International Journal of Emerging Research in Engineering and Technology
Pearl Blue Research Group| 9th ICAILLMBA (ALLAM) 2025-Conference Proceedings
ISSN: 3050-922X | https://doi.org/10.63282/3050-922X.ICAILLMBA-111

Original Article

Improving Osteoporosis Detection Using Deep Learning: A Survey of Techniques, Shortcomings and Implementation Aspects

Anusha Darapureddy[1], Dr. Kunjam Nageswara Rao[2]
[1]Research Scholar, Department of Computer Science & Systems Engineering, Andhra University College of Engineering (A), Visakhapatnam, A.P., India.
[2]Professor, Department of Computer Science & Systems Engineering, Andhra University College of Engineering (A), Visakhapatnam, A.P., India.

Abstract - *Osteoporosis is a severe illness that may be gradually peaked by the reduction of the bone density and increased vulnerability to fracture. Osteoporosis should be identified early to facilitate the disease treatment. In order to discuss and assess deep learning-based methods of screening osteoporosis, point out their mechanisms, constraints and practicability in the context of actual clinical practice. In the recent times, deep learning is a new method that efficiently and accurately offers diagnostic procedures through medical imaging and analysis. This paper will review the general uses of the deep learning technique in identifying osteoporosis and how it can be effectively used in terms of efficiency, limitations, and implementation. The categories of models used in the identification of bone mineral density (BMD) and/or fracture risk include convolutional neural networks (CNN), transfers earning-based, and hybrid-method-based models. Predictive accuracy and robustness of these models are high, although issues with respect to data availability, model generalizability and connecting them to clinical use remain challengeable. The future of such technologies as deep learning in the detection of osteoporosis can contribute to the creation of a clear connection between the technological improvement and the clinical management of osteoporosis, and may translate into positive prognosis with the early diagnosis.*

Keywords - *CNN, Bones Density, Fracture Risk, Osteoporosis Screening, Medical Imaging, Transfer Learning.*

1. Introduction

Osteoporosis is a chronic skeletal disease that is typified by limited bone mineral density (BMD), bone morphology alteration of the bone microarchitecture leading to the increase in the risk of fracture. Osteoporosis is an illness primarily of individuals primarily women who no longer have their menopause puberty age but even individuals of earlier age due to hereditary disorders, a lack of nutrients or lifestyle factors as well. Osteoporosis has been considered to be a silent disease, in the sense that a person does not get an illness until he or she falls into an injury or triggers the other instances that cause injuries to their potential. The prevention of fracture and further treatment of fracture is best achieved by the early and correct diagnosis of osteoporosis [1]. This is because the conventional methods of screenings osteoporosis have draw backs on its availability, cost and sensitivity and consequently new diagnostic instruments should be available. Deep learning represents an artificial intelligence (AI) and has been an efficient instrument of analysis with regards to medical images, and also the medical disease occurrence. Deep learning could be implemented to state various patterns in medical images that human beings will not consider doing with the sophisticated machine learning methods and convolutional neural networks (CNN). Deep learning to assist in the diagnosis of osteoporosis may improve the precision of the diagnosis, the diagnostic time, as well as intervening time [2]. Even though there is continuous interest in the application of the deep learning to diagnostic purposes, there are barriers to the generalization of the model, analysis of the findings, and applicability of the application in the clinic that need to be overcome.

Osteoporosis is a common reality that poses considerable number of fractures hence incubating considerable pressure to the global hospital care systems in the sense of more hospitalizations, morbidity and disability in the long-term, in specific terms in the hip fractures. The risks require the early diagnosis and efficient screenings. DXA and QCT are the latest diagnostic equipment. DXA popularity is made possible by the fact that it is low-cost, non-invasive, yet will not measure bone microstructure fully. QCT also is a more detailed image but also expensive and exposes more radiations to the patients. The fact that these tests are very few particularly to the poor endowed regions or rather the rural areas adds to the problem. Owing to the latest developments in the sphere of artificial intelligence, the methods of deep-learning, and specifically the models of CNN, the future of their application in the mode of radiographic imaging to diagnose bone erosion and forecast fracture-threatening more accurately is positive.

