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Enhancing Osteoporosis Detection with Fuzzy Logic Preprocing and Pre-Trained Deep Convolutional Neural Networks

Woud Majid Abed[1,2,*], Murtadha M. Hamad[1], Azmi Tawfeq Hussein Alrawi[1]
[1] Computer Science Department, University of Anbar, Ramadi, Iraq
[2]Department of Basic Science, College of Dentistry, University of Baghdad, Iraq
Emails: Wou22c1001@uoanbar.edu.iq; dr.mortadha61@uoanbar.edu.iq; azmi.alrawi@uoanbar.edu.iq

This study investigates combining fuzzy logic with deep learning methodologies in classifying X-ray images for osteoporosis detection. Osteoporosis, defined by compromised bone integrity and heightened fracture susceptibility, requires prompt and precise diagnosis for effective treatment. We devised a hybrid approach that amalgamates transfer learning from Convolutional Neural Network (CNN) architectures, including MobileNetV2, AlexNet, ResNet50V2, and Xception, utilizing fuzzy logic during the preprocessing phase to address uncertainty and imprecision in X-ray images, thereby enhancing the quality of the input data for the subsequent pre-trained models. The research entailed the examination of a significant dataset of X-ray images and the implementation of the proposed methodology to categorize images as osteoporotic or non-osteoporotic, attaining a remarkable accuracy of 99.68% and a receiver operating characteristic (ROC) of 100% through the integration of fuzzy logic preprocessing with ResNet50V2. This innovative method may substantially decrease diagnostic inaccuracies and enhance patient outcomes, facilitating additional research and development in applying deep learning techniques in healthcare.

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1. Introduction

Osteoporosis and osteoporotic fractures have emerged as significant global health concerns, particularly due to the increasing aging population. By 2024, an estimated 14 million adults in the United States aged over 50 are projected to have osteoporosis. One in three women over the age of 50 will sustain a fracture attributable to osteoporosis. Consequently, osteoporosis screening is clinically significant for fracture prevention. The US Preventive Services Task Force advocates regular screening of women over 65 [1].

Central dual-energy X-ray absorptiometry (DXA) is universally recognized as the benchmark for detecting osteoporosis. Nonetheless, the utilization of DXA is constrained by its limited accessibility, frequently necessitating patients to journey to referral facilities. Additional obstacles to DXA screening encompass knowledge deficiencies and diminishing financial incentives, leading to over fifty percent of female Medicare patients in the United States not receiving DXA testing. The disparity is particularly evident in China, where merely 4.3% of women aged 50 and above have undergone testing, especially in rural regions where the percentage plummets to 1.9%. Moreover, adipose tissue may affect DXA measurements and do not comprehensively account for bone geometry, dimensions, and microarchitecture. As a result, DXA is insufficiently utilized, and osteoporosis is frequently underdiagnosed, underscoring the want for secure and economical alternatives [2][3][4].

Conventional X-ray apparatus, readily accessible in nearly all hospitals globally, provides potentially valuable insights regarding bone mineral density (BMD). Acquiring BMD data from lumbar spine X-ray scans requested for alternative purposes incurs no supplementary costs, patient time, or radiation exposure. These data can be obtained retroactively, potentially enhancing population-screening initiatives for osteoporosis. Nonetheless, evaluating bone mineral density through visual evaluation of lumbar spine X-ray pictures is difficult [5].

Deep learning, particularly Convolutional Neural Networks (CNN), has lately shown promise in medical imaging applications, including the identification of osteoporosis. CNNs have demonstrated efficacy in medical image classification by learning and extracting features from raw images. Consequently, numerous studies have concentrated on the prospective application of CNNs for classifying osteoporotic vertebral fractures and evaluating bone mineral density from X-ray images. Consequently, these methods frequently encounter inherent ambiguities and inaccuracies in medical pictures, which might impact model efficacy [6][7].

We have proposed a novel technique integrating Fuzzy Logic preprocessing with pre-trained deep learning models, specifically MobileNetV2, AlexNet, ResNet50V2, and Xception[8]. This method employs fuzzy logic during the preprocessing phase to address uncertainty and imprecision, improving input data quality for a pre-trained model. This work aims to enhance the accuracy and reliability of osteoporosis detection in X-ray pictures by using the advantages of fuzzy logic and transfer learning. Present osteoporosis diagnosis tools, including DXA and pre-trained model-based approaches, are deficient in accessibility, expense, image reliability, and accuracy. A precise, comprehensible, and more accessible diagnostic methodology is urgently needed to identify osteoporosis and avert fractures[9][10], [11], [12].

Deep learning, particularly pre-trained models, has advanced medical imaging by enabling the automatic extraction and classification of information. Nonetheless, issues with medical pictures will diminish the model's performance owing to uncertainties and inaccuracies [13][14][15]. The potential of fuzzy logic to manage uncertainties and imprecisions may improve the preprocessing of medical pictures, resulting in higher quality inputs for the pre-trained model and ultimately leading to enhanced diagnostic outcomes. This study incorporates fuzzy logic into deep learning methodologies to address the urgent requirement for a more precise, interpretable, and accessible diagnostic tool for osteoporosis. The results provide opportunities for future research and development in advanced computational methods utilized in healthcare, enhancing medical diagnostics and patient care skills.

Our research makes several key contributions:

Integration of Fuzzy Logic with Deep Learning for Medical Imaging:

1. The research introduces a hybrid approach that combines fuzzy logic preprocessing with pre-trained Convolutional Neural Network (CNN) models. This methodology mitigates uncertainties and inaccuracies inherent in X-ray pictures, enhancing the quality of input data for deep learning models.

2. Application of Transfer Learning Utilizing Multiple Pre-trained Convolutional Neural Network Models: The study employs notable CNN architectures, such as MobileNetV2, AlexNet, ResNet50V2, and Xception. This combination utilizes the pre-trained capabilities of these models for efficient feature extraction and classification in osteoporosis detection.

3. Exceptional Diagnostic Efficacy: The approach attains outstanding outcomes by integrating fuzzy logic preprocessing with the ResNet50V2 model, yielding an accuracy of 99.68% and an impeccable ROC score of 100%. These indicators highlight the approach's efficacy in differentiating osteoporotic from non-osteoporotic patients.

The remainder of the paper is structured as follows: Section 2 examines the literature pertinent to osteoporosis detection and the application of deep learning in medical imaging; Section 3 delineates the methodology of the proposed method, encompassing data preprocessing, model architecture, and training protocols; Section 4 elucidates the experimental results and performance assessment of the proposed method, addressing the implications of our findings, potential limitations, and avenues for future research. Ultimately, Section 5 encapsulates the principal contributions and significance of our research.

2. Related Work

Much of the research in this area has focused on establishing fracture prediction tools and demonstrating their benefit in predicting those at risk. For example, a randomized controlled study by the recent Screening of Older Women for the Prevention of Fractures trial highlighted that dual-energy X-ray absorptiometry was helpful in enhanced risk detection with consideration of fracture. Back then, various more recent imaging modalities and analyses were examined during the earlier stages to diagnose osteoporosis and predict fracture risk at an early phase. For example, this was done by texture analysis [16].

Moreover, promising techniques have been developed for osteoporosis classification from X-ray images using machine and deep learning techniques [17]. Therefore, this research primarily aims to construct predictive models of machine learning algorithms to serve as screening tools to detect osteoporosis among adults over fifty. To assess the effectiveness of such a model, it would be necessary to compare its performance with traditional prediction models. The deep CNN models developed for classifying osteopenia and osteoporosis by lumbar spine X-ray images can provide much more exact or efficient X-ray-based substitutes for dual-energy absorptiometry [18].

The recent developments in this area are represented by the use of convolutional neural network architectures in automatically detecting osteoporosis based on X-ray images. For instance, in one of the studies by Massatith et al. (2023) [19], it has been found that the CNN models may predict the outcomes of the osteoporosis prognosis at a rate of 97.57% compared to traditional KNN models. Such promising results notwithstanding, there are still some limitations in terms of size and diversity that could, however, influence the performance and generalization of models.

Other researchers have also ventured into texture analysis on X-ray images in efforts toward the early detection of osteoporosis. Image quality and patient positioning, among other factors, however, sometimes affect results for these methods. For example, Sollmann et al. (2022)[20] have published a review on imaging techniques and underlined how promising the potential of texture analysis is in assessing bone quality and fracture risk when combined with advanced imaging techniques like CT and MRI.

Moreover, research on image quality improvement has been done, given better performance by deep learning models. Iman et al. (2023)[21] illustrated that the CLAHE algorithm for image enhancement was very accurate in demonstrating that deep learning models could be much more accurate in detecting osteoporosis from images of X-rays.

Despite all such efforts, some problems persist. Most of the studies conducted until now have been done using small datasets, which, to some extent, lead to bias by design and reduce models' robustness. In addition, one of the main challenges with machine learning models is their interpretability, which plays a key role in achieving full trust from clinicians. Table 1 summarizes the most recent works using machine-learning methods in osteoporosis detection.

Table 1: Recent Works on Osteoporosis Detection.

