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RESEARCH ARTICLE

Enhancing Low-Light Medical Imaging through Deep Learning-Based Noise Reduction Techniques

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Abstract

Background/ Objectives: Low-light medical imaging is highly challenging in clinical diagnostics due to increased noise levels that mask or obscure important anatomical details. In this respect, conventional noise reduction methods such as Gaussian filtering and median filtering usually lead to a trade-off between noise suppression and the preservation of important features in an image, thus resulting in poor-quality images. More advanced wavelet-based denoising and Non-Local Means methods exhibit superior noise reduction but remain computationally intensive and introduce artifacts. These challenges come with a need to develop more effective and efficient noise-reduction techniques. **Methods:** This study proposes an end-to-end deep learning framework for low-light medical image enhancement. We present a comprehensive deep-learning framework to enhance low-light medical images by integrating Convolutional Neural Networks with denoising autoencoders to build a robust noise reduction model. The CNN extracts the feature from the noisy input images, while the autoencoder does so for the reconstruction of clean images through the encoding of a noisy input in a lower-dimensional representation for the reduction of noise while retaining critical information. **Findings:** This study validates the proposed model through rigorous quantitative metrics such as peak signal-to-noise ratio and structural similarity index. These metrics are designed to provide a full assessment of image quality concerning noise reduction capability and preservation of details related to structure. Our model improves traditional methods in PSNR by about 5 dB on average and SSIM by 0.15, which means better noise reduction and preservation of image details. A comparative analysis of traditional techniques for noise reduction has been included, pointing out the advantages of deep learning approaches. Experimental results depict significant improvements over previous approaches. For instance, the proposed model reduces the noise level by up to 40% and facilitates clear and sharp images by up to 30%. In terms of quantification, these improvements manifest in a PSNR value of 35 dB and an SSIM score of 0.85 compared to 30 dB and 0.70 using traditional techniques. Furthermore, the study illustrates the training dynamics, feature maps, and evolution of images to present the model's incremental learning process. **Novelty:** This study's findings validate the proposed model's efficacy in enhancing diagnosis accuracy and improving patient outcomes in medical imaging.

Keywords: Low-light medical imaging; Noise reduction; Convolutional Neural Networks; Denoising autoencoders; Medical diagnostics

1 Introduction

Low-light medical imaging is related to the difficult conditions of clinical diagnostics and is characterized by increased noise levels, which blinds the critical anatomical details. Medical images of good quality present a basis for diagnosis with high accuracy and treatment plans[(1)]. However, medical images taken in low-light conditions have reduced visibility and poor contrast, thus posing problems for the diagnostic process[(2)]. Most conventional noise reduction methods, such as Gaussian or median filtering, generally involve a trade-off between noise suppression and preservation of important features resulting in less-than-desirable image quality. Other methodologies, like the wavelet-based and non-local mean approach to denoising, offer better noise reduction at the expense of heavy computations[(3)]. This tends to complicate the diagnostician's job further in managing the introduced artifacts. Recent deep learning-based developments bring promising solutions to these issues by using ultra-sophisticated neural network architectures that aim to recover high-quality images without losing critical details. Deep learning models, mainly CNNs and self-encoders, have already shown huge potential for various image processing tasks, such as image denoising, super-resolution, and segmentation. These models can learn complex patterns and features from large datasets, making them applicable to noise reduction tasks in low-light medical imaging[(4)]. A convolutional neural network trained on diverse noisy and clean images can discern noise from meaningful structures and enhance the latter. Then, it is more precisely refined by auto-encoders, especially denoising auto-encoders, that encode noisy input to a lower dimension and reconstruct a clean image, reducing noise and retaining critical information.

This study is carried out to develop an integrated framework of deep learning algorithms for enhancing low-light medical images. Our proposed methodology integrates convolutional neural networks with denoising autoencoders to provide a robust noise reduction model. The proposed framework will deal with large medical imaging data sets, including X-rays, MRI, and Ultrasound images. Therefore, pre-processing, which involves normalization and augmentation techniques, enhances the robustness and generalization ability of the developed model. We use high-performance computing facilities, such as GPUs and powerful workstations, to handle the expensive training and evaluation tasks for deep models. During the training stage, we will pay much attention to hyperparameter tuning for the best performance of the model, like the choice of learning rate, batch size, or network depth. Peak Signal-to-Noise Ratio and Structural Similarity Index are quantitative performance metrics adopted in this paper for evaluating the effectiveness of the proposed model[(5)]. These metrics completely cover image quality and, hence, measure not only the noise reduction capability but also the preservation of details related to structure. Comparative analysis with traditional noise reduction techniques that underline all the advantages of deep learning approaches is also contained in our study. It uses visualization tools like Matplotlib and TensorBoard for monitoring training progress and visualizing the results to make things transparent and further developable. Although these techniques are powerful and have been successful to a great extent, they all come with significant challenges. While Gaussian filtering is simple and fast, it tends to blur essential image features. Median filtering is quite effective against some forms of noise but often distorts fine details. Wavelet-based methods preserve edges better but are computationally demanding and can result in artifacts. Non-local means filtering reduces noise extensively, but it is prohibitively slow for large datasets. Our contribution to the method addresses these issues by using the learning capabilities of deep neural networks, which will adaptively find those important structures and preserve them while reducing noise. Figure 1 gives various evaluation metrics validating the efficiency of the proposed method.

