OPTIMIZING DEEP LEARNING MODELS FOR OSTEOPOROSIS DETECTION: A CASE STUDY ON KNEE X-RAY IMAGES USING TRANSFER LEARNING

Zahraa Shams Alden[1,2] and Oguz Ata[3]

[1]University of Altinbas, Electrical and Computer Engineering, Turkey
[2]University of Kerbala, Tourism Science, Iraq
[3]University of Altinbas, Information Technology, Turkey

ABSTRACT

Medical image analysis is a very risen area of study and the speed and precision necessary in medical image analysis. Deep learningmay aid in resolving medical image processing issues including labelled datasets by experts to learn effectively.In the medical field, working with limited access to large volumes of labeled data can present significant challenges. Another challenge is the complexity of medical data. Therefore, this study proposed a deep neural network-based model for medical imaging to detect osteoporosis using transfer learning with MobileNetV2. Class weights are used to alleviate class imbalance, and the learning rate schedule improves model adaptability. The model was created in two variants: one with a learning rate schedule and class weights with an accuracy of 96%, and the second model with only a learning rate schedule with an accuracy of 94%. The anticipated experimental results should illustrate the efficiency of the proposed framework for the future designing of deep learningmodels for predicting bone fracture and speeding up medical data analysis and interpretation.

KEYWORDS

Medical image analysis, Machine learning, CNN, Transfer Learning, Osteoporosis, Deep learning, MobileNetV2.

1. INTRODUCTION

Human memory and perception impede the fine details in the visual recall of medical images, leading to misdiagnosis or suboptimal planning of treatments. Such challenges become more critical in diseases like osteoporosis, in which subtle changes in the density and structure of bones often hold the key to early detection and management. Deep learning models analyze images automatically, therefore reducing dependence on human recall.

Image processing has become a part of fields, in modern science including spatial imaging, embedded systems, industrial applications, virtual reality, and medical imaging. Medical imaging includesvarious methods that produce organ representations for medical and scientific purposes. The interpretation of image data is crucial in healthcare as it allows medical professionals to visualize and comprehend the body structure and functions aiding in the prediction and diagnosis of health conditions. Imaging techniques such asMRI scans, CT scans, and X-rays offer insights

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into anatomy and physiology. Techniques for processing medical images can gather valuable data to support diagnosis and treatment planning[1].

Moreover, image analysis contributes significantly to advancing tools and treatment approaches by enabling researchers to explore disease mechanisms and evaluate the effectiveness of novel therapies. The integration of image analysis in healthcare has substantially enhanced the precision and efficiency of diagnosis and treatment. It continues to be a focus area for research, within the field.

The success of various techniques applied for imaging in the detection of osteoporosis depends on the needs for diagnosis. However, there are many challenges regarding medical imaging integrated in healthcare sector:

- Dual-energy X-ray Absorptiometry: It is considered to be the gold standard in measurement with regard to bone density and serves to visualize the general appearance of the bones to highlight obvious abnormalities. DXA would, therefore, be desirable, as it is faster and less expensive and exposes a patient to very low levels of radiation. It also has its shortcomings: insensitivity in the early detection of osteoporosis and analysis of structural details.
- CT scan: Although they provide very small bone details, CTs tend to suit fracture risk assessments rather well. It provides detailed cross-sectional images that are important in the comprehensive study of the microarchitecture of bones to determine risks of fracture.The drawback in their implementation is increased radiation doses and resultant costs.
- MRI: These can be ideal for assessing fracture risk in great detail since they provide good soft tissue contrast without ionizing radiation, therefore enabling better fracture risk assessments with surroundings. Unfortunately, useof very large numbers would be inappropriate due to its extremely high costs and long scanning time.

The emphasis in this review has been placed on such modalities that can play the role of the data source in the training of robust deep learning models, which can integrate both anatomical and physiological understandings in automated osteoporosis detection

2. LITERATURE REVIEW

2.1. Medical Image Processing

The analysis of osteoporosis images involves utilizing computer software to examine bone-related medical images to diagnose and track the development of osteoporosis. Various medical imaging techniques, like computed tomography (CT) scans or X-rays are employed to assess bone density and structure pinpointing areas with reduced bone density that could indicate osteoporosis. By measuring bone density in body regions like the knee, spine or hip valuable data can be extracted to monitor changes over time and provide insights using references. This data aids healthcare professionals in determining the severity of osteoporosis and devising treatment strategies. Besides diagnosis and monitoring medical image processing can also evaluate the efficacy of osteoporosis treatments such as medications or lifestyle modifications by analysing changes in bone density over time.