Study	Method/Technique Used	Findings	Results	Limitations
Massatith et al., 2023 [19]	Machine Learning (CNN, KNN)	High accuracy in predicting osteoporosis prognosis	CNN: 97.57%, KNN: 78.57% accuracy	Small and homogeneous dataset
Zhang et al., 2020 [18]	Deep Convolutional Neural Network	Accurate classification of osteopenia and osteoporosis	High accuracy in classification	Limited by training data diversity
Wen-yu et al., 2021 [17]	Machine Learning Algorithms	Effective screening tool for osteoporosis in adults	Comparable to traditional models	Limited interpretability of models
Sollmann et al., 2022 [20]	Texture Analysis with CT and MRI	Enhanced bone quality and fracture risk assessment	Improved prediction of fracture risk	Image quality and patient positioning
Iman et al., 2023 [21]	CLAHE Algorithm with Deep Learning	Improved image contrast and model performance	96% accuracy with ResNet-101	Susceptible to noise in X-ray images
Küçükçiloğlu et al., 2023 [22]	Unimodal and Multimodal CNNs	High accuracy in predicting bone mineral loss	Balanced accuracy: 98.90%	Need larger patient datasets
Amiya et al., 2022 [23]	Gabor Filter with Modified U-Net	Effective segmentation and classification	Superior performance over classical U-Net	Dependent on image quality
Lee et al., 2019 [24]	Feature Extraction with VGGnet, Random Forest	High accuracy in identifying abnormal BMD	AUC: 0.74, Accuracy: 0.71	Moderate sensitivity and specificity
Smets et al., 2021 [17]	Review of ML Methods	Promising ML applications in osteoporosis management	Moderate to high-quality studies	Incomplete reporting, lack of external validation
Mane et al., 2023 [25]	Deep Learning Models with Transfer Learning	Improved classification performance	Higher accuracy with transfer learning	Need larger, diverse datasets

Despite their significant achievements in osteoporosis detection using machine learning and deep learning techniques, several research gaps remain. Perhaps the most prominent ones are related to the limited sizes and

diversity of the training datasets, which is the reason for these models' generalizability issues. Moreover, factors influencing the performance of these methods include image quality and patient positioning, and many studies do not consider these factors.

This work addresses the above research gaps by integrating pre-trained models with fuzzy logic preprocessing techniques. The fuzzy logic approach improves image quality by reducing noise and enhancing relevant features, which makes these pre-trained models and transfer learning techniques more accurate and robust. This integration enhances detection accuracy and improves model interpretability, making the results reliable and acceptable for clinical application. Our method aims to provide a relatively complete and reliable solution in osteoporosis detection, bridging the gap between current technological capability and clinical needs.

3. Materials and Methods

This section describes the materials and methods used in this study to improve osteoporosis diagnosis by integrating fuzzy logic preprocessing techniques with pre-trained DL models. Following this, the system used in this study is described based on how it might improve the quality and interpretability of X-ray images and increase accuracy in osteoporosis diagnosis. In that order, we will detail the data collection process, preprocessing steps, model architecture, training procedures, and evaluation metrics that show our approach's performance.

Figure 1 illustrates the overall proposed method in this paper. The method includes fuzzy logic-based image preprocessing, and a pre-trained model for osteoporosis detection is proposed. There are the following major steps involved in the proposed technique:

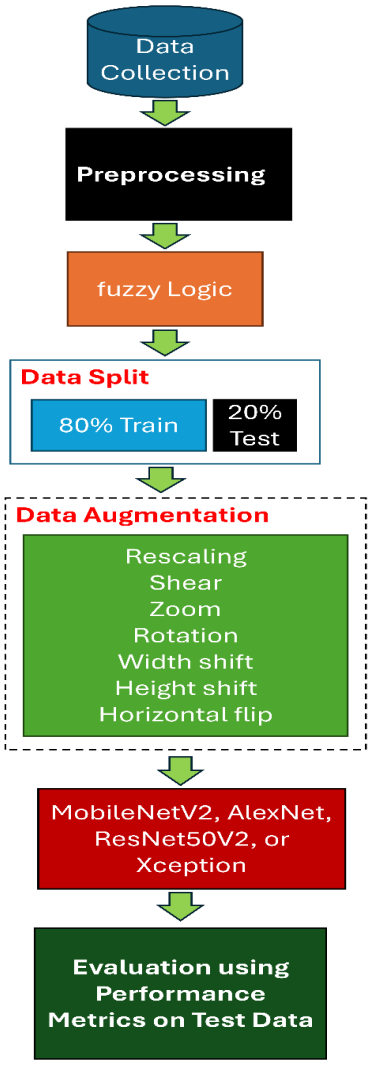


Figure 1. The overall proposed method.

1. Data Collection: Images of the X-ray of osteoporotic and healthy bones were collected from three hospitals in Baghdad, Iraq. The collection would be strictly done with ethical adherence to patient privacy and security.

2. Image Preprocessing Based on Fuzzy Logic: The collected X-ray images were fed into a preprocessing stage for quality enhancement using fuzzy logic-based techniques. This phase included grayscale conversion, histogram equalization, edge detection using a Sobel filter, and fuzzy logic membership functions to improve the edges.

3. Data Augmentation: To make this model more robust and to prevent overfitting, some augmentation techniques were included in this study, such as rescaling pixel values and adding shear, zoom, rotation, width shift, height shift, and horizontal flip.

4. Model Training: This step uses a pre-trained model with preprocessed and augmented images. The architecture of the applied CNN consisted of multiple convolutional layers, using ReLU as the activation function after every convolutional layer, followed by a max-pooling layer. After that, dense layers with dropout for regularization would be applied. In the end, a sigmoid function for binary classification would be used, namely osteoporotic versus healthy.

5. Evaluation of the Model: The model was tested for accuracy, precision, recall, and F1-score, amongst other propositions. In addition, the model's performance is measured through confusion matrices and receiver operating characteristic curves.

6. Result Analysis: The performance of the proposed method was tested and evaluated with existing methods to show its efficiency for accurate classification of osteoporotic vs healthy bone images.

We will describe the dataset preprocessing techniques, followed by an overview of our CNN architecture and specific training methodologies. We then present the evaluation criteria to validate the effectiveness of our proposed method.

3.1 Data Collection

The dataset of this research comprises X-ray pictures of osteoporotic and healthy bones. The data was gathered from three distinct hospitals in Baghdad, Iraq. All ethical considerations concerning patient privacy and data security were addressed during the dataset collection.

The data-gathering method commenced solely after obtaining ethical approval from the relevant committees of the three participating hospitals to ensure compliance with ethical norms and patient confidentiality. Participation in the study necessitated patients undergo an X-ray examination to evaluate bone health. Informed consent from patients was secured, and personal data was anonymized to safeguard their privacy.

X-ray pictures from each institution were acquired under uniform conditions with standard radiography equipment to minimize variability that could result from differing imaging techniques. Radiologists in each hospital classified them as 'abnormal' (osteoporosis) or 'normal' (healthy bone structure) according to accepted diagnostic criteria. This hand classification would ensure the precision and dependability of the labels.

The collection comprises 6,310 photos, with 2,750 categorized as 'abnormal' and 3,560 as 'normal'. Figure 2 illustrates the distribution of this dataset. The figure exhibits a little imbalance: more photos are classified as 'normal' than 'abnormal.' Development data was derived from experimental data collected at three distinct hospitals. Every hospital serves a distinct patient demographic exclusive to that facility. This dataset includes numerous demographic factors, such as age, sex, and ethnicity, to enhance model diversity across different patient populations.

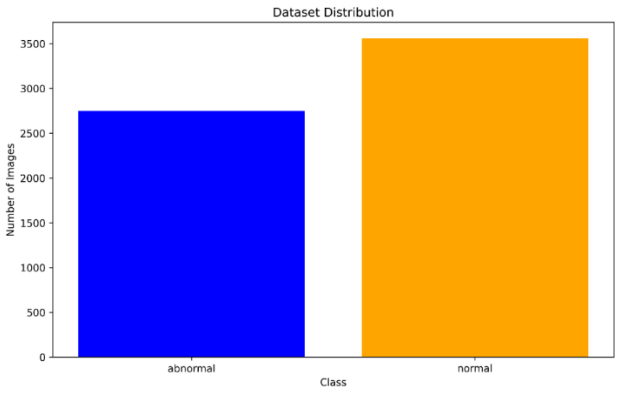


Figure 2. The dataset distribution.

Furthermore, there may be minor discrepancies in the X-ray images attributable to changes in radiographic equipment and settings among different hospitals. The model may be adapted to these fluctuations by incorporating these differences into the training dataset, enhancing its resilience to imaging circumstances. The participation of

numerous radiologists from diverse institutions will guarantee that the classification criteria are impartial to any institution and dependable and uniform across different clinical environments.

3.2 Fuzzy Logic-Based Image Preprocessing

One of the most critical stages of medical image quality enrichment, making it more suitable for further analysis with machine learning models, is image preprocessing by fuzzy logic [26]. The present section describes the applied fuzzy logic techniques as part of our preprocessing pipeline.

Zadeh introduced fuzzy logic in 1965 as a mathematical theory of uncertainty and imprecision, characterizing many real-world applications, including processes related to image processing. Algorithm 1 describes the steps of the Fuzzy Logic preprocessing.

3.2.1 Fuzzy Contrast Enhancement Process

The major steps in our study for image preprocessing based on fuzzy logic are grayscale conversion of the image, histogram equalization, edge detection, and fuzzy logic-based edge enhancement.

