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Cloud based Medical Image De-Noising using Deep Convolution Neural Network

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ABSTRACT
It is difficult to remove noise from images because of the many sources of noise. Among the many sources of noise in imaging, Gaussian, impulse, salt, pepper, and speckle are the most complex. Image processing for medical purposes has no other major aim, such as beautifying an image or generating art, whereas conventional image processing has primary goals such as improving an image's aesthetics. This may include enhancing the picture itself, as well as the extraction of information either manually or automatically, depending on the needs of the work. Deep Convolutional Neural Networks (DnCNN) are the kinds of deep neural networks that do visual processing of images. An old but still relevant area of image processing research is denoising images. This subject has seen a surge with the advent of Deep Convolutional Neural Networks thanks to the several advantages. The first advantage is that, It saves time and affords, Denoising networks that have been pre-trained are very well tuned. There are no noticeable artifacts after denoising and It generates excellent denoising results. In proposed work, The implementation process has been divided into four parts. Working with cloud-based medical images in the initial phase. The previously trained network will be loaded in the second step. In the third stage, the denoised picture is obtained by sending the noisy image to the network and then performing. Afterwards, in the last stage, the resulting image is denoised image. The result is compared with various existing denoising methods. The outcome result is better in the terms of PSNR and SSIM.

Keywords
Deep Convolutional Neural Networks, Cloud, medical image, Denoising, Image processing, Deep Learning

1. INTRODUCTION
The earliest filters employed in image processing were the linear, non-linear, and non-adaptive types [1]. Nonlinear, adaptive, wavelet-based, and partial differential equation (PDE) noise reduction filters are all examples of noise reduction filters. Linear filters minimize noise by multiplying nearby input pixels by their corresponding output pixels. Filters that are non-linear may retain edge information while still suppressing noise. Non-linear filters replace linear filters in the vast majority of filtering applications. Linear filtering is regarded to be a poor filtering approach since it does not maintain edge information [2-7]. The median filter (MF) is a basic non-linear filter. For real-time applications, adaptive filters use statistical components. Wavelet-based filters minimize additive noise by transforming pictures into the wavelet domain [8]. Reference [9, 10] provides a comprehensive overview of several denoising filters. There are many techniques have been introduced that are used in proceesing of images likes machine learning and internet of thing(IoT).The IoT as used to take the images through digital camera. These captured images are stored on cloud for the processing[11-14]. The filters stated in this article have had mixed effects, but overall, they have been rather effective. Poor test phase optimization, manual parameter choices, and unique denoising models are some of the downsides of this technology. However, convolutional neural networks (CNN) have proven to have the potential to overcome these disadvantages [17]. Many issues can be solved with CNN algorithms [18]. This includes image recognition [19], robotics [12], self-driving vehicles, facial expression recognition, natural language processing, handwritten digital recognition, and so many more fields. For picture denoising, CNN (deep learning) was pioneered by Chiang and Sullivan [21]. To eliminate complicated noise, a neural network (weighting factor) was utilized, and then a feedforward network [22] created a balance between efficiency and performance. The vanishing gradient, activation function (sigmoid [23] and Tanh [24]), and unsupported hardware platform made CNN problematic in the early stages. CNN's use of AlexNet since 2012 has made it much more difficult. To improve computer vision, CNN architectures like VGG [25] and GoogleNet [27] have been used. The first time a CNN architecture was employed for picture denoising was in the references [28, 29]. For image denoising, super-resolution, and JPEG image blocking, Zhang et al. employed the denoising CNN (DnCNN). It includes convolutions, back-normalization, rectified linear units (ReLU) [30, 31], and residual learning [32].

Although CNN is most often used to denoise general pictures, it has also achieved great results when used for blind denoising [33], actual noisy images [12], and several other tasks. Only a few academics have presented a comprehensive assessment of CNN algorithms for picture denoising. Using categories based on noise kind, [26] summarized CNN's approaches for picture denoising. Since there are so many techniques for capturing photographs in this review, it would be incomplete without them. Several studies released towards the end of 2020 were accidentally deleted because of the study's failure to take into account more current approaches (those from the year 2020). This review covers denoising techniques for various types of noise (including specific image noise). Image type and noise definition are significant considerations when discussing current state-of-the-art techniques. [34-39].

