Enhancing Osteoporosis Detection with Hybrid Fuzzy Logic Preprocessed Convolutional Neural Networks

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Abstract

This paper applies deep learning techniques in classifying X-ray images to detect osteoporosis. Osteoporosis, a bone weakness condition, increases the risk of fractures; therefore, accurate early diagnosis is essential in management. We have designed a hybrid method called Fuzzy Logic Preprocessed Convolutional Neural Network, or FLPCNN, wherein fuzzy logic is used at the preprocessing step to handle uncertainty and imprecision of features extracted from X-ray images. This paper used a dataset of X-ray images, and the FLPCNN model was applied, classifying them into osteoporotic and non-osteoporotic with quite an accuracy of 100%. Fuzzy logic preprocessing combined with Convolutional Neural Networks (CNN) enhances the model's classification accuracy and interpretable decisions. The proposed method would be a new way to cut down diagnostic errors and improve patient outcomes, opening ways for further research into deep learning techniques applied in healthcare.

Keywords: Osteoporosis Detection; X-ray Classification; Deep Learning; Convolutional Neural Networks, Fuzzy Logic

1. Introduction

Osteoporosis and osteoporotic fractures have become global health issues of major concern, especially with the growth in the aging population. By 2024, approximately 14 million individuals in the United States over 50 are expected to have osteoporosis. One in three women aged over 50 will experience an osteoporosis-related fracture. Therefore, screening for osteoporosis is clinically important for fracture prevention. The US Preventive Services Task Force recommends routine screening for women aged 65 and older [1]. Central dual-energy X-ray absorptiometry (DXA) is globally accepted as the reference standard for diagnosing osteoporosis. However, DXA's application is limited by its low availability, often requiring patients to travel to referral centers. Other barriers to DXA screening include knowledge deficits and declining financial incentives, resulting in nearly half of female Medicare beneficiaries in the United States not undergoing DXA testing. The situation is even more pronounced in China, with only 4.3% of women aged 50 and older having undergone testing, particularly in rural areas where the rate is only 1.9%. Additionally, DXA measurements can be influenced by fat and do not fully consider bone geometry, size, and microstructure. Consequently, DXA is underutilized, and osteoporosis remains underdiagnosed, highlighting the need for safe and cost-effective alternatives [2].

Conventional X-ray devices, widely available in almost any hospital worldwide, offer potentially useful information about bone mineral density (BMD). Retrieving BMD data from lumbar spine X-ray scans ordered for other indications requires no additional cost, patient time, or radiation exposure. These data can be retrospectively acquired, potentially expanding population-screening efforts for osteoporosis. However, assessing BMD on lumbar spine X-ray images by inspection is challenging [3]. Deep learning, especially Convolutional Neural Networks (CNN), has recently been very promising for medical imaging applications, including osteoporosis detection. CNN applied to various problems of image classification in medicine has been successful because it can learn and extract from the raw images; therefore, several studies have focused on the potential use of CNNs for

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classifying osteoporotic vertebral fractures and assessing bone mineral density from X-ray images. These methods thus often suffer from the intrinsic uncertainties and imprecisions existing in medical images, which can affect model performance [4].

In this regard, we have proposed a new technique called the Fuzzy Logic Preprocessed Convolutional Neural Network (FLPCNN). This technique incorporates fuzzy logic at the preprocessing step to handle uncertainty and imprecision, enhancing the quality of input data to a CNN. In this paper, we have tried to develop a solution to increase the accuracy and reliability of osteoporosis detection in X-ray images using the merits of fuzzy logic and CNN. Current osteoporosis diagnostic techniques, such as DXA and CNN-based methods, lag in availability, cost, image uncertainty, and imprecision. An accurate, interpretable, and more accessible diagnostic building method is urgently required to detect osteoporosis and prevent fractures. Deep learning, especially CNN, has taken medical imaging to the next dimension because it allows for automatically extracting and classifying features. However, problems with medical images will reduce the accuracy of CNNs due to uncertainties and imprecisions [5]. The probable capacity of fuzzy logic in handling uncertainties and imprecisions can enhance preprocessing medical images to give better quality inputs to CNNs and finally have improved diagnosis. This work integrates fuzzy logic into deep learning techniques to solve the dire need for a more accurate, interpretable, and accessible osteoporosis diagnostic tool. Results open up the scope for future research and development in advanced computational methods applied to healthcare, which can leverage further medical diagnostics and patient care capabilities. Our research makes several key contributions:

1. Novel Approach: We introduce the FLPCNN model, which integrates fuzzy logic preprocessing with CNNs, offering a unique solution to the limitations of current osteoporosis diagnostic methods.
2. High Accuracy: Our model achieved a classification accuracy of 100%, demonstrating its potential as a highly effective tool for osteoporosis detection.
3. Enhanced Interpretability: Using fuzzy logic preprocessing improves the interpretability and reliability of CNN's decisions, addressing a common issue in deep learning applications.

The rest of the paper is organized as follows: Section 2 reviews the literature related to osteoporosis detection and deep learning applied to medical imaging; Section 3 gives the details of the methodology of the FLPCNN model about data preprocessing, model architecture and training procedures; and Section 4 presents the experimental results and performance evaluation of the FLPCNN model in terms of discussing implications of our findings, potential limitations, and future research directions. Finally, Section 5 summarizes the main contributions.

