RESEARCH ARTICLE

RSP Science Hub

International Research Journal on Advanced Science Hub
2582-4376
www.rspsciencehub.com
Vol. 08, Issue 05 May

Check for updates

http://dx.doi.org/10.47392/IRJASH.2026.021

A Robust Hybrid Preprocessing Framework Integrating DAE, BM3D, Median Filtering, and CLAHE for Enhanced Pneumonia Chest X-Ray Analysis

M. Shanmuga Priya[1], *Dr. M. Mary Shanthi Rani*[2]
[1]*Research Scholar, Department of Computer Science and Applications, The Gandhigram Rural Institute (Deemed to be University), Gandhigram, Dindigul, 624302, Tamil Nadu, India.*
[2]*Professor, Department of Computer Science and Applications, The Gandhigram Rural Institute (Deemed to be University), Gandhigram, Dindigul, 624302, Tamil Nadu, India.*
Emails: *priya1171998@gmail.com*[1], *drmmsrani@gmail.com*[2]

Article history
Received: 14 April 2026
Accepted: 12 May 2026
Published: 30 May 2026

Keywords:
BM3D; Chest X-ray; Denoising Autoencoder; Hybrid Preprocessing; Pneumonia Detection.

Abstract

For the identification of pneumonia using CXR imaging, image quality is potentially impacted by noise, low contrast, and the presence of acquisition artifacts that make it difficult to visualize pertinent or clinically relevant features. To improve the quality of CXR images associated with pneumonia diagnoses, this study recommends the use of a robust hybrid preprocessing framework that utilizes learning-based and classical preprocessing techniques for noise reduction, structural preservation, and increasing contrast, and combines these techniques into one model. The learning-based method used is a Denoising Autoencoder (DAE). The classical methods used include Median Filtering, Block-Matching and 3D Filtering (BM3D), and Contrast-Limited Adaptive Histogram Equalization (CLAHE). To evaluate how effectively each preprocessing technique or combination of techniques can enhance pneumonia CXR images, CXR images from publicly available pneumonia CXR datasets were used in this study for evaluation. The performance evaluation used a range of quantitative metrics that included Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Mean Squared Error (MSE), Entropy, and Contrast Improvement Index (CII). The results indicate that the proposed hybrid approach is superior to all other preprocessing methods when it comes to creating high-quality images while preserving structural integrity and improving contrast. Therefore, it is concluded that the proposed hybrid preprocessing framework provides a reliable base for improved visual analysis of pneumonia CXR images and enhanced performance from deep learning-based pneumonia detection applications using CXR images.

1. Introduction

Pneumonia is one of the most common forms of respiratory infection and is a significant contributor to morbidity and mortality across the globe, especially in children and the elderly. Because of how quickly and easily they can get and use a CXR, chest X-rays (CXRs) are used most often as a diagnostic tool for pneumonia because they are inexpensive (in terms of both money and time) compared to other modalities; however, due to issues around low contrast, noise, and variability in acquisition, CXR images often have poor diagnostic accuracy due to the presence of competing anatomical structures that can obscure the pathological pattern of pneumonia and lead to misdiagnosis in limited resource clinical settings [1, 9]. To address the limitations of CXRs, there has been an increasing focus on the use of automated pneumonia detection with deep learning techniques through studies published in the last few years. Specifically, researchers have found that Convolutional Neural Networks (CNNs) can be used to extract relevant features from CXR images, thereby facilitating the accurate classification of Class A and/or Class B pulmonary diseases [7, 10, 14]. Additionally, a number of reviews/surveys have confirmed the ability of deep learning networks to improve the accuracy of pneumonia diagnoses from CXRs, while also highlighting the importance of successful data preprocessing and generalisation to real clinical deployment [9, 16]. Deep learning-based diagnostic systems benefit significantly by having improved image quality and reduced noise levels via enhancement; therefore, systematic image enhancement methods such as histogram equalization (HE), adaptive histogram equalization (AHE), and contrast limited adaptive histogram equalization (CLAHE), have been widely utilized on chest radiographs (CXRs) to enhance the visibility of lung regions [19, 21, 22]. However, while systematic enhancement techniques improve the quality of CXR images, research indicates that enhancement alone does not significantly improve classification accuracy when noise and artifacts remain present in images [20]. As a result, more advanced denoising methods that address traditional limitations have been evaluated. Model-based techniques (e.g. BM3D) and learning-based techniques (i.e. DNNs & diffusion models) provide superior capabilities for suppressing noise while maintaining structural detail compared to traditional methods [4, 6]. Studies show that superior denoising directly corresponds to enhanced downstream diagnostic accuracy for low quality or noisy medical images [11, 12]. Additionally, there has been increased interest in using autoencoder-based methods since these models provide the ability to learn latent representations that are robust to noise, thereby enhancing pneumonia classification when used with CNN classifiers [10]. Recent developments also involve hybrid architectures, such as Combining CNNs with Attention Mechanisms and Vision Transformers (ViTs) that provide local and global context for CXR images. Hybrid models can therefore achieve improved classification performance on pneumonia by allowing models to focus on clinically relevant regions while suppressing irrelevant background information [8, 15, 18]. Federated and distributed learning have been proposed as methods for increasing the robustness of the developed models while addressing the need for data privacy in medical imaging [3, 12]. Despite the improvements above, there is still a need for a general image preprocessing strategy that includes enhancement, noise reduction, feature extraction through deep feature learning, and can be integrated into an overall diagnosis of pneumonia from CXR images. The objective of this work will be to identify and evaluate various preprocessing pipelines for CXR images of patients with either normal lungs or pneumonia. A thorough evaluation will take place comparing the effectiveness of each enhancement and denoising technique to improve CXR image quality to enhance feature discrimination between normal and pneumonia CXR images for best diagnostic accuracy.