As per studies in[2], it is noted that extracted data from information may sometimes be distorted or compromised. Various techniques for analyzing images are being explored to enhance our understanding of this health data. As a foundation for their work, these medical image operations were divided into these key categories:

- **Registration of Images:** Image registration is an iterative procedure that seeks the optimal mathematical transformation model for aligning two-dimensional (2-D) or three-dimensional (3-D) image data.

- **Segmentation of images**: The fundamental purpose is to organize pixels into distinct image areas, for instance, areas representing certain surfaces, objects, or natural elements of objects.Segmentation of bone structures with accuracy contributes to feature extraction and analyses. Automated segmentation techniques minimize human intervention and reduce inconsistencies

- **Smoothing of Images:** The most basic method is neighborhood averaging, which replaces each pixel with the average value of the pixels around it.

- **Denoising of images:** it's the most important process thatprepares the images for analyzing and extracting useful information. It is very important to understand the characteristics of medical images and how they were captured, like MRI, CT scans, and X-RAY imaging systems. During the capturing process of X-ray and CT images usually have noise like Poisson noise, which obscures features of diagnosis[3] and thus it would be very important to remove these noises to improve the quality of images and therefore improve the ability of medical diagnosis [4].

- **Data Augmentation**: It enhances diversity through augmentation strategies, including rotation, zooming, and flipping that help in improving model robustness and generalization[5].

Integrating image analysis into health care has huge implications for the move toward precision medicine. Enabling automated diagnostic tools means higher quality and speedier diagnosis, especially for resource-constrained settings. Based on this work, the model using MobileNetV2 has shown how image analysis could be used in processing knee X-rays to identify osteoporosis. The model performs better because weight losses have resolved class imbalances and increased adaptability with scheduled learning rates. The integration of these tools in clinical practice will facilitate the process of early detection, enable personalized treatment planning, and ensure the effectiveness of monitoring the course of a disease.

2.2. Machine Learning

Machine learning (ML) methods uses neural networks for the acquisition of significant data or training techniques involved in the evaluation and manipulation of medical images.While convolutional neural networks continue to be one of the best-performing techniques, many researcherscarried out certain preprocessing procedures to find key regions and correlate image sequences[6].

Machine learning methods used in correlation with medical image analysisare still in need of more effort, especially regarding the lack of encouragement of automated diagnosis systems and the lack of annotated image data[7]. Supervised quantification approaches are increasingly being used to predict different diseases, in addition to assisting in diagnosis.

2.3. Deep Learning

Deep learning, a form of machine learning involves teaching networks using vast datasets. In the field of medical image analysis, deep learning algorithms play a role, in examining and interpreting medical images like x rays, CT scans, and MRIs. It can be adopted and used in place of typical machine-learning methods for analyzing medical images. Furthermore, deep learning outcomes can be compared to older methods.Such algorithms can be designed to recognize patterns in images that might indicate specific diseases or medical conditions. For instance, a deep learning system could learn to spot irregularities in x-ray images that might indicate pneumonia [8]. Thus, the need for automated diagnosis systems occurred.

As a result, there is a need for a complete model for medical image analysis that not only aids specialists in diagnosis but also serves as a guide for developers in this area in constructing any medical image-analyzing application. The literature search was done by using the Web of Science for "deep learning and medical image analysis" and for "machine learning and medical image analysis" topics, the search illustrates the growth of several papers concerning these topics as presented in Table (1) below.

Table (1): Literature search for using machine learning and deep learningin medical image analysis.

Year	Machine Learning	Deep Learning	Total
2018	464	292	756
2019	842	768	1,610
2020	1,284	1,485	2,769
2021	1,813	2,403	4,216
2022	2,011	2,864	4,875
2023	2,030	2,892	4,922
2024	13	40	53

The table shows the number of papers that used Deep Learning as a methodology to analyze medical images are increasing over the years which means it was more efficient than other machine learning methods as it can be noticed in Figure (1) below.