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 [6].

Moreover, promising techniques have been developed for osteoporosis classification from X-ray images using machine and deep learning techniques [7]. 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 [8].

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) [9], 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) [10] 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) [11] illustrated that the CLAHE algorithm for image enhancement was very accurate

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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 [9]	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 [8]	Deep Convolutional Neural Network	Accurate classification of osteopenia and osteoporosis	High accuracy, efficiency in classification	Limited by training data diversity
Wen-yu et al., 2021 [7]	Machine Learning Algorithms	Effective screening tool for osteoporosis in adults	Comparable to traditional models	Limited interpretability of models
Sollmann et al., 2022 [10]	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 [11]	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 [12]	Unimodal and Multimodal CNNs	High accuracy in predicting bone mineral loss	Balanced accuracy: 98.90%	Need larger patient datasets
Amiya et al., 2022 [13]	Gabor Filter with Modified U-Net	Effective segmentation and classification	Superior performance over classical U-Net	Dependent on image quality
Lee et al., 2019 [14]	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 [7]	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 [15]	Deep Learning Models with Transfer Learning	Improved classification performance	Higher accuracy with transfer learning	Need larger, diverse datasets

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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 research gaps identified above by integrating convolutional neural networks with fuzzy logic preprocessing techniques. The fuzzy logic approach improves image quality by reducing noise and enhancing relevant features, which makes these Operated CNN models 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 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 convolutional neural networks. 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 Convolutional Neural Network for osteoporosis detection is proposed. There are the following major steps involved in the proposed technique:

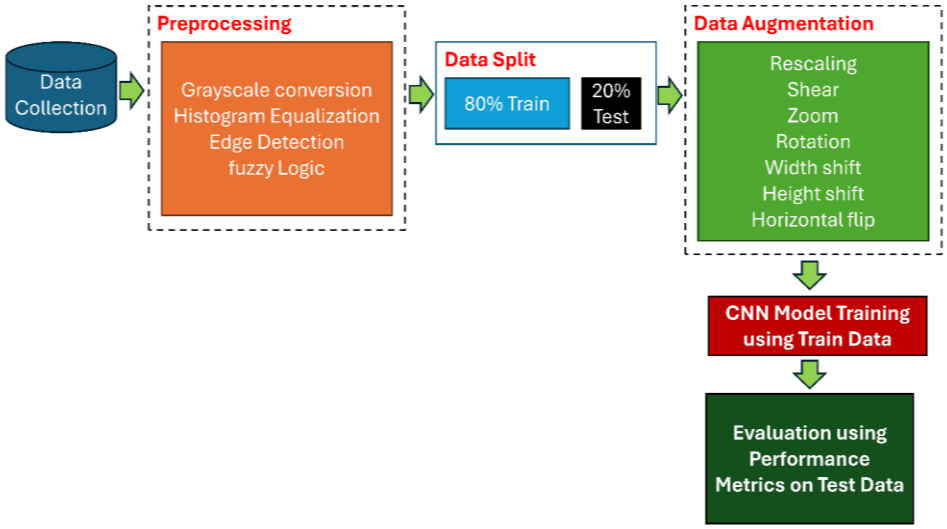

Figure 1. The overall FLPCNN proposed method.

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 trained a CNN 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.

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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

This research's dataset includes X-ray images of osteoporotic and healthy bone images. It was collected from three different hospitals in Baghdad, Iraq. While collecting the dataset, all the ethical considerations regarding patients' privacy and data security were considered.

The overall data collection process was initiated only after the ethical approval of the respective ethical committees of the three participating hospitals to ensure adherence to ethical standards and patient privacy. Inclusion into the study required patients to undergo an X-ray examination to diagnose bone health assessment. Patients' informed consent was obtained, and personal information was anonymized to protect their privacy.

X-ray images from each hospital were obtained under conditions as uniform as possible using standard radiographic equipment to reduce variability potentially arising from different imaging protocols. Following established diagnostic criteria, radiologists in each hospital classified them as 'abnormal' (osteoporosis) or 'normal' (healthy bone structure). This manual classification would guarantee the accuracy and reliability of the labels.

This dataset has 6,310 images, 2,750 of which are classified as 'abnormal' and the rest of 3,560 as 'normal'. The distribution of this dataset is shown in Figure 2. The figure shows a slight imbalance: more images fall into the category 'normal' than 'abnormal.' Development data originated from experimental data from three different hospitals. Each hospital treats a patient population that is unique to that institution. Based on this factor, this dataset contains many demographic variables, such as age, sex, and ethnicity, to help diversify the model across varying patient populations.