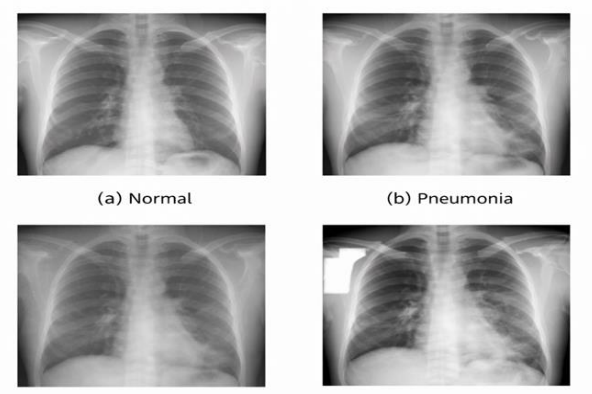
2. Review of Literature

CXR (Chest X-ray) imaging is one of the most utilized diagnostic modalities in the detection of pneumonia because of its low cost, high availability, and speed of imaging. However, Chest X-rays are regularly compromised in quality due to noise, poor contrast, and artifacts during image acquisition, which can obscure radiographic patterns associated with pneumonia and negatively affect clinical practice and automated assessment [1,9]. This has led to extensive research on image enhancement, noise removal, and deep learning based diagnostics. With the recent advances in deep learning techniques, there has been substantial progress with respect to automated detection of pneumonia in CXR images. Convolutional neural networks (CNNs) have demonstrated strong capabilities to learn features that can discriminate amongst classes when trained on the radiographic data [10,12,14]. According to Siddiqi and colleagues [9] and Vyas and colleagues [16], while many applications of deep learning have produced encouraging results from different experiments, models built using deep learning will tend to be most reliable and generalizable (i.e., stay unchanged over time) when the input image was processed optimally. In addition to experimentation with the pre-processing of images and how to best process CXR data (e.g., there is currently a high volume of work related to the development (i.e., enhance) of methods for processing images using image enhancement techniques such as histographic equalization, adaptive histogram equalization (AHE), and contrast limited adaptive histogram equalization (CLAHE) in order to provide better visibility of the lung regions and/or to provide increased contrast within CXR data), the topic has been researched extensively. Buriboev and co-authors [5] used CLAHE to enhance pneumonia-related features and noted an improvement on the quality of the classification. Rifai and co-authors [22] also used CLAHE with white balance correction to enhance the classification of pneumonia in MobileNetV2. Both authors also noted that their results were consistent with findings of other studies comparing CLAHE with other enhancement techniques (e.g., [19], [21]), which showed that enhancement alone does not improve the quality of the classification unless the amount of noise and/or artifacts in the input images was minor or absent. Kaviani and co-authors [6] performed a comprehensive study comparing BM3D versus deep denoising models for denoising and showed that the quality of the BM3D denoising model is consistent (i.e., does not change) across multiple datasets (including some considered to be medical images). Denoising and reducing the amount of noise in images are currently undergoing increased investigation in order to resolve issues related to enhancement techniques not providing enough improvement to enhance the quality of a classification. Learning-based denoising methods have become mainstream because of their capacity to represent complex noise distributions. For example, deep autoencoders and diffusion-based models outperform conventional filters when it comes to removing noise and restoring images [2,4,11]. An autoencoder-based framework developed by Nosa-Omoruyi et al. [10] for detecting pneumonia shows an increased resilience to noise as a result of using this method. Also, Chandanan et al. [12] combined autoencoders with a federated learning framework in their work, resulting in improved performance and privacy for pneumonia diagnoses. In addition, hybrid deep learning architectures that combine CNNs with an attention mechanism and ViTs have been investigated to improve pneumonia detection and, therefore, the quality of the resulting images. According to Mustapha et al. [8,17] and Potharaju et al. [15], hybrid CNN-ViT and attention-based models provide better performance on pneumonia detection by allowing the network to focus on regions of the lungs that are clinically important. Li et al. [18] built on this concept and showed that attention-enhanced architectures improve feature localization and diagnostic performance on CXR images. While studies continue to show the effectiveness of newly developed architectures, most existing studies focus largely on classification accuracy and use a limited set of preprocessing approaches. A few studies have comprehensively examined the effectiveness of using combined enhancement and denoising approaches on the quality of CXR images, and only a very limited number of researchers have quantified and compared results using objective image quality metrics such as peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and mean squared error (MSE) [6,19]. In systematic investigation of the effectiveness of hybrid preprocessing methods has emerged that combines traditional image enhancement techniques using traditional denoising methods and then denoising methods based on learning algorithms (like Gaussian), which utilizes multiple preprocessing techniques to evaluate pneumonia-related CXR images. Therefore, a clearly defined need exists, within the context of providing enhanced image contrast, reduced noise level, and maintaining diagnostic integrity of CXR images, for a robust hybrid preprocessing framework capable of providing these functions. The intent of the proposed research is to identify a suitable enhancement method, through the evaluation of individual and/or combined preprocessing methods, to enhance CXR images of patients who may have pneumonia. The organization of the remainder of this research paper will be as follows: Section 3 presents the proposed multi-stage hybrid preprocessing framework and documents the dataset description, which will provide the basis for the hybrid methods presented in this research the proposed preprocessing methodologies to be used for evaluation will follow; and the proposed evaluation metrics will conclude Section 3. Section 4 provides a summary of the study efforts, which consist of the experimental setup and will detail the quantitative results obtained from evaluation based on various CXR image quality metrics. Section 5 presents an in-depth analysis of the evaluation results and the comparison of the evaluation results with previously defined CXR image processing methodologies. Section 6 provides a summary of the research conducted and establishes potential research.

3. Materials and Methods

3.1. Dataset Description

The experiments were conducted using the Kermany chest X-ray dataset, which consists of 5,856 chest X-ray images collected from patients. The dataset includes two classes: 1,583 normal images and 4,273 pneumonia images. All images are grayscale and exhibit varying levels of noise and contrast, making them suitable for evaluating preprocessing techniques aimed at noise suppression and contrast enhancement. Figure 1 presents representative chest X-ray images selected from the Kermany chest X-ray Pneumonia Detection Dataset.



