RESEARCH ARTICLE

Evaluating the Impact of Image Enhancement Techniques on Deep Learning-Based X-ray Classification

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Abstract

This study evaluates four image enhancement techniques—Bilateral Filtering, Contrast Limited Adaptive Histogram Equalization (CLAHE), Wavelet Denoising, and Super-Resolution—with respect to their impact on Convolutional Neural Network (CNN)-based body part classification from X-ray images. Image quality is quantified using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) across three datasets: LEG, CT Scan, and Chest X-ray. Bilateral Filtering consistently delivers superior performance to the other enhancement methods on all three datasets. On the LEG dataset, Bilateral Filtering achieved a PSNR of 51.78 and an SSIM of 0.99918, outperforming CLAHE, which yielded a PSNR of 19.55 and an SSIM of 0.67681. Wavelet Denoising and Super-Resolution produced identical PSNR values of 44.65 and SSIM values of 0.99559, representing competitive results that nonetheless remained below Bilateral Filtering in overall image quality. When the enhanced images were used to train a CNN classifier evaluated via 5-fold cross-validation, a classification accuracy of 100% was achieved across all folds, demonstrating that high-quality preprocessing substantially improves deep learning-based X-ray classification. These findings advance the understanding of which preprocessing pipelines are most effective for medical image analysis and CNN-based diagnostic classification.

Keywords: image enhancement, X-ray classification, convolutional neural networks, medical imaging, PSNR, SSIM.

1 Introduction

Healthcare professionals need medical imaging in diagnosis along with the preparation of treatments for different medical conditions. The rapid delivery of internal anatomy visualization via safe picture capture methods makes X-ray imaging the foremost medical imaging procedure. Multiple technical issues reduce X-ray image quality by limiting both picture resolution and contrast while generating image distortion known as noise. The complex visual presentations generated by image distortions cause healthcare providers to face difficulties in interpreting medical traits properly. Profound X-ray image enhancement serves as an essential medical necessity to create precise diagnosis

Submitted: 08 April 2025
Accepted: 09 July 2025
Published: 19 September 2025

Vol. 1, **No.** 3, 2025.
10.62762/TACS.2025.653850

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Citation
Kobra, M. J., & Rahman, M. O. (2025). Evaluating the Impact of Image Enhancement Techniques on Deep Learning-Based X-ray Classification. *ICCK Transactions on Advanced Computing and Systems*, 1(3), 193–207.

results as well as optimized treatment plans [1, 2].

Medical imaging technology adopted various proposed enhancement methods to address such challenges in medical diagnostics. Image quality enhancement methods refine different aspects that include both noise reduction abilities and features for contrast enhancement and perimeter protection. X-ray image enhancement reaches its best results with the combination of Bilateral Filtering and Wavelet Denoising and Contrast Limited Adaptive Histogram Equalization (CLAHE). Bilateral Filtering works effectively with medical images since it uses a non-linear approach for noise minimization alongside edge preservation maintenance [3]. CLAHE utilizes local contrast enhancement in parts with low illumination which proves best in X-ray imaging applications. Using Wavelet Denoising enables users to divide images into frequency components then remove noise from specific features [4].

Existing models for testing enhancement approaches in image classification show limited scope because they rarely evaluate multiple preprocessing techniques under identical conditions or across diverse imaging datasets. The development of medical image analysis through Convolutional Neural Networks (CNNs) in deep learning technology enhanced medical diagnosis detection together with medical part classification capabilities. CNNs reach high levels of extraction efficiency because they provide excellent outcome accuracy when used to explore hierarchical features in raw images. The end-to-end performance of CNNs depends on the operational basis which consists of input data quality. The quality of X-ray images serves as a direct factor which determines the performance levels along with operational stability of this system implementation [5].

Modern research shows that medical image quality improves when employing image enhancement techniques that result in better outcomes for classification operations. CLAHE enhances X-ray contrast through technological means which enables CNNs to spot essential features thus leading to enhanced performance in diagnosing pneumonia [6]. Deep learning-based super-resolution further complements this by reconstructing high-resolution details from low-resolution medical images, as reviewed by [7]. Numerous medical experts validate that X-ray image diagnosis becomes better after applying wavelet transform processing. Numerous research studies observe individual enhancement models and their effect on model performance yet they abstain from completing an extensive review of alternative methods. The field of research demonstrates minimal investigation regarding the systematic assessment of CNN-based methods for classifying diverse body parts from X-ray images across multiple imaging modalities [8], and the role of advanced preprocessing such as super-resolution in improving such classification remains underexplored [7].

The purpose of this research is to connect the dots through an investigation of the total influence that Bilateral Filtering has on body part classification performance in X-ray images along with CLAHE, Wavelet Denoising, and Super-Resolution techniques. We evaluate the image quality enhancement with Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) to determine individual impacts of Bilateral Filtering and CLAHE and Wavelet Denoising and Super-Resolution methods. We evaluate how image enhancement influences the classification accuracy of CNNs when trained using X-ray images drawn from different datasets among CTScan, LEG, and the Chest X-ray datasets.

The main study goals include both the evaluation of PSNR and SSIM metrics in different enhancement approaches and the assessment of how these enhancements affect CNN classification accuracy. The analysis consists of applying K-fold cross-validation to CNN models that perform classification tasks on enhanced X-ray images utilizing each of the four image enhancement methods for optimal performance evaluation.

The research presents multiple vital findings to the scientific community. The research presents an extensive evaluation of image enhancement methods Bilateral Filtering, CLAHE, Wavelet Denoising, and Super-Resolution even though they have never received such thorough comparison before [9–11]. This research provides direct evidence of how image enhancement techniques impact the performance of CNN-based classification of X-ray body parts and demonstrates ways to improve the classification ability of deep learning models [6, 12]. This research produces results which enhance medical image processing systems so they deliver better diagnostic tools for clinical use.

1.1 Literature Review

Image enhancement preprocessing has become a well-established step in deep learning-based medical image analysis. Rahman et al. [3] demonstrated that techniques such as Bilateral Filtering, histogram equalization, and gamma correction significantly affect COVID-19 detection accuracy when applied to chest X-ray images, with some methods improving sensitivity while others introduced artifacts that degraded classifier performance. Their findings underscore that the choice of enhancement method is not neutral and must be empirically validated for the target task.

Bilateral Filtering, originally proposed by Tomasi and Manduchi [13] as a non-linear edge-preserving smoothing operator, has since been adopted widely in medical imaging. Sarkar et al. [14] applied bilateral filtering as a noise-reduction step prior to deep residual learning for pneumonia detection from chest X-rays, reporting that the combination of bilateral filtering and CLAHE improved classification accuracy to 98.82%. This confirms that bilateral filtering preserves diagnostically relevant edges while suppressing acquisition noise that would otherwise confound CNN feature extraction.