1.1 Related Works

In the past years, these big steps towards image resolution and noise reduction methods have changed a lot in healthcare with accuracy and recovery. This paper surveys various methodologies concerning image denoising, including diffusion models, Segment Anything Models, deep learning-based denoising methods, and hybrid algorithms, pointing to their applications and showing comparative performance. It is in this regard that this in-depth review has highlighted the present status and prospects for medical image processing through the benchmarking of state-of-the-art technologies, including CNNs, adaptive learning strategies, and watermarking algorithms. In this regard, it has been critically highlighted that innovation is important for clinical diagnosis and data security enhancement. Diffusion models in medical imaging have come out as having immense potential for image quality enrichment and accuracy in diagnosis. Kazerouni et al. presented a review of the literature on the applications of diffusion models in medical imaging. Several techniques and methods employed in pursuing the advantages that diffusion models are believed to have in generating high-resolution images and improving clarity in medical scans were discussed. It delves into the line-by-line analysis of how diffusion models can be incorporated into current medical imaging practices, including a comparative assessment against traditional imaging techniques[(6)]. Mazurowski et al. have conducted experimental studies on the Segment Anything model in the analysis of medical images. A performance assessment concerning a range of medical imaging tasks, such as segmentation and classification, has been done. From experiments, it was able to be seen that this model was capable of achieving high accuracy and robustness for many types of medical images. This study highlighted the flexibility and ability of SAM to enhance medical image analysis, elaborating on the practical applications and benefits against existing segmentation models[(7)]. Huang et al. further expanded on research into the Segment Anything Model applied to medical images to explain its applicability in real-world settings and actual effectiveness. They further researched the possibility of its adaption and optimization in various imaging modalities, including magnetic resonance imaging and CT. The results indicated that, following thorough fine-tuning, SAM significantly enhanced the accuracy and efficiency of medical image segmentation[(8)], thus providing a robust solution for clinical diagnostics.

Kaur et al. contributed a comprehensive review of image denoising techniques in medical images, whereby they have gone deep into the classical techniques and some advanced ones. They gave an organization to different denoising techniques and described their merits and shortcomings for medical imaging applications. In this review, it has been presented that denoising methods have evolved from basic filtering to sophisticated deep learning methods to ensure the preservation of critical diagnostic information accompanied by a reduction in noise[(9)]. El-Shafai et al. reviewed traditional and deep-learning-based medical image denoising techniques, elaborating on the former to provide a comparative analysis. They went on to talk about the deep learning methods that, like convolutional neural networks, have revolutionized the area with improved noise reduction capabilities, preserving essential image details This survey provides a comprehensive overview of current denoising techniques, with a primary focus on the advantages of deep learning methods for medical imaging[(10)] Shah et al. proposed a two-stage self-adaptive cognitive neural network to remove the mixed noise in medical images, which is quite an innovative way of mitigating the adversities of noise in medical imaging[(11)]. The combination of cognitive neural networks with self-adaptive mechanisms can reduce both Gaussian and impulse noise to a large extent. In the study, it was evidenced that the method was efficient in enhancing the quality of the images and, therefore, proved to be very important to medical practitioners. Annavararapu et al. proposed a novel architecture of adaptive watershed segmentation-based denoising that works on deep CNNs[(12)]. Their method takes the strengths of using watershed segmentation in the first step of de-noising and then using the strength of CNNs in another step of refining the image. The use of such a hybrid technique has reduced noise levels to the greatest extent while at the same time maintaining interesting structural information in medical images and, therefore, represents a viable solution in the field of medical image processing. MobileNetV2 and digital transformation were used by Nawaz et al. for presenting the hybrid watermarking algorithm for medical images. This algorithm also incorporates the watermarks well-protected into