2. LITERATURE REVIEW
The use of photographs has skyrocketed in recent decades. During the capture, compression, and transmission processes, images get distorted and contaminated with noise. Images may be affected by noise in a variety of ways, including environmental, transmission, and other channels. Picture noise

is the change in signal (in random form) that influences the brightness or color of the observed image and the extraction of information in images. "Image noise" is a term used in the image processing industry. An incorrect diagnosis might be made due to noise in the images being processed (video processing, image analysis, and segmentation). As a result, image denoising is a crucial part of the picture processing puzzle.In computer-aided analysis, picture denoising algorithms have become a necessity due to an increase in the number of digital photographs taken in less-than-ideal settings. The technique of recovering information to clean up photos from noisy photos has been a pressing issue in recent years. There will be no more noise in your picture after using image denoising processes. How to tell noise from edge and texture from texture is a fundamental issue in picture denoising (since they all have high-frequency components). The most frequently mentioned noises in the literature are AWGN, impulse noise, quantization noise, Poisson noise, and speckle noise [2–6].Impulse noise, speckle noise, Poisson noise, and quantization noise all arise as a result of manufacturing flaws, bit errors, and insufficient photon counts, whereas AWGN occurs in analog circuits. Medical imaging, remote sensing, military surveillance, biometrics and forensics, industrial and agricultural automation, and individual identification are among areas in which image denoising technologies are used. For the removal of medical noise such as speckle, Rician, and quantum in medical and biomedical imaging, denoising algorithms are essential preprocessing stages [8, 9]. Salt and pepper, as well as an additive white Gaussian noise, may be removed from remote sensing images using denoising techniques. SAR pictures allow military surveillance to be carried out from both space and the air [12]. SAR pictures exhibit less speckle thanks to image denoising methods [13]. Furthermore, there is no unique kind of noise in forensic photographs; any noise might damage them. Due to the fact that picture noise may detract from forensic evidence, image denoising techniques have been developed to decrease it [14]. "Image denoising techniques were utilized to filter paddy leaves and identify illness in rice plants." Image denoising is an important topic in academia, and it is studied in a wide range of fields.Image denoising has been suggested using the attention-guided CNN (ADNet) in reference [18]. Four blocks (SB, FEB/AB/RB) comprise the 17 levels of ADNet: sparse block (SB), feature enhancement block (FEB), and attention block It has been shown that applying sparsity to images [19] improves efficiency and performance while also decreasing the denoising framework's depth. Two different forms of Conv + BN + ReLU (one dilated, the other not) make up the SB's 12 layers. Unlike the AB, which only has a single convolution layer, the FEB contains four layers with three different kinds (Conv + BN + ReLU, Conv, and Tanh). When there was a lot of noise, the AB was employed to help direct the SB and FEB.Certain deep learning algorithms generate outstanding results with synthetic noise in images affected by genuine noise, but the majority of this network does not. The noise estimation reduction network was suggested by Guo et al. in their study [20]. (NERNet). NERNet was used to remove noise in photos that had realistically generated artifacts. The noise estimation and noise reduction modules were separated in the design. The symmetric dilated block [22, 23] and the pyramid feature fusion [24] are used by the noise estimation module to adjust the noise-level map. During this time, the noise was being removed by using the estimated noise-level map provided by the removal module. The removal module collected global and local information for maintaining details and texture. To obtain clear pictures, the estimation module's output was sent into the removal module.CNN's ability to understand noise patterns and picture patches is unquestionably impressive. A considerable quantity of training data and picture patches are required for this learning. In light of the above, the patch complexity local split and deep conquer network were presented in reference [25]. (PCLDCNet). According to the clean image patch and conquer block, the network was separated into local subtasks and trained in its local area. The local subtask was used to aggregate each noisy patch weighting mixture. The k network was trained using modified stacked denoising autoencoders and picture patches were sorted according to their complexity [26, 27]. Another issue with a deep learning network is the degradation of the network itself (the deeper the layer, the higher the error rate). There is still potential for development despite the introduction of ResNet [28]. An algorithm suggested by Shi et al. [28] does not need an identity mapping in order to denoise images. Feature extraction, inference, and fusion are all sub-networks of the network. Patches representing higher-dimensional feature maps are extracted using the feature extraction sub-network. Cascaded convolutions in the interference sub-network [30] provide a broad receptive field. A cascading technique was implemented in order to learn noise maps from multiscale information and create tolerable mistakes in noise estimates. Last but not least, a sub-network called the fusion sub-network combines the complete noise map into an estimate.