1. Grayscale Conversion: Grayscaling each X-ray image facilitates ease of processing and emphasizes the changes in intensity.
2. Histogram Equalization: This technique enhances the contrast of the grayscale image by redistributing the intensities. The equalized image $I_{eq}(x, y)$ is obtained using:

$$I_{eq}(x,y) = \frac{I(x,y) - \min(I)}{\max(I) - \min(I)} \quad (1)$$

Where $I_{eq}(x, y)$ represents the intensity of the pixel at the position (x, y), and $\min(I)$ and $\max(I)$ are the minimum and maximum intensity values in the image, respectively.

3. Edge Detection with Sobel Filter: The Sobel filter is applied to the equalized image to detect edges, resulting in an edge-detected image E:

$$E(x,y) = \sqrt{(G_x^2 + G_y^2} \quad (2)$$

where $G_x$and $G_x$are the gradients in the x and y directions, respectively.

4. Fuzzy Logic-Based Edge Enhancement: The edges are enhanced using fuzzy logic membership functions. Three membership functions—low, medium, and high—are defined for the edge intensities as follows:

$$\mu_{low}(x) = \begin{cases} 1 & if\ x \le a \\ \dfrac{b-x}{b-a} & if\ a < x < b \\ 0 & if\ x \ge b \end{cases} \quad (3)$$

$$\mu_{medium}(x) = \begin{cases} \dfrac{x-a}{b-a} & if\ a < x < b \\ \dfrac{c-x}{c-b} & if\ b < x < c \\ 0 & otherwise \end{cases} \quad (4)$$

$$\mu_{high}(x) = \begin{cases} 0 & if\ x \le b \\ \dfrac{x-b}{c-b} & if\ b < x < c \\ 0 & if\ x \ge c \end{cases} \quad (5)$$

Where a, b, and c are the parameters defining the shape of the membership functions.

The enhanced edges $E_{enhanced}$ are computed as:

$$E_{enhanced}(x,y) = \mu_{low}\big(E(x,y)\big).0 + \mu_{medium}\big(E(x,y)\big).0.5 + \mu_{high}\big(E(x,y)\big).1.0 \quad (6)$$

5. Combining Enhanced Edges with Original Image: The enhanced edges are added to the original grayscale image to produce the final preprocessed image.

$$I_{final}(x,y) = I_{gray}(x,y) + E_{enhanced}(x,y) \quad (7)$$

3.3. Convolutional Neural Networks Model Structure Using Pretrained Architectures

This work uses pre-trained CNN architectures (MobileNetV2, AlexNet, ResNet50V2, or Xception) to classify X-ray images into osteoporotic and healthy bones. These architectures are already trained on large-scale image datasets and can extract rich visual features from the start. We then adapt the pre-trained network to our specific classification task by replacing its top layers with new fully connected (dense) layers designed for binary classification. Below is an outline of our adapted model:

1. Input Layer

a. Accepts images of size 224×224 pixels with three-color channels (RGB).

b. This layer feeds the images into the pre-trained base network.

2. Pretrained Base Model

a. Functions as the core feature extractor.

b. Applies multiple convolutional and pooling operations learned from large image databases to capture edges, textures, and complex patterns.

3. Flattening / Global Pooling

a. Transitions from the pre-trained feature maps to the fully connected layers.

b. Converts 2D feature maps into a 1D vector or performs global average pooling to summarize the spatial data.

4. Dense (Fully Connected) Layers

a. Responsible for high-level reasoning based on extracted features.

b. Includes dropout layers to mitigate overfitting.

c. Ends with a sigmoid output neuron for binary classification (osteoporotic vs. healthy).

By employing a pre-trained model, we greatly reduce the data and training time needed while maintaining strong performance and effectively generalizing to our classification task.

3.3.1 Activation Functions

- ReLU (Rectified Linear Unit): The ReLU activation function is used with the convolutional and dense layers to introduce some non-linearity into this model, enabling the network to learn complex patterns and relationships in data by passing only positive values while setting the negative ones to zero:

$$ReLU(x) = \max(0, x) \quad (8)$$

- Sigmoid: The sigmoid activation function is used in the output layer for binary classification. It maps the output to a probability value between 0 and 1.

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (9)$$

3.3.2 Regularization with Dropout

To prevent overfitting, dropout layers are used after the dense layers. Dropout randomly sets a fraction of input units to zero at each update during training time, which helps prevent the model from becoming too dependent on any single feature and encourages the network to learn more robust features.

Bottom of Form

Algorithm 1: Fuzzy Logic-Based Image Preprocessing
Input: Original X-ray image (original_image)
Output: Preprocessed image (preprocessed_image)
1. Convert the original image to grayscale gray_image = convert_to_grayscale(original_image) 2. Apply histogram equalization to enhance contrast equalized_image = histogram_equalization(gray_image) 3. Apply Sobel filter to detect edges edges = sobel_filter(equalized_image) 4. Define fuzzy membership functions for edge intensities Define membership function low: 4.1. if edge_intensity <= a then low = 1 else if a < edge_intensity < b then low = (b - edge_intensity) / (b - a) else low = 0 4.2. Define membership function medium: if a < edge_intensity < b then medium = (edge_intensity - a) / (b - a) else if b < edge_intensity < c then medium = (c - edge_intensity) / (c - b) else medium = 0 4.3. Define membership function high: if edge_intensity <= b then high = 0 else if b < edge_intensity < c then high = (edge_intensity - b) / (c - b) else high = 1 5. Apply fuzzy logic to enhance edges enhanced_edges = zeros_like(edges) 5.1. for each pixel in edges: low = compute_low_membership(edges[pixel]) medium = compute_medium_membership(edges[pixel]) high = compute_high_membership(edges[pixel]) enhanced_edges[pixel] = low * 0 + medium * 0.5 + high * 1.0 6. Combine enhanced edges with the original grayscale image preprocessed_image = gray_image + enhanced_edges preprocessed_image = clip(preprocessed_image, 0, 1) 7. Convert the preprocessed image back to RGB format preprocessed_image_rgb = convert_to_rgb(preprocessed_image)
return preprocessed_image_rgb

By integrating fuzzy logic-based preprocessing with deep learning models, our proposed method enhances the quality of X-ray images, improving the accuracy and robustness of osteoporosis detection.

3.4 Data Augmentation

Data augmentation is one of the most important techniques in machine learning and deep learning. It aims at enhancing the model's generalizing power by artificially increasing the scale of the training dataset. Different transformations applied to the training images will generate many variants of the original images. In this way, it avoids the overfitting of the model to some extent and enhances its robustness toward real-world data. Our model applied data augmentation techniques to the osteoporotic versus healthy bone X-ray images. The following data augmentation techniques were applied:
1. Rescaling: This normalizes image pixel values to a certain range, usually between 0 and 1. This normalization step is very important because it accelerates the convergence of a neural network during training as the inputs are standardized.
2. Shear Transformation: Shear transformation is a process of image distortion where one of the parts is displaced in a certain direction. This transformation will make the model invariant to small image distortions since it is impossible to have an exact match of imaging conditions.
3. Zoom Transformation: In this technique, the image is scaled randomly by zooming in or out. This concept will help our model learn and eventually identify objects of different scales, improving its generalization capacity across other images with different resolutions and sizes.
4. Rotation: this random image rotation by any degree within a specified range will ensure that the model can classify an image independently of its orientation, which is important, especially for medical images, where orientations occur unilaterally.
5. Width and Height Shifts: This width and height shift refers to the translation of the image left right or up down. Given this transformation, the model becomes invariant to the position of objects in the images; hence, it can detect features as long as they are not perfectly centered in the images.
6. Horizontal Flip: This is a method of flipping in the vertical axis of the image. It works on some medical images where orientation does not affect the diagnostic features, providing more variations for tripling learned features from the model.
7. Fill Mode: Fill mode is how the newly introduced pixels are filled due to an image transformation. For example, 'nearest' fill mode fills with the nearest pixel values to the gapped parts of a transformed image so that Realistics are maintained wherever possible.
These data augmentation techniques ensured that our CNN model was trained on a diverse and varied image dataset and increased the efficiency of our model in accurately classifying osteoporotic ally affected bones against healthy ones, leading to a robust, generalizable model.

3.5 Call-backs and Techniques to Avoid Overfitting

To ensure the robustness and generalizability of our Convolutional Neural Network (CNN) model, we implemented several callbacks and techniques to avoid overfitting. Overfitting occurs when a model learns not only the underlying patterns in the training data but also the noise and specific details that do not generalize well to new, unseen data. Here, we discuss the callbacks and regularization techniques used to mitigate this issue. The Callbacks Used are as follows:

ReduceLROnPlateau: The ReduceLROnPlateau callback keeps track of a certain metric and reduces the learning rate upon plateauing this monitored metric. It is related to fine-tuning the model, allowing it to converge more appropriately in case improvements have reached their plateau.

EarlyStopping: This callback allows the training process to stop when the monitored metric — most often validation loss — has stopped improving for the specified number of epochs, thus preventing the model from overfitting; now, training will stop after the performance on the validation set deteriorates.

ModelCheckpoint: The ModelCheckpoint callback saves the model weights at specified intervals. Saving the best model weights during training ensures the model can be restored to its best-performing state if needed.
TensorBoard: The TensorBoard callback enables real-time visualization of training metrics such as loss and accuracy, helps monitor the training process, and identifies any overfitting signs.

The following techniques were used to avoid overfitting:

Dropout: Dropout is a regularization technique in which a fraction of the neurons is randomly set to zero during each training step, which prevents the network from becoming too reliant on any single neuron and encourages the model to learn features that are more robust.