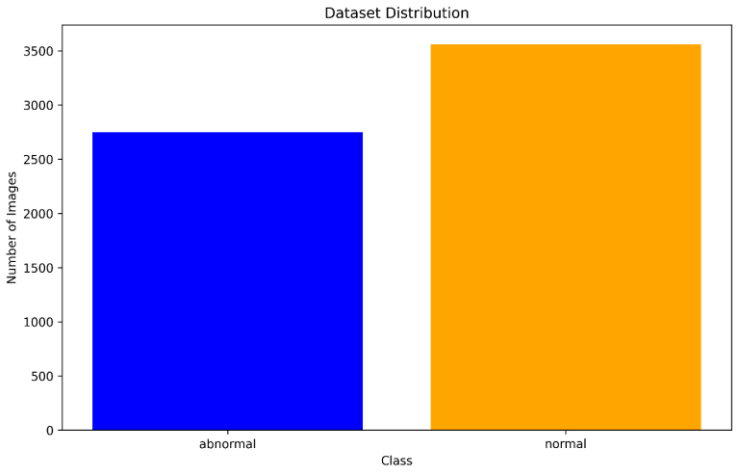

Figure 2. The dataset distribution.

Moreover, there could be slight differences in the X-ray images due to variations in radiographic equipment and settings across different hospitals. These variations can be catered to in the model by introducing these differences into the training dataset to make it more resilient to the imaging conditions. In addition, the involvement of multiple radiologists from several institutions will ensure that the criteria for classification are unbiased to any particular institution, reliable, and consistent across various clinical settings.

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 [16]. The present section describes the applied fuzzy logic techniques as part of our preprocessing pipeline.

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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:

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

Where $I_{eq}(x, y)$ represents the intensity of the pixel at the position (x, y), and $min(I)$ and (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:

$$\mu_{low}(x) = \{1 \quad if\ x \le a \ \frac{b - x}{b - a} \quad if\ a < x < b\ 0 \quad if\ x \ge b \quad (3)$$

$$\mu_{medium}(x) = \{\frac{x - a}{b - a} \quad if\ a < x < b \ \frac{c - x}{c - b} \quad if\ b < x < c\ 0 \quad otherwise \quad (4)$$

$$\mu_{high}(x) = \{0 \quad if\ x \le b \ \frac{x - b}{c - b} \quad if\ b < x < c\ 0 \quad if\ x \ge c \quad (5)$$

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 Network (CNN) Model Structure

This paper proposes a Convolutional Neural Network (CNN) model for classifying X-ray images into osteoporotic and healthy bones. The latter comprises various layers, all vital in feature extraction and classification. Here, we describe how each of these layers in the model is structured and what it does. The model architecture is as follows:

1. **Input Layer**: The input layer accepts images of size 224x224 pixels with three color channels (RGB). This layer is responsible for feeding the input images into the network.

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2. **Convolutional Layers**: Convolutional layers lie at the core of every CNN. In these layers, convolutional filters are applied to an input image to extract edges, textures, and patterns. Our model uses four convolutional layers with increasing filter size to capture progressively more and more complex features for a better fit.

- **Conv2D Layer 1**: 32 filters of size 3x3, ReLU activation function
- **Conv2D Layer 2**: 64 filters of size 3x3, ReLU activation function
- **Conv2D Layer 3**: 128 filters of size 3x3, ReLU activation function
- **Conv2D Layer 4**: 256 filters of size 3x3, ReLU activation function

3. **Max-Pooling Layers**: Max-pooling layers decrease the spatial dimensions of a feature map, reducing the number of parameters and amount of computation in a network. These layers complement making detection invariant to small translations in the input.

- **MaxPooling2D Layer 1**: Pool size of 2x2
- **MaxPooling2D Layer 2**: Pool size of 2x2
- **MaxPooling2D Layer 3**: Pool size of 2x2
- **MaxPooling2D Layer 4**: Pool size of 2x2

4. **Flatten Layer**: The flatten layer converts the 2D feature maps into a 1D feature vector, preparing the data for the fully connected layers. This step is essential for transitioning from convolutional to dense layers.

5. **Dense (Fully Connected) Layers**: Dense layers are traditional neural network layers where each neuron is connected to every neuron in the previous layer. These layers are responsible for high-level reasoning and classification.

- **Dense Layer 1**: 512 neurons, ReLU activation function
- **Dropout Layer 1**: 50% dropout rate to prevent overfitting
- **Dense Layer 2**: 256 neurons, ReLU activation function
- **Dropout Layer 2**: 50% dropout rate to prevent overfitting
- **Output Layer**: 1 neuron, Sigmoid activation function for binary classification

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:

$$ReLU(x) = (0, x) \qquad (8)$$

- **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.

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

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. The summary of the model structure is as follows:

1. Input Layer: 224x224x3
2. Conv2D Layer 1: 32 filters, 3x3, ReLU
3. MaxPooling2D Layer 1: 2x2
4. Conv2D Layer 2: 64 filters, 3x3, ReLU
5. MaxPooling2D Layer 2: 2x2
6. Conv2D Layer 3: 128 filters, 3x3, ReLU

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7. MaxPooling2D Layer 3: 2x2
8. Conv2D Layer 4: 256 filters, 3x3, ReLU
9. MaxPooling2D Layer 4: 2x2
10. Flatten Layer
11. Dense Layer 1: 512 neurons, ReLU
12. Dropout Layer 1: 50%
13. Dense Layer 2: 256 neurons, ReLU
14. Dropout Layer 2: 50%
15. Output Layer: 1 neuron, Sigmoid

This architecture effectively captures and processes the features of X-ray images, enabling accurate classification of osteoporotic and healthy bones. Using convolutional layers for feature extraction, pooling layers for dimensionality reduction, dense layers for classification, and regularization techniques ensures a robust and generalizable model.