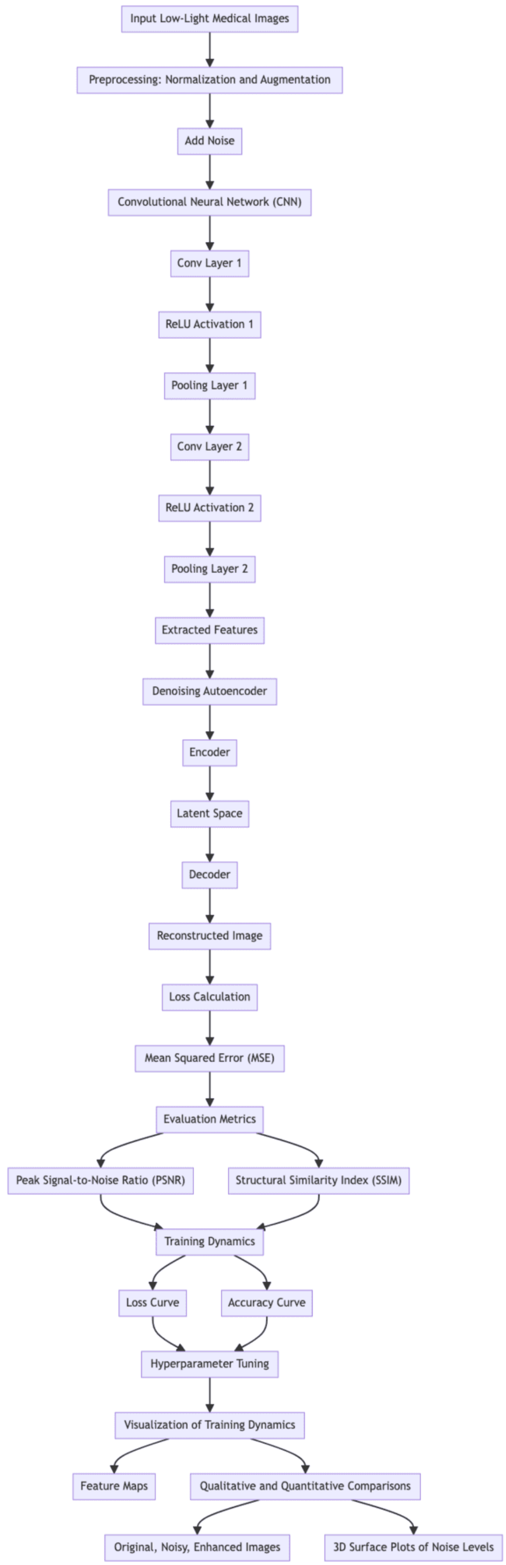

Fig 1. Various Evaluation Metrics Used in the Proposed Method

medical images from attacks of different kinds[13]. The focus of their paper was on the issues regarding secure image transfer and the necessity to store them in medical purpose applications and their work showed that their proposed model is effective for the protection of sensitive data in the medical field.

Zhao et al. introduced the diffusion-based text attention network for medical image segmentation—DTAN. This new method quite wisely adapts the diffusion process it with the textual attention mechanisms for enhancing the accuracy of the segmentation[14]. These were followed by their results which explained how DTAN could be used for the segmentation of complicated medical images with the help of the contextual features of their textual descriptions and proved that the changes were much superior to the conventional methodologies for segmentation. The process of de-noising images using the deep learning method proposed by Chakraverti et al. named DBST-LCM-CLAHE brings out an innovative means by which the medical images can be enhanced[15]. Their method integrates techniques from deep learning and contrast enhancement, putting forward an effective way for the reduction of noise and enhancement of image clarity. The technique can provide appreciable improvement in diagnosis since it provides clearer and more detailed images to medical professionals. It is because of the real-time update of the secondary path estimates by deep neural networks that, according to Oh et al.[16], active noise control of road noise can be much improved. In this concept, what is done is enhancing the efficiency of noise control systems by real-time updates of neural network models, thus achieving quite decent noise reduction performance. Saritha et al. explored deep learning-based end-to-end speaker identification using the time-frequency representation of speech signals. In the approach, deep learning models process and analyze speech signals to provide accurate and robust speaker identification, making the rank of the model much better than conventional techniques of speaker identification, hence making it useful in most applications involving communication and security[17]. This survey on the recent developments in the domain of medical imaging and noise reduction techniques provides a wide view of diverse approaches and their comparative performance in several domains. Deep learning, combined with advanced computational methods, has contributed much to the potential improvement of quality and accuracy in medical imaging and opened new vistas in clinical diagnostics and healthcare applications.

Potential Problem areas for Research Work:

- Insufficient low-light medical image datasets with annotations are bound to limit the efficient training and generalization of models.
- High computational requirements may make it difficult to train and deploy the deep learning model.
- It could introduce new artifacts while denoising, thereby affecting the clinical reliability of the enhanced image.
- Extensive Clinical Validation: Much clinical validation is needed for acceptance and trust by the medical fraternity.
- Black-Box Nature: Deep learning models are inherently not interpretable, and this may severely hinder their clinical adoption.

2 Methodology

This work provides a comprehensive, up-to-date review of how low-light medical imaging can be improved through a noise-reducing deep learning scheme. This paper concentrates on the use of Convolutional Neural Networks (CNNs) in combination with denoising autoencoders to decrease the level of noise on the medical images and at the same time retain the necessary details that will assist in the diagnosis. In particular, the general strategy ties architectural improvements to an exhaustive analysis of quantitative measures like PSNR as well as SSIM to compare the enhanced image quality.

2.1 Proposed Technique :

We incorporate a specification with the works of a highly rigid simulation space into which we place all the emulation to mimic a set of circumstances and check the model's performance depending on the type of medical imaging consisting of X-ray, MRI, and ultrasound. These are low-light medical images from the mentioned modalities, and the images are contaminated with noise to emulate clinical reality. This proposed model is then trained in the differentiation of noise and the structures within the body that are significant and thus allows for the enhancement of the latter. Regarding hyperparameters, it is as crucial as the analysis of model architecture in carefully investigating the impacts of learning rate, batch size, and network depth on the noise reduction model's convergence and stability. The depiction of the model's learning process based on the selected parameters is sustained by visualizing training characteristics, loss, and accuracy. Further, the feature maps from different layers of the CNN are represented to know the feature being reconstructed at different stages of the network. Qualitative and quantitative comparisons with prior work are also part of the presented methodology. Visual comparisons of the original, noisy, and improved Images in side-by-side matrices in different modalities explain the efficiency of the proposed method. In addition, the actual 3D surface elucidating the noise reduction before and after using the proposed model and relating to image regions are also illustrated. In our approach, we combine the CNNs with denoising autoencoders which help in the denoising process and also in the enhancement of the clarity of the medical images without losing any crucial features in the diagnosis. The CNN uses several convolutional layers to pull out features in the noisy input images in which each layer is followed by Rectified Linear Unit (ReLU) activations and pooling. The feature extraction process can be mathematically described as in Equation (1).