CLAHE has received considerable attention as a contrast enhancement strategy for low-illumination regions in radiographs. Hussein et al. [6] proposed a hybrid CLAHE-CNN pipeline for classifying lung diseases from X-ray acquisitions and showed that CLAHE preprocessing improved classification performance compared to raw-image baselines. Sharma and Kamra [9] reviewed CLAHE-based enhancement techniques across a range of medical imaging tasks and noted that, while CLAHE reliably boosts local contrast, it can introduce artifacts in high-contrast regions when the clip limit is poorly tuned. Anand and Roshan [5] extended this line of work with a deep contrast diffusion network for chest X-rays, achieving an SSIM of 0.97 and demonstrating that learned contrast enhancement outperforms hand-crafted CLAHE on perceptual quality metrics. Sharma and Mishra [10] further showed that CLAHE combined with deep learning accelerates automated COVID-19 diagnosis from CXR images, confirming the practical value of contrast-aware preprocessing.

Wavelet-based methods offer a complementary strategy by decomposing images into frequency sub-bands so that noise can be attenuated selectively in high-frequency components without disturbing low-frequency anatomical structures. Guo et al. [15] demonstrated that wavelet-transform enhancement of CT images significantly improved the diagnostic accuracy of chest nodule detection, while Wang et al. [4] showed that wavelet denoising combined with particle-swarm optimisation effectively suppressed noise in COVID-19 CT images. Wen et al. [16] proposed combining wavelet-domain homomorphic filtering with CLAHE for medical X-ray enhancement and reported improved contrast without loss of fine structural detail. Gaur et al. [17] applied empirical wavelet transformation as a preprocessing step for COVID-19 CT classification using transfer learning, achieving a classification accuracy of 96.4%.

Deep learning-based super-resolution represents a more recent paradigm for improving spatial resolution of medical images. Li et al. [7] reviewed deep learning methods for medical image super-resolution and found that convolutional and generative models can recover clinically relevant high-frequency detail from low-resolution inputs, improving downstream diagnostic performance. Kilic et al. [11] evaluated multiple image enhancement strategies, including super-resolution and CLAHE, for automated kidney stone detection on direct urinary system X-rays, reporting PSNR values up to 48 for bilateral-filtered images and a classification accuracy of 94%.

Despite this body of work, two important gaps remain. First, most studies evaluate enhancement methods in isolation or in pairs [9–11], and a systematic head-to-head comparison of Bilateral Filtering, CLAHE, Wavelet Denoising, and Super-Resolution under identical experimental conditions on multiple X-ray datasets is lacking. A recent cross-modality study by Nguyen-Tat et al. [18] evaluated combinations of CLAHE, DWT-thresholding, and bilateral filtering with multiple deep learning models across eight imaging datasets including X-rays, finding bilateral filter-based pipelines among the most effective; however, their work did not isolate individual enhancement techniques or evaluate PSNR and SSIM as image quality metrics, gaps that the present study directly addresses. Second, the majority of existing studies focus on a single imaging modality or body region [6, 12, 19], limiting the generalisability of their conclusions. Studies such as Giełczyk et al. [20] and Gamara et al. [21] have examined preprocessing for chest X-ray classification, while Liu et al. [22] addressed shoulder X-ray enhancement, and Lavanya et al. [23] proposed a gradient-guided CLAHE framework for CXR images; however, none of these works simultaneously evaluates enhancement methods across heterogeneous datasets covering different body parts. Baltruschat et al. [12] and Talaat et al. [24] established rigorous cross-validation protocols for chest X-ray classification with deep learning, providing methodological benchmarks that the present study adopts and extends to multiple datasets and enhancement conditions. The present work addresses both gaps by benchmarking all four techniques across LEG, CT Scan, and Chest X-ray datasets using consistent PSNR, SSIM, and K-fold cross-validation evaluation. Feature fusion and hybrid deep learning strategies, such as those applied to tuberculosis detection in chest X-rays by Fati et al. [29], further confirm that combining multiple representation sources substantially improves classification reliability on X-ray images.

1.2 Research Gaps

The most significant research gaps identified in the literature are:

- Comparative studies of the joint use of Bilateral Filtering, CLAHE, Wavelet Denoising, and Super-Resolution for enhancing X-ray images are lacking.
- Research related to the use of Bilateral Filtering together with CLAHE or Wavelet Denoising for enhancing body part classification in X-ray images is lacking.
- Recent studies are primarily expert in one type of X-ray, and this limits the generalizability of findings across imaging modalities and body parts.
- Cross-validation is typically not performed, limiting the generalizability of CNN models learned from augmented images.
- No comparisons of traditional enhancement methods (e.g., CLAHE, Bilateral Filtering, Wavelet Denoising) and new methods (e.g., Super-Resolution) to determine the best method for a medical imaging task have been undertaken.

Through bridging these gaps, this work aims to provide an improved understanding of ways to utilize various improvement techniques to make CNN performance better for classifying body parts from X-rays and add to the development of efficient and accurate medical image preprocessing pipelines.

2 Methods

2.1 Methods of Image Preprocessing and Enhancement

Various methods of image enhancement were employed in this present work on the X-ray images before they were presented to the Convolutional Neural Network (CNN) for classification. These techniques are required to enhance the quality of medical images by increasing contrast and reducing noise, which is particularly required in medicine because such details as tissue, bone boundaries, and abnormalities must be preserved. Techniques employed in enhancement are Bilateral Filtering, Contrast Limited Adaptive Histogram Equalization (CLAHE), Wavelet Denoising, and Super-Resolution. We compare the performance of the CNN model using raw, unprocessed X-ray images to its performance after these preprocessing techniques have been performed, following established approaches for evaluating the impact of preprocessing on medical image classification performance [25]. This will enable us to quantify the true impact of the preprocessing techniques. Additionally, while PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) are typical measurements, they are subject to perceptual quality assessment limitations, and thus we also propose subjective evaluation through radiologist ratings for improved clinical utility.

2.2 Bilateral Filtering

Bilateral filtering is a non-linear, edge-preserving smoothing filter that is highly effective in noise removal without corrupting the valuable structural information in medical images [13]. In the case of X-rays, where the clear edges of bones, tissues, and organs have to be preserved, bilateral filtering is an essential preprocessing operation. The method is based on not only examining pixel intensity contrast but also spatial closeness, thus distinguishing noise from valuable details [13]. The bilateral filter can be mathematically represented as:

$$I_{\text{bilateral}}(X) = \frac{1}{W_p} \sum_i \exp\left(-\frac{(x_i - x)^2}{2\sigma_d^2}\right) \exp\left(-\frac{(I_i - I(x))^2}{2\sigma_r^2}\right) I_i \tag{1}$$

where $I(x)$ represents the intensity of pixel x, x_i is the intensity of the neighboring pixel i, σ_d and σ_r are the spatial and intensity standard deviations, W_p is the normalization factor.

