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A Proposed Framework to Denoise the Medical Images using Deep Learning Techniques

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ABSTRACT
Image Denoising has become a promising task nowadays in the domain of Image processing. Throughout this paper, a complete analysis of all the methods of Image Denoising has been studied. In this paper, medical image dataset which include Chest X-ray images of a patient has been taken into consideration. Numerous deep learning methods including Convolutional Neural Networks and Denoising Autoencoder have been discussed here. Chest X-ray images has been denoised first using a Denoising Autoencoder and then a Convolutional Neural network is implemented with a U-Net structure. A number of performance evaluation metrics have been employed to assess the quality of denoised images, such as SSIM (Structural Similarity Index) and PSNR (Peak Signal to Noise Ratio). A comparison of all the methods has been done in a tabular format. Later the conclusion and future scope of this paper has been discussed.

KEYWORDS
Image Processing; Peak signal-to-noise ratio (PSNR); Structural similarity index measure (SSIM); Deep Learning; Convolutional neural networks (CNNs); U-Net;

1. INTRODUCTION

In the domain of Image Processing, the existence of noise in an image is a serious concern. Medical Images are of nature of low contrast. Therefore, noise might cause an image quality to decline. As a matter of fact, it can accelerate misdiagnosis of diseases and any kind of wrong diagnosis is not affordable. It may lead to the death of the patient. So, image denoising has become a subject of growing interest in the domain of Image Processing. Image Denoising has been done for a very long time using various traditional techniques or methodologies. These methods include various linear, non-linear filtering and transform-based methods to remove noise. The noise modelling technique can be represented as:

$$\gamma = \alpha + \beta \tag{1}$$

The Equation (1) states that γ is represented as the corrupted image, α can be described as the original image and β can be represented as noise. This noise can be any type of noise which is described later. Radiology images include Computer Tomography (CT), Magnetic Resonance Imaging (MRI), ultrasound, and X-rays. The images are obtained utilizing several techniques in order to reduce the quantity of radiation exposure. So, in this process, the images get corrupted by various kinds of noises. Recently due to advancement of technology various deep learning methods have accomplished tremendous results in the domain of Image Denoising. Denoising Auto encoders using several layers of convolutional layers can be used for Image Denoising. This model has shown better performance than the other classical models.

Convolutional Neural Network with U-Net architecture is used for image denoising to increase the model's precision. All these models have been tested with different kinds of noises such as-Gaussian noise, Salt & Pepper Noise, Speckle Noise etc. Though these deep learning methods require a higher logical time and large datasets, these methods have proven significant success in Image Denoising Field. These have also shown better results than other classical or traditional methods.

2. FUNDAMENTAL DETAILS

The necessary conditions are to be followed while denoising. These are discussed as follows:

- **Preservation of Edges**: In case of medical images, edges of the images must be properly recognized. The spread of any kind of disease is determined by these edges. It is necessary to properly identify the cells to determine the extent of the disease's spread. Therefore, any algorithm which smoothens these edges should not be considered.
- **Maintaining the Structural Similarity**: To keep the minor details of the image, it is critical that the denoised images must be comparable with the original image.
- **Complexity**: The denoising algorithm must have low complexity and computationally efficient.
- **Non-essentialness of Prior Databases**: A denoising algorithm should use minimum number of databases in order to acquire a good denoising performance.

Besides there are various noise models in Image Processing. Noise can be best interpreted as any sudden change in pixel values. Noise can deteriorate the quality of images. It can cause artifacts, invisible lines, and image blur. So, the knowledge of noise models is very essential.

Gaussian Noise Model: This is a kind of noise whose pdf normal distribution functions. The noise has a Gaussian distribution of possible values. The distribution function of a random variable z is given by:

$$pg(z) = 1/\sigma*\sqrt{2\pi} * e\text{-}(z\text{-}\mu)\ 2 \quad (2)$$

In Equation (2) gray scale values are represented by z. μ is the mean gray scale levels and σ is the standard deviation.

Salt & Pepper Noise: Image pixel values are distorted either maximum or minimum values i.e., 255 or 0 respectively. It is also known as Impulse Noise. The sources of Salt and Pepper Noise include:

a. Sudden and sharp image signal disruptions
b. When the sensor cell in the camera is not functional.