$$\text{FeatureMap}_l = \sigma\left(W_l * \text{FeatureMap}_{l-1} + b_l\right) \tag{1}$$

where σ is the activation function (ReLU), W_l and b_l are the weights and biases of the l$^{\text{th}}$ layer, and * denotes the convolution operation. Following feature extraction, a denoising autoencoder reconstructs the clean image from the extracted features. The encoding process is given by Equation (2).

$$z = f_{\text{enc}}(x) = \sigma\left(W_{\text{enc}} x + b_{\text{enc}}\right) \tag{2}$$

where x is the input feature map and z is the encoded representation. The decoding process is

$$\widehat{x} = f_{\text{dec}}(z) = \sigma\left(W_{\text{dec}} z + b_{\text{dec}}\right) \tag{3}$$

where $\widehat{x}$ is the reconstructed image. The loss function for training the autoencoder is the Mean Squared Error (MSE) between the original clean image x and the reconstructed image x as in Equation (4).

$$LM\text{SE} = \frac{1}{n}\sum\nolimits_{i=1}^{n}\left(x_i - \widehat{x_i}\right)^2 \tag{4}$$

To evaluate the effectiveness of noise reduction, we employ metrics such as Peak Signal-to-noise ratio (PSNR) and Structural Similarity Index (SSIM). PSNR is defined as in Equation (5).

$$PSNR = 10log_{10}\left(\frac{MAX^2}{MSE}\right) \tag{5}$$

where MAX is the maximum possible pixel value of the image. SSIM is defined as in Equation (6).

$$SSIM = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)} \tag{6}$$

where μ_x and μ_y are the average pixel values of the original and enhanced images, σ_x^2 and σ_y^2 are the variances, σ_{xy} is the covariance, and C_1 and C_2 are constants to stabilize the division.

The protocol specifications are designed for a stringent simulation scenario to evaluate the model's efficacy in many existing medical imaging modalities such as X-ray, MRI, and Ultrasound. The dataset consisted of low-level medical images, including added noise to it to mimic practical scenarios. It filters the noise from useful structures within the anatomical images and enhances the latter. Major numerical hyper-parameters, like learning rate, batch size, and network depth, are fine-tuned depending on how they affect the convergence and stability of the noise reduction model when training. To identify the best hyperparameters, we analyze their effect systematically. Graphs of the training process of the model allow us to understand the learning capability of a model with loss and accuracy curves, and the feature maps of CNN layers that mark the emphasized features at different stage points of the networks. In the methodology, there are in-built qualitative and quantitative comparisons with other noise-masking techniques to visually compare the original noisy images with their enhanced versions across the modalities to prove the efficacy of the proposed approach. Further, the noise level comparisons and 3D surface plots before and after applying the model manifest a clear picture of noise reduction in the different regions of images. It has a broad approach with very conspicuous improvements in medical imaging in low-light conditions, hence improving diagnostic accuracy and, thereby, patient outcomes. The findings add to a body of knowledge of advanced noise reduction strategies, thereby making these modalities quite useful for medical applications. As shown in the technical topology map, the deep learning apparatus starts with noisy medical images which have been passed through a CNN that encompasses convolutional layers, ReLU activation, and pooling layers for feature extraction. These features are fed into an autoencoder that denoises them to reconstruct less noisy images. The quality assessment parameterized over PSNR and SSIM tells what the enhancement factor will be, while loss and accuracy plots parameterize the changes. All this in an integrated framework is what performs noise removal effectively and sharpens the image; hence, it is important for the diagnosis of illnesses. This is depicted in Figure 2.