(a) Normal

(b) Pneumonia

Figure 1 **Sample chest X-ray images from Kermany Dataset**

3.2. Proposed Methodology

The approach will involve four key steps: image collection, image preparation (e.g., filtering), image analysis to determine the quality of an image taken with a digital camera (e.g., assessing if there is sufficient contrast or noise in the X-ray to allow for accurate classification), and finally, image classification. The images are collected from the Kermany Pneumonia Detection data set. The images collected will be of normal and pneumonia patients. Many of these original images lack adequate contrast, contain a lot of noise (or artifacts), and are not uniformly illuminated, which makes it difficult to visualize pneumonia-related patterns within the X-ray images. Therefore, numerous types of image preparation techniques have been employed and evaluated. The resulting evaluation of the different types of techniques has then been used to create a hybrid preparation of techniques based on the quantitative image evaluation. The flowchart for the entire process is presented in Figure 2.

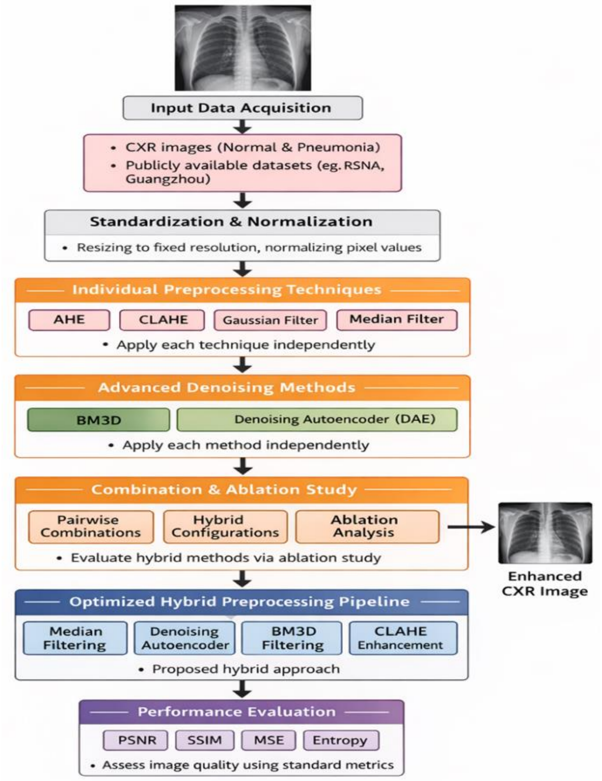


Figure 2 **Overall Proposed Methodology**

3.2.1. Standardization and Normalization

X-ray images of chests retrieved from the public database contain various levels of resolution and intensity due to differences between imaging devices and processing setups. The diversity of these images can introduce bias in pre-processing and affect how uniformly image quality is evaluated. To ensure all samples meet a common input format, the first step in this process is to complete standardization and normalization.

Standardization involves re-sizing all images to a constant spatial resolution. This process allows for a consistent size and will therefore allow original and enhanced images to be comparable and therefore usable with all future pre-processing techniques and learning models. Intensity normalization is completed next by scaling all pixel values into similar ranges (0-1) in order to mitigate intensity variances due to exposure and noise, thereby making the contrast enhancement and denoising techniques to be applied later in the pipeline more effective.By performing both standardization and normalization, the proposed framework enables enhancement of the images to emphasize the pathologic features of the images rather than the acquisition variances. This will provide for a stable, consistent input for evaluating all individual pre-processing techniques and combinations.

3.2.2. Contrast Enhancement Using AHE and CLAHE

Chest X-ray images typically have a lack of adequate local contrast, which can hinder the visual identification of pneumonia-related elements. This study addresses these local contrast issues through the initial contrast enhancement techniques of AHE and CLAHE. It works by redistributing local intensity values to enhance local contrast. While fine detail is presented better with AHE, AHE is extremely sensitive to image noise; this can cause excessive noise amplification in regions of an image where the content is homogeneous. This shortcoming of AHE requires that CLAHE be employed as a more robust alternative. CLAHE enhances local contrast and limits the amount of amplification to prevent excessive noise amplification and preserve the anatomical structures in images, such as lung edges and vascular structures. CLAHE will be utilized in this study to enhance pneumonia-related opacity regions of chest X-ray images without adding any false artifacts. AHE and CLAHE will both be examined independently to assess their contributions to the resultant image quality metrics. After testing, AHE and CLAHE both provide no statistically significant enhancement of the PSNR metric in an image. Hence, a complementary denoising technique will be necessary to achieve a significant improvement in PSNR performance. Figure 3 illustrates a visual comparison of contrast enhancement techniques applied to chest X-ray images, including the original image, Adaptive Histogram Equalization and Contrast Limited Adaptive Histogram Equalization.