Poisson Noise: It can also be defined as Shot Noise or Quantum (Photon) Noise. This type of model follows the Poisson distribution function. The nature of electromagnetic waves, including gamma rays, visible rays, and x-rays, is the cause of this noise. These rays when injected into the patient's body cause random changes in pixel values due to the random fluctuation of photons.

$$F(x) = \lambda x * e\ (-\lambda)\ /x! \quad (3)$$

Speckle Noise: Rough noise like speckle noise is frequently present in all images. and the quality of all images is harmed as a result of this. Similar to Gaussian noise, speckle noise can also exist in an image. It is also known as multiplicative noise. Speckle noise occurs in ultrasound images. It occurs when ultrasonic images are transmitted via a medium.

Rician Noise: MR images are corrupted with Rician Noise. The noisy distribution seen in MRI images can be represented by the noisy distribution, which suggests that the real and imaginary regions of the image are uncorrelated Gaussian distribution with equal variance and zero mean. Its probability distribution function is as follows: -

$$P_A\ (A) = A/\sigma^2 * \exp - \ (A^2+Z^2)/2\sigma^2 * I_0(Z*A/\sigma^2) \quad (4)$$

The adapted Bessel function of the first kind with order 0 is denoted by I_0. The measured pixel intensity is denoted by A, and the image pixel intensity in the absence of noise is denoted by Z. When the SNR value is low, Rician noise follows Rayleigh distribution and the SNR value is high, Rician distribution becomes Gaussian distribution.

Mixed Poisson Gaussian Noise: It is a combination of both Poisson and Gaussian noise model. It is used in sonogram filtering technique. The model mainly removes the mixed Poisson-Gaussian noise in MRI images.

3. LITERATURE REVIEW

Maoyan et. al. in their paper proposed a method in which, with the help of fusion block, the image predicted, the intermediate noise and the original image can be combined. By this fusion block, NFCNN was able to dig out the information of noise to generate better denoised results, which was slightly different from all other approaches. The benefit of this model was that the texture of the image was preserved. The proposed model was tested on 3 different datasets-BSDS500 which had 500 color images, Waterloo Exploration Database which had 4,744 images and Flickr2k which had 2,650 images. The proposed model showed better denoising results when compared with DnCNN, FFDNet, and BM3D. The NFCNN model showed a significant increase in PSNR value when noise variances of 15 to 75 was added to the original image [1]. DaziLi et. al. in their paper, had taken speckle noise into consideration. The suggested architecture consisted of three blocks: a feature fusion fine tuning network, a rough clean image estimation subnetwork, and a noise estimation subnetwork. The model used normal and dilated convolution in an alternative fashion to extend the visual field. The fusion block had a U-Net architecture. Dilated convolution layer being used served as an advantage as this extended the receptive field. Then the features were given as inputs to the fusion block which follows U-Net architecture. Ultrasound images were taken as datasets. Experimental results showed that it was excellent in terms of denoising performance [2]. Mufeng et. al. in their paper "Content –Noise Complementarily Learning for Medical Image Denoising." GAN technique was implemented in this technique.