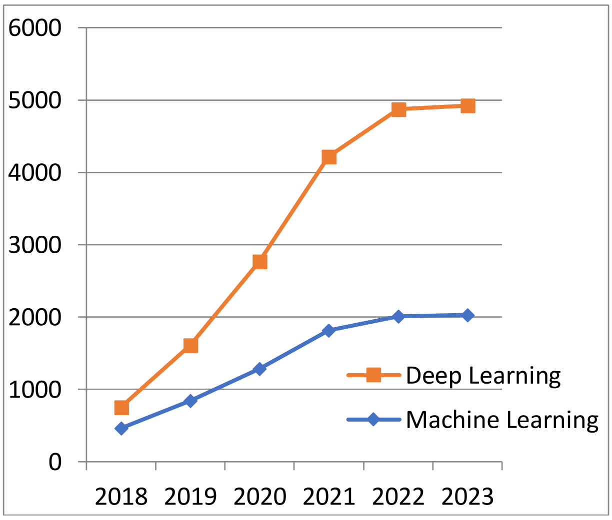

Figure (1): Diagram of deep learning and machine learning usage in medical image analysis

Despite the promise of the deep learning methods applied to medical imaging, a few challenges are there with the approach:

1. Data Scarcity: Because of privacy issues, the labour-intensive nature of annotating medical images, and other challenges; it is very difficult to collect large-scale, labelled datasets.
2. Generalizability: If deep learning models are not trained on diverse datasets, they may not generalize across populations and introduce biases.
3. Noisy Nature of Medical Images: Usually, the changes due to osteoporosis are slight, and might be camouflaged by noise or other artifacts in the image modality, such as X-rays and computed tomography.

These challenges are ameliorated in this research by incorporating various techniques into this work, including transfer learning and data augmentation. In the future, generating synthetic data could be done with GANs for dataset diversification, to enhance model robustness and reduce overfitting

3. PROBLEM STATEMENT AND RESEARCH GAP

The application of learning in identifying osteoporosis is an area of study, with ongoing advancements. Generally speaking, deep learning algorithms can be taught to recognize patterns in images that may signify the presence of osteoporosis. Typically, the process involves providing the algorithm with labeled images. These labels indicate whether a particular image shows signs of osteoporosis. The algorithm then uses this data to understand and identify the patterns linked to osteoporosis in images.

This study'smain aim is to improve the accuracy and reliability of deep learning algorithms in this field. The initiatives will involve developing models to train datasets to enhance the quality and quantity of training data accessible, to these algorithms. This could bring benefits to individuals with osteoporosis by assisting in identifying those to fractures and offering guidance on treatment options. The challenges of osteoporosis detection research can be emphasized in ways. Firstly, deep learning algorithms amounts ofhigh quality training data to make precise predictions and learn effectively which must be expertly labeled to provide accurate information for the algorithms. Gathering quantities of comprehensive medical data for algorithm training can be a challenging task due to its complexity [9]. Osteoporosis is a condition that presents differently across populations and existing datasets may not adequately capture this diversity. Consequently deep learning models might struggle to generalize across populations resulting in subpar performance, in identifying osteoporosis. Another potential limitation lies in the nature of data[10]. Medical images especially can be quite intricate. May encompass an array of characteristics that pose challenges, for a deep-learning model to decipher[11]. This complexity can hinder the development of deep learning models for applications.

Another hurdle lies in the dependency of deep learning algorithms on the quality of their training data. Should the data exhibit bias or errors the algorithms predictive accuracy may be compromised. This issue is particularly pronounced in healthcare, where data collection can be arduous and not always reflective of the population.Furthermore, the intricate nature of deep learning algorithms can obscure their workings making it tough for professionals to grasp how predictions are made. This opacity complicates efforts to assess accuracy and reliability while also hindering error detection and correction within the algorithms.

In conclusion, leveraging learning for purposes remains an active area of exploration, with numerous obstacles and constraints yet to be addressed in developing effective algorithms for predicting bone fractures.

Moreover, the absence of techniques for assessing the effectiveness of deep learning algorithms in detecting osteoporosis poses a challenge when trying to compare and assess strategies.

4. METHODOLOGY

4.1. Selecting the Best Image Acquisition Method

Due to the significant impact of symptomatic osteoporotic vertebral fractures on health outcomes and associated costs early diagnosis and prompt treatment of vertebral fractures are crucial [12]. DXA (energy x ray absorptiometry) CT (computed tomography) and MRI (magnetic resonance imaging) are commonly utilized for osteoporosis detection and fracture prediction. Every imaging method comes with its own strengths and limitations, and the best choice depends on the specific situation.

DXA is often regarded as the preferred method for osteoporosis diagnosis [13], due to its speed, noninvasiveness and cost-effectiveness. Using a dose x-ray DXA measures bone density over time. However DXA may not effectively detect early stage osteoporosis. Provide insights into bone microarchitecture.

CT scans find use across medical fields[14]. While more costly, than DXA and involving radiation exposure CT scans offer bone images.

This makes it helpful, in spotting signs of osteoporosis and pinpointing areas in the bones that could fracture. However, CT scans are not commonly employed for osteoporosis screenings because they are less effective than DXA at tracking changes in bone density over time.