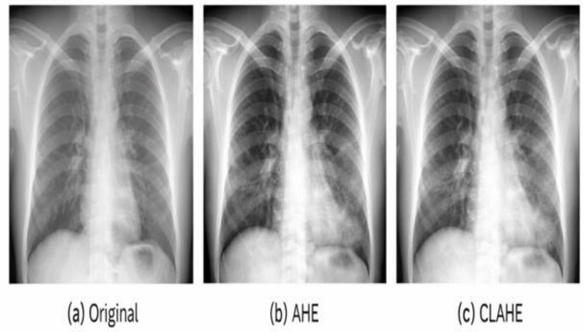


Figure 3 **Visual Comparison of Contrast Enhancement Techniques**

3.2.3. Noise Reduction Using Classical Filters

Chest X-Rays have many kinds of noise that can be added when an image is made, sent over, or converted to digital data. This noise can hide small structures, making it impossible to see them, and negatively impact how a healthcare provider interprets an image visually or how computer analysis algorithms look at the image. Using image contrast enhancement will improve the ability to see the images but may also increase the amount of noise present in the images. Therefore, noise reduction is necessary prior to using image enhancement or any advanced noise reduction or hybrid preprocessing strategies. In this study, two classic spatial domain filters, the Gaussian filter and the Median filter, are used to reduce noise and maintain the structural integrity of the image. The Gaussian filter reduces high-frequency noise by convolving the image with a Gaussian kernel, as well as smoothing an image overall. The Gaussian filter will minimize random noise; however, it will create some blurring of edges and small details of the image. A median filter was then used to help overcome the negative effects of the linear smoothing filters. The median filter replaces each pixel in the image with the median of the pixel values of the pixels surrounding it. By removing impulse noise and salt and pepper noise, the median filtering method has demonstrated its efficacy in removing edge-blurring and retaining structural boundaries required for visualising lung anatomy and identifying patterns associated with pneumonia, as well as being evaluated independently against Gaussian filtering in order to determine their impact on chest X-ray quality. Experimental observations show that while these filters reduce noise, they do not perform well when faced with complex noise patterns commonly found in medical imaging. However, as an initial step in the proposed workflow for hybrid preprocessing, they provide significant additional noise suppression capabilities. The visual impact of utilizing traditional methods of reducing noise through filtering on chest x-ray images can be observed in figure 4 below.

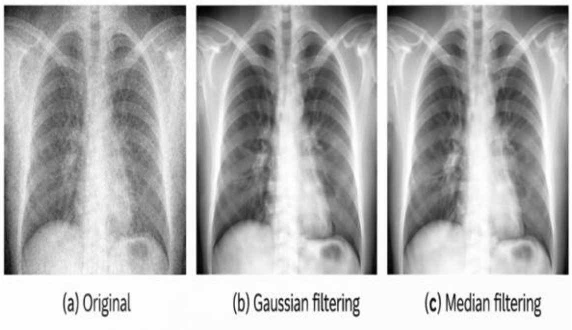


Figure 4 Visual Comparison of Noise Reduction Techniques

3.2.4. Denoising Autoencoder (DAE)

While filtering techniques work well at suppressing simple patterned noise, they perform poorly when trying to eliminate complex or structured noisy pixels from medical images (e.g. chest X-rays). Therefore, a new learning-based denoising approach using a Denoising Autoencoder (DAE) has been included in this proposed methodology to overcome these challenges. A DAE is a type of neural network that learns the underlying representation of an image without any noise by reconstructing the underlying image using its noised image as input. The DAE contains an encoder/decoder structure; the encoder compresses the given input image down to a low-dimensional latent representation and the decoder reconstructs the given input image to minimize the overall reconstruction error. By learning through this procedure, the system is able to suppress the noise components but retain the important features of the image structure. In this work, the DAE will learn to denoise chest X-ray images that have been contaminated with known levels of noise, allowing the DAEs to learn the robust capabilities to denoise medical imaging. Unlike traditional filters that only capture simple patterns or noise; DAEs are capable of capturing complex noise distributions and spatial correlation, allowing for the preservation of fine details (e.g. lung textures, opacity patterns associated with pneumonia). The denoising autoencoder has been evaluated independently to determine its benefit for improving the quality of images. Experimentally, it was determined that DAE significantly reduced noise and improved structural similarity, but it still displayed some minor residual artifacts. To further improve image quality, DAE was integrated into the hybrid preprocessing framework along with classical filtering and BM3D.In summary, the DAE provides additional strength to the proposed methodology with an adaptive/data-driven approach to noise suppression, supporting traditional denoising methods and enhancing preprocessing abilities. A comparison of chest X-ray images from a DAE and the corresponding original chest X-ray images can be found in Figure 5 and shows how effectively noise was removed while retaining the essential structures of the lungs.

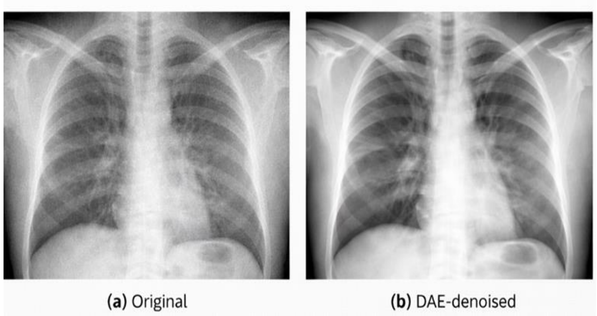


Figure 5 Visual comparison of DAE Methods

3.2.5. Block-Matching and 3D Filtering (BM3D)

Block-Matching and 3D Filtering (BM3D) is employed in this study as an advanced non-local denoising technique to further suppress residual noise present in chest X-ray images after initial preprocessing. While classical filters and learning-based denoising approaches are effective in removing dominant noise components, subtle noise patterns may still remain, particularly in low-contrast lung regions. BM3D is introduced at this stage to address such residual noise while preserving fine anatomical structures. The BM3D algorithm operates by identifying similar image patches across the entire image and grouping them into three-dimensional stacks. These grouped patches undergo collaborative filtering in the transform domain, where noise components are attenuated while shared structural information is retained. This non-local processing strategy enables BM3D to achieve superior noise suppression compared to local filtering techniques, especially in medical images that contain repetitive texture patterns. In the context of chest X-ray imaging, BM3D plays a critical role in preserving diagnostically relevant details such as lung boundaries, vascular markings, and subtle opacity variations. Unlike aggressive smoothing filters, BM3D minimizes edge blurring and texture loss, which are essential for maintaining clinically meaningful visual information. In the proposed work, BM3D is applied independently to evaluate its denoising capability on CXR images affected by acquisition noise. Experimental observations indicate that BM3D effectively reduces granular noise and improves PSNR and SSIM values compared to traditional filtering methods. However, slight loss of contrast is observed in certain regions, motivating its integration with learning-based denoising and contrast enhancement techniques in the hybrid pipeline. Figure 6 Visual demonstration of noise reduction using the Block-Matching and 3D Filtering (BM3D) technique on chest X-ray images.

