming. Early identification is critical for successful care and lowering the risk of fracture. Over the last few decades, deep learning has been more prominent in the field of picture analysis. The findings from the previous research indicate that employing machine- learning models may assist clinicians in early detection of Osteoporosis, thereby mitigating the risk of fractures.

Keywords: Knee osteoporosis; Machine learning; Medical imaging; Image preprocessing

Introduction

Knee pain is a common ailment among individuals of all ages. It is also an irreversible condition that creates problems and has a bearing on our lives and future. The most prevalent joint ailment is knee osteoarthritis, and the second is knee osteoporosis, which can proceed without symptoms until a bone is fractured. The latter starts with osteopenia, which is a decrease of bone mass or mineral density, and progresses to osteoporosis. Osteoporosis is diagnosed when both bone mineral density and bone mass decline, causing structural defects in bone tissue. The normal bone involves the formation of new bone and the elimination of existing bone. Osteoporosis produces asymmetry in this process, resulting in faster bone loss than bone creation. Its symptoms are rarely visible, yet it causes fractures in many people, resulting in pain, disability, and loss of independence. As a result, detecting both at an early stage is critical for improving treatment outcomes. These two illnesses are the current knee problems diagnostic systems, which require time and competent physicians to diagnose knee diseases and interpret X-ray pictures in order to avert further bone mass loss and provide appropriate medical care. Figure 1 depicts an X-ray picture from three different cases: normal, osteopenia, and osteoporosis knee.

(a) Normal **(b) Osteopenia** **(c) Osteoporosis**

Figure 1: X-ray images for normal, osteopenia and osteoporosis knee.

Osteoporosis can affect several aspects of the human body, including the teeth, hip, spine, hand, and knee. As a result, automated methods can detect specific changes in bone density and structure that may indicate osteoporosis. Several studies have been recommended for osteoporosis in Tooth [1], Hip [2], and Spine [3], but few have been addressed to the knee. Osteoporosis occurs despite the fact that the knee is the most stressed joint since it carries the body's weight and is responsible for mobility. With an aging population, the occurrence of osteoporotic fractures around the knee grows, particularly among women. In the identification of osteoporosis, X-ray scans have been used extensively. It is the most used imaging tool among the medical community to discover bone diseases because it takes images of whole body. X-ray images greatly help in fracture diagnosis, dislocation of joints, and detecting changes in the bone density and architecture. Although it is the main tool for the doctors to diagnose Osteoporosis, it does not always easily detect Osteoporosis unless the doctor is professional. There are some researches that dedicated their work to Osteoporosis detection [4-14].

Related Work using Machine Learning

Previous research into the landscape of AI applications in medical imaging has mostly focused on picture identification, feature extraction, and diagnostic help. In this part, we will provide a quick overview of the most current work in these two disciplines. Machine learning is useful in understanding the diagnosis and treatment of osteoporosis because its algorithms can examine big datasets to uncover trends in how people respond to different therapies. It can also track health changes over time and extract important information from electronic health records using Natural Language Processing (NLP) techniques, allowing for a more unified examination of patient histories. Convolutional Neural Network (CNN) models have grown in popularity [15,16] due to their revolutionary success in diagnosing a variety of diseases from images, as well as many other useful applications such as brain tumor detection and segmentation [17], COVID detection [18], cancer detection [19], human activity identification [20], age and face detection [21], and many more.

Wani A et al. [10] used transfer learning based on convolution neural networks to diagnose osteoporosis in knee X-rays, utilizing a multiclass dataset from Mendeley data [22]. The four models utilized were AlexNet, VGG-16, ResNet, and VGG-19, with accuracies of 91%, 86.30, 86.30%, and 84.20%, respectively. Kumar et al. [11] used a fuzzy rank-based ensemble model to accurately diagnose knee osteoporosis, which was created with three models: Inception v3, Xception, and ResNet 18. Knee X-ray images were analyzed using a multiclass dataset from Mendeley data [22]. The models' accuracies were: Inception v3 (89.8%), Exception (90.9%), and ResNet 18 (91.4%). Abubakar et al. [14] applied transfer learning models for osteoporosis classification on knee radiographs of RGB and grayscale pictures utilizing a binary knee X-ray image dataset from Kaggle [23,24]. Two models were used: GoogleNet with 90.0% accuracy and VGG-16 with 87% accuracy.

Yang et al. [25] used deep learning to identify and categorize knee disorders (osteoporosis and osteoarthritis) based on X-ray pictures. Knee X-ray images were analyzed using a binary-classes dataset from Kaggle et al. [24,26,27]. They tested three models: Custom CNN (77% accuracy), Late-Fusion (71% accuracy), and VGG-16 (82% accuracy). Dodamani D et al. [9] used a binary dataset from Zydus Hospital [28,29] for spine, hand, leg, knee, and X-ray pictures to classify osteoporosis using transfer learning. Five models were trained: VGG-16, VGG-19, DenseNet-121, ResNet-50, and Inception V3, with reported accuracies of 78%, 86%, 93%, 89%, and 90%, respectively. An overview of prior X-ray-based knee osteoporosis diagnoses using deep learning models is provided below, along with their accuracy in Table 1. As a result of these investigations, which evaluated the use of deep learning models for osteoporosis detection using knee X-ray pictures, we discovered that the performance (measured as model accuracy) is low. More improved models are needed to improve the diagnostic accuracy of knee osteoporosis [30-42].

