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Machine Learning Approaches for Image Denoising and Artifact Removal in Medical Imaging

[1]Aastha Gour, [2]Kapil Rajput

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Abstract: This study introduces a novel Recurrent Neural Network (RNN) for medical picture denoising that makes use of lengthy short-term memory-based batch normalisation. At first, noisy CT lung pictures are used as input. Denoising the input picture using an RNN. The training of deep neural networks that are feed-forward may now be sped up with the use of a technique known as batch normalisation. Batch normalisation is used in long-term short-term memory (LSTM), and it is shown to speed up optimisation and enhance generalisation. The Particle Swarm Optimisation (PSO) technique is used to choose the batch size in batch normalisation. MATLAB was used to create the suggested system. The experimental findings are compared to the current setup.

***Keywords**: Recurrent Neural Network (RNN), CT lung images, Long Short-Term Memory (LSTM)*

1. Introduction

The fields of medicine and science make effective use of images by visually representing the innate parts of the body for laboratory testing analysis and by revealing the structure that lies hidden beneath the skin and bone. The photograph plays a crucial part in diagnosing the patient's conditions. Imaging techniques in medicine have established themselves as crucial in modern illness diagnosis. Since the last couple of decades, many medical imaging modalities have been developed for specific uses. These techniques are useful because they allow for the acquisition of pictures of the inside anatomical structures that need to be studied, without actually opening the body. Popular medical imaging modalities now employed for identifying the various disorders include X-rays, CT scans, nuclear imaging, MRI scans, and ultrasound scans. However, noise is a significant obstacle for many imaging methods. Noise is the undesired effects created in medical imaging, and it manifests itself when the values of the intensity of pixels in the image exhibit various values rather than genuine pixel values. In medical imaging applications, noise reduction is crucial for improving and preserving the intricate picture data as much as feasible.

Type of Noises

Different types of noise introduce distortion into a picture during capture, transmission, reception, storage, and retrieval. The degree to which the noise affects the picture depends on the types of distortion present.

Integer-Rate Error The signal is spread uniformly across the background of Gaussian noise. Therefore, the value of each pixel in the noisy picture is the sum of the value of the true pixel plus the noise, which is randomly distributed according to the Gaussian distribution. The level of noise is independent of the value of each pixel. In the case of white Gaussian noise, the values at any given pair of times are distributed uniformly and are statistically independent of one another. Akin to white light, white noise takes its moniker from its absence of colour. The most common causes of Gaussian noise in digital photographs occur during the collection process. These include, for example, sensor noise caused by insufficient lighting, excessive heat, or poor transmission.

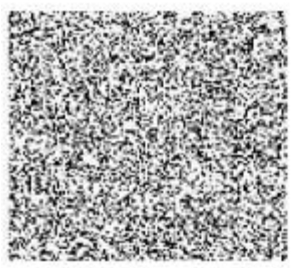

Fig 1. Gaussian noise (mean=1.5, variance=10)

Overview of Medical Image Noising

An important challenge and an exciting opportunity for those working in the area of image processing have arisen as a result of the burgeoning field of biomedical imaging. Existing models are notoriously inaccurate for several types of biomedical imaging, such as X-ray,

[1]*Asst. Professor, Department of Comp. Sc. & Info. Tech. Graphic Era Hill University, Dehradun Uttarakhand 248002,* agour@gehu.ac.in
[2]*Asst. Professor, Department of Comp. Sc. & Info. Tech. Graphic Era Hill University, Dehradun Uttarakhand 248002,* kapilrajput@gehu.ac.in

ultrasound, magnetic resonance imaging (MRI), computed tomography (CT), etc. The level of non-static ultrasound speckle noise is set by attenuation of the ultrasonic waves and sub-resolution scatterers in the tissue. Numerous factors during the CT process might impact the level of noise in the resulting image. The tube current-time product and the thickness of the slices are two such factors. However, the Signal-to-Noise Ratio (SNR) of MR images depends on many different things, including the pulse sequence used, the radiofrequency coil(s) used for signal detection, the strength of the static magnetic field, and the acquisition parameters, which include the echoes and repetition times, flip angle, field of view, slice thickness, acquisition matrix, receiver bandwidth, and the number of signal averages. Therefore, understanding the specific physical and visual characteristics of medical imaging is crucial for efficient image denoising. Restoring and enhancing images is useful in a variety of real-world situations. Poor image extraction, using photos captured in a noisy environment, or communication channel noise are all potential sources of Additive White Gaussian Noise (AWGN) contamination. Linear filtering and smoothing procedures have seen extensive use in the area of picture reconstruction because of their efficacy and relative simplicity. Despite their usefulness, these approaches have several serious limitations due to the static and linear assumptions they make about the visual input. Real-world medical imaging generally uses dynamic rather than static statistics. They are generated by multiplying the reflectance of the item or scene of interest by the intensity distribution of the light entering the scene. There are also a number of adaptive and nonlinear techniques for restoring images that take into account local statistical features. Enhancement and reconstruction of images are greatly aided by these techniques, with original high-frequency information such as edges being preserved in the process.