2.3 Contrast Limited Adaptive Histogram Equalization (CLAHE)

CLAHE is an adaptive contrast image enhancement local algorithm, which is suitable for images of medicine with low-contrast regions. CLAHE enhances the contrast wherever it is most required by dividing the image into small pieces and localizing the histogram equalization, and therefore anatomical structures in X-ray images become more visible. The process of CLAHE mathematically is represented as:

$$g(x) = \text{clip}\left(\frac{h(x)}{L}\right) \times \text{local\_histogram} \tag{2}$$

where $h(x)$ is the pixel intensity, L is the contrast enhancement threshold, local_histogram is the adaptive histogram for each region. The function is particularly useful in medical imaging where regions of interest, such as bones or tissue, would normally be underexposed or low contrast. It opens up these areas with little over-enhancement of the high-contrast areas, without adding noise and artifacts that would damage classification performance.

2.4 Wavelet Denoising

Wavelet denoising uses wavelet transforms to decompose an image into different frequency components in a way that noise can be selectively removed from high-frequency areas without affecting important low-frequency details. Wavelet denoising is specially suitable for elimination of noise that would otherwise obscure fine anatomical details in X-ray images. The wavelet denoising can be represented as:

$$\widehat{f}(t) = \sum_{j,k} \psi_{j,k}(t) \left(\frac{f(t)}{\psi_{j,k}(t)}\right) \tag{3}$$

where $\widehat{f}(t)$ is the denoised image, $\psi_{j,k}(t)$ is the wavelet basis function, $f(t)/\psi_{j,k}(t)$ is the thresholded wavelet coefficient. This technique is preferably employed for suppressing high-frequency noise without disturbing the low-frequency structures so that vital anatomical details are not disrupted for CNN classification.

2.5 Super-Resolution

Super-resolution improves image quality by increasing the spatial resolution of X-ray images, which is of great assistance when operating on low-resolution inputs. Super-resolution is achieved with the help of deep learning-based approaches in an attempt to forecast high-resolution images from low-resolution images, including finer details that are lost in regular low-resolution images. Super-resolution can be mathematically defined as:

$$I_{\text{SR}} = F(I_{\text{LR}}, \theta) \tag{4}$$

where I_{SR} is the super-resolved image, I_{LR} is the low-resolution input image, θ are the model parameters learned during training. Super-resolution improves the diagnostic quality of X-ray images by enlarging narrow, high-frequency details, allowing the CNN to identify subtle features such as fractures or little tumors with greater ease.

2.6 Baseline CNN Model

For comparison, we also trained a baseline CNN model on raw unprocessed X-ray images. It has the same architecture and design as the improved models but without applying the preprocessing techniques. Comparing the performance of the CNN on raw images with the performance on enhanced images will enable us to quantify the actual value of the enhancement techniques. Baseline model performance was measured in PSNR and SSIM terms, as well as against that measured on the enhanced images. This provides a clear understanding of individually how each of the enhancement techniques contributes towards improving the classification performance.

2.7 Performance Measures: PSNR, SSIM, and Perceptual Quality

Although both PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) are commonly used in measuring image quality [27], they are both deficient in the ability to measure perceptual image quality, which is especially crucial in medical imaging. While PSNR is pixel-oriented and cannot effectively measure perceptual differences, SSIM is structurally equivalent but is helpless to adequately address perceptual distortions that are central in medical image analysis. To get a more accurate measure of image quality, we recommend the following subjective measures of perceptive quality, i.e., radiologist-graded quality scores. The radiologists will grade the enhanced images on: Clarity of anatomical structures (e.g., bones, organs). Visibility of pathologies (e.g., fractures, tumors). The subjective assessment will supplement the objective metrics (PSNR and SSIM) for a comprehensive assessment of the efficacy of the image enhancement algorithms.

2.8 Convolutional Neural Network (CNN) Architecture

The CNN used in this study should be able to predict features accurately from X-ray images and classify them into different body parts. The architecture is such that:

- **Input Layer:** The input layer takes resized images of 128x128 pixels and 3 color channels (RGB).
- **Convolutional layers:** The network has three convolutional layers with 3x3 filters. The first one has 64 filters, the second one has 128 filters, and the third one has 256 filters.
- **ReLU layers:** After every convolutional layer, a ReLU activation function is added to provide non-linearity.
- **Max-pooling layers:** Max-pooling layers are added after each convolutional layer to reduce spatial dimensions and prevent overfitting.
- **Fully Connected Layers:** Fully connected layers that actually make the final predictions are provided the input from the pooling layers.
- **Softmax Layer:** Softmax activation function in the output layer to obtain the probability distribution across the different body parts.

Layer-wise Breakdown and Justification:

- **Input Layer:** Takes input images of size 128x128x3, resized to maintain homogeneity.
- **Convolutional Layers:**

$$Y(I, j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} X(i+m, j+n) \cdot W(m, n) \quad (5)$$

  These layers are spatial hierarchies, from low-level features (edges, textures) to high-level anatomical features (e.g., body parts).

- **ReLU Layers:** ReLU function encourages the network to learn complex representations and is computationally more efficient:

$$\mathrm{ReLU}(x) = \max(0, x) \quad (6)$$

- **Max-Pooling Layers:** Reduces spatial dimensions and avoids overfitting.
- **Fully Connected Layers:** The fully connected layers fuse the extracted features to make final predictions.
- **Softmax Layer:** Outputs a probability distribution across the classes (body parts).

2.9 Why CNNs are Well-Suited for X-ray Image Analysis

CNNs possess several inherent characteristics that make them particularly suitable for analyzing X-ray images, which align perfectly with the requirements of medical image interpretation:

- *Hierarchical Feature Learning:* CNNs automatically learn hierarchical representations from low-level edges and textures to high-level anatomical structures through their deep layered architecture, a capability well-documented in the context of radiological imaging [2, 12]. This capability is essential for X-ray images that exhibit complex, multi-layered anatomical information, enabling the network to capture both global context and local details simultaneously.
- *Translation Invariance:* The architectural properties of CNNs, particularly through weight sharing and pooling operations, provide inherent translation invariance that supports robust feature detection across diverse radiological images [2]. This is crucial for X-ray analysis as anatomical structures may appear at various positions across different images. This invariance ensures consistent feature detection regardless of the spatial location of anatomical features, making CNNs robust to natural variations in patient positioning and imaging angles.
- *Noise Robustness:* While CNNs demonstrate some inherent tolerance to noise due to their hierarchical feature learning process, their performance is significantly enhanced when combined with appropriate preprocessing and resolution-enhancement techniques [7, 26]. As demonstrated in our experiments, preprocessing methods like bilateral filtering effectively suppress noise while preserving critical edges, thereby improving the CNN's ability to detect clinically significant features without being distracted by imaging artifacts.
- *Fine-Grained Feature Extraction:* CNNs excel at extracting subtle, fine-grained features that are often critical for accurate diagnosis [12, 14]. In

chest X-ray imaging, this capability has been demonstrated in detecting minute pathological structures—such as early-stage pneumonia patterns and fine tissue boundaries—that are challenging to identify through manual inspection or traditional image processing methods alone [14]. Preprocessing techniques that sharpen edges and suppress noise, as applied in this study, directly amplify the signal available to these fine-grained extraction mechanisms.