The illustration demonstrates a complete pipeline of the bone fracture detection based on deep-learning in the inference of medical images. The first step is the input data which is a database of raw X-ray images. These images are first subjected to an image pre-processing stage that involves compressing the size of the images to a fixed size of 224x224 pixels. This kind of standardization converts photos of similar sizes before transmission to the model. These pixel values are then scaled between 0 and 1 and they come in to stabilize training and will improve the ability of the neural network to learn similar patterns across multiple samples.

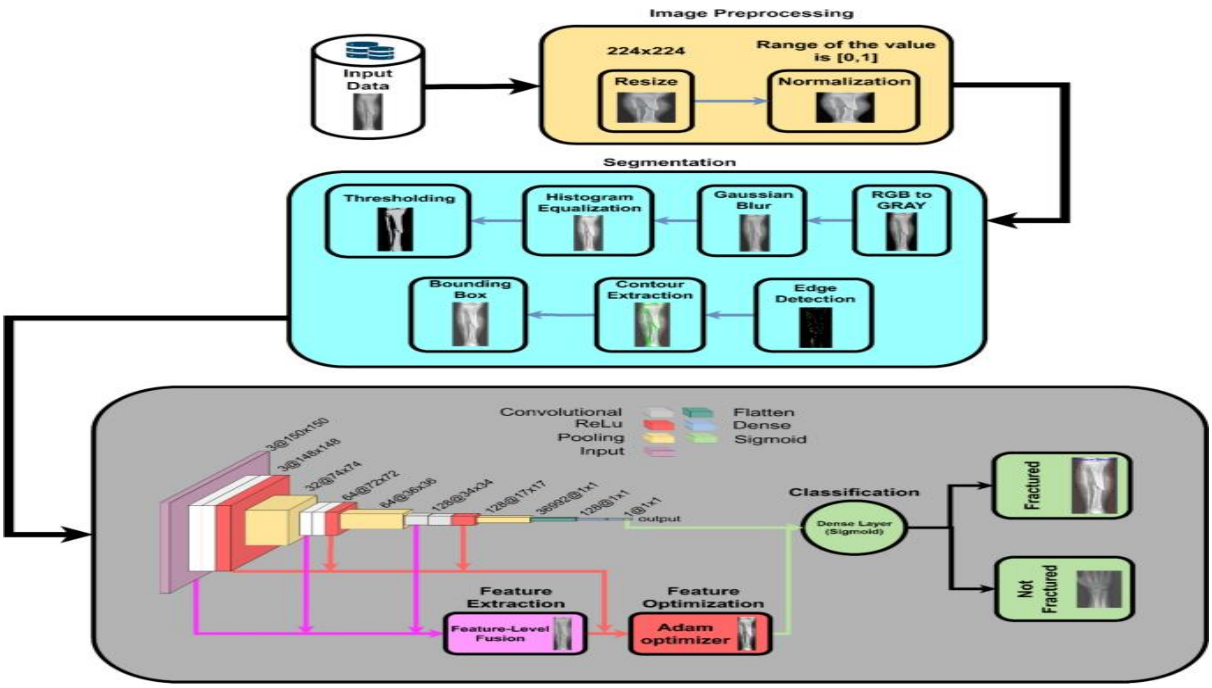

Fig 1: Deep Learning Architecture to detect bone Osteoporosis Fractures

The images are subsequently pre-processed and then go through the segmentation stage where they are subjected to a series of classical image processing operations. These images are first converted to gray scale because they are simplified to examine. The procedure is followed by the Gaussian blurring to remove noise, followed by the amplification of the bone structures through the histogram equalization. The thresholding is performed to distinguish the background and the bone region. It is succeeded by the edge detection to trace the edges of the bone and subsequent contour extraction to mark the visible edges. A binding box is then placed on the detected bone part and isolates the region. This region is at some point introduced into the model with the aim of reducing the redundant background knowledge and maximizing the accuracy of the classification.

The second component of the diagram is the deep learning model, which consists of several layers of convolutional and pooling and activation functions. The layers scan past the bone images to uncover meaningful motifs such as the texture of the images, shapes, and structural form. They are stripped out to feature extraction component where a fusion mechanism exposes a mixture of degree information among different levels in order to provide a bright combined representation of the image. Then feature optimization with Adam optimizer is applied to optimize the fused characteristics by updating the model parameters during training to reduce the classification error. Finally, the refined features are used in a dense layer, a sigmoid activation, which does the binary classification. The model provides either a fractured or a non-fractured bone in the picture. The latter decision is presented as the completion of the entire pipeline, i.e. the completion of the automated process of fracture-detection.