Image Denoising

In digital photography, "image denoising" describes the process of eliminating noise. There will always be some background "noise" in an image. It might be added anywhere from the recording stage through the transmission stage of the image creation process. Figure 2 depicts the result of applying additive noise n(x, y) on the medical input image f(x, y), which is a noisy variant of the original image. With knowledge of the additive noise n(x, y), the denoising approach may approximate the genuine medical image with a value f(x, y). The accuracy of the estimate relative to the actual medical input image is crucial to the system's performance. In general, the more we know about n(x, y), the more closely f (x, y) will approximate f(x, y). Additive white Gaussian noise (AWGN) dominates, which encompasses a wide variety of other types of noise such as speckle vibration, impulses noise, Poisson noise, etc.

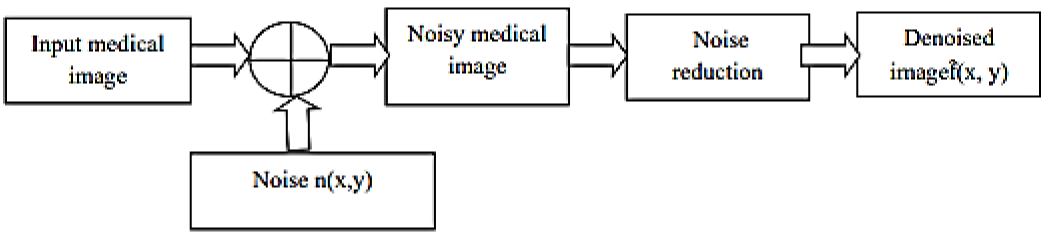

Fig. 2 A model of the image denoising process

The average linear filter is another name for the mean filter. As each corrupted section of the image is averaged out, the average value of the entire current block is used as the new value for the centre pixel of that section, and so on, until the corruption pixels in the image are maintained by shifting the block over the entire image. However, it has trouble keeping its edges. To solve the mean filter issue, the conventional median filter is suggested. The median filter is an example of a nonlinear filter because it calculates the median of the corrupted block and then uses that value as the one for the central pixel of the current block. This process is continued until the whole corrupted region of the picture is restored. However, if the mask size is reduced (to say, 3 by 3 pixels), the quality of the filtered picture improves. In addition, the Gaussian filter may be used to effectively blur pictures, making it possible to get rid of both noise and fine detail. An example of a non-uniform low pass filter is the Gaussian filter. Salt-and-pepper sounds is not effectively muffled. Salt and pepper noise, which manifests as white and black splotches in the real picture, is targeted for elimination via the development of a non-linear filtering method. Comprehensive Median Filter (CMF) gets its name from the all-encompassing approach it takes to bettering the traditional median filter. Using Mean Square Error (MSE) as a quality assessment measure, the CMF method improves upon the usual median filter during picture reconstruction. The one and only downside of CMF is the need for complex and non-economic computing. The aforementioned issue may be fixed and denoised photos' quality can be improved using a variety of machine learning and optimization-based approaches.