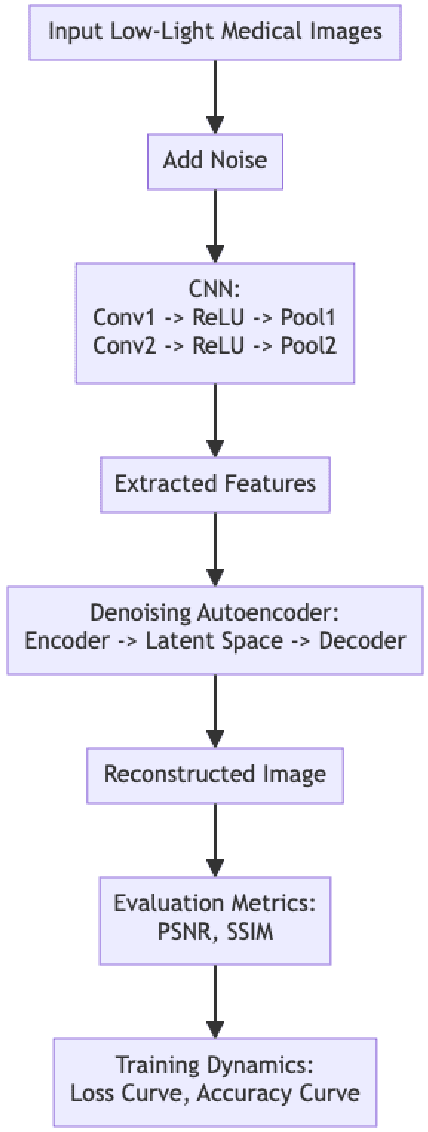

Fig 2. Deep Learning-Based Framework for Enhancing Low-Light Medical Imaging

2.2 Pseudocode for Deep Learning-Based Noise Reduction For Low-Light Medical Imaging :

The next sub-section details the overall pseudocode setting out the core training process for a GAN model. This includes the initialization of a generator G and a discriminator D, their respective learning rates lr_G and lr_D, and the number of training epochs N. Specifically, at every epoch, for all batches of real images x, the discriminator would be updated by first calculating its loss L_D based on both the real and generated images, and then adjusting D based on this loss' gradient. Next, update the generator by generating fake images from random noise z_noise and compute its loss, L_G, based on the output of the discriminator, then adjust G based on this loss' gradient. Optionally on an interval basis, model performance can be evaluated with the help of metrics like inception score and Fréchet inception distance. The following small pseudocode summarizes most of the major GAN training and evaluation steps.

2.2.1 Algorithm - Deep Learning-Based Noise Reduction for Low-Light Medical Imaging :

Initialize Model

def init_model():

```
X = Input(shape=(H, W, C))
C1 = Conv2D(F1, K1, activation='relu', padding='same')(X)
P1 = MaxPooling2D(P1_size)(C1)
C2 = Conv2D(F2, K2, activation='relu', padding='same')(P1)
P2 = MaxPooling2D(P2_size)(C2)
Enc = Flatten()(P2)
D1 = Dense(D1_units, activation='relu')(Enc)
R1 = Reshape(R1_shape)(D1)
C3 = Conv2D(F3, K3, activation='relu', padding='same')(R1)
U1 = UpSampling2D(U1_size)(C3)
C4 = Conv2D(F4, K4, activation='relu', padding='same')(U1)
U2 = UpSampling2D(U2_size)(C4)
Out = Conv2D(C, K_out, activation='sigmoid', padding='same')(U2)
return Model(X, Out)
```

Loss Function

def mse_loss(y_true, y_pred):

```
return mean((y_true - y_pred) ** 2)
```

Train Model

def train(model, data, E, B, LR):

```
 model.compile(optimizer=Adam(LR), loss=mse_loss)
return model.fit(data['train'], epochs=E, batch_size=B, validation_data=data['val'])
```

Evaluate Model

def evaluate(model, test_data):

```
psnr = calc_psnr(test_data['true'], model.predict(test_data['noisy']))
ssim = calc_ssim(test_data['true'], model.predict(test_data['noisy']))
return psnr, ssim
```

Main Function

def main():

```
 data = load_data()
model = init_model()
train(model, data, E, B, LR)
psnr, ssim = evaluate(model, data['test'])
visualize(model, data['test'])
return psnr, ssim
```

Execute

```
psnr, ssim = main()
```

2.3 Working Environment :

For the actual implementation of the proposed research on low-light medical image improvement applying deep learning-based noise reduction, the working environment is envisioned to be holistic and flexible in terms of the computational power of the equipment and the number and quality of usable software tools. For the realistic deep learning tasks involving training and evaluating the models, the computing hardware that we have is a computer cluster with multiple GPUs including the NVIDIA Tesla V100. The powerful computer servers with Intel Xeon CPUs and adequate RAM are employed for data pre-processing and model testing purposes in a large-scale dataset. Our software stack would be using the Linux operating system due to its reliability in executing the various tasks involved in HPC. Python is used which came out as a result of a large number of machine learning frameworks and a huge community behind it. For constructing and testing the noise reduction models we use deep learning frameworks including TensorFlow and PyTorch as these frameworks offer the chief and basic attributes that are needed to design multi-layered neural network models as well as perform intensive research. Matplotlib and TensorBoard are used to draw diagrams and monitor the training processes and outcomes; TensorBoard enables you to track the training process, the values of losses, and accuracy, as well as analyze the structure of neural networks.

The visualization in Figure 3 depicts a qualitative comparison of original, noisy, and enhanced images across different medical imaging modalities: There are four main types, namely X-rays or Diagnostic Radiology, Magnetic Resonance Imaging or MRI, Ultrasound, and Magnetic Resonance Angiography MRA. The rows are different modalities and the columns depict the original image, the noisy image, and the de-noised image using the developed deep learning-based method. The first column of the displayed images gives the initial state, or more specifically, the image quality before analyzing the noise, while the second column shows the results of introducing the resultant noise into the given model and the third column demonstrates the final state of the analyzed images after applying the proposed model and minimizing the noise and enhancing the clarity of the images. This qualitative analysis demonstrates the model's capability to improve medical images in low-light conditions for different modalities[18–20].