2. Literature Review

According to He, Y., et al., with radiologic images (especially X-ray, CT and MRI) a system is suggested that uses a deep learning technique to perform some screening and diagnosis of osteoporosis. Based on the findings received upon evaluating 40 studies, the researcher proposed categorizing the existing work into osteoporosis screening, bone mineral density prediction, and fracture risk detection. This trend shows that AI is associated with a growing potential in opportunistic osteoporosis. The study also pointed out though that even good results of the models, there is a great challenge of such diagnostic model clinical commercialization [3].

Ong et al. conducted an analysis of how artificial intelligence can be used to improve the precision of the existing CT imaging in osteoporosis treatment. They found that machine learning models could produce tiny features of bone which would otherwise be difficult to detect by the traditional methods of assessment. The findings reveal that AI has the potential to enhance the accuracy of patient diagnoses and support clinicians in decision-making. [4].

Smets et al. reported on the application of machine learning to detect osteoporosis assessment improvements, citing as useful algorithm types in osteoporosis fracture-risk, fracture prediction, and fracture diagnosis. The authors, through their analysis, highlighted the interdisciplinary nature of multimodal clinical, imaging, and demographic data and why such models might be applied to maximize diagnostic outcomes. The promise of the data-based approaches to promoting more specific osteoporosis treatment is noted in the review. [5].

Kawade et al. compare applying deep learning models and traditional techniques to identify osteoporosis as a disease in hip X-ray images. They proved that neural networks are currently superior to the conventional approaches because they are more capable of capturing finer structural detail in bone tissue. The article identifies the advantages of reading with DL-based techniques to filter osteoporosis more precisely and autonomously. [6].

Inigo et al. provide a comprehensive review of medical imaging modalities and artificial intelligence pipeline to predict osteoporosis, describing the advances in DXA, QCT, and artificial intelligence-based approaches. Their article is concerned with the capacity of AI-assisted image interpretation to augment professional accuracy and automated clinical processes. Among the prevailing issues noted in the review are constraints of the available data sets and the necessity to embrace standard evaluation organization procedures, among others. [7].

Liu and coworkers developed the idea to treat osteoporosis via radiographic imaging with the help of artificial intelligence models. The study found that deep learning architectures perform better on the diagnostic level compared to conventional feature-based designs. By doing this, the researchers found out that there were limitations in data quality and validation practices. The researcher based on the findings made recommendations to standardize the data further and to externally test the clinical readiness. [8].

Qiu et al. proposed a framework where these models of both deep learning and conventional machine learning are compared and contrasted to predict osteoporosis. This study uncovered that in metric complexity clinical patterns, deep learning structures perform better compared to classical classifiers. Following this comparative approach, the authors have succeeded in identifying crucial predictors that are engaged in model performance. Based on the research conclusions, the researcher recommended combining advanced AI pipelines with a clinical workflow to prioritize on high-risk detection at an early stage. [9].

Alden et al. have conducted a critical review of the osteoporosis prediction models, and tested their efficacy across different datasets and under varied analytic conditions. Based on the analysis, it was identified that machine learning and deep learning approaches differed significantly in their accuracy, sensitivity, and model reliability. A second argument that these authors advanced is that, to improve clinical applicability, there must be a benchmarking periodically. Their paper emphasizes the the significance of comprehensive validation schemes on the risk of osteoporosis prediction in future research. [10].

The current solutions are associated with several vulnerabilities including the small and non-diversity data sets that constrain the model power in broadening the population. Clinicians also depend on these systems because the decision-making process becomes not interpretable. The level of diagnosis often overlooked by combining medical imaging with other important information pertinent to the patient can be enhanced. The absence of unified laws, evaluation standards, and ethical considerations is also an impediment to its use across the clinical environment.

3. Methodology

The proposed model employs a deep-learning methodology to perform the classification of knee X-ray images into three (normal, osteopenia, and osteoporotic) categories [10]. The methodology consists of a number of stages: data collection, preprocessing, training on the pre-trained Convolutional Neural Networks (CNNs), and prediction [11]. Overall, the pipeline of classifications will contribute to a high degree of efficiency and precision within a deep learning approach through the application of transfer learning functionality. Its processing begins with gathering a labeled set of X-ray images of each class as the quality and size of annotated samples is critical to forming a reliable model. After collection of data, the data is divided into training and test data sets to establish the capability of the model to operate on new data. The training set is further augmented with the distribution techniques such as rotation, flipping, zooming and shifting. These mutations are similar to real variations in images in the world, and they help to minimize over fit and enhance the ability of the model to generalize. The approach ultimately implements the pre-trained CNNs and transfer learning to render the classifications more respective and energy efficient.