Table 1: Previous work for knee osteoporosis.

Author	Bone Type	Image Type	Classes	Dataset	Classifier	Reported Model Accuracy
Wani & Arora [10]	Knee	X-ray	Multiclass	Dataset from Mendeley Data [22]	AlexNet	91%
					VGG-16	86.30%
					ResNet	86.30%
					VGG-19	84.20%
Kumar et al. [11]	Knee	X-ray	Multiclass	Dataset from Mendeley Data [22]	Inception v3	89.80%
					Xception	90.90%
					ResNet 18	91.40%
Abubakar et al. [14]	Knee	X-ray	Binary	Dataset from Kaggle [24]	GoogleNet	90%
					VGG-16	87%
Yang [25]	Knee	X-ray	Binary	Dataset from Kaggle [24]	Custom CNN	77%
					Late-Fusion	71%
					VGG-16	82%

Dodamani & Danti [9]	Spine, Hand, Leg, Knee	X-ray	Binary	Zydus Hospital Dataset, Dahod, Gujarat.	VGG-16	78%
					VGG-19	86%
					DenseNet-121	93%
					ResNet-50	89%
					Inception V3	90%

Classification Metrics

The subsequent deep learning classification metrics were employed to gain a deeper insight into the models' performance across the two different image formats.

$$AUC = \frac{TP}{FP} \times 100\%$$

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \times 100$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100 \quad Specificity = \frac{TN}{TN + FP} \times 100$$

$$\Pr ecision = \frac{TP}{TP + FP} \times 100 \quad Recall = \frac{TP}{TP + FN} \times 100$$

$$F1 - Score = \frac{2 \times \Pr ecision \times Sensitivity}{\Pr ecision + Sensitivity}$$

$$Error\,rate = \frac{FN + FP}{TN + TP + FN + FP} \times 100\%$$

Where:

i. True Positives (TP): The number of instances that were correctly predicted as positive by the model when they are actually positive.

ii. True Negatives (TN): The number of instances that were correctly predicted as negative by the model when they are actually negative.

iii. False Positives (FP): The number of instances that were incorrectly predicted as positive by the model when they are actually negative.

iv. False Negatives (FN): The number of instances that were incorrectly predicted as negative by the model when they are actually positive.

References

1. Balaha HM, Balaha MH, Ali HA (2021) Hybrid COVID-19 segmentation and recognition framework (HMB-HCF) using deep learning and genetic algorithms. Artif Intell Med 119: 102156.
2. ElShennawy NSE, Sarhan A (2022) Utilizing deep learning models in CSI-based human activity recognition. Neural Computing and Applications 34: 5993-6010.
3. Sathyavathi S, Baskaran KR (2023) An intelligent human age prediction from face image framework based on deep learning algorithms. Information Technology and Control 52(1): 245-257.
4. Lee K, Jung SK, Ryu JJ, Shin SW, Choi J, et al. (2020) Evaluation of transfer learning with deep convolutional neural networks for screening osteoporosis in dental panoramic radiographs. J Clin Med 9(2): 392.
5. Feng S, Lin S, Chiang Y, Lu M, Chao Y, et al. (2023) Deep learning-based hip X-ray image analysis for predicting osteoporosis. Applied Sciences 14(1): 133.
6. Zhang B, Yu K, Ning Z, Wang K, Dong Y, et al. (2020) Deep learning of lumbar spine X-ray for osteopenia and osteoporosis screening: A multicenter retrospective cohort study. Bone 140: 115561.
7. Chen Z, Zheng H, Duan J, Wang X (2023) GLCM-based FBLS: A novel broad learning system for knee osteopenia and osteoporosis screening in athletes. Applied Sciences 13(20): 11150.
8. Sebro R, Garza-Ramos CD (2022) Machine learning for opportunistic screening for Osteoporosis from CT scans of the wrist and forearm. Diagnostics 12(3): 691.
9. Dodamani PS, Danti A (2023) Transfer learning-based osteoporosis classification using simple radiographs. International Journal of Online & Biomedical Engineering 19(8): 66-87.
10. Wani MI, Arora S (2023) Osteoporosis diagnosis in knee X-rays by transfer learning based on convolution neural network. Multimedia Tools and Applications 82(9): 14193-14217.
11. Kumar S, Goswami P, Batra S (2023) Fuzzy rank based ensemble model for accurate diagnosis of osteoporosis in knee radiographs. International Journal of Advanced Computer Science and Applications (IJACSA) 14(4): 262-270.
12. Ashames MM, Ceylan M, Jennane R (2021) Deep transfer learning and majority voting approaches for osteoporosis classification. International Journal of Intelligent Systems and Applications in Engineering 9(4): 256-265.
13. Dzierżak R, Omiotek Z (2022) Application of deep convolutional neural networks in the diagnosis of osteoporosis. Sensors 22(21): 8189.
14. Abubakar UB, Boukar MM, Adeshina S, Dane S (2022) Transfer learning model training time comparison for osteoporosis classification on knee radiograph of RGB and grayscale images. WSEAS Transactions on Electronics 13: 45-51.
15. Cooper C, Campion G, Melton LJ (1992) Hip fractures in the elderly: A world-wide projection. Osteoporos Int 2(6): 285-289.
16. The Global Health Observatory. World health statistics report.
17. Bone Health Survey (2023) World Osteoporosis Day.
18. Li Q, Cai W, Wang X, Zhou Y, Feng DD, et al. (2014) Medical image classification with convolutional neural network. Proceedings of the IEEE 13th International Conference on Control Automation Robotics & Vision (ICARCV) pp. 844-848.
19. Yadav SS, Jadhav SM (2019) Deep convolutional neural network based medical image classification for disease diagnosis. Journal of Big Data 6(1): 1-18.
20. Mahmud I, Mamun M, Abdelgawad A (2023) A deep analysis of brain tumor detection from MR images using deep learning networks. Algorithms 16(4): 176.
21. Arafa DA, Moustafa HED, Ali HA, Ali-Eldin AMT, Saraya S, et al. (2022) A deep learning framework for early diagnosis of Alzheimer's disease on MRI images. Multimedia Tools and Applications 83: 1-33.