Data Augmentation: Data augmentation involves creating new training samples by applying random transformations to the existing data, increasing the diversity of the training set, and helping the model generalize new data better. Techniques used include rescaling, shear transformation, zoom transformation, rotation, width and height shifts, and horizontal flips.

Batch Normalization: Batch normalization normalizes the activations of each layer to have zero mean and unit variance, stabilizing and accelerating the training process and making the model more resilient to overfitting.
Class Weights: When dealing with imbalanced datasets, class weights can give more importance to the minority class, which helps the model pay more attention to underrepresented classes and improves its generalization ability.

These callbacks and techniques guarantee that our CNN model is accurate and generalizes well to new, unseen data. We are diminishing the overfitting risks by decreasing the learning rate if needed, halting training at the right time, saving the best model, visualizing the training progress, and applying regularization techniques; hence, a more robust and reliable model for osteoporosis detection.

3.6 Loss Function Used

We trained our CNN in osteoporosis detection with binary cross-entropy loss. Binary cross-entropy loss is defined as a measure of the performance of a classification model whose output is between 0 and 1. The binary cross-entropy loss shall be defined by:

$$Binary\ Cross - Entropy\ Loss = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)] \qquad (10)$$

Where:
N is the number of samples.
y_i is the true label of the iii-th sample (1 for osteoporotic, 0 for healthy).
p_i is the predicted probability of the iii-th sample being in a positive class (osteoporotic).
The loss function calculates the difference between the actual and predicted probabilities and takes the average over all samples. The goal of training is to minimize this loss, thereby improving the model's accuracy in predicting the correct class.

The combination of binary cross-entropy loss with an Adam optimizer aids in the minimization of the loss function for better performance attainment. Using a binary cross-entropy loss function, we ensured that our CNN model effectively learns about osteoporotic vs. healthy bones and would present a very accurate and reliable prediction in practical applications.

3.7 Model Evaluation

In order to ensure that it is reliable and effective in classifying images of osteoporotic and healthy bone, a quality-checking process needs to be performed for the Convolutional Neural Network model. This section presents all evaluation metrics and methods for assessing the model's performance.

3.7.1 Accuracy

Accuracy is a fundamental metric for classification tasks, measuring the proportion of correctly classified instances out of the total instances. It provides a general overview of the model's performance. The accuracy is calculated as follows:

$$Accuracy = \frac{(TP+TN)}{(TP+FP+FN+TN)} \qquad (11)$$

Where TP is true positive,
TN is true negative,
FP is false positive, and FN is false negative.

3.7.2 Precision

Precision measures the ratio of true positive predictions to the total predicted positives. It indicates the accuracy of the positive predictions made by the model, ensuring that the identified osteoporotic cases are indeed correct. It is calculated as follows:

$$Precision = \frac{TP}{(TP+FP)} \qquad (12)$$

3.7.3 Recall (Sensitivity)

Recall, or sensitivity, measures the ratio of true positive predictions to the total actual positives. It evaluates the model's ability to identify all relevant instances, ensuring it correctly detects most osteoporotic cases. It is calculated as follows:

$$Recall = \frac{TP}{(TP+FN)} \quad (13)$$

3.7.4 F1-Score

The F1-Score is the harmonic mean of precision and recall, providing a single metric that balances both. It is particularly useful when the class distribution is imbalanced. It is calculated as 2 * (precision * recall) / (precision + recall).

$$F1 - score = \frac{Precision*Recall}{(Precision+Recall)} \quad (14)$$

3.7.5 Confusion Matrix

The confusion matrix provides a detailed breakdown of the model's performance by showing the counts of true positives, true negatives, false positives, and false negatives, helping understand the model's errors and their impact.

3.7.6 ROC Curve and AUC

The Receiver Operating Characteristic (ROC) curve plots the true positive rate (recall) against the false positive rate, illustrating the trade-off between sensitivity and specificity at various threshold settings. The Area Under the ROC Curve (AUC) provides a single value summarizing the model's ability to distinguish between classes, with a higher value indicating better performance.

AUC-ROC is an area under the receiver operating characteristic curve that has become a popular performance measure for classification problems at different threshold settings. ROC is a probability curve portraying TPR against FPR with varying threshold values. The AUC, therefore, describes how well the model can separate the classes.

AUC provides a single value comparable across different models. Unlike accuracy, AUC does not depend upon any specific threshold; hence, it is a more robust metric for evaluating model performance. Furthermore, it balances sensitivity and specificity: AUC considers both TPR and FPR and hence gives a balanced evaluation of the model regarding its prowess in identifying positive and negative instances. By calculating and analyzing the AUC, we can assess whether our CNN model can distinguish between osteoporotic and healthy bone images that can be relied upon in practical applications.

4. Results and Discussion

In this paper, a thorough evaluation was conducted on four pre-trained convolutional neural networks—AlexNet, MobileNetV2, ResNet50V2, and Xception—to classify bone X-ray images into osteoporotic (abnormal) or healthy (normal) categories. Each model was examined twice, first using only standard preprocessing (resizing and normalization) and then applying a fuzzy contrast enhancement step designed to sharpen edges and accentuate local differences in grayscale intensity. Although the primary aim was to investigate whether fuzzy preprocessing could further improve the already-strong performance of pre-trained networks, the findings shed light on how architecture depth, data characteristics, and edge highlighting interact to shape final classification outcomes.

Table 2: Performance Metrics without Fuzzy Logic Preprocessing

Model	Validation Accuracy	Validation Loss	Precision (Abnormal)	Recall (Abnormal)	Precision (Normal)	Recall (Normal)	F1 (Abnormal / Normal)
AlexNet	0.9876	0.0563	1.00	0.97	0.98	1.00	0.99 / 0.99
MobileNetV2	0.9897	0.0375	0.99	0.99	0.99	0.99	0.99 / 0.99
ResNet50V2	0.9968	0.0079	1.00	0.99	1.00	1.00	1.00 / 1.00
Xception	0.9842	0.0519	0.99	0.97	0.98	0.99	0.98 / 0.99

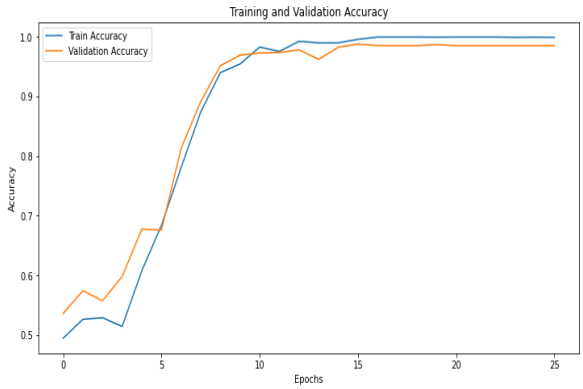
A close inspection of Table 1, which compiles the models' performance without fuzzy logic, reveals remarkably high accuracies for every network. ResNet50V2, in particular, approaches near-perfect classification, surpassing 99.6% accuracy and recording a minimal validation loss that reflects an exceptionally robust internal representation of the data. MobileNetV2 also achieves high reliability, with precision and recall values that hover around 0.99. Xception and AlexNet, while marginally behind in raw numerical scores, nonetheless maintain accuracy levels well above 98%. These results underscore the potency of transfer learning for medical imaging applications and indicate that the pre-trained feature extractors are highly effective in isolating the critical skeletal cues relevant to osteoporosis identification.

Table 3: Performance Metrics with Fuzzy Logic Preprocessing

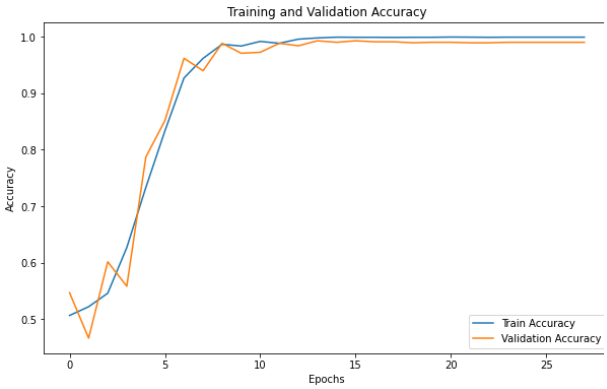
Model	Validation Accuracy	Validation Loss	Precision (Abnormal)	Recall (Abnormal)	Precision (Normal)	Recall (Normal)	F1 (Abnormal / Normal)
AlexNet	0.9912	0.0585	1.00	0.98	0.99	1.00	0.99 / 0.99
MobileNetV2	0.9889	0.0445	0.99	0.98	0.99	0.99	0.99 / 0.99
ResNet50V2	0.9905	0.0386	1.00	0.98	0.98	1.00	0.99 / 0.99
Xception	0.9810	0.0699	0.99	0.97	0.97	0.99	0.98 / 0.98

Moving from Table 1 to Table 2, which presents the same metrics for the fuzzy-preprocessed experiments, reveals the subtle nuances that fuzzy logic can introduce. AlexNet, for instance, shows a modest but consistent improvement in validation accuracy, increasing from approximately 98.76% to 99.12%. This gain is paired with enhanced recall in the abnormal (osteoporotic) category, suggesting that sharper edges and heightened local contrast enable the model to detect better minute signs of bone degeneration that might go unnoticed. Because AlexNet is shallower and lacks the extensive feature maps of more modern architectures, the additional signal clarity provided by fuzzy preprocessing seems to compensate for its relatively limited representational capacity.
In contrast, models such as ResNet50V2 and Xception exhibit minimal or even slightly negative changes when fuzzy logic is introduced, an outcome that becomes more intuitive once one considers the depth and sophistication of their pre-trained layers. These advanced architectures likely already incorporate multiple stages of learned edge and texture detection, which can overshadow or even conflict with external contrast manipulations. Consequently, their overall accuracies remain at or near their baseline levels, hovering between 98% and 99% in most configurations, regardless of whether the images undergo fuzzy preprocessing. Although one might initially expect fuzzy-enhanced edges to benefit all networks equally, the near-ceiling performance of deeper models leaves little room for measurable improvement.