MRI, unlike other methods, does not involve ionizing radiation, making it a safer option for patients. It offers images of bones and their surrounding soft tissues aiding in the identification of fracture risks. [15]. Nonetheless, MRI is pricier and more time-consuming compared to DXA or CT scans. Is not as adept at monitoring changes in bone density over time.

Therefore, this study deems DXA as the option for osteoporosis screenings due to its speed, painlessness, and affordability. While CT and MRI excel at detecting early-stage osteoporosis or identifying bone areas prone to fractures they come with higher costs and longer examination times.

4.2. Selecting the Best Deep Learning Technique

The selection of the most effective deep learning methods for osteoporosis detection hinges, on individual circumstances and the objectives of the imaging study [16]. In general, various techniques are commonly employed in this field including networks (CNNs) recurrent neural networks (RNNs) and generative adversarial networks (GANs). CNNs are adept at analyzing images like detecting osteoporosis from images due to their connection and weight-sharing characteristics. [17], they can learn patterns within images to make predictions about their content.

On the hand, RNNs excel at processing data such as time series or text. Their capacity to grasp information is notable as neurons in the hidden layer relay feedback signals to one another [18].In the context of imaging RNNs could be utilized for tracking changes in bones over time and identifying signs of osteoporosis.

When it comes to imaging, GANs might be utilized to create images, for training deep learning systems. This could potentially enhance the effectiveness of algorithms.GAN has emerged as a strong tool for enhancing application performance in medical imaging with deep learning where itoperate by training two networks collaboratively [19]. GANs generate realistic, synthetic images that extend the training datasets and improve the performance of a model. In detecting osteoporosis, GANs mitigate the limitation in the dataset with various representations of bone density changes and enable the deep models, such as MobileNetV2, to learn robust features. This further reduces reliance on real-world datasets, which generally involve time consumption, and allows for quicker development and deployment of systems using deep learning.

According to Web of Science, many research papers discuss the possibility of using CNN, RNN in medical image analysis, the following Figures (2) and (3) respectively show the count of papers using these methods from 2018 – 2023.

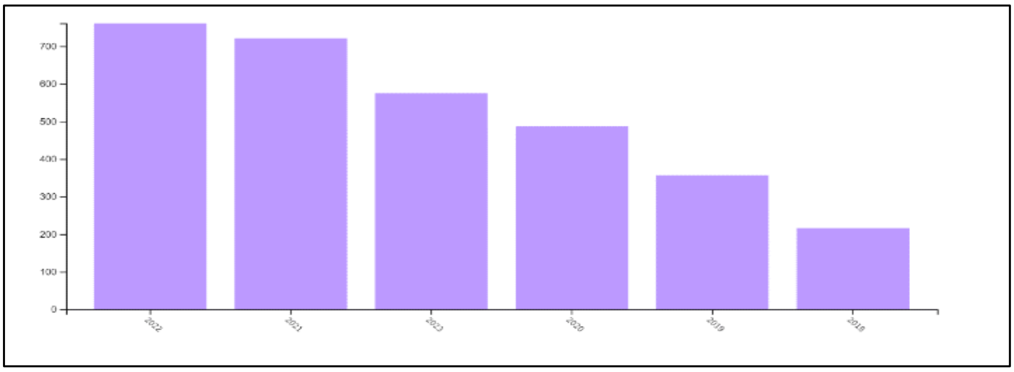

Figure (2): Using Convolutional Neural Networks (CNN)

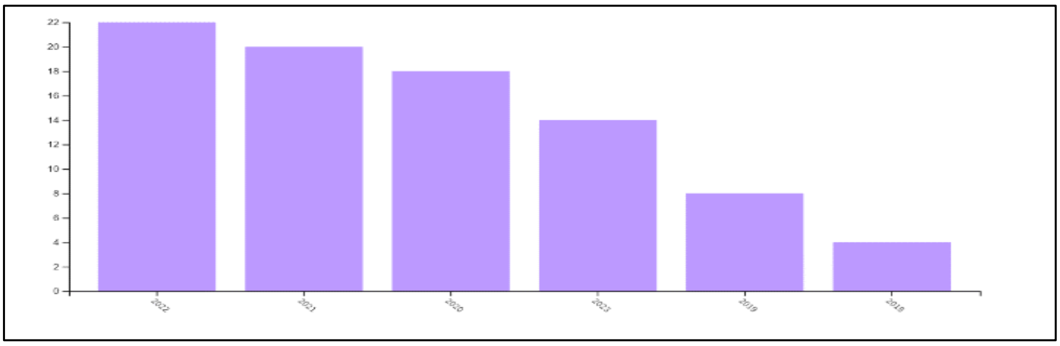

Figure (3): Using Recurrent Neural Networks (RNN)

According to these charts, it can be concluded that CNN has been used widely over the last five years, which can indicate the powerfulness of this method to analyze medical images to help with efficiency in extracting the features that are most likely to be useful in making a diagnosis.