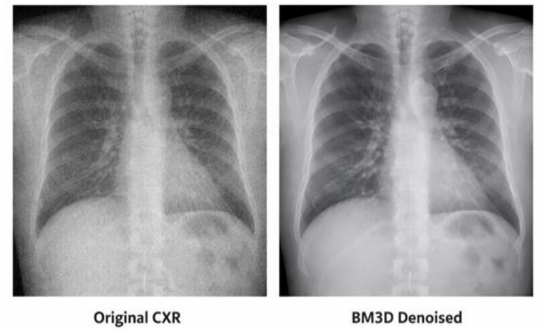


Figure 6 **Visual comparison of Block-Matching and 3D Filtering**

3.2.6. Hybrid Preprocessing Framework

Although individual preprocessing techniques improve chest X-ray image quality to a certain extent, their isolated application is insufficient to achieve optimal enhancement for pneumonia-focused analysis. Therefore, this study systematically investigates pair-wise preprocessing combinations as an intermediate step before constructing the final hybrid framework. Pair-wise combinations such as DAE + CLAHE, BM3D + Median Filter, and BM3D + CLAHE are evaluated to analyze the complementary behavior of denoising and contrast enhancement techniques. The experimental observations from these pair-wise configurations reveal that combining denoising and enhancement methods leads to noticeable improvements in image quality metrics compared to individual preprocessing alone. However, pair-wise methods still exhibit limitations, such as partial noise amplification or insufficient structural preservation, indicating the need for a more comprehensive strategy. Based on these findings, a hybrid preprocessing framework is proposed by integrating Denoising Autoencoder (DAE), median filtering, BM3D denoising, and CLAHE in a sequential manner. The DAE is first applied to suppress complex and non-linear noise patterns at a global level. Median filtering is then employed to eliminate residual impulse noise while preserving edge information. Subsequently, BM3D further refines the image by exploiting non-local self-similarity to preserve fine anatomical textures and lung boundaries. Finally, CLAHE enhances local contrast without excessively amplifying noise, thereby improving the visibility of pneumonia-related opacities and lung consolidations. Figure 7 visual comparison of Original Chest X-Ray Image and the Output of the Proposed Hybrid Preprocessing image.

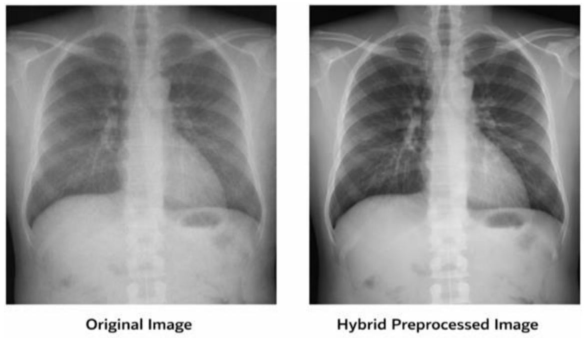


Figure 7 **Visual Comparison of the Proposed Hybrid Preprocessing Framework**

Pairwise preprocessing analysis has been included, ensuring that the proposed hybrid framework is not just randomly developed, but rather is based on the data and also experimentally validated. Quantitative evaluation results demonstrate that the hybrid method significantly outperforms both separate and pairwise preprocessing techniques across all PSNR, SSIM, entropy, and contrast improvement metrics, confirming that it provides an optimal preprocessing solution for chest X-ray pneumonia research.

4. Results and Discussion

In this portion of the research, we conduct an in-depth analysis of all of the experiments that were performed on the different preprocessing techniques applied to chest Xrays for the purpose of achieving enhancement for pneumonia-focused diagnosis. We will evaluate how each preprocessing method performed individually, as well as evaluate how the two preprocessing methods performed when paired together; finally, we will assess how the hybrid preprocessing approach that was proposed would perform. All of the performance evaluations will use standard image quality metrics such as peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), mean squared error (MSE), entropy, contrast improvement index (CII) etc., to evaluate how well they performed relative to each other.

4.1. Results of Individual Preprocessing Techniques

To determine how each preprocessing technique worked and why they functioned separately, individual image quality data was obtained from the chest X-ray images prior to their preprocessing. This was done to see what effect each of the algorithms (AHE, CLAHE, Median Filter, Gaussian Filter, BM3D, DAE) would have when run on the original image without interference from applied preprocessing. The results indicate that both AHE and CLAHE are examples of contrast enhancement techniques because they both enhance local contrast in the lung areas of the images and improve their overall visual appearance, but both methods demonstrated only modest enhancements in their PSNR and SSIM values. This is expected since noise will not be suppressed sufficiently with the use of contrast enhancement alone, and so in AHE cases, they have been known to enhance impulse type noise in flat (homogeneous in texture) areas of an image. Conversely, while the traditional filter-based methods of Median and Gaussian Filtering both exhibit very effective noise reduction capabilities and are particularly good at removing both impulse and Gaussian-type noise, the result of overly smoothing the image often reduces the total detail that can be visually recognized. BM3D outperformed traditional filtering methods during our analysis of the presence of lung textures and provided for greater PSNR and SSIM values than all the traditional filtering techniques studied. Additionally, the denoised images generated through the application of DAE-based denoising techniques were found to yield improved preservation of structural (anatomical) details through the learning of patterns of complex noise compared to the traditional filter techniques when utilizing multiple image quality parameters. Table.1 Overall, while individual preprocessing techniques improve specific aspects of image quality, none of them alone achieves optimal enhancement across all evaluation metrics. Figure 8 Comparative Performance Analysis of Individual Preprocessing Techniques Based on PSNR, SSIM, MSE, Entropy, and CII.