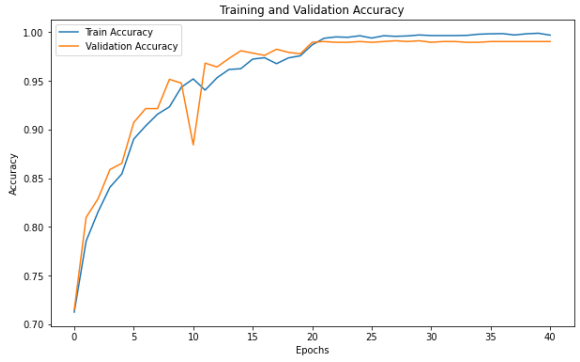
The interplay between these metrics is further clarified when correlating the tables with the visual outputs. The smooth convergence curves in the training and validation phases (Figure 3) confirm that the models readily adapt to the dataset. At the same time, confusion matrices demonstrate that misclassifications are rare across all runs. In scenarios where AlexNet's baseline approach showed occasional misses in the abnormal category, the fuzzy-enriched input alleviates some errors by focusing the model's attention on delicate micro-fractures or subtle density variations along bone surfaces. Conversely, for ResNet50V2 and others, the same enhancement has negligible impact; extensive skip connections and complex residual blocks likely absorb any improvement that an external sharpening might otherwise provide, preserving their near-perfect classification rates in either configuration. These outcomes underscore how model complexity and data preprocessing work in tandem. When the architecture is comparatively simple and relies heavily on explicit edge information, fuzzy logic proves advantageous for highlighting relevant structures and reducing ambiguity in grayscale images. When the network is deeper and embedded with powerful multiscale feature learning, additional edge sharpening scarcely alters the training or final classification metrics. Clinically, all models—aided by fuzzy preprocessing or not—demonstrate suitability as diagnostic aids, as they consistently produce near-ideal precision, recall, and f1-scores.



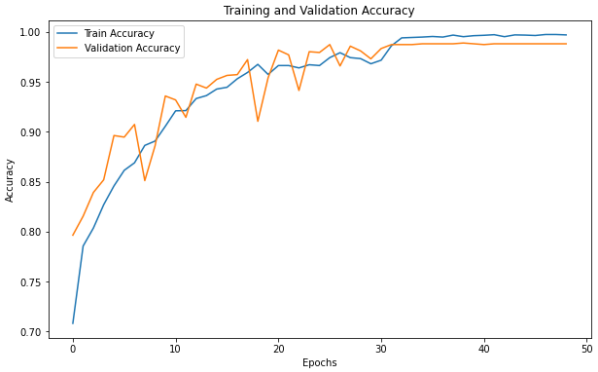
AlexNet



AlexNet with Fuzzy

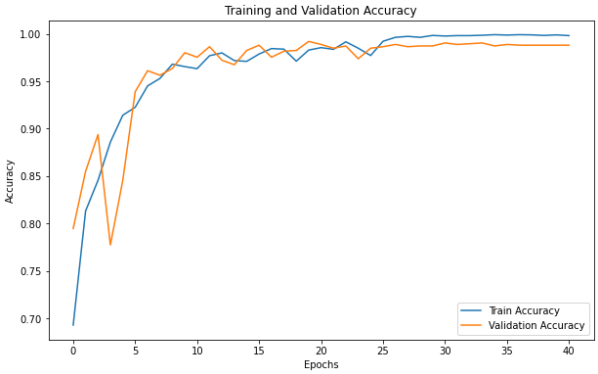


MobileNetV2



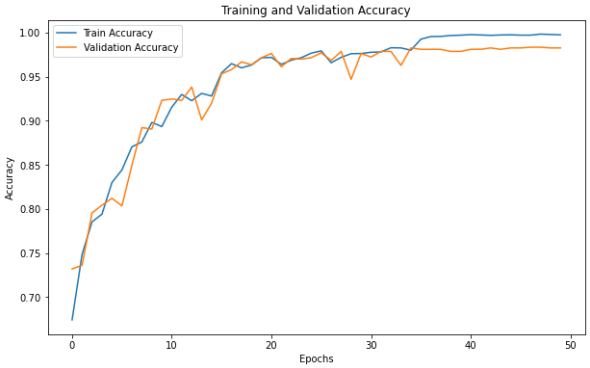
MobileNetV2 with Fuzzy

ResNet50V2



ResNet50V2 with Fuzzy

Xception



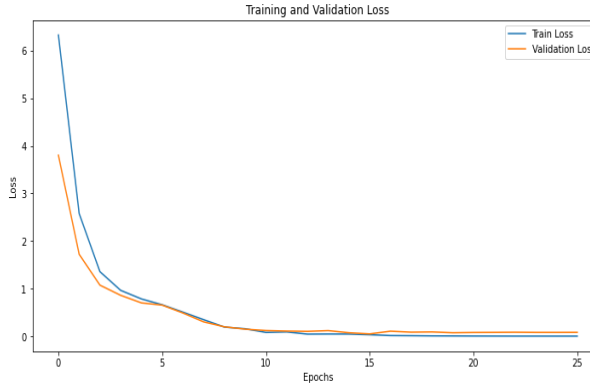
Xception with Fuzzy

Figure 3. The training and validation accuracy curves

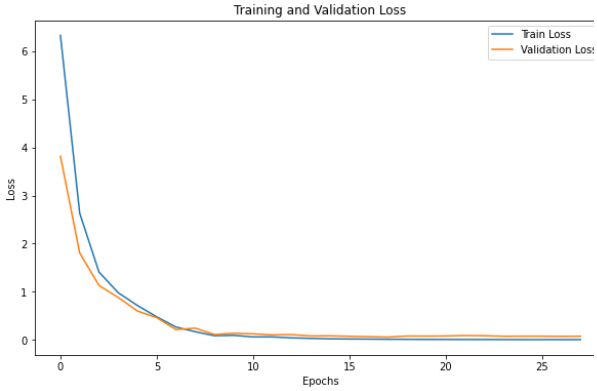
Nevertheless, the slight boost in AlexNet's performance when introducing fuzzy logic speaks to the utility of carefully tailored preprocessing in resource-limited settings or when older architectures must be used. The numerical comparisons in Tables 1 and 2 confirm that pre-trained CNNs excel at detecting bone density anomalies in standard X-ray images, a conclusion further reinforced by the consistently steep ROC curves and low validation losses. The additional insight gleaned from fuzzy preprocessing underlines how the choice of architecture and input enhancement strategies must be balanced, considering the potential for shallow networks to benefit more from external edge highlighting. These findings suggest that fuzzy logic may not universally boost accuracy in every pre-trained CNN, but it can still confer a clinically significant improvement for models less endowed with deep hierarchical layers.

The training and validation accuracy curves (Figure 3) offer an initial insight into how effectively the models learn from the dataset and how quickly they converge. Across all networks, the curves rise steeply within the first 10–15 epochs, and then gradually plateau at high accuracy levels ($\geq 98\%$). This rapid convergence highlights the potency of transfer learning: because these models were trained on extensive image databases (e.g., ImageNet), they already possess robust feature extraction capabilities, requiring minimal fine-tuning to adapt to the osteoporotic vs. healthy bone task.

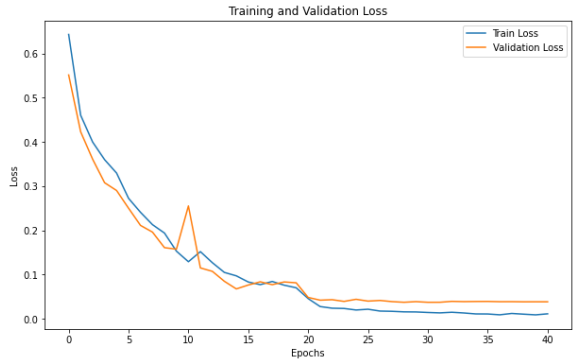
Concurrently, the training and validation loss curves (Figure 4) confirm that the models descend to relatively low loss values. ResNet50V2 typically exhibits the most dramatic drop, reflecting its deep residual structure that preserves the integrity of gradients during backpropagation. Some minor fluctuations are observed in certain fuzzy-preprocessed runs (most noticeably with Xception), yet the losses stabilize at sufficiently low levels to yield strong classification metrics. One may infer that fuzzy preprocessing slightly shifts the input distribution, leading to these small, short-lived oscillations in the loss.