The backbone of automatic medical image analysis is CNNs because they are superior in the extraction of hierarchical features. This study demonstrated the performance of the MobileNetV2-

CNN architecture in knee X-ray image analysis, which resulted in a test accuracy of 96%. The lightweight model architecture and efficient feature extraction by the proposed model enable fast and accurate detection of osteoporosis, and it may prove to be highly useful for clinical applications.

5. TRANSFER LEARNING USING MOBILE NET MODEL

Transfer learning is an approach to machine learning in which a model generated for one job is reused as the foundation for a model for a different task. Transfer learning in neural networks is frequently accomplished using pre-trained models. These models are trained on big data sets for a given goal, such as image classification[20], andthe idea is that the features learned by the pre-trained model during its previous task capture broad patterns and representations that may also apply to the current task.This method is especially useful when significant annotated datasets are required, as it eliminates the requirement for costly annotation of target data[21].Figure (4) shows the analysis of the current state of art of using transfer learning in medical image analysis.

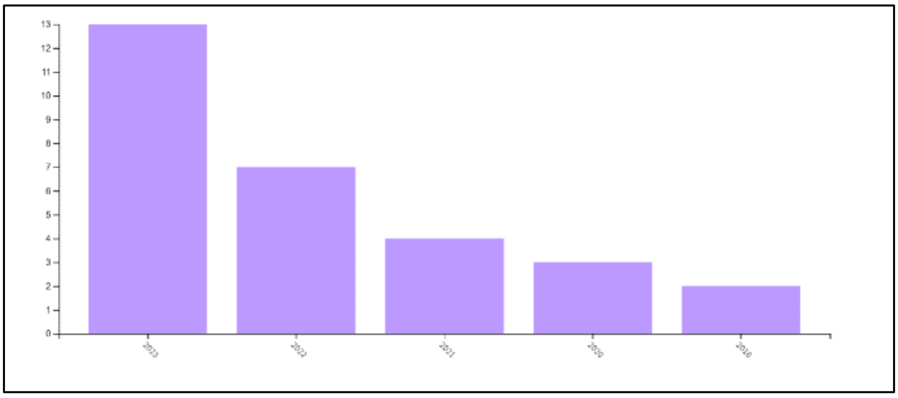

Figure (4): Analysis of the current research of using transfer learning in medical image analysis

Transfer learning, especially with a pre-trained model like MobileNetV2, solves data scarcity and computational problems associated with medical imaging. MobileNetV2 boasts efficient architecture with depth wise separable convolutions using inverted residuals, enabling better performance at reduced computational overhead. Fine-tuning a model on knee X-ray datasets in this work showed very promising results from the model for detecting osteoporosis with high degree of precision and recall. The performance was further refined using learning rate schedules and class weighting, thus underlining some utilities of transfer learning in the development of high-performance lightweight diagnostic models

MobileNetV2 model is composed of depth-wise separable convolutions and is pre-trained on the ImageNet Dataset which givesthe proposed model the highest importance and further enhancesthe model performance since it extracted important features from the ImageNet dataset[22]. MobileNetV2 prioritizes reducing latency while enabling small networks to operate efficiently with inputs of any size. Its design leverages ReLU6 as the activation function in each layer, combined with batch normalization, to deliver excellent performance[23]. The key advantage of this approach is that it builds lightweight deep neural networks while reducing the number of parameters compared to other networks[24].

6. RELATED WORK

Many researchers have developed models to detect osteoporosis to predict future bone fractures based on different deep learning models including using Transfer Learning, the following points will show some of these previous research:

1. Ogundokun, et al., 2023[25]proposed a deep learning model using a transfer learning model to analyze breast cancer histology scans with a high accuracy to 91%. However, their model shows limitations as it relies on one dataset. Other limitations includes time consumption for training the model.
2. A systematic review by Kutbi in 2024 [26] shows the powerfulness of AI in the healthcare sector in predicting various diseases and enhancing the diagnosis process. It also shows research gaps and future work to enhance the quality of data including generalizability of the model, technical issues, legal and ethical concerns.
3. Nguyen et al. 2021 [27]Developed a model based on CNN algorithm, their model successfully evaluate the BMD of hip bone based on x-ray images and can treat a large dataset in a short time. One of their limitations is the limits of their datasets since it didn't cover enough data from both genders equally and their was not enough information about other features of the bone to predict fracture.
4. Sivasakthi et al. 2022 [16] discussed various machine learning approaches in a comparative study to illustrate which method to detect osteoporosis and conclude that RNN would be the best choice. The only limitation of their work is the number of hidden layers is randomly chosen which affects the efficiency of their model. it is important to include an algorithm to effectively modify the weight of RNN model to prevent false learning process.
5. Sollmann et al. 2022 [28] present a review paper of 3D imaging modality such as MRI or CT scans evaluate the osteoporotic spine. It showed how important these methodologies are in providing important data about bone structure and other fearures that are important to predict osteoporosis.
6. Akito Yabo et al, 2021 [29] created a CNN model to diagnose osteoporosis fracture using MRI imaging, successful results were obtained. However, several limitations were stated, including the diversity of MRI systems used for image acquisition and then converting them to 2D images where many features were lost.
7. A literature review done by Hee E. Kim, et al [30]emphasizes the advantage of using Transfer Learning (TL) in medical image analyzing. By addressing the data scarcity problem and saving time and hardware resources, transfer learning using convolutional neural networks has made a substantial contribution to medical image processing.
8. Transfer Learning in Breast Cancer by [31]illustrates the benefit of pre-processing approaches in increasing the accuracy of transfer learning in breast cancer diagnoses via ultrasound imaging and overcoming the challenge of acquiring a large data set of training data.

There are likely to be many challenges and limitations to overcome to develop effective algorithms for detecting osteoporosis and predicting bone fractures. One of the main challenges, especially in medical applications, is to build models from scratch using newly acquired training data. Therefore, Transfer Learning is used in this study.

7. OSTEOPOROSIS DATA SET

The data set was collected from Kaggle database[32]which contains 372 Normal and 372 Osteoporosis knee X-ray images. The data set was processed and analyzed to extract only useful images for medical image classification and prediction of osteoporosis. Then the data set was splited into training and validation sets,where 460 images belonging to 2 classes for training and 92 images belonging to 2 classes for validation, these two classes were Osteoporosis and Normal classes as shown in Figure (5).

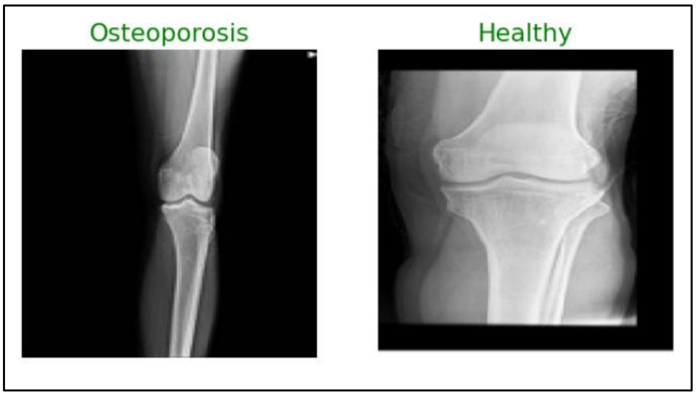

Figure (5): Osteoporosis x-ray images

8. PROPOSED MOBILENET-CNN MODEL

Transfer learning has the potential to save computing resources and time, particularly when dealing with limited labeled data for the new task. It is a prevalent strategy in deep learning, with popular pre-trained models such as VGG, ResNet, and MobileNet trained on huge datasets such as ImageNet[33]. In this study, Mobile Net Model is used as the base model for the proposed model. MobileNetV2, which was published in 2018, builds on the success of MobileNetV1 and advances its efficiency-oriented architecture. While all versions share the essential concept of depth wise separable convolutions, MobileNetV2 incorporates various innovative concepts and design choices that improve the architecture's accuracy and performance [34]. MobileNetV2's architecture is built on a structure block known as the "inverted residual with a linear bottleneck." Because of this building block structure, the network can capture complicated properties with fewer parameters, making it computationally efficient. The proposed MobileNet-CNN model was designed using class weights and scheduling the learning rate that can help improve training and model performance.