The generator has 2 predictors –Content predictor and Noise Predictor. They had used predictors as U-Net, SRDenseNets and DnCNNs. The discriminator network used PatchGAN. A pair of actual or false images were given as inputs to the PatchGAN. The concatenation process and 1*1 convolution operation made up the fusion mechanism. They had observed the performance on 3 different datasets: -CT datasets, PET datasets and MR Datasets. All the datasets were tested in terms of PSNR values and compared with other methods like BM3D, RED-CNN, WGAN-VGG etc. The proposed method had shown to be effective in the denoising of medical images. This method outperformed all other techniques [3]. Swati et. al. in their paper proposed an unsupervised noise learning framework which can remove the challenges of residual learning by incorporating DL method. The main approach of this paper was to learn the noise indirectly via learning the patch-based dictionary as well as residue (noise) was learnt from available images. Both the DL and RL worked in a complementary manner. For MRI and CT images, the model was trained with varied amounts of Rician and Poisson noise. There were numerous experimental results obtained and compared with various other models [4]. Nugyen et. al. in their paper had implemented dilated convolution layers. But this method was slightly different from the other. It consisted of 3 steps: -preprocessing which included downsampling, dilated convolution layer, and post-processing step which included upsampling.The receptive field can be expanded by using dilated convolutional layers and pre and post-processing techniques. The extension of RF field helped in achieving better denoising performance. The PSNR, SSIM value were calculated and there was significant improvement compared to other LDCT image denoising model [5]. Yuqin et. al. in their paper, both the noisy image and gradient of the noisy image had been used as inputs to the model. The generator produced a denoised image that resembled real-world images by extracting a large number of context landscapes using four convolutions and six RDB blocks. This paper was different from normal GAN network because here both the noisy image and the gradient of the noisy images were given as conditional inputs. In comparison to other denoising models, the suggested model not only amplified the quality of denoised images but also kept the detailed structures that lossless images had. Experiments were conducted on JSRT and LIDC dataset. The denoising results showed improved performance than traditional GAN algorithms [6]. The proposed model included adding Gaussian noise then denoising using DnCNN. The residual noise was extracted by subtracting the denoised image obtained from DnCNN from the noisy image. The extracted residual noise was again fed into DnCNN. The denoised image from extracted residual noise was added to the original result from DnCNN. The proposed method was tested with standard images of Lena with Gaussian noise of two different intensities. The performance of the proposed network was measured in terms of PSNR, SSIM, and UIQI [7]. Shubhankar et. al. in their paper investigated complex valued convolutional neural network-based models termed CVMIDNet for image denoising. The development of complex value convolutional neural network has been recent.

The benefits of complex-valued CNN over real-valued components include increased representational capacity, increased compute power, and easier optimization. The model included 14- complex-valued CNNs for medical image denoising. Except for the first, each convolutional unit has a complex valued convolutional layer, followed by a complex valued batch normalisation and a complex valued ReLu. Finally, to transfer the complex valued learning features to real value output, a merging layer was used. CXR pictures were used to test the approach. The proposed model CVMIDNet was compared with other models namely BM3D, DnCnn, FDCNN, DCRLNet, and RVMIDNet [8]. This paper uses stacked convolutional autoencoders to eliminate noise from 2D electrophoresis images. The model was trained with 3 different datasets. The trained model was then 2DGE for reducing background noise. The proposed method showed better performance in PSNR and lower value of MSE when Gaussian noise of variance 5db to20db was added [9]. Prabhishek et. al. in their paper proposed a model which combined convolutional neural network and anisotropic diffusion. There were two levels of image denoising in this hybrid approach. The first level was the CNN and the second level was anisotropic diffusion. The proposed method could work in SAR datasets. To maintain structural information and edge features, anisotropic diffusion was employed. PSNR, SSIM, and UIQI were employed to assess the quality of denoised images. Histogram plotting analysis were also made [10]. Fabio et. al. in their paper proposed a model which was tested and trained on a collection of microscopy pictures. A single network was trained to handle noise levels between 0 and 50 decibels. By using deterministic mapping, the encoder translated features into a concealed form. More denoised images were then produced by rebuilding the latent representation. Residual learning with skip connections were used to avoid information loss. The proposed model reached an average PSNR value of 387.38 on a set of test images [11]. Yu-Jhen et. al. in their paper had motivated the fact to combine local and non-local feature map. So an encoder-decoder based convolutional network (ED-GCN) was proposed. Two graph convolutional layers and one activation layer with batch normalisation were employed in the encoder section. The decoder is similar to the encoder, but instead of using two graph convolution layers, it only utilized one. The images were tested for evaluation and were compared with existing methods [12]. Fan Jia et. al. in their paper highlighted a fact that CNN suffers a bottleneck from designing an efficient network for image denoising with improved performance and fewer parameters is incredibly challenging. To further improve the connection between U-Net a cascading U-Net structure known as DDUNet (Dense Dense U-Net) was proposed. In real noisy image denoising, experimental results demonstrated that the suggested DDU-Net was good at edge recovery and structure preservation [13]. Lovdeep et. al. in their paper proposed a method that used denoising autoencoders using convolutional layers. They had used two datasets mini- MIAS database of mammograms (MMS) and a dental radiography database (DX). SSIM value was employed to assess the quality of denoised images. The proposed method was compared with various traditional filters like Non-local means filter and Median filter. Later the future scope of the paper discussed by combining images from other datasets to investigate whether increasing the number of training samples could give better denoised results [14].