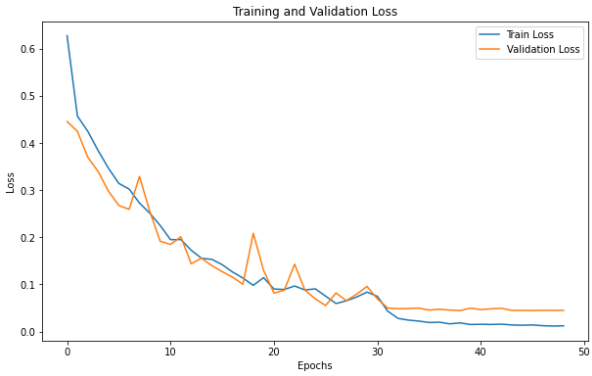
AlexNet



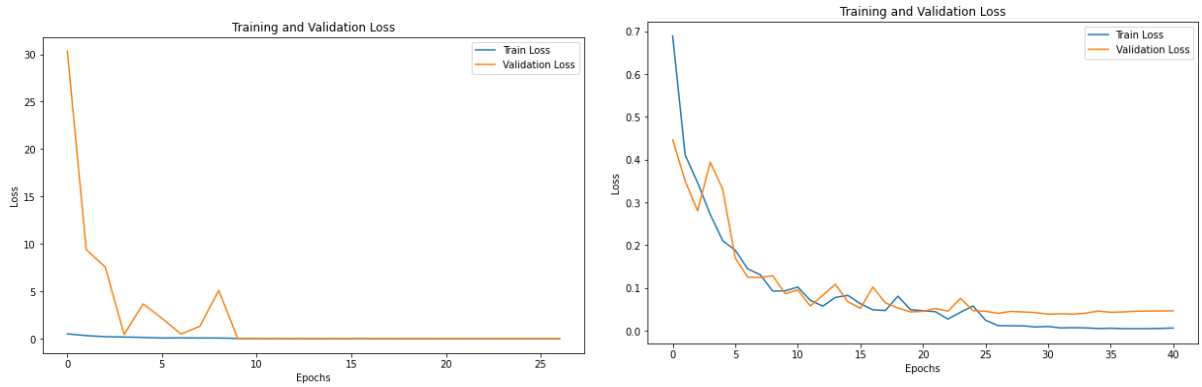
AlexNet with Fuzzy



MobileNetV2

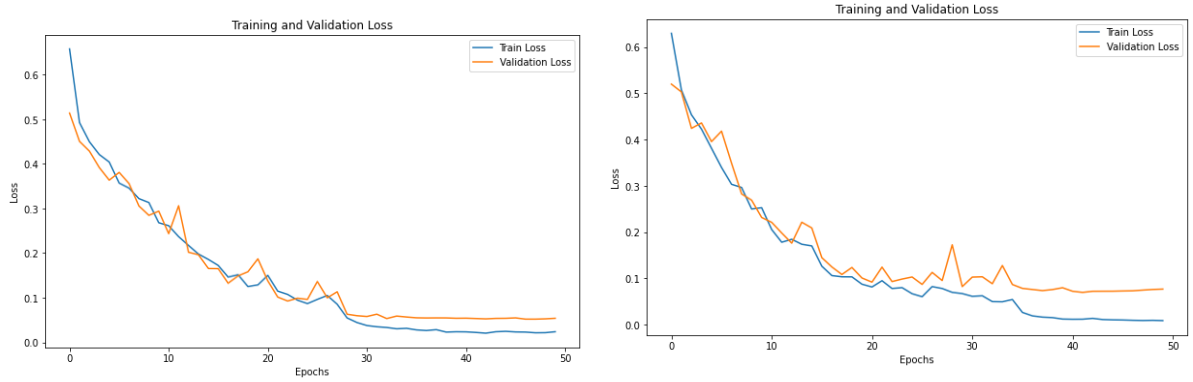


MobileNetV2 with Fuzzy



ResNet50V2

ResNet50V2 with Fuzzy



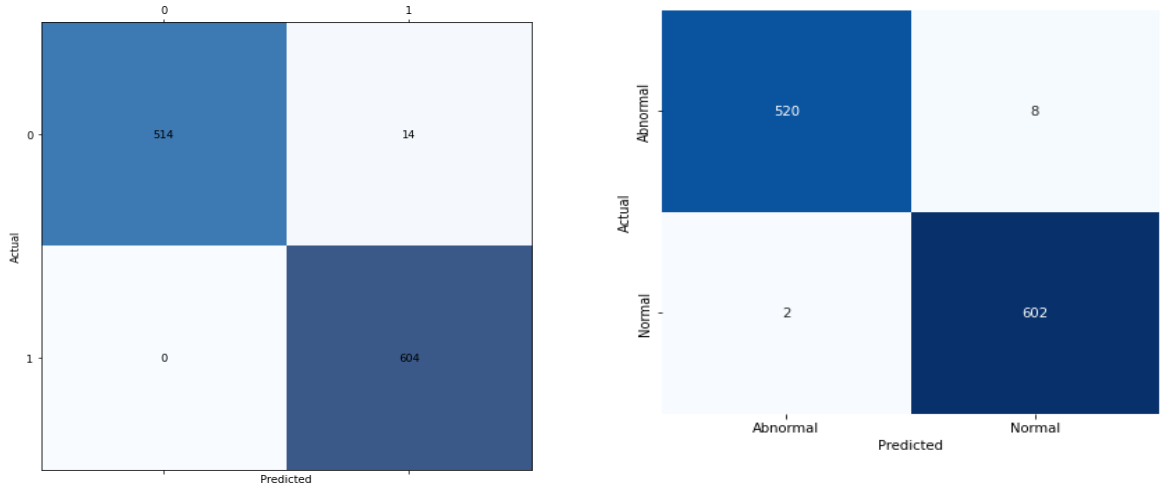
Xception

Xception with Fuzzy

Figure 4. The training and validation loss curves

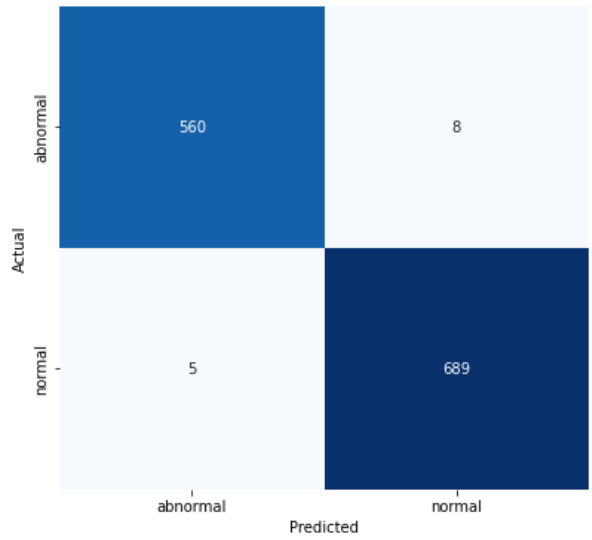
AlexNet—an older and shallower architecture—notably benefits more from fuzzy logic than deeper, more advanced models. The training and validation accuracy curves for AlexNet are lower at the early epochs, but once fuzzy processing is in place, the network reaches a slightly higher final accuracy. This improvement reflects the advantage of enhanced edge clarity and local contrast for a model that lacks the refined hierarchical filters present in deeper architectures like ResNet50V2.

The confusion matrices and classification reports (summarized in Tables 1 and 2 and visualized in Figures 5) provide a deeper look at model performance per class. All four architectures, whether using fuzzy logic or not, exhibit exceptionally high precision and recall—commonly above 0.97 and often reaching 1.00. These metrics indicate that the networks rarely mislabel osteoporotic bones as healthy or vice versa.