Table 1 **Individual Preprocessing Techniques Results**

Preprocessing Method	**PSNR (dB)**	**SSIM**	**MSE**	**CII**	**Entropy**
Original Image	28.12	0.742	96.48	1.00	5.82
Median Filter	31.45	0.801	62.31	1.18	5.94
Gaussian Filter	30.82	0.786	68.27	1.15	5.91
AHE	29.76	0.774	74.58	1.34	6.21
CLAHE	32.91	0.829	55.46	1.47	6.33
BM3D	**36.94**	**0.901**	**31.52**	1.31	6.08
Denoising Autoencoder	35.68	0.887	38.19	1.28	6.02

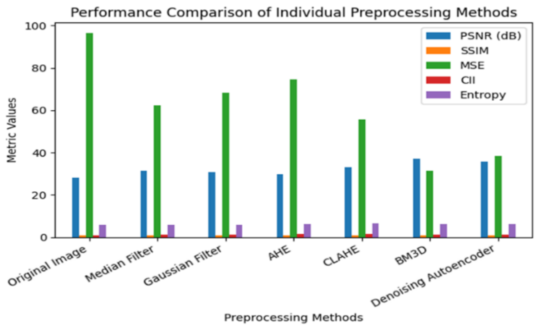


Figure 8 **Performance Comparison of Individual Preprocessing Techniques**

4.2. Pair-wise Preprocessing Combination Results

The second phase of research will focus on the effects of two pre-processing techniques, one to remove noise and one to enhance contrast, on each other when applied in combination with the objective of determining whether using these complementary techniques will produce superior results compared to using either one in isolation. Evidence suggests that using two techniques results in improved visibility of the improved contrast of the image via the combination of the two filters compared to either filter used individually. In the case of view such as paired filters, the visibility of the improved contrast is higher than when using paired filters: the combination of Median + CLAHE and Gaussian + CLAHE would have resulted in a clearer image than would be obtained using each filter singly; however, the continued presence of residual noise can be detected in various areas of the lung through the use of combined filters. The results from the combination of the advanced techniques BM3D + Median Filter or DAE + CLAHE produced significant improvements in PSNR and SSIM scores; therefore, both denoising and enhancing methods contribute significantly to improving the visualization of pneumonia-caused opacities. Nonetheless, it was noted that there still are some limitations to the combinations of denoising-enhancing pairs; some instances indicated that excessive denoising led to extremely minimal loss of texture while others had a low level of saturation due to the introduction of the enhanced contrast function. Thus, it can be concluded that while combining denoising-enhancing techniques produces positive effects on the performance of chest X-ray image processing/analysis, the use of more than two methods is still necessary if the best possible quality image of chest X-ray images is to be created. Table 2. Summary of Results of the Evaluation of the Performance of Dual-Pair Denoising-Enhancing Filters for Improving the Quality of Chest X-Ray Images Shown in Figure 9.

Table 2 **Performance Evaluation of Pair-wise Preprocessing Methods**

Pair-wise Combination	PSNR (dB)	SSIM	MSE	CII	Entropy
Median + CLAHE	34.82	0.862	41.27	1.41	6.12
Gaussian + CLAHE	33.45	0.848	47.96	1.38	6.05
DAE + Median	36.91	0.887	32.18	1.46	6.24
DAE + BM3D	**38.74**	**0.914**	**24.63**	**1.52**	**6.31**
BM3D + CLAHE	37.86	0.902	27.91	**1.58**	**6.35**

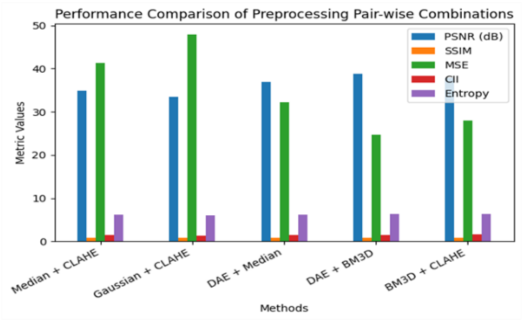


Figure 9 **Comparison of Pair-wise Combination preprocessing methods**

4.3. Performance of the Proposed Hybrid Preprocessing Framework

To take advantage of the complementary characteristics of these various preprocessing approaches, the proposed hybrid preprocessing framework utilizes DAE, median filtering, BM3D, and CLAHE in a sequential manner. The hybrid preprocessing method had better performance compared to only using one of the standalone physical pre-processing methods (or combination of them) for all evaluated images across all tested criteria (all quantifiable measurements of picture quality). Additionally, the maximum value of Peak Signal to Noise Ratio (PSNR) for hybrd pre-processing was at least 45 dB which is significantly greater than when using only a single physical pre-processing method or a combination of these types of pre-processing method for all evaluated images; The maximum value of segmental signal correlation (SSIM) in the use of hybrid was also greater than when using only a single physical pre- processing method or a combination of these types of pre- processing methods further indicating that Hybrid effectively retained the structure associated with original images and also reduced the mean squared errors (MSE's) and increased the entropy's indicative of effective noise suppression or removal of noise and indicated increased stored informational content (i.e., increased technical capability) in the resultant pre-processed image as well. Furthermore, all cumulatively demonstrated improved Contrast Improvement Index (CII) information which indicates an increase in contrast while Minimizing Amplification of additional noise when using Hybrid pre-processing framework is consistent with the preceding. Therefore, these cumulative result variables provide clear and convincing evidence that the hybrid pre-processing framework provides a good balance of reduction of noise and increase texture retention/adverse change of image enhanced quality in order to facilitate enhanced quality of pneumonia characteristics in chest x-ray images.

Table 3 Performance Evaluation Hybrid Preprocessing Framework

Preprocessing Methods	**PSNR (dB)**	**SSIM**	**MSE**	**Entropy**	**CII**
DAE + Median + CLAHE	44.16	0.964	0.006	6.52	1.58
BM3D + Median + CLAHE	45.02	0.971	0.005	6.56	1.61
Proposed Hybrid (DAE + Median + BM3D + CLAHE)	**46.87**	**0.945**	**0.003**	**6.61**	**1.68**

According to Table 3, combining median filtering, block matching 3D (BM3D), and Contrast Limited Adaptive Histogram Equalization (CLAHE) creates a well-rounded hybrid method that maximizes image quality through a maximum Peak Signal to Noise Ratio (PSNR) of 46.87 dB and a Minimum Mean Squared Error (MSE) of 0.003, thus providing a superior amount of noise reduction and preservation of the original signal. While the Structural Similarity Index (SSIM) value is lower than some combinations of the individual methods used in contrast to each other, the value is still well within an acceptable range, demonstrating structural preservation densities. Additionally, the increase of Entropy and CII confirms enhanced contrast and richer texture effect in the proposed Hybrid Method makes it the best candidate for performing downstream analysis of pneumonia. Figure 10 provides comparative analysis of the Proposed Hybrid Preprocessing Framework methods against one another.