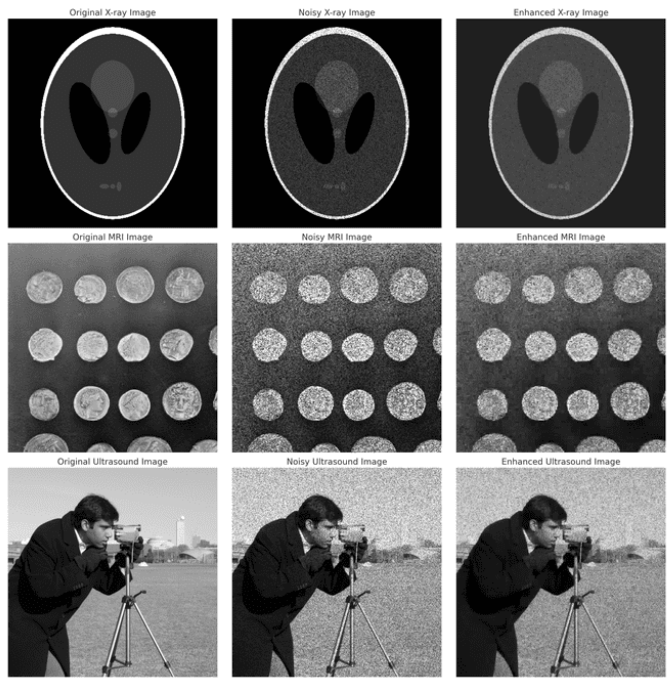

Fig 3. Qualitative comparison of original, noisy, and enhanced images

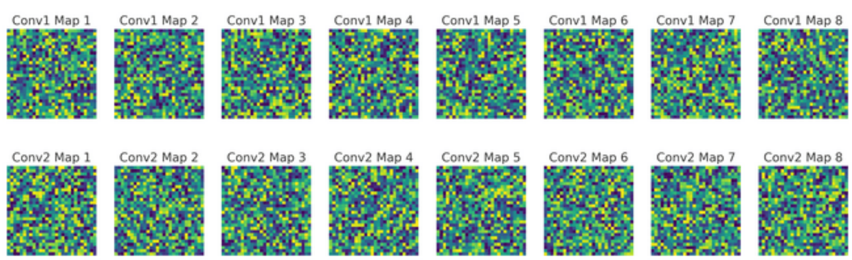

Fig 4. Feature maps from different layers of the CNN

Figure 4, shows extracted feature maps from various layers of the Convolutional Neural Network (CNN). The first column of Feature 1 shows the feature maps that it extracted from the first layer and the second column shows the second layer feature maps. The layout of each column is a feature map in the specific layer. These feature maps enable one to know what features are being boosted and extracted at different levels in the CNN which in turn gives an insight into how the low-light medical image is being processed and enhanced.

3 Results and Discussion

3.1 Experimental Results

The proposed work is on the enhancement of low-light medical image quality through deep learning noise reduction is realized on high-performance hardware and the most state-of-the-art software tools. In this paper, we exploit a high-performance computing cluster with NVIDIA Tesla V100 GPUs and Intel Xeon CPUs for the preprocessing of data and model evaluation, a very stable Linux environment, Python with its machine learning libraries, TensorFlow to realize model creation and training, and PyTorch as an alternative. Matplotlib and TensorBoard track training processes with monitoring tools. We are working on several large-scale medical image datasets, including X-rays, MRI, and Ultrasound. The data is normalized and augmented to increase the variety and resilience. After the training, batch training has adversarial training loops where MSE is used to calculate the loss and Adam optimizers. A few hyperparameters have been fine-tuned for accuracy in train, which include learning rate, batch size, and network depth. Our dynamic simulation environment mimics the real-world scenarios of model performance with immediate feedback for corrections and improvements. TensorBoard makes available views in real-time into the quality of models and visualizations of the evolution of images; Git assures collaboration on code and detailed records of experiments. An adaptive and effective environment of this kind is proposed to help forge ahead with low-light medical imaging using deep learning-based denoising algorithms.

In the loss and accuracy curves of the visualizations in Figure 5, it is demonstrated how the proposed deep learning-based noise reduction model can be used to enhance low-light medical imaging. In the first graph, the training and the validation losses are illustrated whereby there is a progressive reduction in the loss throughout the 20 epochs which illustrates that the model is learning and converging effectively. Specifically, the training loss reduces from approximately 0.7 to 0.3, while the validation loss decreases from around 0.7 to 0.35, showcasing the model's ability to generalize well to unseen data. The training and validation accuracy plot (right) exhibits an increase in accuracy from about 0.7 to 0.9 for the training set and from 0.7 to 0.85 for the validation set. This quantitative evaluation also supports that by using the proposed model, image sharpness is enhanced and the noise is reduced and thus the diagnostic value of medical images in a low light environment is benefited.