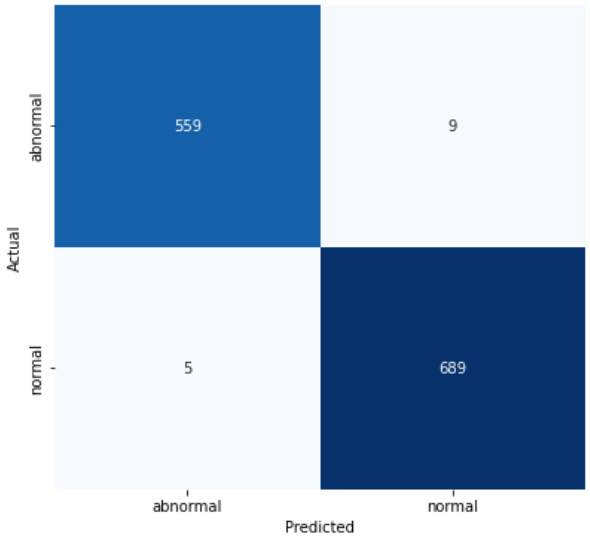


AlexNet

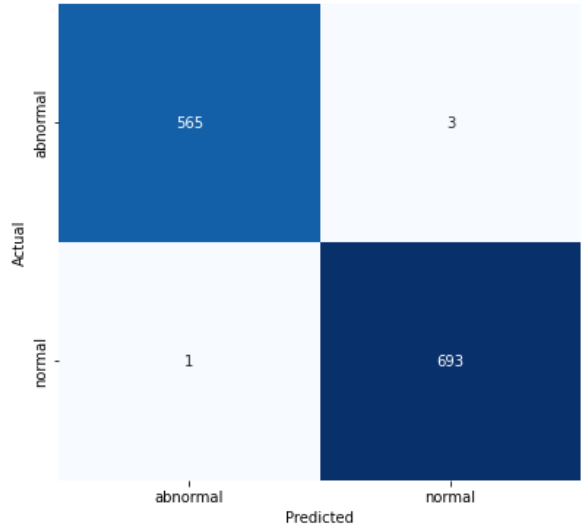
AlexNet with Fuzzy



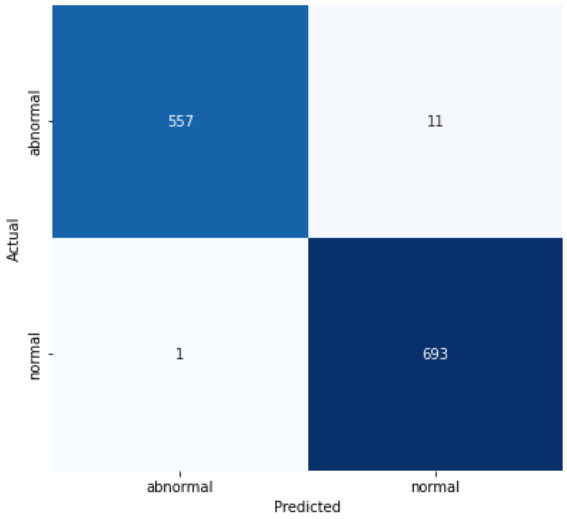
MobileNetV2



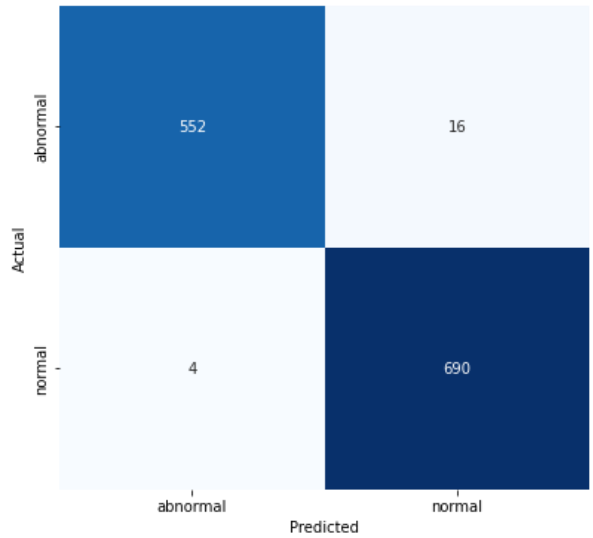
MobileNetV2 with Fuzzy



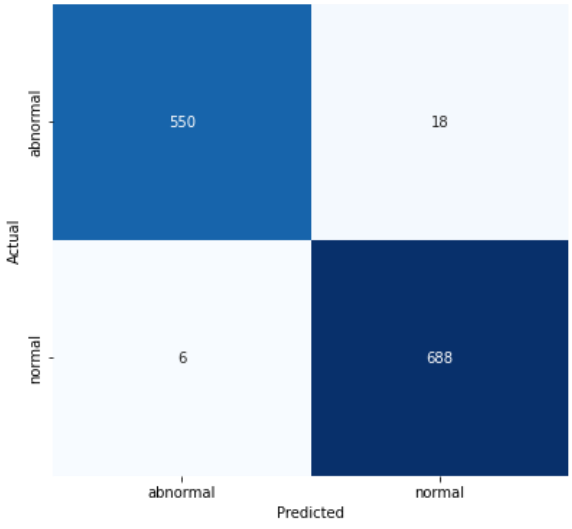
ResNet50V2



ResNet50V2 with Fuzzy



Xception



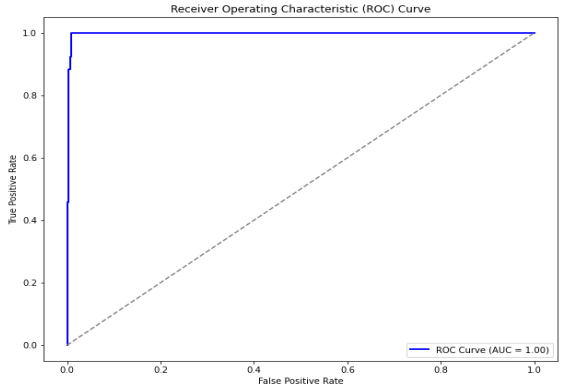
Xception with Fuzzy

Figure 5. The confusion matrices

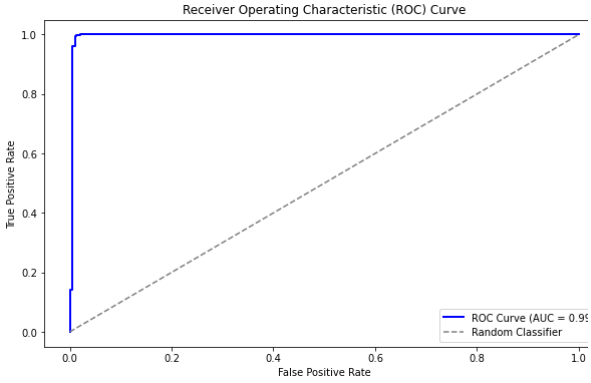
When focusing on the confusion matrices for AlexNet, it becomes evident that introducing fuzzy logic benefits recognition of the "Abnormal" category; misclassifications in which truly osteoporotic images are labeled as "Normal" decline noticeably. Since AlexNet relies heavily on the quality and clarity of low-level features, such as edges and gradients, the enhanced contrast and sharper details furnished by fuzzy preprocessing help the model discern subtle bone irregularities associated with osteoporosis.

In contrast, deeper architectures—MobileNetV2, ResNet50V2, and Xception—already incorporate sophisticated feature extraction and transformation stages, making them more robust to slight variations in local contrast. The confusion matrices for these models remain nearly perfect even without additional preprocessing, with few off-diagonal entries and near-perfect classification metrics. Hence, fuzzy logic tends to have a negligible (and sometimes slightly negative) impact on their final accuracy. This outcome underscores that while fuzzy-based contrast improvements can benefit shallower or older networks, advanced CNNs might not significantly gain from external image enhancements, particularly when the source images are already of adequate quality.

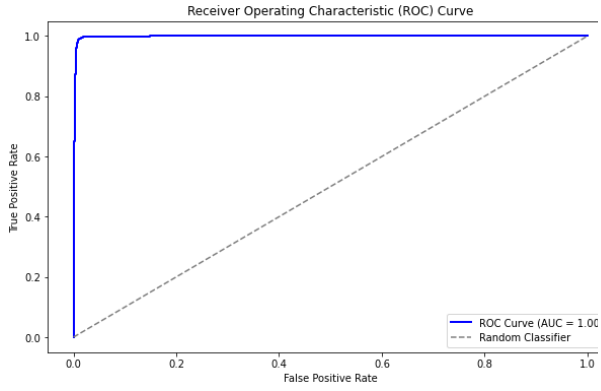
Further corroborating these findings, the ROC curves plotted in Figure 6 reveal that baseline and fuzzy-preprocessed models achieve extremely high AUC values, frequently approaching or reaching 1.00. In a clinical context, an AUC near 1.00 signifies near-flawless separation between osteoporotic and healthy bone X-rays under various classification thresholds. For conditions like osteoporosis, minimizing false negatives is critical; a missed diagnosis can have serious consequences. The consistently steep ROC curves across all models and preprocessing conditions highlight a reliable capacity to capture and discriminate the patterns most indicative of bone density deterioration.