22. Majeed WI, Sakshi Arora (2021) Knee X-ray Osteoporosis database. Mendeley Data.
23. Kaggle Datasets.
24. Osteoporosis Kaggle.
25. Yang TS (2022) Recognition and classification of knee osteoporosis and osteoarthritis severity using deep learning techniques. Doctoral dissertation, Dublin, National College of Ireland, Ireland.
26. Osteoporosis Knee Dataset (Preprocessed-128x256).
27. Osteoporosis Knee X-ray Dataset, Kaggle.
28. Vishnu T, Saranya K, Arunkumar R, Devi MG (2015) Efficient and early detection of osteoporosis using trabecular region. Proceedings of the IEEE Online International Conference on Green Engineering and Technologies (IC-GET) pp.1-5.
29. Bengio Y (2012) Deep learning of representations for unsupervised and transfer learning. Proceedings of ICML Workshop on Unsupervised and Transfer Learning pp. 17-37.
30. Hosny KM, Kassem MA, Foaud MM (2019) Classification of skin lesions using transfer learning and augmentation with Alex-net. Plos One 14(5): e0217293.
31. Krizhevsky A, Sutskever I, Hinton GE (2012) Imagenet classification with deep convolutional neural networks. Communion of the ACM 25: 1097-1105.
32. Lu S, Wang SH, Zhang YD (2021) Detection of abnormal brain in MRI via improved AlexNet and ELM optimized by chaotic bat algorithm. Neural Computing and Applications 33: 10799-10811.
33. Salih SQH, Abdulla HKH, Ahmed ZSH, Surameery NMS, Rashid RDH, et al. (2020) Modified alexnet convolution neural network for COVID-19 detection using chest X-ray images 5(3): 119-130.
34. Guo M, Du Y (2019) Classification of thyroid ultrasound standard plane images using resnet-18 networks. Proceedings of the IEEE 13th International Conference on Anti- counterfeiting, Security and Identification (ASID) pp. 324-328.
35. He K, Zhang X, Ren S, Sun J (2016) Deep residual learning for image recognition. Proceedings of the IEEE conference on computer vision and pattern recognition pp. 770-778.
36. Liu D, Liu Y, Dong L (2019) G-ResNet: Improved ResNet for brain tumor classification. Proceedings of the International Conference on Neural Information Processing pp. 535-545.
37. Yu X, Wang SH (2019) Abnormality diagnosis in mammograms by transfer learning based on ResNet18. Fundamenta Informaticae 168(2): 219-230.
38. Ghahnavieh AE, Luo S, Chiong R (2019) Transfer learning for Alzheimer's disease detection on MRI images. Proceedings of the IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT) pp. 133-138.
39. Howard J, Gugger S (2020) Fastai: A layered API for deep learning. Information 11(2): 108.
40. Khan Z, Khan FG, Khan A, Rehman Z, Shah S, et al. (2021) Diabetic retinopathy detection using VGG-NIN a deep learning architecture. IEEE Access 9: 61408-61416.
41. Militante SV (2019) Malaria disease recognition through adaptive deep learning models of convolutional neural network. Proceedings of the IEEE 6th International Conference on Engineering Technologies and Applied Sciences (ICETAS) pp. 1-6.
42. Simonyan K, Zisserman A (2015) Very deep convolutional networks for large-scale image recognition. ArXiv preprint pp. 1-14.