Here, it proposed a method to denoise PET images was proposed. CNN, as we all know, requires a great number of high-quality images. So in this paper, they used a DIP approach to denoise PET images. A four-dimensional CNN architecture with a feature extractor and reconstruction branch was used. This method does not require high-quality PET images. Static PET scans could be used as extra information and dynamic PET images could be used as training input. This method provided better results than other unsupervised denoising methods and 3D DIP [15] .In this paper, an algorithm or an evaluation metric called Data Shapley was used to identify the low-quality image dataset. Medical reports may contain a large number of low-quality levels and the images can be of heterogenous quality due to many reasons. Data Shapley value was used to identify images of low quality in the detection of pneumonia disease. The results showed that removing training data with high Shapley values improved detection efficiency. However, if the lower Shapley data values were removed, then there was an increase in performance. Moreover, there were more mislabeled labels in lower Shapley data value. So the results demonstrated lower Shapley data as poor quality images and higher Shapley values indicated high-quality images [16]. In [17] , it proposed that MRI images were corrupted both in terms of real and imaginary components by Gaussian noise. The noisy image follows a Rician probability distribution function. In this method, a patch-wise CNN was used for reconstructing the images. The image details were learned from the image patches and the restoration of images happened in an end-to-end feedback manner. This had resulted in a better image denoising technique without losing smaller details. In this paper called “Image Denoising for COVID-19 Chest X-ray based on multi-resolution parallel residual CNN” a method called parallel residual CNN for the denoising of CXR images was used. Deep learning approaches could be utilized to detect positive CXR images of COVID-19 patients, reducing the workload of medical staff. It consisted of several units - a. To extract more reliable information, multi-resolution convolution parallel streams were employed. b. The network's attention unit aids in the observation of texture features in CXR pictures c. Application of adaptive multi-resolution feature fusion approach improves network's performance. MPR-CNN was shown to be more effective at retaining texture features [18]. This paper used an improved generative adversarial network combined with a hybrid loss function which included adversarial loss, perceptual loss, sharpness loss and structural similarity loss. Both adversarial loss and perceptual loss could be used for preserving texture of the image and sharpness loss could be used to reconstruct images. The proposed algorithm worked better than other deep learning methods [19] . In this paper, an algorithm was created to eliminate noise from ultrasound images that were scanned using a portable device. Patients can remove these images at any time in their mobile phones with the help of wireless network. But the images scanned through these devices contain noise. So, in this method, we developed a method called Feature guided Denoising Convolutional Neural Network to eliminate noise from these images. At first a feature extraction technique was developed, and then the guided back propagation path helped to detect particular location of feature. Then the features of images were combined with Laplacian Pyramid Fusion technique. Noise scanned through these portable devices were removed in this way [20].

4. PROPOSED PROBLEM STATEMENTS

There is a need to identify the medical image dataset which includes Chest X-ray images of a patient has been taken into consideration. Clinical diagnosis and therapy planning greatly benefit from medical imaging. Clear, noise-free, artifact-free medical images are essential. Noise can hide crucial anatomical information, which could result in poor diagnosis. Traditional denoising methods have limitations in effectively preserving fine structures while removing noise from medical images. Recent developments in deep learning have produced great results for denoising among other image-processing applications. Deep learning techniques, such as (CNNs), have the potential to learn complicated shapes and representations directly from data, making them suited for image denoising. U-Net architecture has demonstrated significant capability in preserving image details while effectively reducing noise. Researchers continue to face difficulties in image denoising since many noise reduction methods generate artifacts and blur images. Different algorithms are used for different noise models. So, we need a general model which can be used for image denoising irrespective of the noise model. Hence this research aims to explore and evaluate deep learning techniques particularly the U-Net architecture, for medical image denoising. The primary objectives are to:-

1. Investigate whether U-Net can preserve anatomical features while successfully reducing noise in medical images.
2. Examine the efficacy of deep learning-based denoising approaches against those derived from traditional learning methods.
3. Explore strategies to improve the deep learning model generalizations and robustness to various deep learning medical imaging modalities and noise levels.