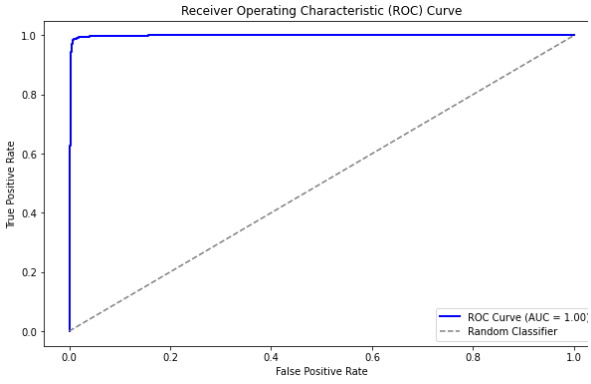
AlexNet



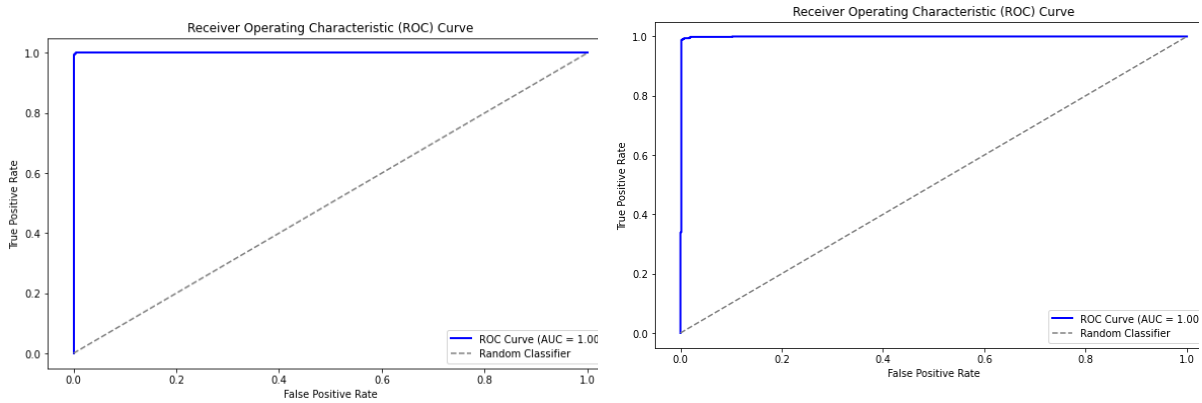
AlexNet with Fuzzy



MobileNetV2

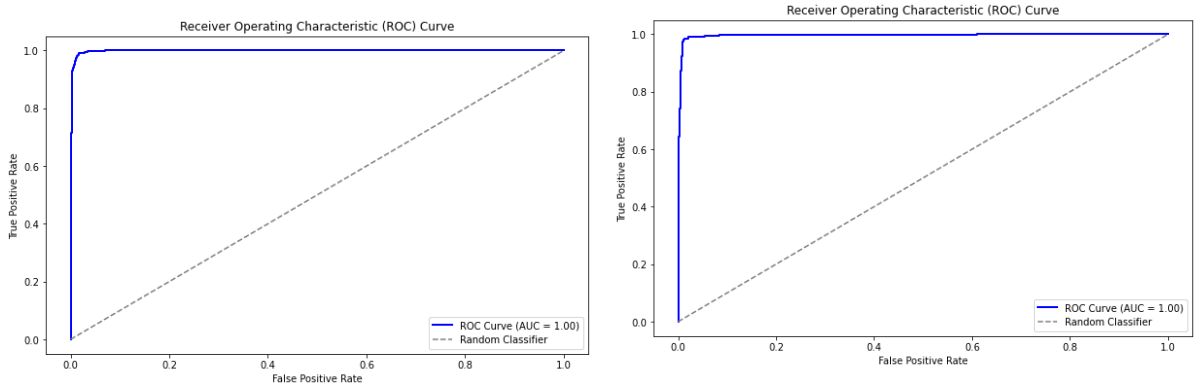


MobileNetV2 with Fuzzy



ResNet50V2

ResNet50V2 with Fuzzy



Xception

Xception with Fuzzy

Figure 6. The ROC curves

4.1 Discussion of Fuzzy Logic's Role

While fuzzy preprocessing may not universally improve performance in deeper networks, its effect on AlexNet underscores the importance of image quality and clarity in the learning process of shallower architectures. Modern pre-trained models have numerous layers capable of implicitly learning edge, texture, and contour representations. For them, an external sharpening or contrast boost confers only marginal gains or even inconsequential changes in metrics. By contrast, AlexNet's depth that is more limited and smaller filter banks see tangible improvements when local detail is more pronounced, allowing the network to distinguish subtle degenerative signs in bone structures.

Collectively, these outcomes underline how critical model capacity and data quality are in designing an optimal osteoporosis detection framework. When employing advanced models like ResNet50V2 or Xception, the baseline performance is already near the ceiling, leaving little room for further improvement. Conversely, fuzzy logic remains a viable strategy to enhance important edge features for architectures or datasets where raw images may be excessively noisy, low in contrast, or not well-illuminated.

4.2 Concluding Observations

The results across training/loss curves, confusion matrices, classification metrics, and ROC analyses demonstrate that transfer learning with deep CNNs offers a powerful approach to diagnosing osteoporosis from X-ray images. Accuracy values consistently exceed 98%, with ResNet50V2 notably surpassing 99% in many instances. Fuzzy preprocessing, while not universally beneficial, provides a modest accuracy boost for AlexNet and underscores the adaptability of CNN-based pipelines to various image enhancement methods. These findings hold significant potential for clinical application, as near-perfect classification metrics suggest that a deep learning–assisted system could serve as a dependable second opinion for radiologists or be employed in automated screening environments.

Nevertheless, these results highlight the value of tailoring preprocessing steps to the specific CNN in use. Future work might probe additional edge or contrast enhancement strategies, investigate data augmentation tailored to bone imaging, or explore interpretability techniques like Grad-CAM to pinpoint precisely which regions of the X-

ray drive classification decisions. In all cases, the consistency and robustness of these outcomes underscore the promise of combining pre-trained networks with targeted preprocessing, thus paving the way for improved efficiency and accuracy in medical image analysis.

The training and loss curves, confusion matrices, and ROC curves (Figures 3–6) collectively validate the numerical story told by Tables 1 and 2. While all architectures achieve excellent performance, the improved metrics for AlexNet with fuzzy logic highlight how sharpening edges in X-ray images can help a less complex network recognize subtle signs of osteoporosis. Conversely, the negligible changes seen for MobileNetV2, ResNet50V2, and Xception reflect that these models can already capture complex features due to their depth and pre-trained weights.

Ultimately, both tables' high precision, recall, and F1-scores reaffirm the potential for CNN-based systems to function as reliable screening or diagnostic aids. Near-ceiling performance is particularly important in medical imaging contexts, where the cost of false negatives can be clinically significant. Although fuzzy logic does not universally elevate accuracy, its selective benefit for AlexNet underscores the value of tailoring preprocessing to the network architecture and dataset characteristics.

4.3 Comparative Analysis of Our Results with Recent Works.

Our research in terms of osteoporosis detection using a convolutional neural network with fuzzy logic preprocessing has huge developments vis-à-vis traditional methods. In this section, we have tried to compare our results with those from recent works in this field by delving deep into their methodologies, findings, and efficacy of approaches. Table 3 shows key features of our work and recent studies.

Table 4: A comparison of the proposed method with the recent studies.

Study	Methodology	Accuracy (%)	Key Advantages	Key Limitations
Our Study	ResNet50V2	99.68	High accuracy, robust preprocessing, detailed evaluation metrics (Precision, Recall, AUC)	Requires preprocessing
[19] (2023)	CNN and KNN on X-ray films	97.57	High accuracy with simple CNN	Limited dataset size, less complex preprocessing
[27](2023)	Signal-processing with CNN	100	Integrated signal attributes	Dependency on signal processing attributes
[17] (2021)	Review of ML in osteoporosis management	-	Highlights ML advances	Lacks experimental validation
[28] (2020)	Semi-supervised ML with XGBoost and CNN	78	Combines semi-supervised and supervised	Accuracy lower than supervised approaches
[29] (2022)	Comparison of various ML algorithms	-	Identifies best-performing algorithms	Did not explore preprocessing techniques
[30] (2020)	CNNs and SSM on dental panoramic radiographs	-	Outperforms traditional methods	Specific to dental images
[31] (2021)	Transfer learning with pre-trained CNNs	96	Effective use of transfer learning	Focused on osteosarcoma
[32](2023)	Comparison of deep learning models	93.4	High accuracy	Did not explore hybrid models or preprocessing

The approach using ResNet50V2 gives an accuracy of 0.9912. Hence, this approach outperforms the traditional CNN models in terms of performance and lays down very detailed evaluation metrics, which include precision, recall, and AUC elaborative values for the comprehension of model performance to prove that the model is robust and reliable for medical diagnoses.

Most recent studies have not reported high accuracy, precision, recall, or AUC (which informs about balanced sensitivity and specificity) after attainment. For example, [19] achieved 97.57% accuracy using just a simple CNN and KNN applied to X-ray films, and [27] reported 100% accuracy via signal-processing techniques combined with CNN. However, these studies did not provide detailed metrics that might give a clue regarding the diagnostic reliability of the model.

More exactly, the table emphasizes some additional inherent benefits of our approach in the preprocessing. For example, fuzzy logic preprocessing enhances the model's capability to detect subtle features in images taken by medical diagnostic tools, enhancing diagnostic accuracy and reducing misclassification rates. These are all topics not explored by [29], where the first focuses on comparing different machine learning algorithms, while the second uses transfer learning.

While many recent studies have made big strides in the osteoporosis detection problem using different machine learning techniques, our study has a distinct edge on all these methods by a robust and detailed evaluation framework within which fuzzy logic preprocessing is integrated, along with comprehensive reporting of its assessment metrics, therefore making the model very accurate and hence reliable for clinical applications.

5. Conclusion

This study demonstrates that deep convolutional neural networks, fine-tuned from pre-trained models, can classify osteoporotic versus healthy bone X-ray images with striking accuracy and reliability. Even older architectures, such as AlexNet, attain high levels of performance once trained on the dataset. However, they benefit more noticeably from fuzzy logic preprocessing by sharpening edges and enhancing local contrast. Fuzzy processing highlights subtle skeletal variations—small cracks or density differences—that might otherwise go undetected, thereby increasing AlexNet's classification confidence. In contrast, deeper models such as ResNet50V2, MobileNetV2, and Xception, endowed with extensive layers and powerful feature extraction capabilities, already operate near the theoretical accuracy ceiling, with minimal change when fuzzy preprocessing is introduced.

Notwithstanding these promising results, important limitations remain. While sufficient for proof of concept, the dataset may not capture the full spectrum of bone conditions encountered in diverse clinical contexts. Further, the evaluation focuses on a binary classification scheme without addressing intermediate or multifactorial conditions. Another concern is the interpretability of network predictions, which—despite high accuracy—are often regarded as "black box" outputs. Therefore, Future work should include larger, more heterogeneous datasets, incorporating additional imaging modalities and interpretability tools that illuminate model decision-making. Exploring adaptive or context-aware fuzzy logic preprocessing is vital, potentially elevating classification performance for deeper networks and enhancing overall diagnostic confidence in real-world clinical applications.

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Conflicts of Interest: “The authors declare no conflict of interest.”

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