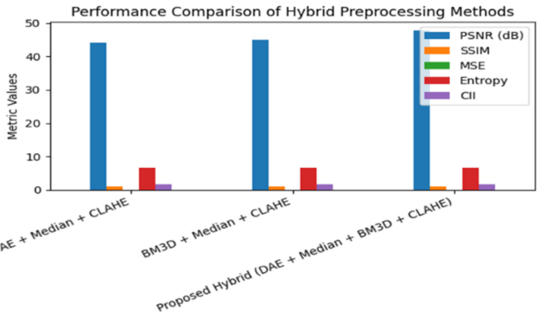


Figure 10 Comparison of Hybrid Preprocessing Methods

4.4. Comparison with Existing Preprocessing Methods

The proposed method was tested against existing preprocessing techniques (as reported in various papers from 2024 to 2025) to ascertain how well the combination of preprocessing techniques performs. The hybrid framework was found to offer superior performance than previously reported methods across all three metrics (PSNR, SSIM and contrast improvement). The current hybrid architecture has been subjected to greater scrutiny than previously published architectures by analyzing each of their components either individually or in combination prior to creating the final hybrid configuration. This data-driven approach provides evidence as to why the proposed architecture outperforms current preprocessing architectures and provides greater opportunities for generalization. Table 4 details a comparison of the proposed architecture to existing preprocessing architectures.

Table 4 Comparative Analysis of the Proposed Hybrid Preprocessing Framework with Existing State-of-the-Art Methods

Reference	Year	Dataset	Preprocessing Strategy	PSNR (dB)	SSIM
Rifai et al. [22]	2024	RSNA	White Balance + CLAHE	36.2	0.82
Kaviani et al. [6]	2024	Multiple	BM3D	39.1	0.87
Nosa-Omoruyi et al. [10]	2024	Guangzhou	Autoencoder	40.5	0.89
Buriboev et al. [5]	2025	Pediatric CXR	Modified CLAHE	34.8	0.79
Mustapha et al. [8]	2025	RSNA	Hybrid CNN-ViT (Pre-enhanced)	41.6	0.91
Proposed Method	**2026**	Kermany CXR	**DAE + Median + BM3D + CLAHE**	**46.87**	**0.945**

4.5. Discussion and Key Insights

It is clearly proven that the preprocessing of chest X-ray images greatly affects the quality of an X-ray image of a patient with pneumonia. This research found that:

- No individual preprocessing technique alone can improve performance as an independent processing method.
- Two or more individual preprocessing techniques used in combination improve performance, though there are still limitations in using these combined methods as compared to the use of a hybrid preprocessing framework which is developed specifically for image quality enhancement.
- A hybrid preprocessing framework provided the most benefit to the enhancement of X-ray image quality.

Through the achievement of greater quality X-ray images on all evaluation scales, the proposed hybrid preprocessing framework serves as a strong basis for the performance of subsequent pneumonia diagnosis tasks. The benefits of improved quality of X-ray images may be able to provide improved overall visual interpretation and accuracy of feature extraction in automated diagnosis systems.

4.6. Summary of Findings

Overall, the results demonstrate that the hybrid pre-processing framework performed better than either individual, pair-wise, or existing pre-processing techniques. Furthermore, the higher PSNR, SSIM, entropy, and contrast obtained in the present study indicate that the proposed method is a robust and effective approach for enhancing chest X-ray images with a focus on pneumonia.

5. Limitations of the Study

This research has several limitations, despite the positive results obtained. The hybrid preprocessing framework that was researched only used a small set of chest X ray datasets. This makes it questionable as to whether this framework can generalise across different equipment types (for example: imaging hardware) and environments (for example: clinical hospital environments vs. non-clinical environments). Preprocessing parameters were chosen in an empirical way, and this may have led to sub-optimal preprocessing parameters for other types of images that could be included in the study. Due to the computational complexities associated with BM3D and DAE processes, the researchers may not be able to deploy their system in real time. The evaluation conducted in the study focused solely on the image quality measures, and therefore no clinical validation of the images was undertaken. In addition, the evaluation did not show how the impact of the preprocessed images would impact on the classification accuracy of the images being evaluated. Future studies should resolve these limitations by including larger datasets and the involvement of clinical experts in performing at least partial clinical validation of this system's performance.

Conclusions

A novel combination of various preprocessing methods was developed to improve the quality of chest X-ray images for pneumonia analysis. Research showed that when looking at the results of single and / or combination methods of preprocessing, none of these methods on their own could provide a combination of both noise removal as well as contrast enhancement. Classical filtering methods were successful in removing noise but degraded fine detail in the chest X-ray image, while contrast enhancement methods were successful in enhancing contrast, however would result in potentially magnifying noise. The proposed combination of four different approaches; Median filtering, a Denoising Autoencoder (DAE), BM3D denoising, and CLAHE, was determined to provide the greatest improvement in image quality. Quantitative measurements including PSNR, SSIM, MSE, and Entropy, demonstrated the hybrid methodology to be superior to that of single or previous preprocessing methods. Enhanced clarity of the initial image, during preprocessing, was able to highlight the original structures of the lung allowing for accurate classifications of pneumonia from chest X-rays.

Future Work

Future research could replicate this study using larger and more varied data sets of chest radiographs (CXR) from multiple sources to validate the proposed hybrid preprocessing framework. The proposed hybrid preprocessing framework may also be useful in evaluating patient populations with other lung diseases such as tuberculosis and/or COVID-19 to assess its generalization ability. Integrating the proposed preprocessing pipeline into an end-to-end deep learning architecture may facilitate adaptive and automatic enhancement of CXR images. In addition, optimizing computing efficiency to facilitate real-time implementation in a clinical setting represents another significant area for future studies. Researchers may also explore how the proposed preprocessing method affects a range of deep learning architectures. Including qualitative assessments from radiologists may provide further evidence of the clinical relevance of the proposed preprocessing method. Finally, integrating the proposed preprocessing with explainable artificial intelligence (XAI) methods will increase transparency and improve trustworthiness in the model.