When capturing a picture, noise often messes things up. Researchers still face difficulties when attempting to eliminate noise in the original picture. Important diagnostic information about human organs is carried by medical images. Methods for cleaning up images without losing any of the crucial elements or information were presented in this effort. Estimating the unresolved noise in a distorted or noisy picture is the core idea underlying this study, which is also known as "denoising" an image. Restoring a picture that has been corrupted by noise may be done with the aid of a few different methods. Getting the right technique is crucial to capturing the right shot. Before an image may be shown or processed further (via segmentation, feature extraction, object identification, texture analysis, etc.), denoising must often be performed. The goal of denoising is to effectively remove noise while preserving edges and other crucial qualities, such as sharpness and contrast, to the greatest degree feasible. Minimising noise power as much as possible and recovering finer features and edges in a picture is required for real-time applications like television, photo-phones, etc. In addition, for online and real-time applications, it is crucial to be computationally simpler so that the filtering process may be completed in a shorter time period. As a result, this thesis seeks to develop an efficient filtering and batch normalisation method to get rid of AWGN and impulse noise at medium and high power levels under medium and high noise levels without causing excessive corruption and blurring. The unique algorithms and methods are then compared to the state-of-the-art methods in terms of Peak Signal-to-Noise Ratio (PSNR) and processing speed. High dimensional and nonlinear situations benefit greatly from the use of the Firefly method as well. One drawback is that it's hard for a single metaheuristic to get to the best possible answer in a timely manner. Therefore, the disadvantage of a single metaheuristic algorithm may be avoided by the integration of metaheuristics. As a forward-thinking approach, researchers must deal with fireflies in a variety of problems, such as determining the best path for newly constructed tracks while adhering to many limitations, such as minimising environmental impact and maximising the number of tracked objects.

Problem Definition

Multiple recent technological and non-technical uses make heavy use of photographs. Images such as those used in portraiture, videography, biomedicine, geophysics, satellite imagery, microarray analysis, forensics, etc. Noise in pictures occurs as a result of flaws in the methods used to acquire, process, condition, and transmit them. Not only does noise reduce the overall picture quality, but it also obscures crucial details, making feature extraction from noisy images a challenging task. Denoising images is a prerequisite for many other types of image processing, including but not limited to recognition, authentication, compression, segmentation, medical diagnostics, forensic verification, and so on. The subject of picture denoising has been explored extensively, and several research efforts have yielded numerous effective image denoising methods. However, as there are several denoising factors involved, increasing levels of complexity are desired in order to enhance denoising quality. Therefore, studying picture denoising is a viable academic pursuit. Mathematically, picture noise may be characterised by a variety of probability functions, including the Gaussian, Impulse, Poisson, Rician, Speckle, and so on. Images may also display a mixture of these sounds. To correctly restore signal from noisy photos, insight into the nature of the noise present is essential. However, picture denoising is still a tough topic since a good denoising algorithm can only be declared successful if only noise is eliminated without degrading the critical features and singularities such as contours, curves, lines, textures, etc. Image denoising is a particularly difficult problem in medical image processing. In low-noise conditions, many picture denoising algorithms have excelled. However, when exposed to a lot of background noise, their effectiveness decreases. In addition, wavelet and contourlet-based image denoising techniques cannot accurately depict sharp transitions or singularities and provide less obvious directional geometry. It is challenging to differentiate between similar pictures with distinct patterns since the basic functions used for transform domain approaches are pre-defined. Computational complexity increases with sparse representation based on synthesis. This study was prompted by the need that noise be removed from biological pictures without severely degrading their edges or other high-frequency components.

2. Literature Review

Jifara et al. (2019) studied design in deep framework, regularisation strategy, and learning approach to model deep feeding forward denoising convolutional networks for medical picture denoising. Compare our model's effectiveness to other medical image denoising techniques by calculating the denoised or reconstructed picture's superiority in common image quality metrics like peak signal to noise conversion and structural similarity.

Priyanka & Wang (2019) a fully symmetric convolutional-deconvolutional neural network (FSCN) is a highly anticipated deep neural network for image denoising. In the proposed model, a novel architecture is used, consisting of a series of symmetric convolutional-deconvolutional layers that are successively added. End-to-end, without the use of image priors, this system learns convolutional-deconvolutional mappings from damaged to clean pictures. By acting as a feature extractor, convolutional layers encode the most important aspects of an image while also cleaning up any corruptions; subsequent deconvolutional layers enhance the picture's details by decoding the resulting abstractions. Reconstruction loss is minimised by using an adaptive moment optimizer, which works well with both noisy images and large datasets.

Sun et al. (2017) tested the hypothesis that a reconfigured convolutional neural network could turn low-quality pictures produced from a digital radiography equipment into high-resolution images with reduced noise. As evaluated by peak signal-to-noise ratio (PSNR), the predicted experiment on the test dataset of 5 X-ray pictures demonstrated that the expected strategy beat existing approaches (i.e., bicubic interpolation and 3D block-matching approach) by roughly 1.3dB, while maintaining similar levels of accuracy.