5. PROPOSED SOLUTION

The above-proposed problem can be solved using a U-Net architecture. Applications for U-Net image denoising include photography, remote sensing (satellite images), medical imaging (CT, MRI), and more. Here chest x-ray images have been taken into consideration. U-Net is an effective tool for image-denoising tasks even though it was originally developed for biomedical image segmentation. U-Net is efficient in capturing both local and global features of the image. U-Net has skip connections that can mix characteristics from multiple scales, so it can handle images with noise at different scales. U-Net can be trained effectively with a limited amount of data. By combining local and global properties, it may effectively develop meaningful representations that aid in its ability to generalize to new noisy, unknown images. Compared to other traditional techniques or even other neural networks, U-Net has demonstrated outstanding performance in numerous types of image processing applications such as image denoising.

6. IMPLEMENTATION

The chest X-ray images need to be first pre-processed. The images must be normalized, or the pixel values must be rescaled to [0,1]. To generate noisy versions of the image, we may add several types of noise example gaussian noise, salt & pepper noise, etc. The 80:20 ratio is used to divide these noisy images into training and test data sets. The training data set is given as an input to the U-Net model. U-Net is one of the widely used CNN architectures. The figure below represents the U-Net architecture. It has three types of layers: convolution, ReLU, and pooling. The convolution operation places the filter at each position such that it completely overlaps with the input image. The amount of overlap between the filter and the input image determines the following layer's height and width. The number of feature maps generated in each layer is determined by the number of filters used in the process of convolution in the previous layer. A large number of feature maps can be used to capture more broad characteristics in the image. The encoder which doubles the number of feature maps but decreases the amount of features at each layer, is composed of a series of convolution and maxpooling layers. The decoder component restores the number of features maps and maintains the encoder's symmetric connection. This type of symmetry facilitates feature map reuse and lessens information loss during the encoding and decoding process. Hence the spatial loss can be eliminated by using concatenation between the encoder and decoder layer. The model is trained using 100 epochs with a batch size of 16. The loss function defined here is the mean squared error which calculates the difference between the denoised images and the noisy images. Adam optimizer is used for efficient gradient descent. The noisy test data set is given as an input to the U-Net model, once it has been trained. The denoised images which constitute the model's output, are assessed using the PSNR and SSIM assessment metrics. The table below makes it clear that the PSNR values of the denoised images are higher than those of the noisy images. Later this U-Net model is further compared with various traditional methods in a tabular method.