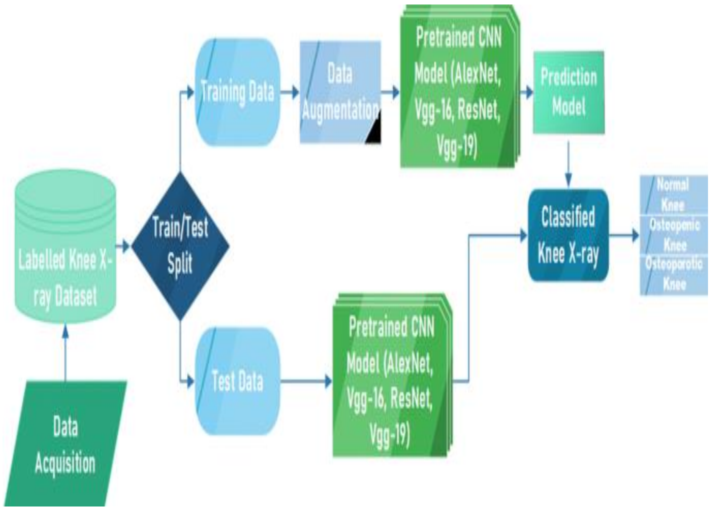

Fig 2: Classification of knee X-ray images workflow

These steps encompass data collection by building a highlighted dataset of knee X-ray images as the first step. These images consist of the various classes such as normal knees, osteopenia knees, and osteoporotic knees that are required to train a powerful classification model. Once the dataset is ready, it is further divided into training and testing portions, with one portion of the information being incorporated to simulate the information and the other used to predict the model performance. This will enable the model to test its ability to predict on data it has never seen so that it can be able to estimate its predictive ability.

The training subset of data is subsequently data augmented a technique employed to synthetically inflate the quantity of data through transformations generated by rotations, flips, or contrast manipulations. The improved data augment the generalization ability of the model, since more diverse patterns of images become available to the model. These altered images are then fed into the pre trained networks of the convolutional neural network (CNN) containing AlexNet, VGG-16, ResNet and VGG-19. These pre trained models are already trained to extract meaningful contents in images that can be optimized to the problem of knee X-ray classification. The output of this process is the prediction model, which can be used to classify new images.

Initially processed test data subset is then subjected to identical pre trained CNN models to verify performance of the model. Using this information, the system generates the final classified results, which categorize the knee X-ray images as being normal or osteopenia or osteoporotic. This systematic flow ensures that the procedures related to the training and verification of the model are taken effectively; leveraging the strength of the most effective deep learning networks to diagnose the health of the bones based on X-ray images with perfect accuracy.