3. METHODOLOGIES

Deep Convolutional Neural Networks for Image Denoise Image processing is performed via the Deep Convolutional Neural Network (DnCNN), a kind of deep neural network. Image denoising is a well-established yet active area of image processing research. There has been a surge in interest in this subject with the introduction of Deep Convolutional Neural Networks because of its many advantages, like saving time and money, are two of its primary benefits. Denoising networks that have been pre-trained is quite effective.

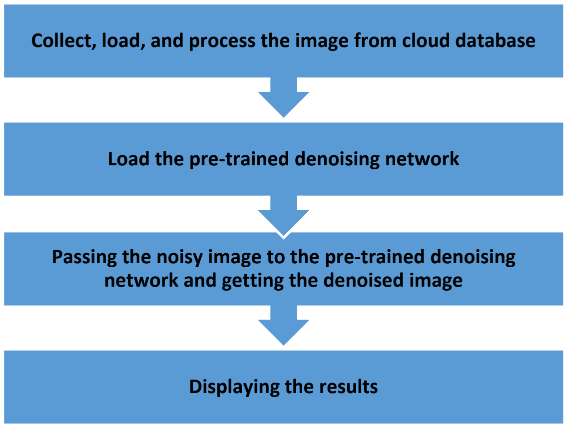

Fig 1: Process of Implementation

The approach in this paper is to consider picture denoising as just another kind of discriminative learning. That is, The noise in a picture is removed using feed-forward convolutional neural networks (CNN). There are three main reasons for using CNN. It is important to note that CNNs with a highly deep architecture are more capable and flexible when it comes to utilizing picture properties. Second, significant progress has been made on regularization and learning approaches for training CNN, including Rectifier Linear Unit (ReLU), batch normalization, and residual learning. Faster training and better denoising performance may both be achieved by incorporating these techniques into the CNN system. The last benefit is that powerful contemporary GPUs can make use of the parallelism inherent in CNN's design to speed up processing. The GPU may be used to enhance the overall performance of the application.

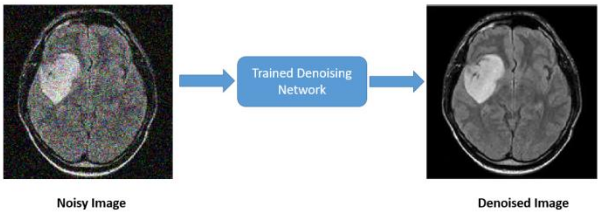

Fig 2: Pre Trained denoised Network

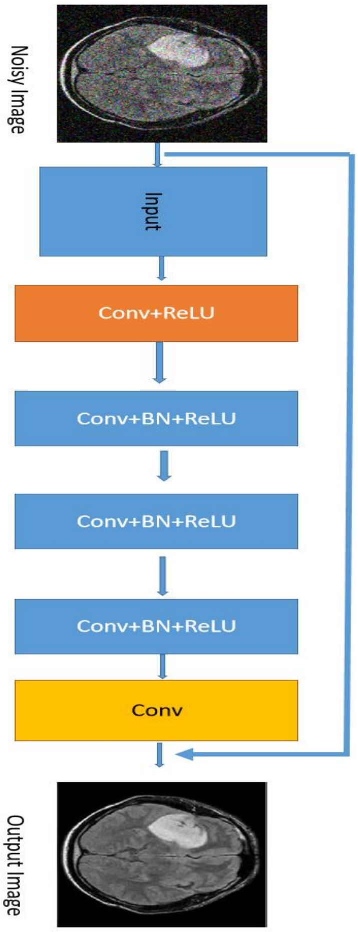

Fig 3: Proposed Architecture

4. RESULT ANALYSIS

Denoising performance has been compared to some previous work (Buades et al., 2005; Manjon et al., 2015; Chen et al., 2016; Jiang et al., 2018; Zhang et al., 2018). On the basis of PSNR, Table 4 gives a comparative results of various approaches. Each of the seven approaches is compared at a range of noise levels (i.e., 3, 5, 7, 9, 11, 13, and 15 percent), and the results are summarized in this table. There are two techniques of comparison in this table. FFDNet (Zhang et al., 2018) and MCDnCNNg (Jiang et al., 2018) are CNN-based approaches, while NLM (Buades et al., 2005), PRINL-PCA (Manjon et al., 2015), and CNLM (Chen et al., 2016) are non-CNN-based methods. Both CNN and non-CNN techniques were trained using the same training data, so that the comparisons were fair. Non-CNN techniques have used search and similarity windows of 7/7 and 3/3, respectively. Table 4 shows that CNN-DMRI results are among the best in the industry. However, with noise levels ranging from 5% to 15%, it outperformed all datasets in terms of performance.

