Turkish Online Journal of Qualitative Inquiry (TOJQI)
Volume 12, Issue 9, August, 2021: 1948 – 1958

Research Article

Removal Of Random Noise Based On Convolutional Neural Network With Optimization Technique

Mr. M. Arun Prasad[1], Dr. N. P. Subiramaniyam[2]

Abstract

Noise corrupted the digital image because of environmental factor. A new convolution neural network for removing images is presents. The proposed system comprises of convolution neural network with optimization techniques. At first, the digital image is applied into the Batch normalization process for better normalization process. Secondly, the image is given into the Convolution Neural Network (CNN) with Leaky rectified linear unit where the feature is extracted. The CNN process reconstructs the attributes of the recovered image. Finally, to learn and refine the extracted features, the resolved image is introduced in the MSE loss function and the Adam optimization approach. The effectiveness of the proposed framework is tested across a variety of noise levels and compared with various pads and strides. The suggested framework's results show that it outperforms previous denoising algorithms in terms of peak signal-to-noise ratio (PSNR), and it produces the best results.

I. INTRODUCTION

The digital image gives information of research applications such as medicine, astronomy, biology, material science and so on **(EminYüksel and AlperBaştürk, 2003).** Digital images are frequently affected by various types of noise during acquisition and transmission. The noise of Poisson, the noise of speckle and a few other noises that affect the quality of the image. Therefore preprocessing techniques are needed to enhance the digital image and eliminate the noises from the digital image **(Rui Zhang, 2015).** The preprocessing technique is an important step in the field of image processing to give the better recognition rate.

CNNs are used in several areas such as image recognition, natural language processing, video analysis, object detection **(Ren et al., 2015 and Dai et al., 2016)**, classification **(Krizhevskyet al., 2012 and CireşAn et al., 2012)** [10, 11], image segmentation**(Long et al., 2015 and Noh et al., 2015)** [12, 13], speech recognition**(Hannun et al., 2014)** [14], and image generation with adversarial networks **(Schwenck et al., 2017 and Ledig et al., 2017)** [15, 16]

[1]Ph.D. Research Scholar, Department of Electronics, Nehru Arts and Science College, Coimbatore, Tamil Nadu, India. Email ID: arunprasad1012@gmail.com
[2]Professor, Department of Electronics, Nehru Arts and Science College, Coimbatore, Tamil Nadu, India. Email ID: nalsunil@gmail.com

application of artificial intelligence in medical field such as organ segmentation **(Ronneberger et al., 2015 and Milletari et al., 2016)** [17, 18], image denoising **(Wang et al., 2016, Kang et al., 2017 and Chen et al., 2017)** [19–21], and cancer detection **(Cireşan et al., 2013)** [22] etc. The convolution neural network is becoming more important due to several reasons. In tradition networks, the system has to design the feature extractors. But in the case of CNNs, it will act as feature extractors and classifier with weight of the convolution layer and fully connected layer during training process.

The traditional neural network is used for noise reduction before 2010 although it is not suited for very complex images. So, in this paper CNN is used for removal of noise in the digital images. The CNN is working in large images as well as it doesn't need any traditional preprocessing **(Jose et al., 2005)**.

The (burger et al., 2012) presented a MLP algorithm is applicable of specific types of noise processing. The drawback of this system is not adapted for various type of noise intensity.

(Xie et al., 2012) have implement K-Singular Value Decomposition (K-SVD) for image denoising. The shallow linear structure is used in this system to train the dictionary for better results in images. The drawback of this system is limitation in the learning ability.

(Chen et al., 2016) have developed a trainable nonlinear reaction diffusion framework (TRDF) for image denoising. (Zhang et al., 2017) have used to neural network for the removal of noises in the picture. In this method the pictures are divided into blocks in which the cleaning process is obtained. It provides better denoising results. The drawback of this system is it takes more time for their training model as well the cost of the system is high.

The objective of this paper is to train the CNN: (1) to improve the wide range of random noise in digital images, (2) to estimate the performance analysis of CNN denoised images through various denoising metrics and (3) to find best results by tunning padding and strides in CNN.