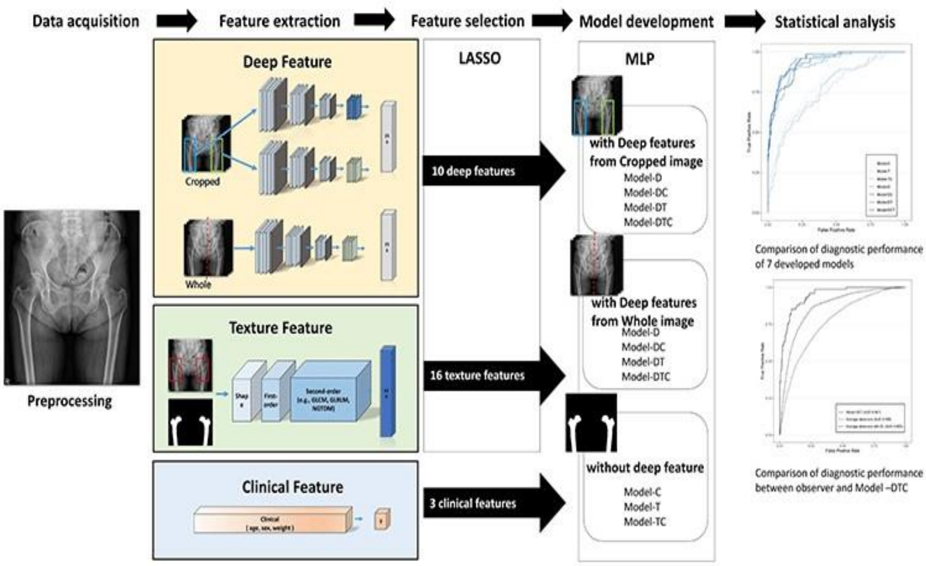

Fig 3: Feature Extraction and Diagnostic Model Development End-to-End Pipeline

Fig 3 presents a detailed medical imaging and multimodal combination of features-based osteoporosis diagnosis flow chart [12]. The Pelvic X-ray images are obtained and processed, and the pre-processing phase initiates the workflow, after which it moves to the real analysis of the data. These features, based on these images, generate three types of features, and these are namely, deep features, texture features and clinical features. Convolutional neural networks (CNNs) are utilized to extract deep representations on both the cropped regions and the full picture that reflects high-order exotic characteristics of bone forms. The texture features, in turn, deal with local image patterns, and are approximated using second-order statistical methods, such as GLCM, GLRLM, and NGTDM, to characterize bone microarchitecture [13]. Clinical features include personal information of patients including age; sex and weight which are risk factors of osteoporosis.

Following extraction, feature selection is performed using the LASSO algorithm to reduce the dimension and select most informative features and identifies 10 deep features, 16 features of texture, and 3 clinical features[14]. The selected features are then fed into model construction with multilayer perceptron (MLP) classifiers being trained: deep features, deep-texture features, and clinical features, and texture features and no deep features. Finally, statistical analysis will be conducted to determine diagnostic accuracy and efficacy of the developed models, as well as how they analyze the data in comparison to their analysis using an observer as the measure. This is organized pipeline, pointing at assessment of the advanced imaging examination, machine learning, and clinical data, as to improving osteoporosis diagnosis ratio.

4. Results

Deep learning has become a powerful tool to complement osteoporosis diagnosis and offer automated-diagnosis and increased early-diagnosis capabilities. It has always been true in convolutional neural network-based research that the accuracy of the classification is always higher in comparison to the traditional diagnostic method. The process of separating bone structure of osteoporotic and normal bones uses DXA and QCT images trained models. In various studies, CNNs have shown an accuracy of more than 90 in comparison to more conventional machine-learning algorithms, which uses hand-designed features. These findings illustrate the evolution along with the growing potential of AI in clinical estimation of osteoporosis.

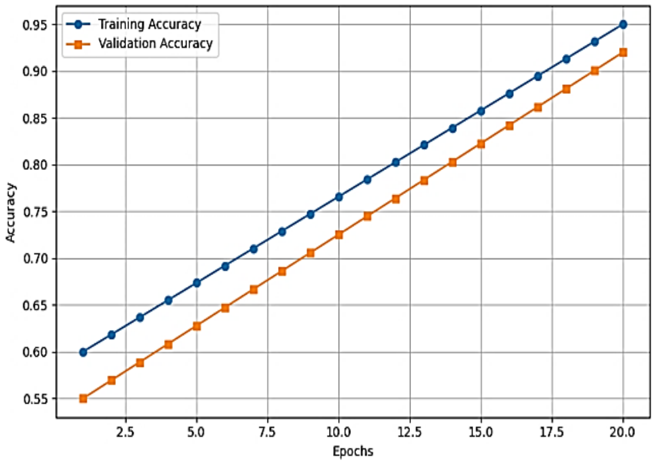

Fig 4: CNN Training and Accuracy Curve validation

Fig 4 shows how the model accuracy increases and decreases over 20 training epochs. The x-axis shows the epoch that is, how many times the model passes through the training data. The y-axis is marked by accuracy ranging between 0.55 and 0.95. Training (blue line) approximates the accuracy of the training (blue line), which increases steadily between about 0.6 and 0.95 with more training. The validation accuracy is the orange line that rises with the approximation of 0.55 to about 0.92. The two curves are moving in the same upward direction that means that the model is not being over technical and it is reacting well with unknown data. Overall, the graph depicts a steady learning pattern and satisfactory performance on unknown data.