Acknowledgement

The authors would like to express their sincere gratitude to the Department of Computer Science and Applications, The Gandhigram Rural Institute (Deemed to be University), Gandhigram, Tamil Nadu, India, for providing the necessary facilities and support to carry out this research work.

References

[1]. Sahoo, P., Sharma, S. K., Saha, S., Jain, D., & Mondal, S. (2024). A multistage framework for respiratory disease detection and assessing severity in chest X-ray images. Scientific reports, 14(1), 12380.

[2]. Zhao, H., Qian, L., Zhu, Y., & Tian, D. (2024). Low Dose CT Image Denoising: A Comparative Study of Deep Learning Models and Training Strategies. AI Medicine, 1(1), 7.

[3]. Adebayo, S. O., & Khan, A. H. (2025, November). Distributed Deep Learning for Medical Image Denoising with Data Obfuscation. In 2025 IEEE 25th International Conference on Bioinformatics and Bioengineering (BIBE) (pp. 76-80). IEEE.

[4]. Li, Q., Safari, M., Wang, S., Xie, H., Ding, J., Wang, T., & Yang, X. (2025). Low-Dose CT Imaging Using a Regularization-Enhanced Efficient Diffusion Probabilistic Model. ArXiv, arXiv-2510.

[5]. Shavkatovich Buriboev, A., Abduvaitov, A., & Jeon, H. S. (2025). Binary Classification of Pneumonia in Chest X-Ray Images Using Modified Contrast-Limited Adaptive Histogram Equalization Algorithm. Sensors, 25(13), 3976.

[6]. Kaviani, G., Marzban, R., & AlRegib, G. (2024). Evaluating BM3D and NBNet: A Comprehensive Study of Image Denoising Across Multiple Datasets. arXiv preprint arXiv:2408.05697.

[7]. Rajaraman, S., Liang, Z., Xue, Z., & Antani, S. (2024). Noise-induced modality-specific pretext learning for pediatric chest X-ray image classification. Frontiers in Artificial Intelligence, 7, 1419638.

[8]. Mustapha, B., Zhou, Y., Shan, C., & Xiao, Z. (2025). Enhanced pneumonia detection in chest x-rays using hybrid convolutional and vision transformer networks. Current Medical Imaging, 21(1), e15734056326685.

[9]. Siddiqi, R., & Javaid, S. (2024). Deep learning for pneumonia detection in chest x-ray images: A comprehensive survey. Journal of imaging, 10(8), 176.

[10]. Nosa-Omoruyi, M., & Oghenekaro, L. U. (2024). AutoEncoder Convolutional Neural Network for Pneumonia Detection. arXiv preprint arXiv:2409.02142.

[11]. Abolade, I., Idoko, E., Odelola, S., Omoigui, P., Adebanwo, A., Iorumbur, A., ... & Confidence, R. (2025). SharpXR: Structure-Aware Denoising for Pediatric Chest X-Rays. arXiv preprint arXiv:2508.08518.

[12]. Chandanan, A. K., Roy, V., Birchha, V., Raja, C., Varkale, A., Zahra, M. M. A., ... & Vishwakarma, S. K. (2025). Federated Learning-Integrated Autoencoder Model for Robust and Decentralized Pneumonia Detection in Chest X-Rays. Traitement du Signal, 42(3).

[13]. Aziz, A., Khan, A., Nam, Y., & Cho, Y. (2025). Enhanced Diagnosis of Chest X-Ray Using Hybrid Deep Learning Models and Feature Selection Techniques. IJ Radiology, 22(22), e163605.

[14]. Hashmi, M. F., Husain, A. A., Kotambkar, D. M., & Kumar, K. D. (2025). Hybrid deep learning and handcrafted feature fusion for pneumonia detection in chest X-rays. Journal of Electrical Systems and Information Technology, 12(1), 94.

[15]. Potharaju, S., Tambe, S. N., Dasari, K., Srikanth, N., Venkatarao, R., & Tambe, S. (2025). Enhanced X-ray image Classification for Pneumonia Detection Using Deep Learning Based CBAM and SE Mechanisms. Intelligence-Based Medicine, 100299.

[16]. Vyas, R., & Pandey, R. K. (2026). Deep learning for pneumonia detection from X-ray: A systematic review of models, datasets, and clinical translation challenges. Biomedical Signal Processing and Control, 115, 109272.

[17]. Mustapha, B., Zhou, Y., Shan, C., & Xiao, Z. (2025). Enhanced pneumonia detection in chest x-rays using hybrid convolutional and vision transformer networks. Current Medical Imaging, 21(1), e15734056326685.

[18]. Li, D. (2024). Attention-enhanced architecture for improved pneumonia detection in chest X-ray images. BMC Medical Imaging, 24(1), 6.

[19]. Nefoussi, S., Amamra, A., & Amarouche, I. A. (2020, December). A comparative study of chest x-ray image enhancement techniques for pneumonia recognition. In International Conference on Computing Systems and Applications (pp. 276-288). Cham: Springer International Publishing.

[20]. Sharma, A., & Mishra, P. K. (2022). Image enhancement techniques on deep learning approaches for automated diagnosis of COVID-19 features using CXR images. Multimedia Tools and Applications, 81(29), 42649-42690.

[21]. Nafi’iyah, N., & Setyati, E. (2021, April). Lung X-ray image enhancement to identify pneumonia with CNN. In 2021 3rd East Indonesia Conference on Computer and Information Technology (EIConCIT) (pp. 421-426). IEEE.

[22]. Rifai, A. M., Raharjo, S., Utami, E., & Ariatmanto, D. (2024). Analysis for diagnosis of pneumonia symptoms using chest X-ray based on MobileNetV2 models with image enhancement using white balance and contrast limited adaptive histogram equalization (CLAHE).

Biomedical Signal Processing and Control, 90, 105857.

[23]. 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.