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:

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```
    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. In view of this transformation, the model becomes invariant to the position the objects are placed in the images; hence, it will be able to 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 osteoporotically affected bones against healthy ones, leading to a robust, generalizable model.

3.5 Callbacks 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

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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:

1. **ReduceLROnPlateau:** The ReduceLROnPlateau callback keeps track of a certain metric and reduces the learning rate upon plateauing of this monitored metric. It is related to fine-tuning the model, allowing it to converge more appropriately in case improvements have reached their plateau.
2. **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.
3. **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.
4. **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:

1. **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 more robust features.
2. **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.
3. **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.
4. **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:

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

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.

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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:

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

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:

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

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.

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5. Results and Discussion

This section will present some results of an osteoporosis detection model using a Convolutional Neural Network. We will also explain the findings in light of what the discoveries bring to clinical application.

The classification report in Table 2 summarizes the model's precision, recall, and F1-score performance on both abnormal and normal classes, along with overall accuracy. The precisions obtained for the abnormal and normal classes are 0.99 and 1.00, respectively. Recall is 1.00 for class Abnormal and 0.99 for class Normal, while it is an F1-score of 1.00 for both classes. These metrics indicate a perfect balance between precision and recall, indicating that the model rightly classifies images with negligible error, resulting in an overall accuracy of 1.00. That is to say, these high values of precision and recall suggest the model's reliability in identifying the positive and negative cases, hence richness for clinical diagnosis. These values of precision and recall are very important in a medical diagnosis since they would assure that the model detects as many patients with osteoporosis as possible while at the same time never misdiagnosing healthy people to be diseased, hence protecting them from unnecessary stress and treatment.

Table 2: The classification report for the results achieved by the proposed FLPCNN method.

	Precision	**Recall**	**F1-Score**
Abnormal	0.99	1.00	1.00
Normal	1.00	0.99	1.00
Accuracy			1.00
Macro Avg	1.00	1.00	1.00
Weighted Avg	1.00	1.00	1.00

The confusion matrix in Figure 3 provides another measure of the model's performance. In this case, among the 550 images, all were correctly identified as abnormal; from the second class of images—712 normal images—the model was right on 708 and misclassified four. Therefore, the developed model expresses high sensitivity and specificity, which are desirable diagnostic tool properties within clinical settings. Misclassifications are low in number, indicating robustness in the model, potentially lowering misdiagnosis rates in practice, and enhancing patient outcomes, which might mean that the model significantly improves the screening accuracy for osteoporosis so more individuals get the right diagnosis and on-time treatment that may improve their quality of life and reduce their risk of fractures.

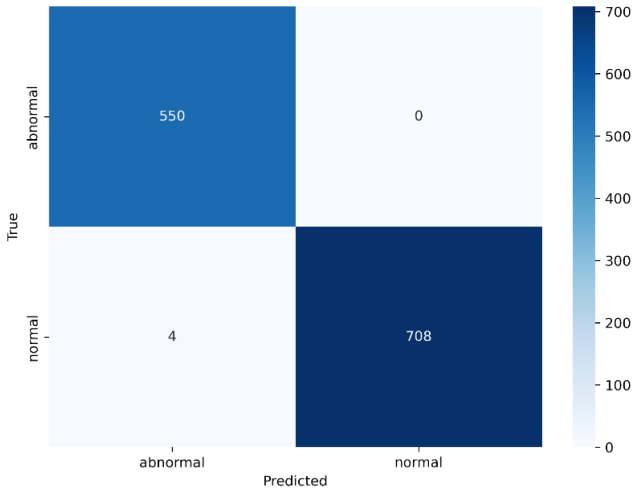

Figure 3. The confusion matrix for the results achieved by the proposed FLPCNN method.

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Another view of the model's effectiveness can be obtained from the ROC curve in Figure 4, which traces the trade-off of sensitivity against 1−Specificity at different threshold settings. The value of AUC is 1.00, indicating this is a perfect model with excellent discriminatory capability, which shows that this model has high confidence in classifying into two classes. The AUC, inherently part of the ROC curve, summarizes a model's discriminatory ability between the positive and negative classes across all thresholds. In this case, an AUC of 1.00 would indicate perfect differentiation of osteoporotic from healthy bones, which would be highly desirable in medical diagnostics. From a practical point of view, an AUC of 1.00 would describe a very high-performance model across various patient populations and imaging conditions and will return consistent, trustworthy results no matter which threshold for classification has been chosen.