1. Class Weight: When dealing with imbalanced datasets, where some classes have much fewer samples than others, class weights can be helpful[35]. Adjusting the class weights in the network's loss function is essential to ensure that less frequent classes are given more weight compared to those with larger numbers.
2. Learning rate scheduling is a strategy for adjusting the learning rate during training. A learning rate scheduler, which modifies the learning rate according to a specified schedule, is a typical strategy. This combination can help the transfer learning model perform better, especially when dealing with imbalanced datasets and fine-tuning a pre-trained model.
3. Image augmentation is a procedure that is frequently used to artificially increase the size and diversity of a dataset by making major changes to the current data[36].The image augmentation process can benefit the proposed model in the following key points:

    - Increased Data Diversification: Augmentation alters the X-ray images of the knee, allowing the model to perceive alternative perspectives, orientations, and scales[37].
    - Robustness to Variations: Exposing the model to augmented photos makes it more resistant to changes in patient placement, image quality, and other factors.

- Overfitting is avoided by augmenting the model such that it does not memorize specific information from the training set but instead generalizes effectively to new, previously unseen data[38].
- Improved Model Generalization: The supplemented data allows the model to generalize across a wider range of knee X-ray images, resulting in superior performance on the validation and test sets.

The results of the image augmentation process for the knee x-rays can be presented inFigure (6).

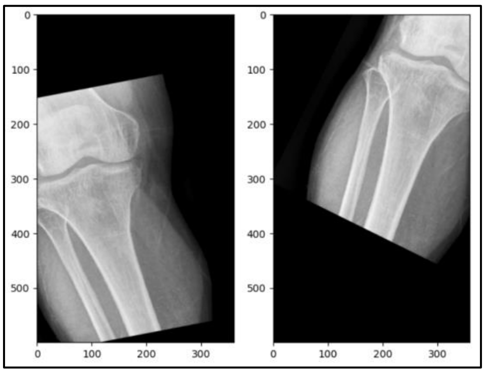

Figure (6):Image augmentation of knee x-rays dataset including rotation and zooming.

As defined in the image augmentation process for the training data set, the generated images include variables such as rotation, zoom, width shift, height shift, and shear[39]. The goal of data augmentation is to increase the diversity of the training set artificially, allowing the model to generalize better to diverse variances in the input data.In this proposed MobileNet-CNN model, medical metrics are used to enhance model accuracy and increase model performance[40]. Itis a utility function used to assess the performance of a binary classification model, especially in medical image applications,it computes several metrics that are often utilized in medical image analysis such as Confusion Matrix, Recall, F1Score, Area Under Curve (AUC), and Accuracy.

The structure of MobileNet-CNN is composed of two combined models, the base model MobileNetV2 model and CNN model. The architecture of these two models are shown in Figures (7) and (8) respectively:

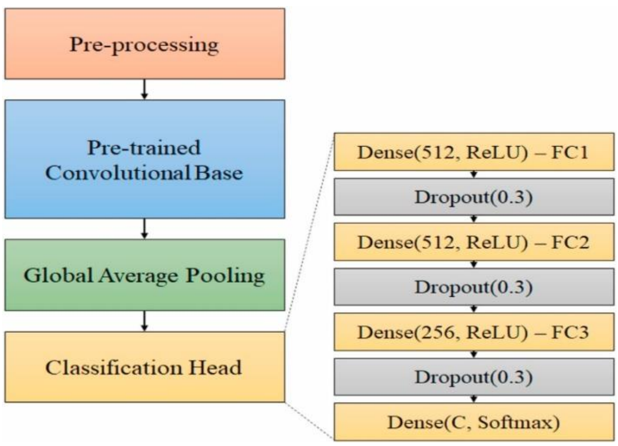

Figure (7):MobileNetV2 Model Architecture

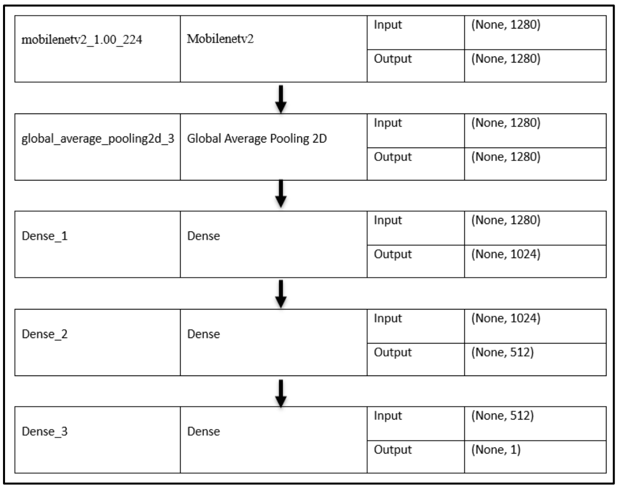

Figure (8): MobileNetV2-CNN Model Architecture

9. RESULTS

During this study, two models were developed using the same architecture, however, during the training of the models, either class weight and/or learning rate schedule were used. The results of these models are shown in Table (2) below:

Table (2): Medical metrics results of the proposed MobileNetV2-CNN Model.