What can be envisioned as promising, however, are combinations of deep learning and Radiomic features to improve diagnostic output and deliver more interpretable outcomes, where the diagnostic of osteoporosis has been conventionally based on the BMD measurements through DXA scans, which could be influenced by human error and uncertainty. AI-driven systems can also process significant amount of data in a few seconds to assist with timely clinical decision-making. However, many deep learning approaches are still to be fully clinically tested, and until then, only large and properly designed efforts can assist in further embedded them into the daily routine of medical practice.

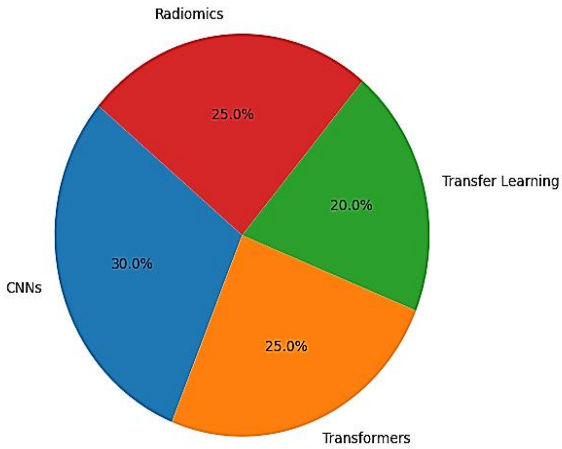

Fig 5: Contribution of Techniques in Osteoporosis Detection

The pie charts compare the approaches utilized in imaging of osteoporosis. Convolutional Neural Networks (CNNs) occupy the largest portion (30%), which suggests that they are the most commonly used method. The 1/2 place belongs to Radiomics with 25 percent share and Transformers with 25 percent share, and the difference indicates that the two approaches are highly present in the existing literature. The other 20 percent, which indicates that it is still used but comparatively less frequently is called transfer learning. Overall, the chart suggests that a plethora of techniques exist, yet CNNs remain common, and other advanced techniques continue to become increasingly popular.

Regardless of its potential, the complete execution of the osteoporosis diagnosis to deep learning is hindered by several obstacles. The majority of the models rely on small/localized data sets, which limit their applicability in broader populations. The other problem is oversampling, since the lower frequency of cases of osteoporosis will miscarry and destabilize the model. The challenge of interpretability is another problem: most deep learning systems are black boxes, and it is hard to make clinicians trust their conclusions. The explainable AI work that is being pursued today, via saliency maps and attention mechanisms, will address these issues, and increase transparency.

Fig 6 is a stacked area chart that shows the evolving contribution of various deep learning solutions based on specifically CNNs (Convolutional Neural Networks), Transformers and Transfer Learning across 20 training cycles. The number of training cycles is plotted on the X-axis and the contribution to the absolute model performance is the contribution to the methods contribution is plotted against that number in the Y-axis.

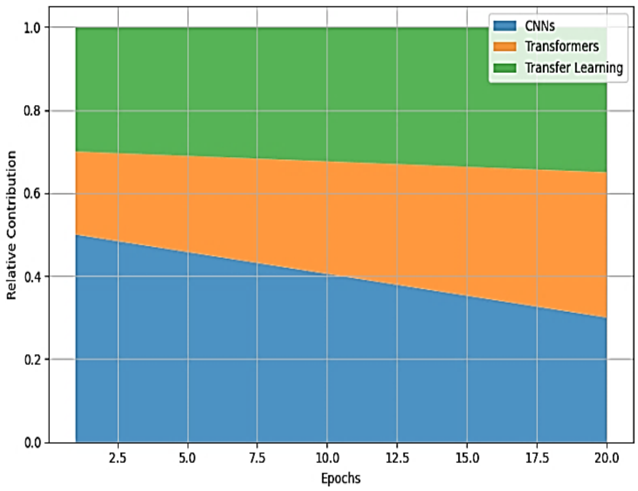

Fig 6: Technique Contribution vs Epochs

CNNs are leading the pack in the graph with a small contribution bordering about 50 percent but gradually slowing down to nearly 30 percent at the twentieth epoch, indicating their leading role in the initial stages of the education. The transformers, however, pick up and eventually, after the 35 contribution to the information (commencing with 20 contribution), this means that they would gradually assume more complex designs as they train. The contribution involvement in Transfer Learning, a graph that shows a green area, is relatively consistent (30-35) throughout the entire learning process, which represents its consistency in its contribution to the offer of feature knowledge that has been initially trained. By and large, the chart indicates that there is a way in which CNNs have become less dependent over the years yet Transformer Learning has always been a constant boost in the performance of the model.