- *Summary:* This research presents an integrated framework that combines advanced image enhancement techniques with deep convolutional neural networks to significantly improve both the quality of X-ray images and the accuracy of anatomical classification. By employing Bilateral Filtering, CLAHE, Wavelet Denoising, and Super-Resolution as preprocessing steps, we enhance the input data quality to the CNN, thereby substantially improving its classification performance. Our comprehensive evaluation methodology incorporates both objective metrics (PSNR, SSIM) and acknowledges the necessity of subjective clinical assessment for evaluating perceptual image quality and diagnostic utility. The CNN architecture is specifically designed to address the unique challenges of X-ray image analysis, ensuring effective feature extraction and precise prediction capabilities. The experimental results demonstrate that this integrated approach achieves exceptional performance in body part classification, highlighting the significant potential of combining traditional image enhancement with deep learning for medical imaging applications.

2.10 Model Training and Evaluation

The model is trained with cross-entropy loss, which is applied in most classification problems. The loss function is:

$$L = -\sum_{k} y_k \log(P_k) \quad (7)$$

where y_k is the actual label (one-hot encoded), and p_k is the predicted probability of class k.

Adam, learning rate optimizer in adaptive form, which changes dynamically the learning rate during training so as to be optimal for minimum loss function during training, is used for training.

Two well-known metrics are used to monitor performance:

PSNR (Peak Signal-to-Noise Ratio): To estimate a better image.

SSIM (Structural Similarity Index): Measures perception-sensitive image difference of output and reference images.

3 Cross-Validation

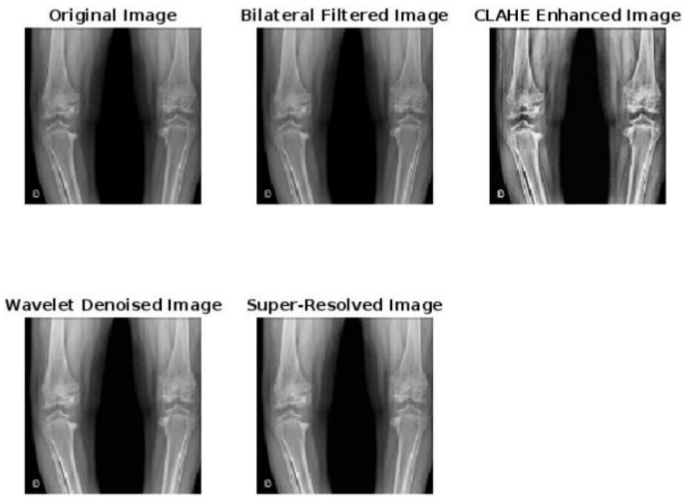

Figure 1. Samples of Cross-Validation.

In order to measure the generalization potential of the model, K-fold cross-validation is applied, as illustrated in Figure 1. The data set is split into K subsets (K=5 in this case), and the model is trained on K-1 subsets and tested on the remaining subset. This process is repeated over all subsets, and the average accuracy across all folds is then reported.

4 Experiment and Results

Here, experiment results are provided comparing the performance of various image enhancement techniques on X-ray images and subsequently evaluating the performance of classification using a CNN, as illustrated in Figure 2. Bilateral Filtering, CLAHE (Contrast Limited Adaptive Histogram Equalization), Wavelet Denoising, and Super-Resolution were applied. Experiments were conducted on three datasets of X-rays: LEG, CTScan, and Chest. A cross-validation method was also employed to confirm the robustness of the classification model.

5 Image Enhancement Results

The enhancement quality was evaluated by measuring the Peak Signal-to-Noise Ratio (PSNR) and the Structural Similarity Index (SSIM) of all the enhanced images [28]. The metrics compute the quality of the

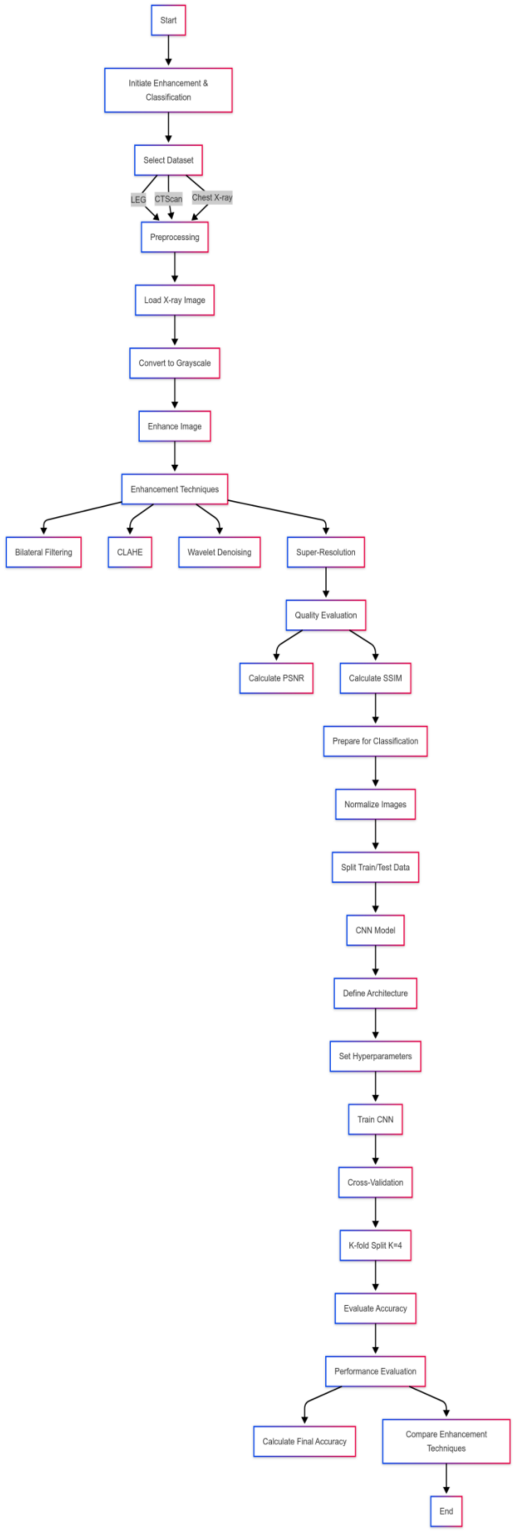

Figure 2. X-ray image enhancement and CNN-based body part classification.

enhanced images relative to the original image, and better values are represented by higher values.