Medical Metrics	Model_1: with class weight and no learning rate schedule.	Model_2: with class weight and learning rate schedule
Confusion Metric	[88 12] [22 78]	[[87 13] [18 82]]
AUC	85%	85%
Precision	86%	86%
Recall	78%	82%
F1 Score	82%	84%
Test Accuracy	94%	96%

Let's compare the two models based on precision, recall, F1 score, and accuracy:

1. Accuracy:

- Model_2 has the highest accuracy (0.9647), indicating better overall performance.
- Model_1 follows with an accuracy of 0.94.

2. F1 Score:

- Model_2 has the highest F1 score (0.841).
- Model_1 follows with an F1 score of 0.8205.

3. Precision and Recall:

- Model_2 has a good balance of precision and recall, indicating better performance in binary classification.
- Model_2 also performs well in terms of precision and recall.

In summary, Model_2 appears to be the best-performing model, considering both accuracy and F1 score. The addition of class weight and learning rate schedule seems to contribute to better performance.

In comparison to other researchers who used the same approach to analyze medical data, the proposed model outperforms other models and achieves higher results than any other models. The comparison between the proposed model and other models is illustrated below:

1. A study conducted by Fradi M, et al,2020 [41] to predict osteoporosis from Ultrasonic Computed Tomographic Images using a deep learning approach. They used transfer learning techniques to analyse the dataset and predict healthy, mild, or osteoporosis bone by using MobileNet as a base model for their CNN model. They achieved an accuracy of 87%.
2. Abdelbaki Souid, et al. 2021 [23] used the MobileNetV2 model as a base model along with 3 layers CNN model, their model was designed to classify and predict 14 different lung diseases by analyzing chest X-Rays and the accuracy of their proposed model was 90%.
3. Another study of analyzing oral histopathological images into malignant and benign lesions by Panigrahi S, et al, 2023 [42]. Their finetuning MobileNetmodel achieved a higher accuracy of 95% while their proposed DCNN model achieved 93% accuracy.
4. Transfer learning was used to detect glaucoma in a Latino population using an OCT's RNFL thickness map. The researchers in[43]used twoMobileNet model for left eye and right eye. They achieved an accuracy of 86% for the left eye, and right eye at 90%.
5. Priyanka Yadlapalli, et al, 2021 [44] used a deep learning model to classify chest CT scans to detect lung malignancies. They used several transfer learning models including MobileNet and achieved an accuracy of 85.60%.

10. CONCLUSION

The inherent complexity of osteoporosis, as well as the complexities of medical picture interpretation, limit the construction of efficient deep-learning models. Concerns about biased or error-prone training data, as well as the interpretability of complicated algorithms, underscore the complexities involved with deep learning medical applications. The limitations of the existing research are acknowledged, including difficulties in obtaining big, tagged, and representative medical datasets.In this regard, a proposed model based on MobileNetV2 could utilize such capabilities to correctly identify osteoporosis patterns within knee X-ray images with accuracy as high as 96%. This increased precision underlines automated systems' potential to disrupt diagnostic processes past their inherent human limitations.

This research utilizes learning methods to tackle the requirement, for accurate and consistent identification of osteoporosis emphasizing the enhancement of predictive model efficiency. The study involved the creation of two models; one incorporating class weights and a learning rate schedule and the other relying solely on a learning rate schedule. The results underscore the significance of these strategies in improving model performance.Employing transfer learning with the MobileNetV2 model emerges as an approach that enhances efficiency and parameter optimization. The research emphasizes how class weights and learning rate schedules play roles in handling datasets refining pre trained models and ultimately boosting model effectiveness. Image augmentation techniques such as rotation, zooming, width and height adjustments and shearing help diversify datasets contributing to model generalization. When evaluated against standards the proposed MobileNet CNN model shows promising outcomes for osteoporosis detection. Model_2 integrating both class weights and a learning rate schedule outperforms others in terms of accuracy and F1 score with an accuracy rating of 96% and an F1 score of 0.841. This underscores the importance of strategies in constructing models while offering insights into future advancements in medical image analysis, for osteoporosis detection.

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AUTHORS

Zahraa Shams Alden, ECE Phd Candidate at Altinbas University- Turkey ,Msc in Computer Science – University of Salford –UK

Oguz Ata, Head of Department (Software Engineering)- Altinbas University- Turkey