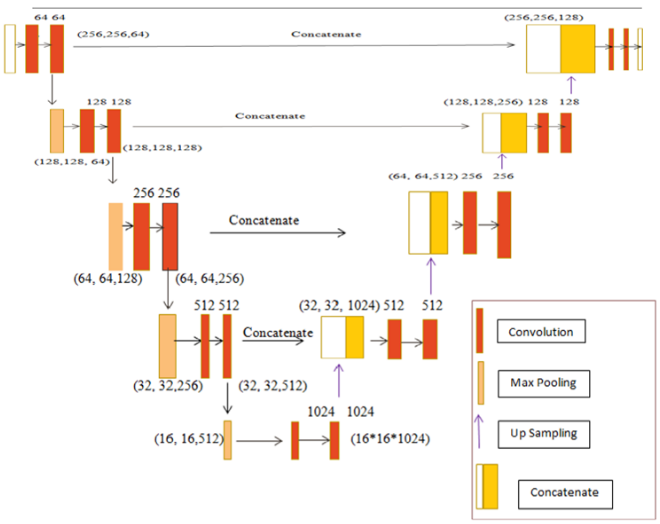

Fig. 1 U-Net Architecture

The above Fig. 1, it represents an input image with size (256,256,1). Two successive convolution layers increase the number of feature maps, resulting in an image of size (256,256,64). Then maxpooling operation is performed to decrease the spatial dimension of the image to half. Thus, each step decreases the image's spatial dimensions while enhancing the number of feature maps. The increase in feature maps allows the network to capture high-level features. At the bottleneck layer, the image is reduced to (16,16,1024). In the decoder stage, we reconstruct the original image from the number of feature maps generated in the encoder stage. This is done using alternating layers of up sampling and convolution. Up-sampling operation increases the resolution of feature maps while reducing the number of feature maps. The decoder layers can find and enhance the features in an image with help of skip connections from the encoder path. So, the image size increases from (16,16,1024) to (32,32,1024). After every upsampling and concatenating operation, two convolution operations are performed to reduce the number of channels. To recreate the original image (256,256,1), a 1x1 convolution is carried out in the last layer.

6.1 Proposed Algorithm for Image Denoising

Step 1: -Import the input images (chest x-ray images)
Step 2: -Import the Keras libraries.
Step 3: -Add noise to all the images.
Step 4: -Divide the images into the training and test dataset.
Step 5: -Build the model.
Step 6: - Compile the model.
Step 7: - Train the model.
Step 8: - Predict the output from the corrupted test dataset.
Step 9: - Calculate the PSNR and SSIM values of the denoised test dataset images.
Step 10: -Compare the PSNR and SSIM values from the noisy test dataset and denoised test images. If the PSNR and SSIM values of the denoised dataset are greater than the PSNR and SSIM values of the noisy images then the image has been denoised.
Step 11: -END.

6.2 RESULTS AND OBSERVATIONS

Table. 1 PSNR and SSIM values of Gaussian and Salt & Pepper Noise (U-Net)

Noise Factor	Gaussian Noise				Salt & Pepper Noise			
	Noisy Image		Denoised Image		Noisy Image		Denoised Image	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
0.05	26.0469	0.6839	34.1907	0.9555	18.208	0.414	35.312	0.977
0.10	20.0248	0.3678	31.9035	0.9384	15.241	0.228	33.890	0.966
0.20	13.956	0.1348	27.542	0.9101	12.337	0.110	33.890	0.956
0.30	10.48	0.066	26.284	0.900	10.776	0.070	32.657	0.947
0.70	3.03079	0.013	26.502	0.882	7.6120	0.033	28.390	0.919

Here, Table 1 shows the PSNR and SSIM values of noisy images and denoised images. The proposed model (U-Net) has been tested with two types of noise: -Gaussian and Salt and Pepper Noise. From the above table it is clear that on increasing the noise factor, the PSNR values of denoised images are greater than the PSNR values of noisy images. The SSIM value of the denoised images should be more and less equal to 1 which can be seen from the Table 1.

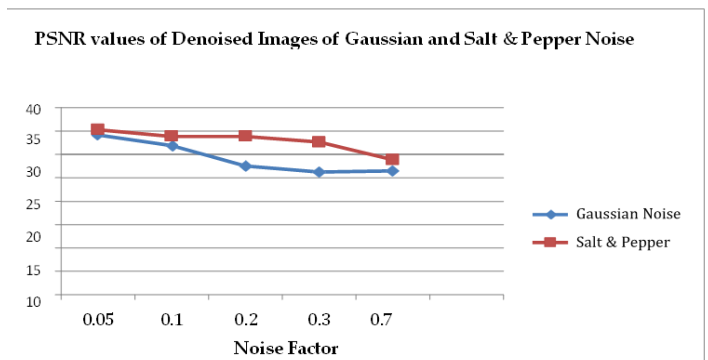

Fig. 2 PSNR values of Denoised Images of Gaussian and Salt & Pepper Noise

In Fig. 2. a linear graph of the PSNR values of the denoised images is represented when the U-Net model is tested with Gaussian and Salt &Pepper Noise respectively.