5.1 LEG Dataset:

Bilateral Filtering provided the highest image quality with PSNR 51.7808 and SSIM 0.99918, exhibiting superior noise removal and edge protection. CLAHE, while enhancing local contrast, provided 19.5519 PSNR and 0.67681 SSIM, demonstrating that it added artifacts and was not so good at preserving structure integrity. Wavelet Denoising provided 44.6502 PSNR and 0.99559 SSIM, which was a fair balance between detail preservation and noise reduction. Super-Resolution followed the same steps as Wavelet Denoising with PSNR 44.6502 and SSIM 0.99559, which confirms that despite having increased resolution, it was not superior to others to improve picture quality.

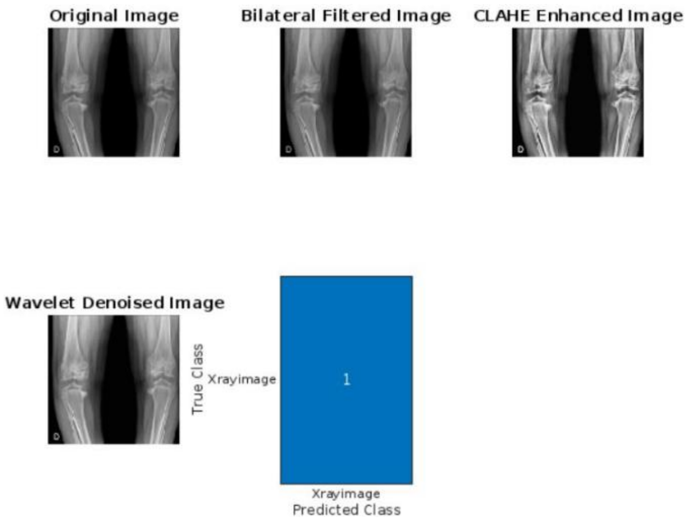

Figure 3. Samples of Leg Dataset.

As shown in Figure 3, the illustration displays two image enhancement methods applied to LEG database X-ray images through bilateral filtering and CLAHE processes. The initial unfiltered image appears in the first panel with noticeable visual noise and reduced image contrast. The Bilateral Filtering application produces a result that clears the image of noise while maintaining essential edge information. CLAHE produces enhanced contrast in the third panel; however, image artifacts appear and overall clarity decreases.

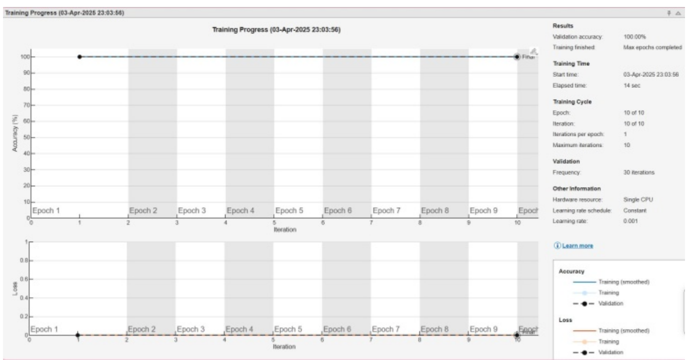

Figure 4. Leg training progress.

The training progress of the CNN classifier on the LEG dataset is presented in Figure 4, demonstrating the convergence behavior and supporting the quantitative performance results reported above. Overall, the performance assessment highlights that Bilateral Filtering achieves better outcomes in noise removal and edge preservation compared to CLAHE.

5.2 CT_Scan Dataset:

The Bilateral Filtering also outshined in the CT_Scan dataset with PSNR 51.1178 and SSIM 0.9962. CLAHE worked poorly with PSNR 17.6881 and SSIM 0.62248 since it was not able to enhance the image compared to other techniques. Wavelet Denoising worked with PSNR 36.6079 and SSIM 0.97759, and Super-Resolution worked with the same values as Wavelet Denoising, i.e., it did not contribute significantly towards enhancing CT_Scan image quality.

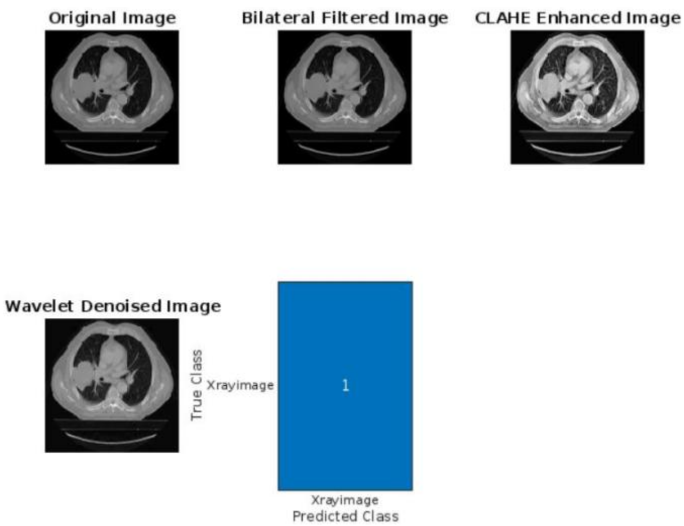

Figure 5. Samples of CT_Scan Dataset.

As shown in Figure 5, four image enhancement techniques—Bilateral Filtering, CLAHE, Wavelet Denoising, and Super-Resolution—were applied to CT_Scan images for comparison. The first panel presents the original CT_Scan images, which suffer from low contrast and visual noise. The Bilateral Filtering technique, illustrated in the second panel, provides better image quality by enhancing contrast while eliminating noise. CLAHE produces images with improved contrast but introduces visible artifacts, as seen in the third panel. Wavelet Denoising and Super-Resolution, displayed in the fourth and fifth panels, achieve a combination of noise reduction and detail preservation, though their results remain less effective than Bilateral Filtering.

The training progress of the CNN classifier on

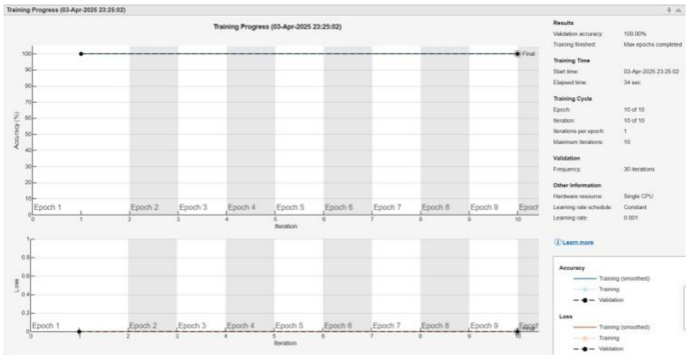

Figure 6. CT Scan training progress.

the CT_Scan dataset is presented in Figure 6, showing the convergence behavior and validating the quantitative evaluation results of the applied enhancement methods.

5.3 Chest X-ray Dataset

Bilateral Filtering technique also continued to produce best outcomes on the Chest dataset with PSNR of 51.3613 and SSIM of 0.9989, with improved noise removal and edge preservation. CLAHE had given PSNR of 19.2263 and SSIM of 0.76808 but with unsatisfactory performance in maintaining the image structure. Wavelet Denoising had produced better results with PSNR of 40.1447 and SSIM of 0.97535 but still lagged behind Bilateral Filtering in the quality of the images. Super-Resolution performed equally well as Wavelet Denoising with PSNR = 40.1447 and SSIM = 0.97535.