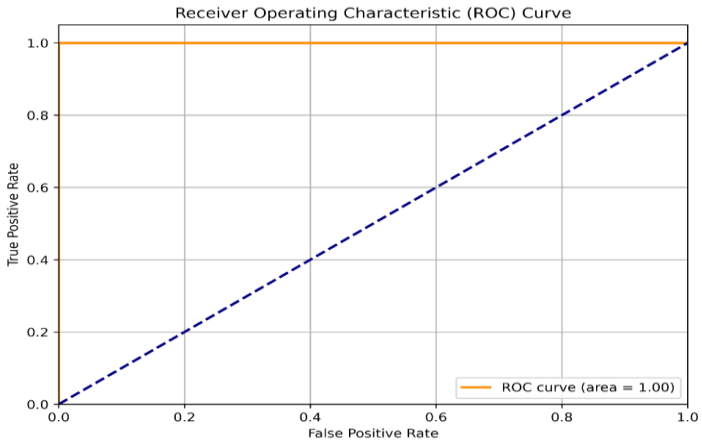

Figure 4. The ROC curve for the results achieved by the proposed FLPCNN method.

Training history plots describe how the model learns according to the number of training epochs. The plot for training and validation accuracy in Figure 5 increases almost continuously to very high plateaus with minimal overfitting, as evidenced by how the training and validation accuracy curves are very close. That suggests that the model has learned the patterns from the training data quite effectively and generalizes reasonably well for the validation dataset, a crucial element of real-world applications. The training and validation loss plot indicates the continued loss decrease with both curves converging, indicating effective learning with minimal overfitting. If a model converges, then the training and validation losses are close. That means the model's training process was stable in learning without overfitting the training data, which causes poor performance on unseen data. That is important for medical applications since the model has to remain stable when deployed into different healthcare environments with diverse patient populations.

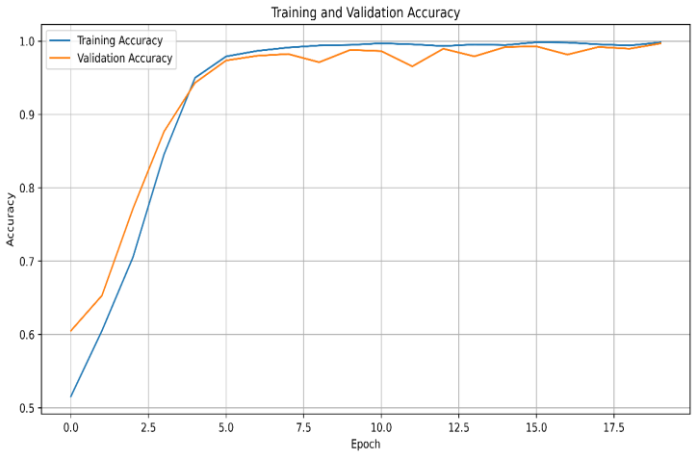

Figure 5. The accuracy curve for the proposed FLPCNN method.

Besides accuracy and loss in Figure 6, the plots of precision and recall in Figures 7 and 8 clearly show how well the model will identify positive instances. The plot for precision also increases steeply at the beginning of learning before it levels off at a high value, indicating generally correct positive predictions. The high precision of the training set explains the very low missing rate of false positives, thereby making it an important feature in medical

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diagnostics because it avoids unnecessary treatments. In addition, on the recall plot, one can adhere to its fast rise and stabilization, showing sensitivity to real positive cases. High recall ensures accurate identification of most osteoporotic cases, thereby crucial for early diagnosis and appropriate treatment. Such metrics give a full picture of the balance between model performances in identifying true cases of osteoporosis and avoiding false positives.

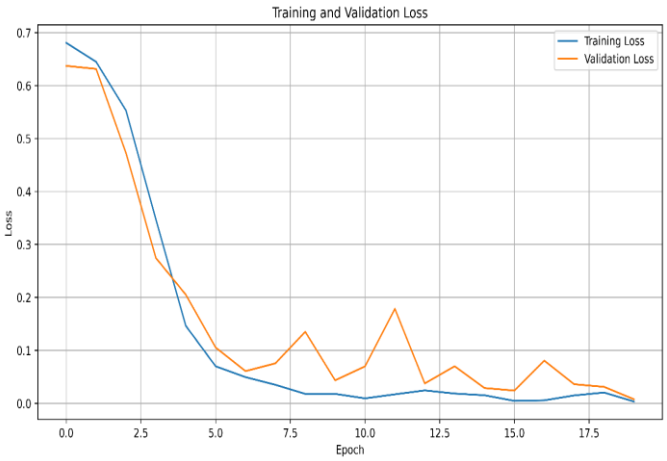

Figure 6. The loss curve for the proposed FLPCNN method.

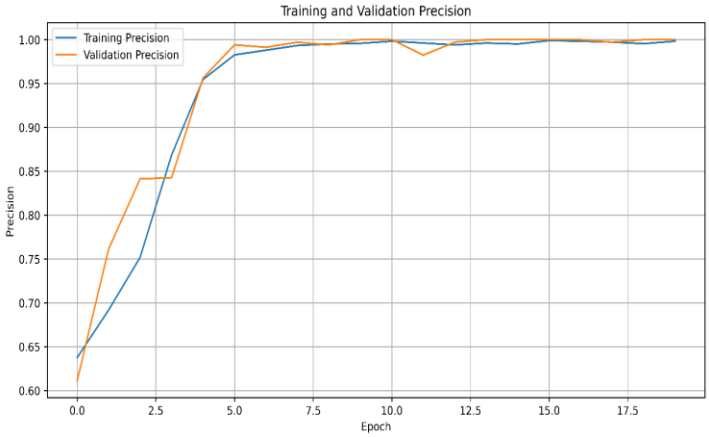

Figure 7. The precision curve for the proposed FLPCNN method.