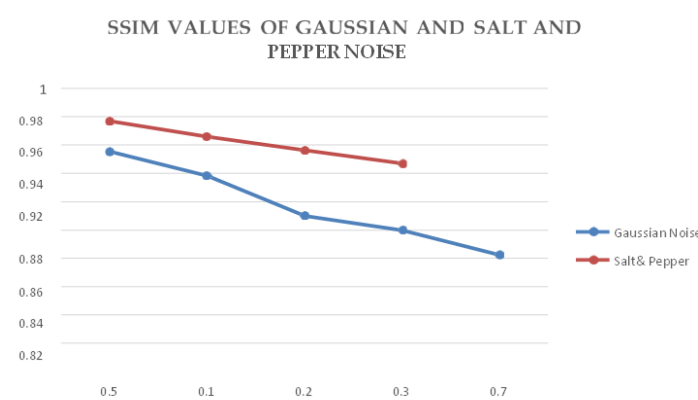

Fig. 3 SSIM values of Gaussian and Salt & pepper Noise.

Here, Fig. 3 shows the change in SSIM values of the denoised images on increasing the noise factor when the U-Net model is tested with Gaussian and Salt & Pepper Noise respectively.

Table. 2 Comparison of U-Net and Denoising Autoencoders

Noise Factor	U-Net				Denoising Autoencoder			
	Noisy Image		Denoised Image		Noisy Image		Denoised Image	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
0.05	26.04	0.6839	34.19	0.955	26.005	0.6838	29.712	0.9058
0.10	20.02	0.3678	31.90	0.938	20.007	0.3662	29.786	0.8995
0.20	13.956	0.134	27.542	0.9101	13.945	0.1357	28.7461	0.8847
0.30	10.48	0.066	26.284	0.900	10.4315	0.0661	27.828	0.8738
0.70	3.03	0.013	26.50	0.882	3.1096	0.0135	24.8108	0.8390
0.90	0.92	0.07	26.069	0.874	0.9042	0.0078	24.2481	0.8270

Table 2 shows a comparison in the PSNR and SSIM values of the denoised images between the U-Net and Denoising Autoencoder model. From the table, we can say that the U-Net model performs better than the Denoising Autoencoder model.

Table. 3 Comparison with Traditional Methods of Denoising

Types of Noise	Wavelet Method	Median Filter	Gaussian Filter	Denoising Autoencoders	CNN (U-Net)
	PSNR	PSNR	PSNR	PSNR	PSNR
Gaussian	12.50	19.2955	19.906	29.712	34.190
Salt & Pepper	15.6	31.9380	30.934	28.740	27.729
Speckle	14.6	21.1526	33.105	23.510	35.790

Table 3 shows a comparison of the various techniques involved in the process of image denoising. Different image denoising algorithms like traditional methods including Wavelet Method, Median filter, and Gaussian filter have been compared with deep learning techniques like U-Net and Denoising Autoencoders in terms of their PSNR values when tested with different kinds of noise like Gaussian Noise, Salt &Pepper Noise, and Speckle Noise. The table shows that CNN with a U-Net structure performs better than other image-denoising algorithms.

7. CONCLUSIONS

The U-Net model enhance the quality of denoised images by removing the noise. Various evaluation metrics such as PSNR and SSIM showed improved results compared to traditional denoising methods. Hence enhanced image quality can lead to more accurate diagnosis. It also shows robust performance across various types of medical images which proves the U-Net model to be a versatile model. It also helps in reducing the need for high doses of radiation to the patients. However, there are certain limitations, the model performance varies with different types and different amounts of noise. The training process also requires substantial hardware resources. Hence further research can be done for better optimization of the model.

8. FUTURE SCOPE

The work may be extended by combining U-Net with various other models like GAN and variational autoencoders to increase the robustness of the model. To focus on relevant features, U-Net can be integrated with various attention mechanism. We can explore this technique with different image modalities like MRI, and PET images. To check the efficiency of the denoising algorithm in actual clinical contexts, comprehensive clinical trials may be conducted. We can create strategies for adaptive denoising models that can adapt to the unique properties of various imaging modalities on their own.

REFERENCES

[1] M. X. X. Xu, "NFCNN:toward a noise fusion convolutional neural network for image denoising," *Signal Image and Video Processing*, vol. 16, pp. 175-183, 2022.

[2] D. Li, W. Yu, K. Kang, D. Jiang and Q. Jin, "Speckle noise removal based on structural convolutional neural networks with feature fusion for medical image," *Signal Processing Image Communication 99:116500*, 2021.