5. Conclusion

Deep learning will be an effective tool in the recognition of osteoporosis, which is more precise in examining the DXA and QCT scanner and enables the discovery of the disease at earlier stages and robotic screening of the disease. Its progress is however hampered by a dearth of large, varied and well labeled dataset and resides on the inability to carry out models that are comprehensible by and plausible by clinicians. Multirenal studies, a stronger explainability, and broader clinical testing will all be the solution to these problems. The development of the ethical and regulatory standards should also be viewed as a component of future to ensure privacy of the data and inclusion of other information about a patient to increase reliability. In total, deep learning can transform the process of osteoporosis detection by helping to detect osteoporosis at an earlier stage, enhance the clinical process and guide more individual osteoporosis therapy.

References

[1] Gaudin R., Otto, W., Ghanad, I., Kewenig, S., Rendenbach, C., Alevizakos, V... & von See, C. (2024). Enhanced osteoporosis detection using artificial intelligence: A deep learning approach to panoramic radiographs with an emphasis on the mental foramen. *Medical Sciences*, *12*(3), 49.

[2] Ogbonna, C., & Onuiri, E. E. (2024). Predictive Diagnostic Model for Early Osteoporosis Detection Using Deep Learning and Multimodal Imaging Data: A Systematic Review and Meta-Analysis. *Asian Journal of Engineering and Applied Technology*, *13*(2), 28-35.

[3] He, Y., Lin, J., Zhu, S., Zhu, J., & Xu, Z. (2024). Deep learning in the radiologic diagnosis of osteoporosis: a literature review. *Journal of International Medical Research*, *52*(4), 03000605241244754.

[4] Ong, W., Liu, R. W., Makmur, A., Low, X. Z., Sng, W. J., Tan, J. H., ... & Hallinan, J. T. P. D. (2023). Artificial intelligence applications for osteoporosis classification using computed tomography. *Bioengineering*, *10*(12), 1364.

[5] Smets, J., Shevroja, E., Hügle, T., Leslie, W. D., & Hans, D. (2020). Machine learning solutions for osteoporosis a review. *Journal of bone and mineral research*, *36*(5), 833-851.

[6] Kawade, V., Naikwade, V., Bora, V., & Chhabria, S. (2023, July). A comparative analysis of deep learning models and conventional approaches for osteoporosis detection in hip X-Ray images. In *2023 World Conference on Communication & Computing (WCONF)* (pp. 1-7). IEEE

[7] Inigo, S. A., Tamilselvi, R., & Beham, M. P. (2024). A review on imaging techniques and artificial intelligence models for osteoporosis prediction. *Current Medical Imaging*, *20*(1), E080623217779.

[8] Liu, R. W., Ong, W., Makmur, A., Kumar, N., Low, X. Z., Shuliang, G., & Hallinan, J. T. P. D. (2024). Application of artificial intelligence methods on osteoporosis classification with radiographs—a systematic review. *Bioengineering*, *11*(5), 484.

[9] Qiu, C., Su, K., Luo, Z., Tian, Q., Zhao, L., Wu, L. ... & Shen, H. (2024). Developing and comparing deep learning and machine learning algorithms for osteoporosis risk prediction. *Frontiers in Artificial Intelligence*, *7*, 1355287.

[10] Wani, I. M., & 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] Mohammed, A. Z., & George, L. E. (2022). Osteoporosis detection using convolutional neural network based on dual-energy X-ray absorptiometry images. *Indones. J. Electr. Eng. Comput. Sci*, *29*(1), 315.

[12] Alden, Z. N. A. M. S., & Ata, O. (2024). A comprehensive analysis and performance evaluation for osteoporosis prediction models. *PeerJ Computer Science*, *10*, e2338.

[13] Basavaraja, P. H., & Ganesarathinam, S. (2022). An Ensemble-Of-Deep Learning Model with Optimally Selected Features for Osteoporosis Detection from Bone X-Ray Images. *International Journal of Intelligent Engineering & Systems*, *15*(5).

[14] Suh, B., Yu, H., Kim, H., Lee, S., Kong, S., Kim, J. W., & Choi, J. (2023). Interpretable deep-learning approaches for osteoporosis risk screening and individualized feature analysis using large population-based data: development and performance evaluation. *Journal of medical Internet research*, *25*, e40179.