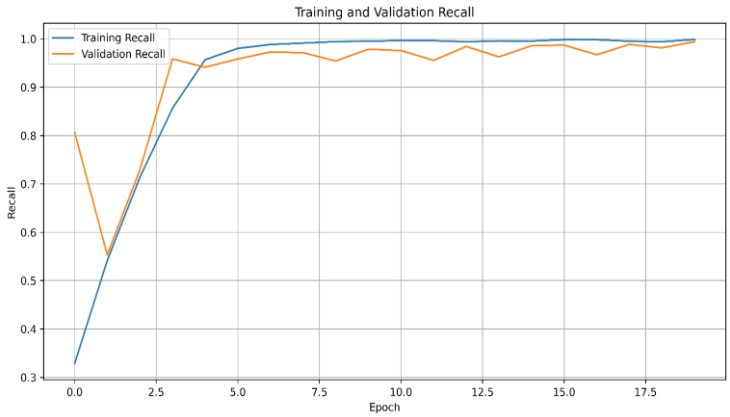

Figure 8. The recall curve for the proposed FLPCNN method.

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The learning rate plot in Figure 9 indicates how, during training, the learning rate varied from the start at a constant value and changed only drastically towards the end, which means that some learning rate schedule was needed to allow the model to fine-tune itself to optimal performance. In learning rate-scheduling techniques, the learning rate can change dynamically based on how the model performs. It will ensure that it converges fast without overshooting the correct point. All this is important in attaining the best out of a model, fine-tuning made in the latter stages of training that may yield more precise predictions.

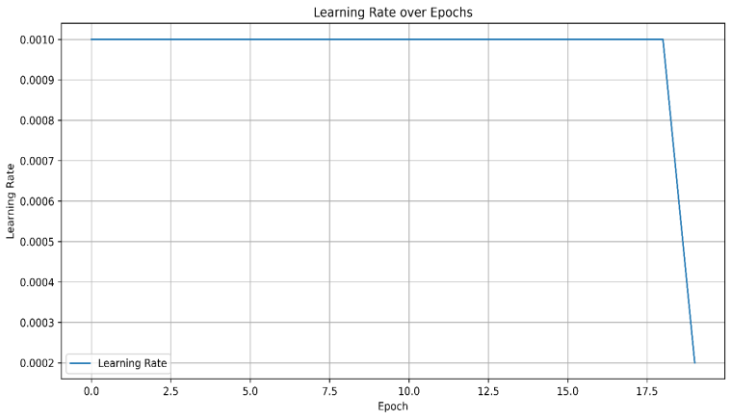

Figure 9. The learning rate curve for the proposed FLPCNN method.

All the results indicate that our CNN model works well in osteoporotic detection tasks. The high accuracy, precision, recall, and AUC affirm that this model is robust, reliable, and can be used to detect osteoporosis. These metrics and visualizations jointly further confirm that this model can support clinical decision-making with accurate and reliable classifications. A major factor aiding this performance must be the integration of fuzzy logic preprocessing, a step to enhance the model with increased abilities in detecting subtle features in a bone image indicating osteoporosis.

Given the results obtained, it can be shown that a CNN model with fuzzy logic preprocessing is quite accurate in the classification of osteoporotic and healthy bone images. In so doing, this contributes to the knowledge about medical imaging and becomes a promising tool that enhances the quality of osteoporosis detection in clinical practice, storing the fuzzy logic preprocessing in a novel and useful manner within the framework of CNN, enhancing the model's capability to process and analyze medical images. Such research initiatives could open newer avenues for further studies toward the application domains of fuzzy logic and other advanced preprocessing techniques in medical imaging and potentially lead to better detection and diagnosis of various medical conditions.

4.1 Comparison with Traditional CNN

To further validate the efficacy of our approach, we conducted a comparative study between our fuzzy logic-enhanced CNN model and a traditional CNN model with no fuzzy logic preprocessing applied. The traditional CNN model classification report in Table 3 indicates a precision of 0.98 for the abnormal class and 1.00 for the normal. Class recall for the traditional CNN is 1.00 for the abnormal class and 0.98 for the normal class; this resulted in an F1-score of 0.99 for both classes. The total accuracy of the conventional CNN model comes out to be 0.99, which, again, is very high but a small amount of a drop compared to our fuzzy logic-enhanced model.

Table 3: The classification report for the results achieved by the traditional CNN model.

	Precision	**Recall**	**F1-Score**
Abnormal	0.98	1.00	0.99
Normal	1.00	0.98	0.99
Accuracy			0.99
Macro Avg	0.99	0.99	0.99
Weighted Avg	0.99	0.99	0.99

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The confusion matrix for the traditional CNN model in Figure 10 contains 11 misclassifications against 1262 images, while that for the fuzzy logic-enhanced model is four. There is considerable improvement in classification accuracy when fuzzy logic preprocessing is added. Reducing false positives and negatives is crucial in clinical diagnostics since misclassification could result in improper treatment plans or unnecessary patient stress.