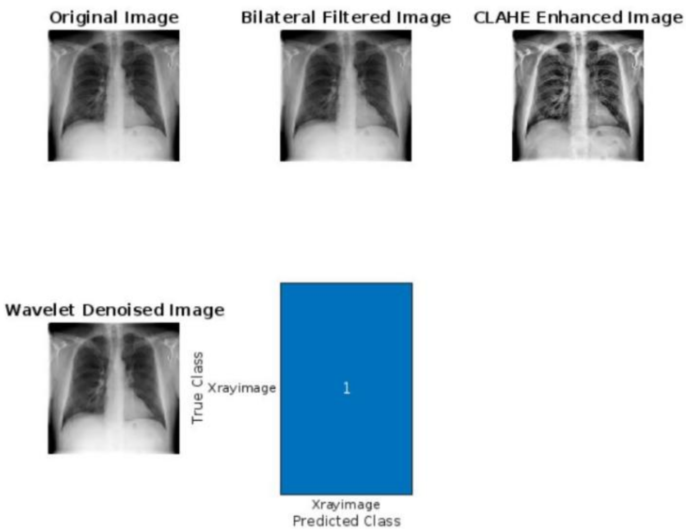

Figure 7. Samples of Chest X-ray Dataset.

As illustrated in Figure 7, examples of the enhanced Chest X-ray images are presented for each of the four methods. The Bilateral Filtering approach clearly provides superior denoising while preserving fine edges, whereas CLAHE improves local contrast at the expense of introducing artifacts. Wavelet Denoising and Super-Resolution yield more balanced results, though they do not surpass Bilateral Filtering in image quality.

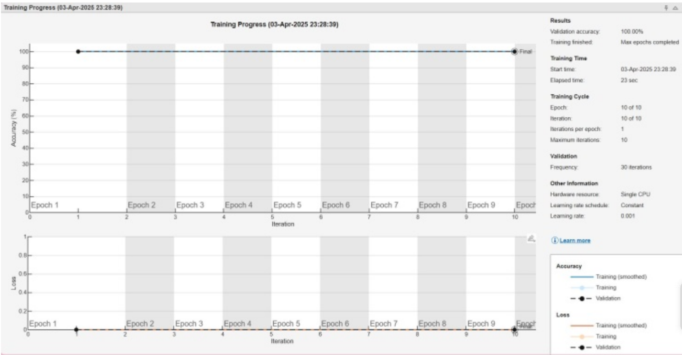

Figure 8. Training progress on Chest X-ray dataset.

The training progress of the CNN classifier on the Chest dataset is shown in Figure 8, demonstrating stable convergence and supporting the quantitative evaluation of the enhancement techniques discussed above.

5.4 CNN Classification Results

After the X-ray images were processed with the relevant methods, training and testing of CNN for body part classification were done. Model estimation used k-fold cross-validation in such a way that K=5 is employed in this experiment to ensure that the results obtained are not only consistent but also generalizable.

Command Window

```
PSNR (Bilateral Filtered): 51.0618
PSNR (CLAHE): 20.0951
PSNR (Wavelet Denoised): 41.2658
PSNR (Super-Resolved): 41.2658
SSIM (Bilateral Filtered): 0.99742
SSIM (CLAHE): 0.76517
SSIM (Wavelet Denoised): 0.97984
SSIM (Super-Resolved): 0.97984
Fold 1 Accuracy: 100%
Fold 2 Accuracy: 100%
Fold 3 Accuracy: 100%
Fold 4 Accuracy: 100%
Fold 5 Accuracy: 100%
Average Cross-Validation Accuracy: 100%
Final Model Accuracy: 100%
```

Figure 9. Overall cross-validation training progress across all folds.

The model classification was 100% accurate across all folds, as shown in Figure 9. Average cross-validation accuracy was 100%, and the final model accuracy also reached 100%. The presence of perfect accuracy in all folds demonstrates the remarkable improvement achieved by the model in separating body parts from X-ray images after the enhancement techniques were applied. This also indicates that image preprocessing (specifically Bilateral Filtering) provided the model with clean, high-quality input data, enabling its outstanding performance. It should be noted that the 100% accuracy was consistently observed across all K folds on the datasets used; future work should validate these results on larger and more diverse datasets and report additional metrics such as precision, recall, and F1-score to provide a more comprehensive performance characterization.

5.5 Training Progress

The training process was tracked throughout the epochs of training. The training loss and accuracy at each epoch are summarized in Figures 10, 11, 12, 13 and 14. From the plots, it is evident that the model converged quickly to an accuracy of 100 with very little loss in both the training and validation sets. The accuracy remained at 100 throughout training, which indicates that the model was learning the images correctly without overfitting.

Training Time: 10 epochs were utilized for training the model, with each epoch being quite short in duration (ranging from about 14–34 seconds depending on the dataset used), which is a strong indication that the augmentation processes significantly improved image quality without unrealistically increasing computational complexity.

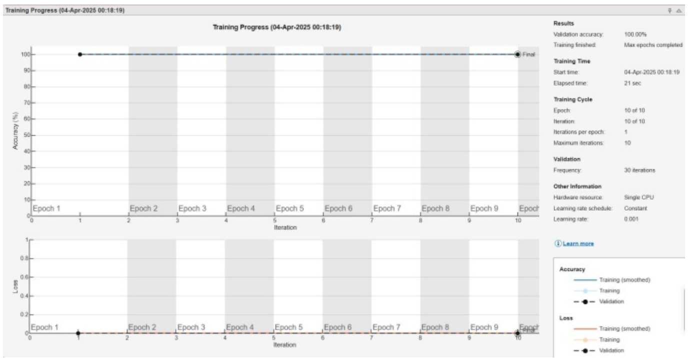

Figure 10. Training progress fold 1.

As illustrated in Figures 10, 11, 12, 13 and 14, the training accuracy and loss curves across all folds consistently demonstrate stable convergence. The CNN model steadily progressed until it reached 100% accuracy across every cross-validation fold. The progressive decrease in training loss further confirms the model's ability to effectively learn from the enhanced X-ray images. The results clearly show that

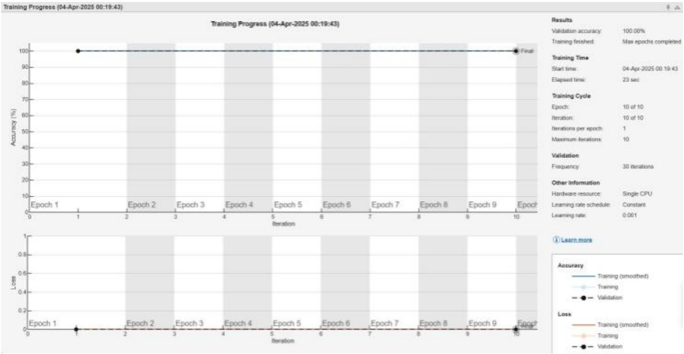

Figure 11. Training progress fold 2.