3. Methodology

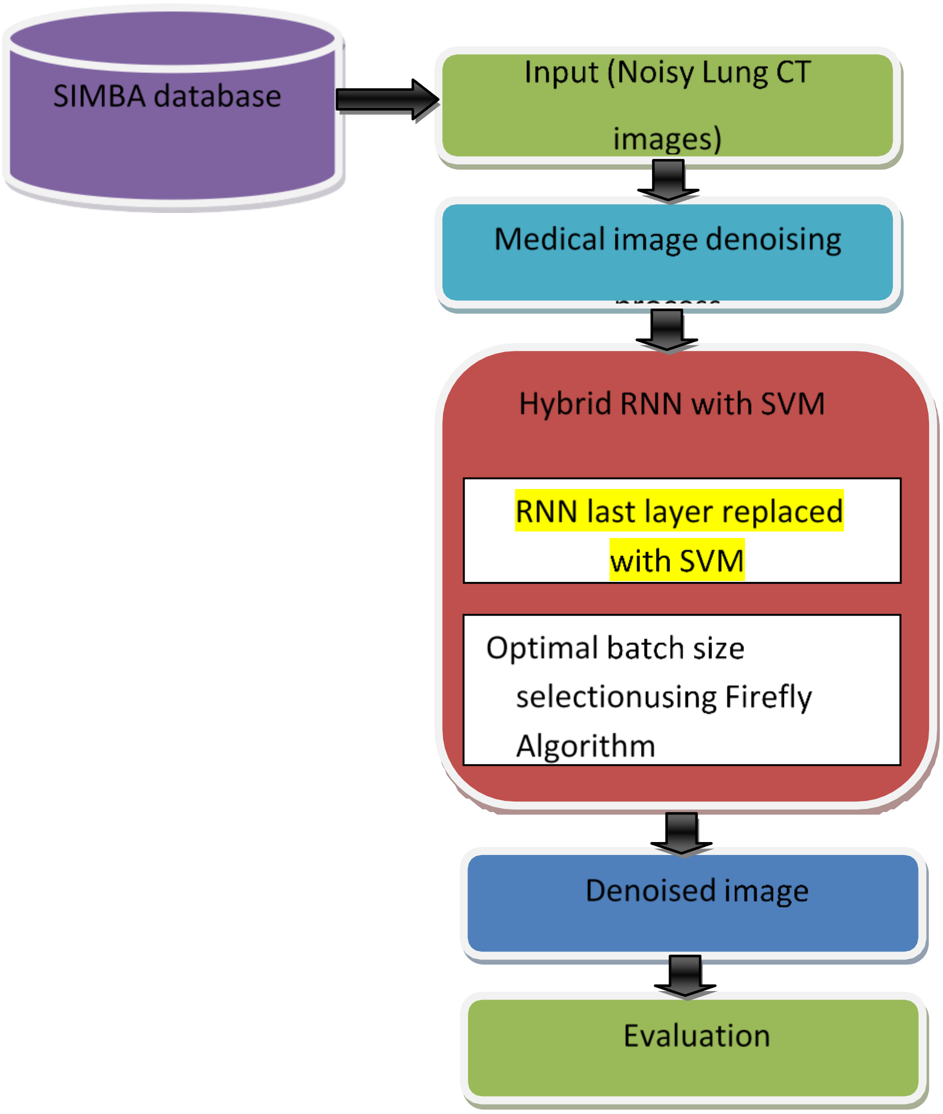

Fig 3. Flow diagram of proposed hybrid Recurrent Neural Networks with Support Vector Machine based denoising approach

This study proposes a new method for denoising medical images using a combination of Recurrent Neural Networks (RNNs) and Support Vector Machines (SVMs). The SIMBA database is mined for lung CT images; next, the Hybrid RNN -SVM is suggested to filter out the Gaussian, white, salt and pepper, and speckle noises. To enhance denoising performance, SVM is recommended to replace the RNN's last hidden layer. In this case, a Long Short-Term Memory (LSTM) method is used to carry out the batch normalization. The batch size in batch normalization is determined using FA. The process flow for the proposed work is shown in Figure 3.

4. Results

In order to carry out the planned study, MATLAB was used. The SIMBA dataset is used for the experiments. The experimental outcomes are shown based on four different types of noise: white noise, salt and pepper noise, gaussian noise, and speckle noise. Existing image denoising techniques including CNN, DnCNN, and RNN are compared to the proposed HRNN-SVM scheme's performance in terms of PSNR, MSE, and accuracy.