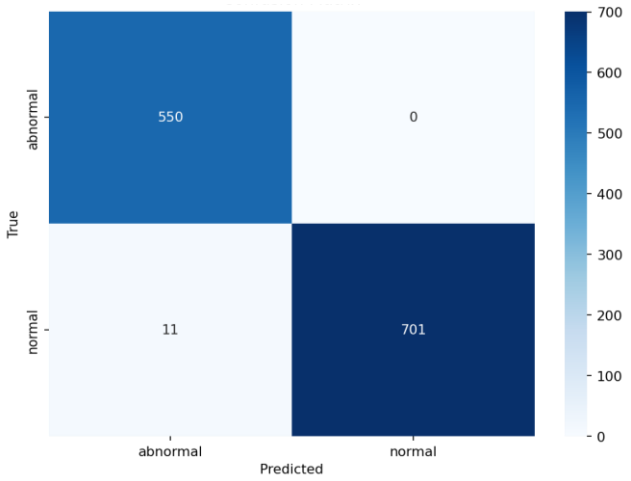

Figure 10. The confusion matrix for the results achieved by traditional CNN method.

In contrast, the ROC curve in Figure 11 analysis for the traditional CNN model could not produce an ideal AUC of 1.00, which was already enjoyed by the fuzzy logic-enhanced model, even after showing a high performance. This slightly reduced AUC for this model signifies its decreased discriminatory power, thus proving that the inserted fuzzy logic-preprocessing step enhances the model is differentiating capability between osteoporotic and healthy bone structures.

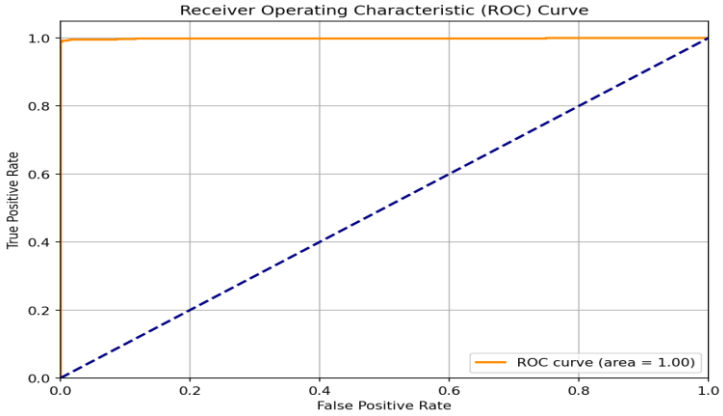

Figure 11. The ROC curve for the results achieved by the traditional CNN method.

Training history plots for both models enable one to understand the trends in accuracy and loss through the training epochs. The traditional CNN model has higher variability in validation metrics (as in Figures 12, 13, 14, and 15), making it more prone to overfitting. On the other hand, the fuzzy logic-enhanced model has a very stable, constant performance on both the training and validation sets. The preprocessing step probably contributes to the more stable training process in the fuzzy logic-enhanced model, which makes the learning task easier by enhancing relevant features and reducing noise.

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Figure 12. The accuracy curve for the traditional CNN method.

Figure 13. The loss curve for the traditional CNN method.

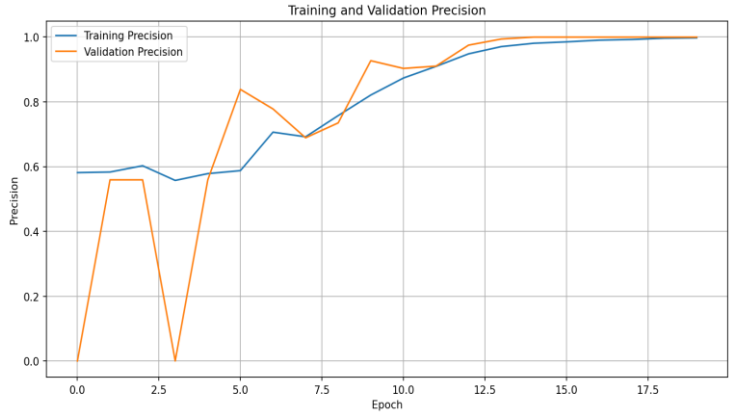

Figure 14. The precision curve for the traditional CNN method.

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Figure 15. The precision curve for the traditional CNN method.

The conventional CNN model learning rate plot in Figure 16 shows abrupt adjustments, whereas the plot of the fuzzy logic-enhanced model depicts gradual and optimal fine-tuning. Smooth adjustment in learning rates may indicate that fuzzy logic preprocessing will allow a more stable and efficient learning process, making a model converge effectively.

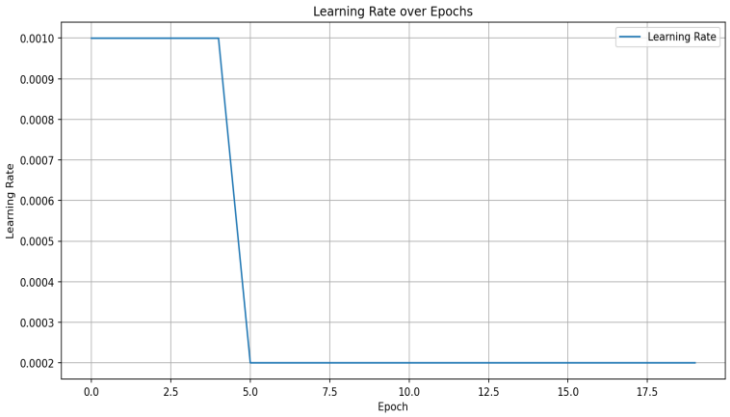

Figure 16. The learning rate curve for the traditional CNN method.