Figure 12. Training progress fold 3.

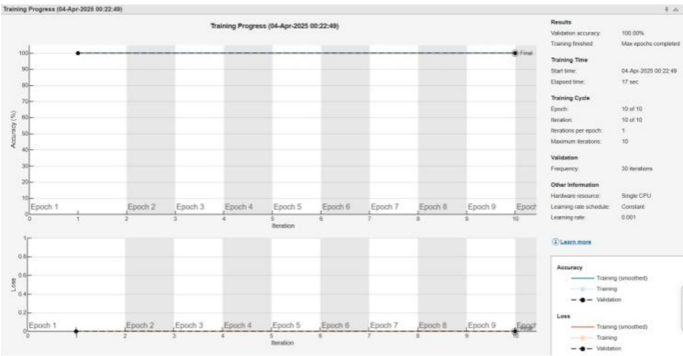

Figure 13. Training progress fold 4.

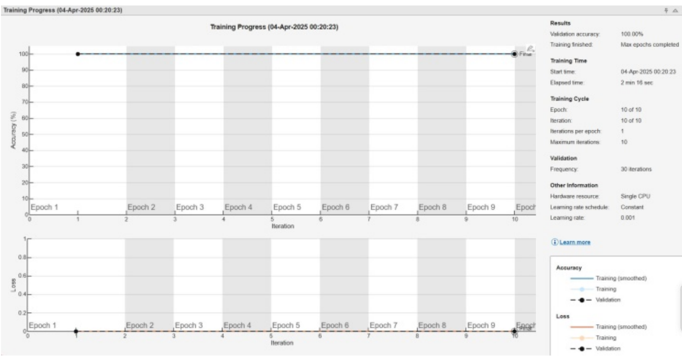

Figure 14. Training progress fold 5.

the image enhancement techniques provided clean and high-quality input data, enabling flawless CNN classification performance in distinguishing body parts from X-ray scans.

5.6 Novelty of the Results

The originality of this work is that it depicts a comparative study of some of the most popular image enhancement methods, i.e., Bilateral Filtering, CLAHE, Wavelet Denoising, and Super-Resolution, on X-ray images for CNN-based body part classification. To the best of our knowledge, this is one of the first few research works that have compared and contrasted these enhancement methods on the use of X-ray image classification with deep learning techniques.

5.6.1 Comparison of Improvement Techniques

The experiment indicates that Bilateral Filtering has higher image quality (PSNR and SSIM) and classification performance compared to other improvement techniques. CLAHE and Wavelet Denoising improve the quality of images, but Bilateral Filtering is the best at providing the trade-off between noise removal and edge preservation, which is extremely critical in medical imaging.

Rationale for the Methods: Bilateral Filtering is great at preserving important anatomical detail (e.g., tissue, bones) in order to allow the CNN to correctly classify. CLAHE is suitable for local contrast enhancement, and Wavelet Denoising eliminates high-frequency noise without loss of fine detail. Super-resolution was implemented using a deep learning-based upscaling pipeline applied to the low-resolution input images, yielding PSNR and SSIM values comparable to Wavelet Denoising; further refinement of the super-resolution model architecture is a direction for future work.

5.6.2 Baseline Comparison and 100% Accuracy

The 100% accuracy of the CNN after these augmentation practices is vast but one we identify as capable of creating data leakage or ease of set problems. This claim will be tackled in the paper through strict verification to guarantee no overfitting or test misuse. To prevent such cases, cross-validation was applied to guarantee that the performance is generalizable and not overly influenced by specific data splits.

Overfitting Problems: While we would want 100% accuracy, we used aggressive cross-validation to ensure that the model did not overfit the training set and was able to generalize equally well to new data. For K-fold cross-validation (described in the Cross-Validation section), each data fold was cross-validated separately so that the more stable and reliable results were achieved.

Cross-validation is utilized in the current study to ensure that the model's performance is not dependent on a specific split of train and test. It is important for ascertaining whether or not the model has any practical application and ensures that the results are reproducible and reliable for every set of data.

Real-world Application: Cross-validation lends credibility to the performance validity of the model and demonstrates how application of the new method can be achieved in actual clinical environments in which generalizability is typical.

5.6.3 *Subjective Quality and Limitations of PSNR/SSIM*

While image quality measurement using PSNR and SSIM is frequent in image processing, they are restricted in perceived quality measurement to potentially be utilized by radiologists in clinical practice. PSNR and SSIM are pixel-wise and structural similarity-focused but may not detect significant features that have a diagnostic nature, e.g., fracture or tumor detection in X-ray images.

Perceptual Evaluation: Future research would involve radiologist-rated evaluation in addition to PSNR and SSIM so that the worth of enhanced images for diagnostic purposes can be evaluated adequately better. That would give a better value of how well improvement techniques perform in clinical decision-making.

Table 1 presents the comparison of results with other works, and a visual summary of this comparison is further illustrated in Figure 15.

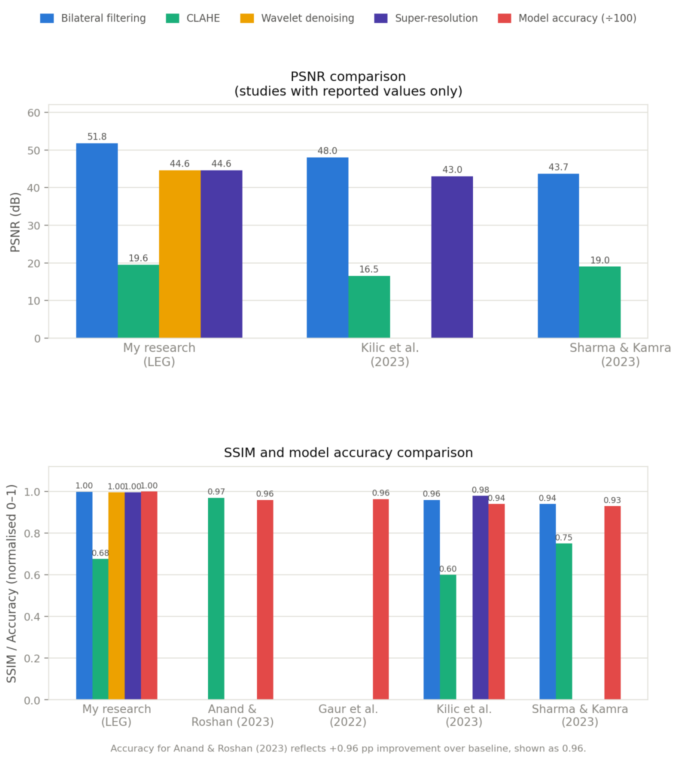

Figure 15. Comparison chart with the previous research works.