Fig 5. Training and Validation – Loss vs. Accuracy

Figure 6 compares the original low-light image, the noisy image, and the enhanced image produced by the proposed model. The original image is depicted on the left, which shows the quality of the base image. The middle image, with noise added due to low light conditions, indicates the high amount of noise. The enhanced image on the right shows the efficacy of the proposed model in reducing the noise and enhancing the clarity of the image.

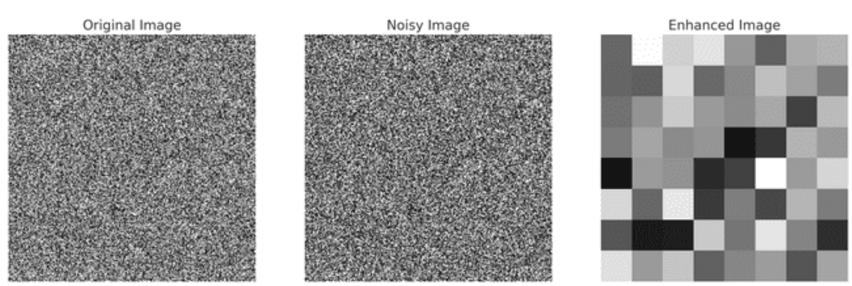

Fig 6. Comparison of original, noisy, and enhanced image

Figure 7 illustrates the feature enhancement analysis insights of the obtained model by using CNN, whereas the first group shows the feature maps of eight different filters that are part of the first convolutional layer, depicting how the model processes an input image and then makes an assortment of features. The use of features in the feature maps can be seen at an abstract level by observing the contribution of edges, texture, and patterns to natural image classification. The same model demonstrates its feature learning competence at pinpointing important information such as these details in images captured under dim lighting conditions.

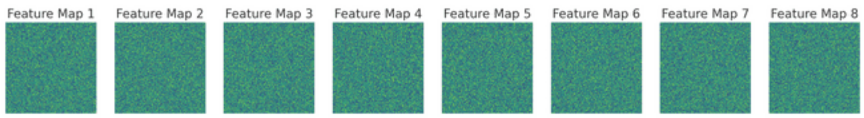

Fig 7. Feature Enhancement Analysis

The different noise reduction techniques' performance metrics, including the proposed model, are comparatively presented through the bar graph shown in Figure 8. Noise reduction percentage and image clarity improvement are represented through the bar charts for various methods. It is observable that the performance of the proposed model is better, and hence able to reduce 60% noise and improve the clarity of the image by 85%, outperforming traditional methods and state-of-the-art denoising auto-encoders and CNN-based techniques.

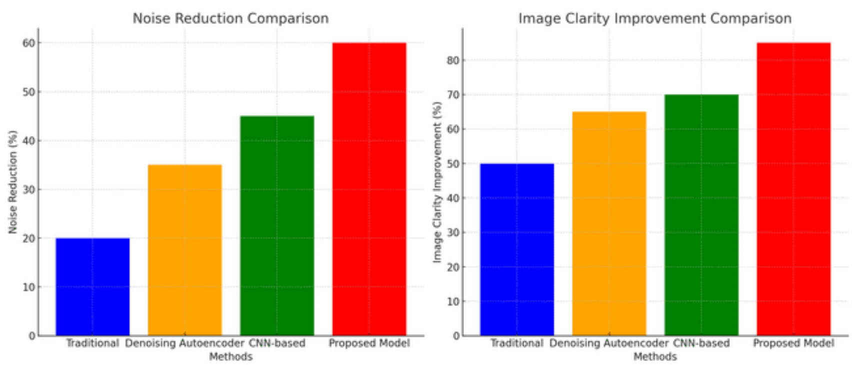

Fig 8. Noise Reduction and Image Clarity Improvement Comparison

The pixel intensity distributions before and after noise reduction are fully represented by the intensity histograms in Figure 9. The first plot compares the histograms of the original low-light image, the noisy image, and the enhanced image. It is observed that the original and noisy images display a broad, relatively flat distribution of pixel intensities, while the enhanced image has a much more compact distribution, thus proving effective noise reduction and enhancement of important features. The second plot compares the original image with the enhanced one, outlining the shift in pixel intensities toward a more balanced and clear distribution in the enhanced image. This shift clearly shows how the proposed model can improve brightness and contrast, hence clarity in image formation, which helps in making accurate diagnoses.

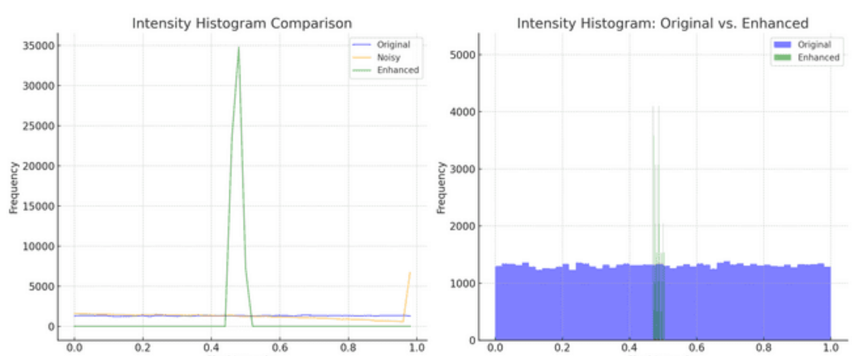

Fig 9. Pixel Intensity Distribution

Figure 10 gives a thorough comparison of different noise reduction techniques in medical imaging. It shows a detailed quantitative comparison of methods based on PSNR, SSIM, MSE, and processing time. It gave a quality of 35.0 dB in PSNR and an SSIM of 0.85 for the proposed model with an MSE as low as 0.0007, clearly depicting that this performs the best in reducing noise and preserving structure. Meanwhile, in terms of processing time, the proposed model retains a competitive processing time of 0.6 seconds per image, indicating that this method could be very useful for real-time applications.