Due to the use of GPU compute, CNN-based algorithms are able to denoise more quickly. For CNN-based techniques, the NVIDIA Tesla K-80 GPU was utilized.

While MCDnCNNg and FFDNet have taken 0.48 and 0.29 seconds to denoise an MRI image, CNN-DMRI has taken 0.32 seconds. For GPU compute acceleration, The CuDNN library was used in this project.On an Intel Core i5 CPU, it took 45.7 seconds for the multi-threaded CNLM implementation to denoise an MRI, compared to 43.1 seconds for NLM and 41.8 seconds for PRI-Nl-PCA.

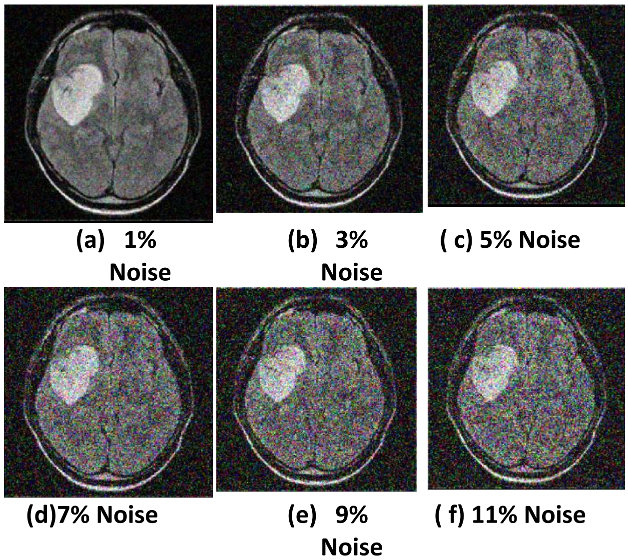

Fig 4: Noisy Images with different noise level

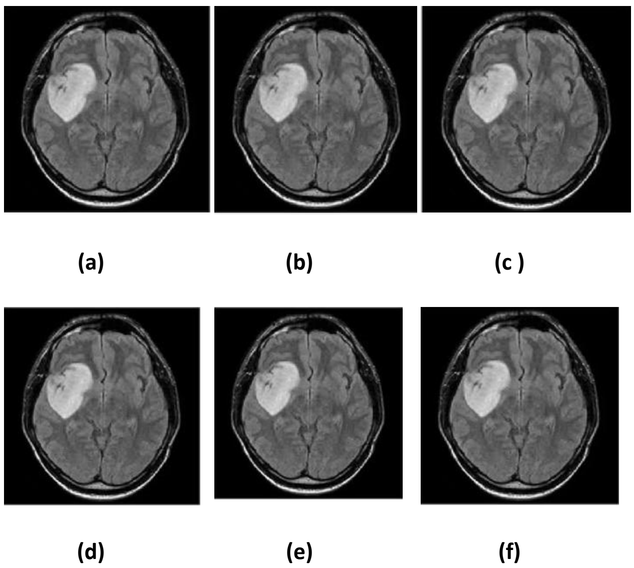

Fig 5: De-noised Images after applying proposed method

A collection of genuine MRI pictures with pre-existing noise was also denoised using CNN. Figure 6 shows the results of denoising a few different photos. There is a considerable level of noise in these MRIs. Denoising outcomes are clearly seen in this graph. Denoised MRI scans, as seen in the first and second images, clearly maintain the ventricular structure. It's hard to see where the tumor's boundaries are in the noisy photos. These photographs have been denoised, and you can clearly see the tumor's border in the highlighted areas. Here are the denoising findings in terms of PSNR and SSIM, which are shown in Table 1. The table shows the findings for five datasets, each with a different degree of background noise. The tested noise levels range from 1% to a maximum of 29%. After checking with many radiologists in the area, This range has been developed. In MRI images performed with a 1.5 Tesla scanner, the noise range [1, 15] may be more common. Scans done in short periods of time or with incorrect radio-frequency coil settings tend to raise the upper limit. A wide range of noise levels, ranging from 1% to 29%, have been examined in this proposed work. Table 1 shows that the findings for the Brainweb dataset are marginally superior to those of the other datasets. This is due to the fact that the network is trained on the Brainweb dataset.