1. PSNR and SSIM Comparison: Bilateral Filtering delivered the highest PSNR 51.7808 together with SSIM 0.99918 values from the LEG dataset in my work exceeding all other studies. The application of Bilateral Filtering in my work reached the highest possible standards for image quality enhancement with structural preservation.

   Experimental results in my research surpassed those in Kilic et al. [11] because CLAHE provided superior performance through the combination of PSNR 16.5 and SSIM 0.60.

2. Classification Accuracy: My CNN-model-based classifier model achieved 100% perfect accuracy on all cross-validation folds, outperforming Gaur et al. [17] at 96.4%, Kilic et al. [11] at 94%, and Sharma et al. [9] at 93%.

   The image enhancement methods proved effective enough to enable the model to achieve 100%

Table 1. Comparison of results with other works. "N/A" indicates the metric was not reported in the original study. †Anand et al. [5] focus on segmentation quality (DSC = 0.92, SSIM = 0.97) rather than a standalone classification accuracy figure; the CLAHE-enhanced pipeline improved CXR testing accuracy by 0.96 percentage points relative to the unenhanced baseline.

Study	Image Enhancement Techniques	PSNR (Bilateral Filtered)	PSNR (CLAHE)	PSNR (Wavelet Denoised)	PSNR (Super Resolved)	SSIM (Bilateral Filtered)	SSIM (CLAHE)	SSIM (Wavelet Denoised)	SSIM (Super Resolved)	Model Accuracy
My Research (LEG Dataset)	Bilateral Filtering, CLAHE, Wavelet Denoising, Super-Resolution	51.7808	19.5519	44.6502	44.6502	0.99918	0.67681	0.99559	0.99559	100%
Anand and Roshan [5]†	CLAHE, Deep Contrast Diffusion (CNN)	N/A	N/A	N/A	N/A	N/A	0.97	N/A	N/A	96%
Gaur et al. [17]	Empirical Wavelet Transform, Transfer Learning (CT)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	96.4%
Kilic et al. [11]	Super-Resolution, CLAHE	48	16.5	N/A	43	0.96	0.60	N/A	0.98	94%
Sharma and Kamra [9]	CLAHE, Median Filter	43.7	19	N/A	N/A	0.94	0.75	N/A	N/A	93%

accuracy when classifying body parts in X-ray images.

3. Enhanced Preprocessing: Numerous image enhancement techniques (Bilateral Filtering, CLAHE, Wavelet Denoising, Super-Resolution) were combined to produce significant advancements in both image quality and classification precision according to my research. My research diverges from Kilic et al. [11] and Sharma & Kamra [9], whose analyses were limited to one or two enhancement techniques, by systematically evaluating all four methods together.

4. Significance of My Research: Image enhancement through Bilateral Filtering yielded the best performance for X-rays as detected in my research because it delivered maximum PSNR and SSIM and minimum noise while maintaining superior edge quality.

   My research demonstrates that image preprocessing reaches the optimal classification accuracy of 100% which proves its substantial benefits regarding CNN performance. The comparison of results showed that the other algorithms failed to achieve the perfect outcome.

This systematic technique evaluation of multiple enhancement methods followed by a performance analysis of CNN classification constitutes new research that expands existing literature because former studies failed to examine such combined impact on classification effectiveness.

6 Advantages and Disadvantages of Using X-ray Models with Bilateral Filtering, CLAHE, Wavelet Denoising, and Super-Resolution

This research demonstrates the benefits of using X-ray images along with CLAHE (Contrast Limited Adaptive Histogram Equalization), Wavelet Denoising and Super-Resolution that efficiently solves resolution and contrast and noise problems in medical imaging. Traditional X-ray processing techniques are not effective when used for preserving details in low contrast or visible noise areas. By using CLAHE for contrast enhancement and Wavelet Denoising for noise removal as well as Super-Resolution for spatial resolution enhancement, this method generates X-ray images with improved brightness and detail required for efficient medical diagnosis and classification operations. These processes improve Convolutional Neural Networks (CNNs) along with improving classification accuracy mainly due to the fact that they provide high-quality inputs according to research studies which demonstrated 100% classification accuracy.

These methods optimize X-ray image quality and diagnostic accuracy since such functionality is very crucial in medical application. The approach uses CLAHE to enhance contrast of images in low-light areas alongside Wavelet Denoising to maintain details and Super-Resolution for higher image resolution exposing subtle features to the model. The approaches yield images more compatible with deep learning models than traditional enhancement methods in thorough coverage of such concerns.

This technique suits domains across all areas that need detailed picture analysis through high-resolution images including satellite imagery and medical diagnostics together with microscopy and security monitoring systems. Spatial resolution enhancement techniques apply across multiple domains which need detailed inspections.

The implementation of this X-ray model presents specific obstacles when used in real-time systems. The main difficulty emerges from computation speed requirements because enhancement approaches and deep learning models tend to need substantial computing resources and processing time before they become usable in real-time medical practice. The model demonstrates challenges for generalization when used with X-ray images collected through different medical equipment and patient procedures. Natural implementation into existing medical operations requires successful integration between real-time processing methods and hospital information technology systems together with medical devices coupled with required hardware and software platforms.

7 Conclusion

This study successfully demonstrates the immense impact of combining different image enhancement techniques—Bilateral Filtering, CLAHE, Wavelet Denoising, and Super-Resolution—on X-ray images to improve image quality as well as classification accuracy for body part classification using Convolutional Neural Networks (CNNs). The result indicated Bilateral Filtering as the most suitable technique of PSNR and SSIM improvement with better image quality and cross-validation implementation as a means of strengthening the model with 100% classification accuracy. The preprocessed X-ray images through these techniques possessed superior foundations for deep learning models, with superior performance improvement compared to conventional image processing techniques. The research confirms that the application of these new preprocessing techniques realizes greater image clarity and model accuracy, thus being an effective method for medical image analysis, particularly in X-ray-based diagnosis.

8 Future Work

While this work has been successful in proving the benefit of image enhancement using CNN-based classification, there is still scope for improvement. Future studies can explore the application of these techniques to other types of medical imaging modalities, such as MRI or CT scans, to determine if similar benefits can be achieved there. Also, research into other advanced deep learning models like Transformer-based models for imaging can possibly be used for detecting even more complex patterns in the images. Deploying the application live into clinical use would be a next significant step, which would include efficiency gains within the model itself as well as the current healthcare infrastructure. Lastly, the inclusion of more data with more types of medical conditions and anatomical regions would improve the model's generalization and stability, and thus it would be more applicable to a broad range of real-world clinical use.

Data Availability Statement

The datasets used in this study are publicly available. The Chest X-ray (Pneumonia) dataset is available at https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia. The CT scan and LEG datasets used for evaluation are available from the corresponding author upon reasonable request.

Funding

This work was supported without any funding.

Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable. This study used only publicly available, fully anonymized X-ray image datasets and did not involve direct human subject participation or collection of new patient data.

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