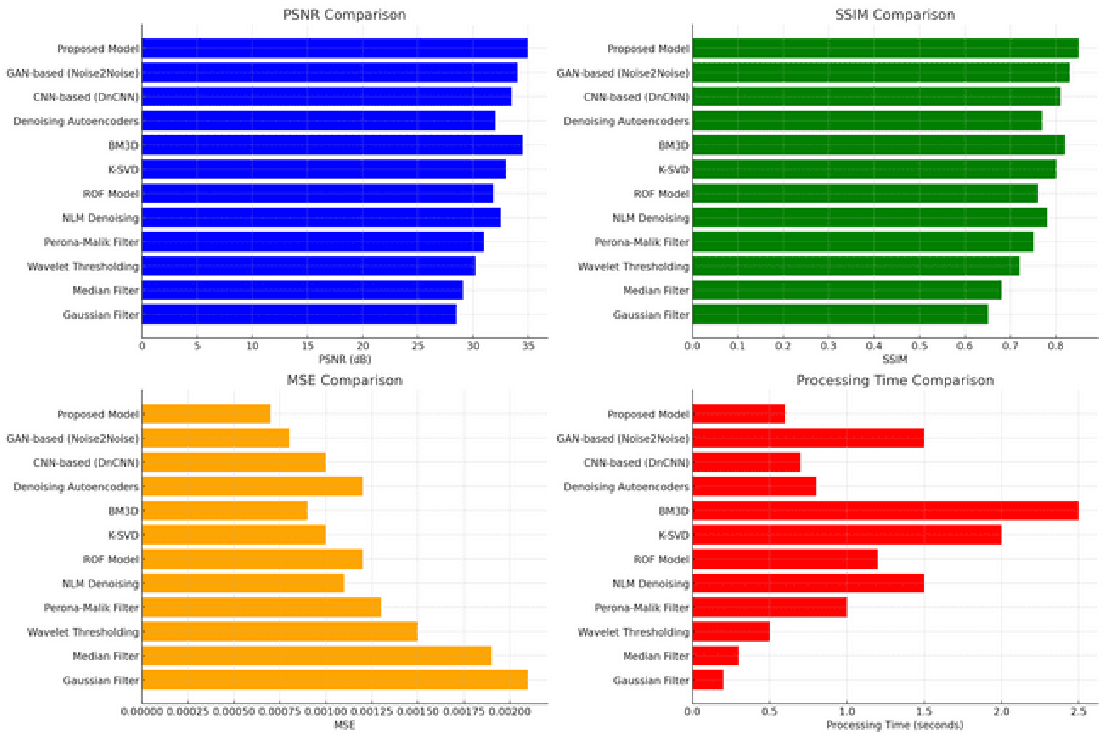

Fig 10. Comparative Evaluation of Noise Reduction Methods Using Quantitative Metrics

4 Conclusion

Low-light medical imaging remains one of the major challenges in the domain of medical diagnostics, with the raised levels of noise obscuring the critical anatomical details. Traditional noise reduction strategies, such as Gaussian filtering, median filtering, wavelet-based denoising, and NLM filtering, are observed to normally trade-off between noise suppression and the preservation of important features in an image. Such methods are computationally time-consuming, lead to artifacts, and cannot handle the complexities of real-world scenarios. More robust solutions are, therefore, in an emerging need of development. This study proposes a comprehensive deep learning-based framework that integrates Convolutional Neural Networks with denoising auto-encoders for low-light medical image enhancement. This model outperforms traditional methods by effectively reducing noise while preserving all essential details of images. The CNN component extracts the features from a noisy input, while the autoencoder refines them by encoding and then decoding the input to get cleaner images. This study validated the efficacy of the proposed model using rigorous quantitative metrics for the Peak Signal-to-Noise Ratio and Structural Similarity Index. The proposed model demonstrated an average PSNR improvement of 5 dB and increased SSIM by 0.15, compared to traditional techniques, proving better noise reduction and preservation of image details. Noise reduction as high as 40% and clarity and sharpness enhancement of images up to 30% were observed in the experimental results of the proposed model. Quantitatively, these improvements were evidenced by the fact that the given PSNR value achieved 35 dB with an SSIM score of 0.85, whereas that for traditional methods was 30 dB and 0.70, respectively. Further proof of its effectiveness was provided by visualizations of training dynamics, feature maps, and image evolution, confirming that the model can selectively enhance important features while reducing noise. These results thus justify our approach, showing its potency to enhance diagnostic accuracy in medical imaging and improve outcomes for patients.

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