[3] M. Geng, X. Meng, J. Yu, L. Zhu and L. Jin, "Content-Noise Complementary Learning for Medical Image Denoising," *IEEE Transactions on Medical Imaging*, vol. 41, no. 2, pp. 407-419, 2022.

[4] S. Rai, J. S. Bhatt and S. K. Patra, "Augmented Noise Learning Framework for Enhancing Medical Image Denoising," *IEEE Access*, vol. 9, pp. 117153-117168, 2021.

[5] N. T. Trung, D. H. TrinH and M. Luong, "Low-dose CT image denoising using deep convolutional neural networks with extended receptive fields," *SIViP 16*, vol. 16, pp. 1963-1971, 2022.

[6] Y. Li, K. Zhang, W. Shi and Z. Jiang, "A Novel Medical Image Denoising Method Based on Conditional Generative Adversarial Network," *Computational and Mathematical Methods in Medicine*, no. 1, 2021.

[7] A. Chakraborty, M. Jindal, E. Bajal, P. Singh and M. Diwakar, "A multi-level method noise based image denoising using convolution neural network," in *Journal of Physics: Conference Series*,, Greater Noida,Delhi, 2020.

[8] S. Rawat, V. Kumar and K. Rana, "A novel complex-valued convolutional neural network for medical image denoising," *Biomedical Signal Processing and Control*, vol. 69, 2021.

[9] A. S. Ahmed, W. H. E. Behaidy and A. A. Youssif, "Medical image denoising system based on stacked convolutional autoencoder for enhancing 2-dimensional gel electrophoresis noise reduction," *Biomedical Signal Processing and Control*, vol. 69, no. 102842, 2021.

[10] P. Singh and A. Shankar, "A novel optical image denoising technique using convolutional neural network and anisotropic diffusion for real-time surveillance applications," *Journal of Real-Time Image Processing*, vol. 18, pp. 1711-1728, 2021.

[11] F. H. G. Zuluaga, F. Bardozzo and R. Tagliaferri, "Blind microscopy image denoising with a deep residual and multiscale encoder/decoder network," in *43Rrd Annual International Conference of the IEEE Rngineering in Medicine and Biology Society(EMBC)*, Mexico, 2021.

[12] Y.-J. Chen, C.-Y. Tsai, X. Xu and H. Yuan, "Ct Image Denoising With Encoder-Decoder Based Graph Convolutional Networks," in *2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI)*, Nice, France, 2021.

[13] F. Jia, T. Zeng and W. H. Wong, "DDUNet: Dense Dense U-Net with Applications in Image Denoising," in *2021 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*, Montreal, BC, Canada, 2021.

[14] M. Gupta, A. Goel, K. Goel and J. Kansal, "Medical Image Denoising using Convolutional Autoencoder with Shortcut Connections," in *2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT)*, 2023.

[15] F. Hashimoto and H. Ohba, "4D deep image prior: dynamic PET image denoising using an unsupervised four-dimensional branch convolutional neural network," *Physics in Medicine and Biology*, vol. 66, no. 1, 2021.

[16] S. Tang, A. Ghorbani, R. Yamashita and S. Rehman, "Data valuation for medical imaging using Shapley value and application to a large-scale chest X-ray dataset," *Scientific Reports*, pp. 1-9, 2021.

[17] R. Singh and L. Kaur, "Magnetic Resonance Image Denoising using Patchwise Convolutional Neural Networks," in *8th International Conference on Computing for Sustainable Global Development (INDIACom)*, New Delhi,India, 2021.

[18] X. Jiang, Y. Zhu, Y. Dawei and B. Zheng, "Images denoising for COVID-19 chest X-ray based on multi-resolution parallel residual CNN," *Machine Vision and Applications 32*, vol. 32, 2021.

[19] Z. Li, W. Shi, Q. Xing, Y. Miao and W. He, "Low-Dose CT Image Denoising with Improving WGAN and Hybrid Loss Function," *Computational and Mathematical Methods in Medicine*, 2021.

[20] G. Dong, M. Yingnan and A. BASU, "Feature-Guided CNN for Denoising Images," *IEEE Access*, vol. 9, pp. 28272-28281, 2021.

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