It was used solely for testing purposes with the other four datasets. In addition, the findings for the additional datasets reveal that the proposed denoising network has a good generalization capability. The PSNR of noisy and denoised pictures were compared to show how denoising improves image quality. Improvements in PSNR values on several datasets are visually shown in Figure 7. These graphs show that there has been tremendous progress for noise levels greater than 3%.

Even though FFDNet is slightly faster than CNN, the suggested denoising network may be a better choice for MRI denoising based on the improved results.

Table 1: The results of proposed method when training with noise range

		Noise Level					
Data Set	Metric	1%	3%	5%	7%	9%	11%
Brainweb	PSNR	41.30	40.55	39.73	39.11	38-55	38.0 1
	SSIM	0.846	0.847	0.841	0.828	0.825	0.825
IXI	PSNR	40.19	39.38	38.40	37.56	36.83	36.18
	SSIM	0.870	0.862	0.850	0.836	0.829	0.820
MS	PSNR	37.87	39.51	38.95	38.27	37.56	35.88
	SSIM	0.982	0.980	0.976	0.971	0.965	0.958
Prostale	PSNR	37.79	37.35	36.67	35.87	35.03	34.24
	SSIM	0.961	0.954	0.943	0.929	0.912	0.895
Proposed Method	PSNR	**40.49**	**39.82**	**39.02**	**39.22**	**39.47**	**39.77**
	SS M	**0.986**	***0.979***	**0.980**	**0.940**	**0.971**	**0.971**

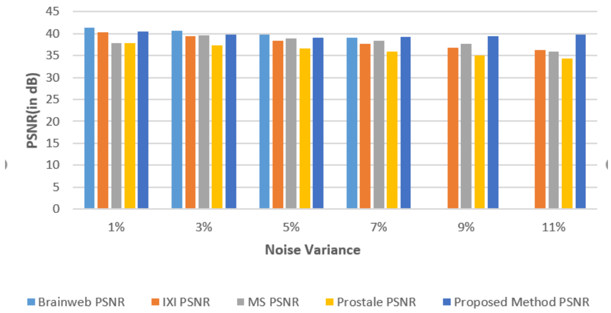

Fig 6: Average noise removal performance of our proposed method and existing filtering methods

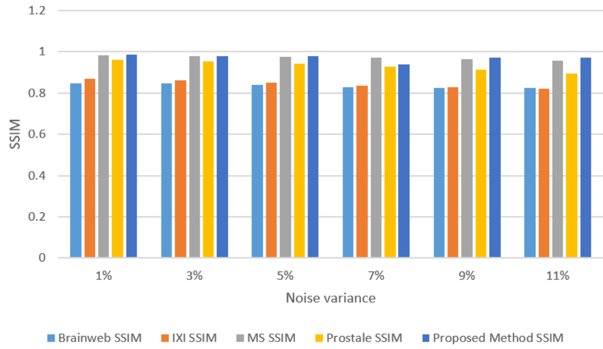

Fig 7:SSIM performance of proposed method and existing filtering methods

5. CONCLUSION

It was the goal to minimize rician noise in MRI pictures by creating the Deep Convolutional Neural Networks model known as "DnCNN".Using several convolutions, the suggested CNN captures a variety of picture information while removing the inherent noise. In addition, the encoder-decoder structure of the proposed technique conducts down-and up-sampling of pictures throughout the denoising process. The suggested DnCNN model also includes residual learning. Synthetic MRI images are used to train the network. For the purpose of evaluating the outcomes, it has been shown that the suggested approach can yield promising denoising outcomes both qualitatively and quantitatively. In addition, the network's performance has been examined at levels of invisible or blind noise. A comparison study has shown that the CNN idea is better than what is being done now. Existing approaches have been outperformed by the newly proposed CNN. DnCNN is used to remove the noise from the supplied (Fig 5) pictures and produce a noise-free image. A high degree of denoising was accomplished by using the methods presented here. Denoising using DnCNN methods is shown to be more effective because of their high PSNR value than other filtering techniques. The picture may be denoised more successfully than with traditional methods because of the greater image denoising and quality ratio.The suggested method's noise extraction properties are superior to those of current approaches, as shown in figures 6 and 7.By using noise-reduction methods, the investigation may be carried out even further.Compared to other approaches, our suggested method performs better than others. If the image's noise can't be removed pixel by pixel, we'll have to use some other method, This research might be furthered by using strategies for reducing the quantity of background noise.

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