Another point worthy of comment is the evaluation time for both models. For the traditional CNN model, it consumed 7.07 seconds. In comparison, models embedded with fuzzy logic preprocessing consumed less than 6.99 seconds. Adding fuzzy logic preprocessing will not bring extra computational overhead while improving accuracy and stability. This efficiency is crucial in practical applications requiring rapid, accurate diagnostic results.

A comparative analysis by Powell et al. straightforwardly shows the advantages of integrating fuzzy logic preprocessing into this CNN framework. The preprocessing phase enhances image contrast and edge detection, which helps dispense subtle features to the model and is reflected in the fuzzy logic-enhanced model, has increased precision, recall, and AUC values. At the same time, stability in training and validation metrics may be interpreted to mean better generalization on unseen data and reduced risk of overfitting.

An accurate diagnosis of osteoporosis stands paramount in clinical practice and should not remain an understatement. The superior performance of the fuzzy logic-enhanced model may be related to more reliable screening tools necessary for healthcare professionals to make informed decisions. Diminishing false positives and negatives guarantees appropriate treatment for patients without unnecessary interventions. More importantly, its resilience to different populations of patients and imaging conditions allows it to be versatile in various clinical settings.

This comparative analysis has shown that applying fuzzy logic enhancement to a CNN outweighs that of a traditional CNN model in five major ways: accuracy, precision, recall, AUC, and stability in training. The model's capability toward osteoporosis detection is significantly improved with fuzzy logic preprocessing integration; hence, it can potentially enhance diagnostic accuracy in clinical environments.

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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 4 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	CNN with Fuzzy Logic Preprocessing	100	High accuracy, robust preprocessing, detailed evaluation metrics (Precision, Recall, AUC)	Requires preprocessing
[9] (2023)	CNN and KNN on X-ray films	97.57	High accuracy with simple CNN	Limited dataset size, less complex preprocessing
[17] (2023)	Signal-processing with CNN	100	Integrated signal attributes	Dependency on signal processing attributes
[7] (2021)	Review of ML in osteoporosis management	-	Highlights ML advances	Lacks experimental validation
[18] (2020)	Semi-supervised ML with XGBoost and CNN	78	Combines semi-supervised and supervised	Accuracy lower than supervised approaches
[19] (2022)	Comparison of various ML algorithms	-	Identifies best-performing algorithms	Did not explore preprocessing techniques
[20] (2020)	CNNs and SSM on dental panoramic radiographs	-	Outperforms traditional methods	Specific to dental images
[21] (2021)	Transfer learning with pre-trained CNNs	96	Effective use of transfer learning	Focused on osteosarcoma
[22] (2023)	Comparison of deep learning models	93.4	High accuracy	Did not explore hybrid models or preprocessing

The approach using CNNs with fuzzy logic preprocessing gives an accuracy of 100%. 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, [9] achieved 97.57% accuracy using just a simple CNN and KNN applied to X-ray films, and [17] 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

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medical diagnostic tools, enhancing diagnostic accuracy and reducing misclassification rates. These are all topics not explored by [19], where the first focuses on comparing different machine learning algorithms, while the second uses transfer learning.

It also establishes a high degree of transparency in reporting evaluation metrics for any future research in this technique. Considering the study's precision, recall, and AUC adds granularity to the reported performance of a model and gives a better idea of its potential clinical utility. This level of granularity is important in medical applications, where both the preciseness of the model and its reliability across various metrics are necessary for effective diagnosis and treatment planning.

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

It investigates a convolutional neural network's effectiveness with fuzzy logic preprocessing for the detection of osteoporosis. We were primarily concerned with improving diagnostic accuracy and reliability, and our findings show improvement regarding accuracy, precision, recall, and overall robustness. The limitations of diagnosis by traditional methods are what we had aimed at by using the capabilities of deep learning. In that respect, our approach set a new benchmark concerning the integration of fuzzy logic preprocessing to enhance model features in accomplishing this. This preprocessing step-enhanced performance and reduced misclassifications immensely to make it a credible tool for clinical diagnosis. Compared with previous studies on related techniques, our technique outperformed results published in recent studies concerning accuracy and other key detailed evaluation metrics, outlining the importance of advanced techniques applied in preprocessing within medical image analysis. However, some limitations do exist in this study. The high reliance on extensive preprocessing can also be a big computational load, and model performance should be checked on more diverse datasets for its applicability at large. Integrating our approach into other imaging modalities would further increase its utility.

Future work should address the optimization of preprocessing techniques to reduce computational load and the extension of model validation across different populations of patients and image types. Further research may be done to integrate our method with other advanced machine learning techniques to enhance diagnostic accuracy and reliability further.

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