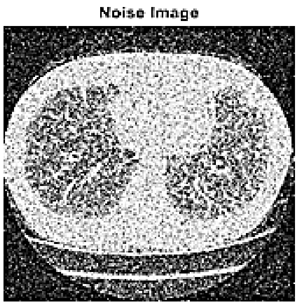

Figure 4 **Input image with white noise**

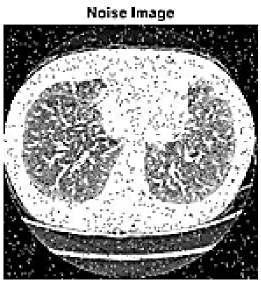

Figure 5 **Input image with salt and pepper noises**

Figure 6 **Denoised image for Gaussian noise**

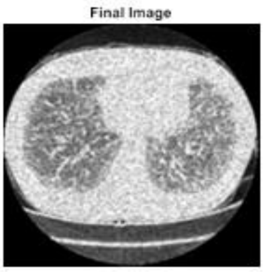

Figure 7 **Denoised image for speckle noise**

The CT lung images are denoised and the PSNR evaluated. The PSNRvalue is represented in table 1.

Table 1 PSNR comparison

No of images	PSNR comparison			
	CNN	**Dn-CNN**	**RNN**	**HRNN-SVM**
Image 1	38.56	39.63	44.38	46.25
Image 2	36.85	38.56	43.63	45.96
Image 3	37.25	39.87	41.96	43.52
Image 4	39.02	40.10	42.21	44.32
Image 5	35.12	36.65	37.65	40.54

Image 6	35.85	37.12	39.33	41.21
Image 7	34.51	36.12	38.54	40.24
Image 8	34.02	35.95	37.41	40.00

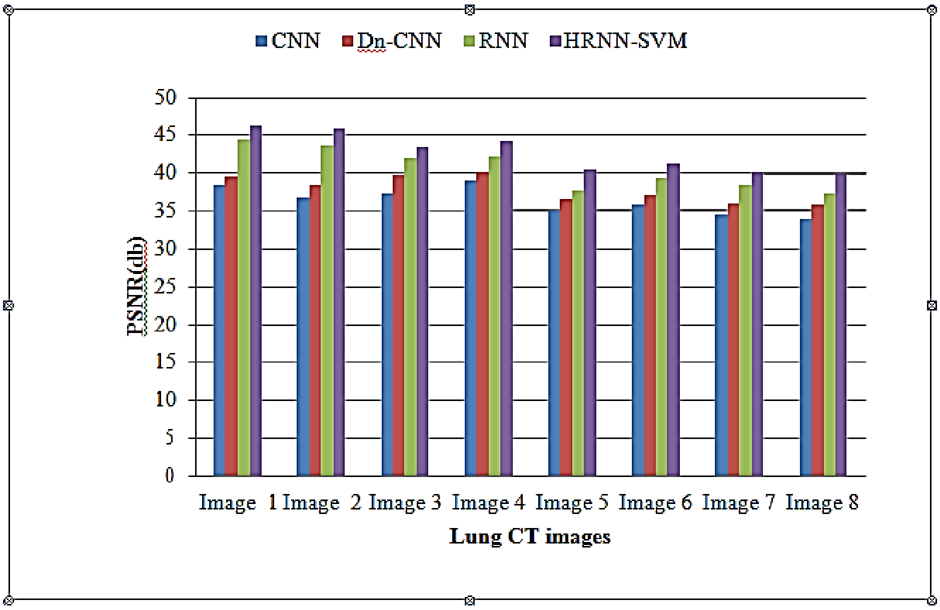

Fig 8. Experimental results of PSNR comparison for lung CTimages

5. Conclusion

This paper proposes a novel method for effectively denoising and classifying lung CT images by combining Recurrent Neural Networks (RNN) and Support Vector Machines (SVMs). Three types of noises—gaussian, white, salt & pepper, and speckle—are used here. The suggested work begins by implementing the SVM in the RNN's output layer in an effort to boost its performance. Batch normalization is used with residual learning to speed up the learning process while increasing accuracy. Comparing the proposed HRNN-SVM to various denoising methods like DnCNN, CNN, and RNN, the PSNR and MSE results reveal that the suggested HRNN-SVM achieved superior results. The suggested method's denoising capacity is confirmed by comparison experimental findings, suggesting it offers a viable solution to the problem of picture denoising.

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