II. Proposed framework

Let I denote a clean digital image, R denotes the random noise. Next, the noisy image model is set as follows:

$$Y = I + R \quad (3)$$

The proposed framework is proposed to removal the noise from the input digital image. This system preserves edge information of the given input image illustrated in Figure 1:

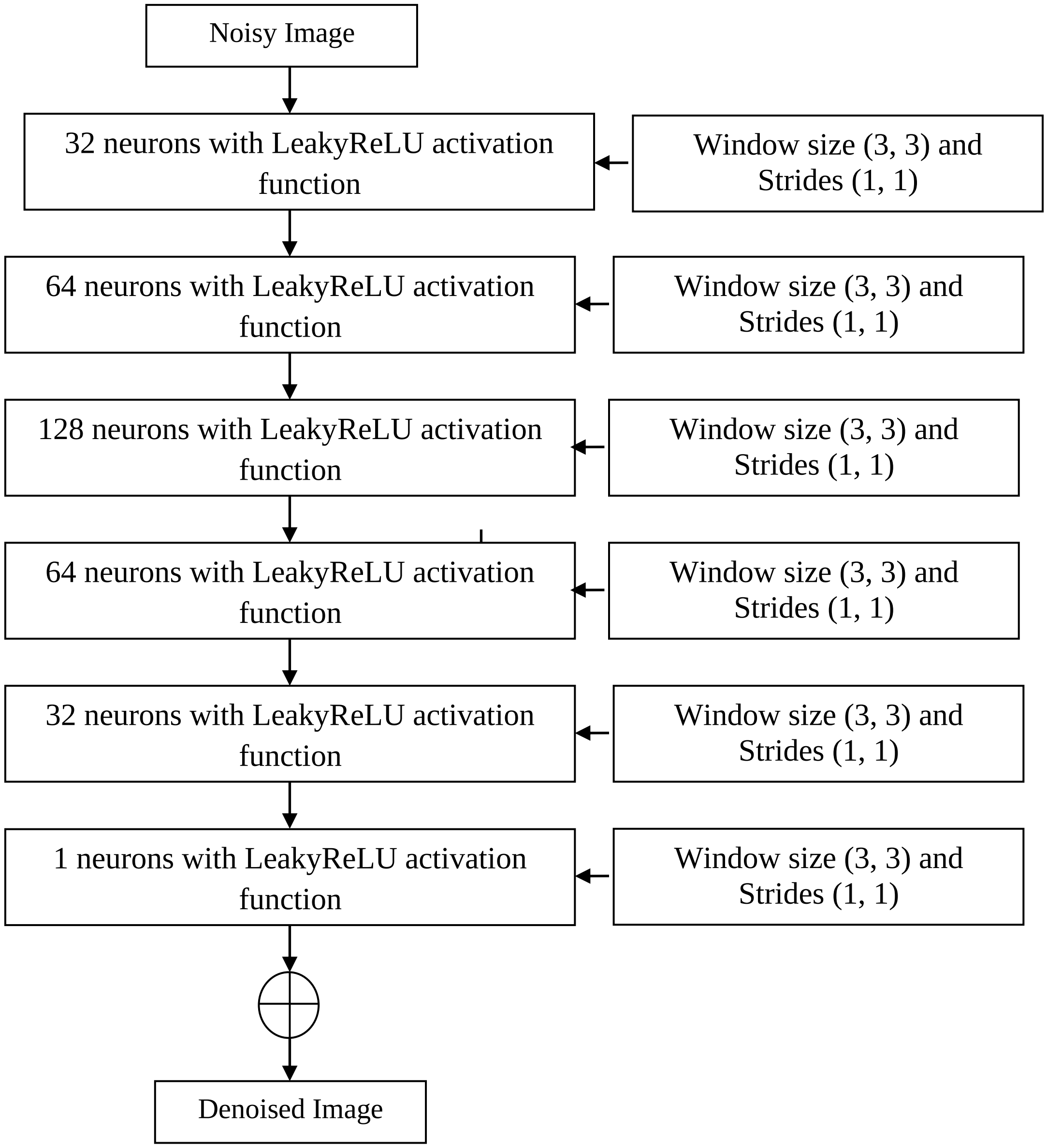


Figure 1: Architecture of Proposed framework

Architecture of CNN:

The CNN has 4 layers such as non-linear, sampling, convolution and fully connected.

- The pixel values of the given image are given by input layers.
- The output of the neuron is determined by convolution layer. The output is connected to the input local regions with scalar product.
- The given input is performed into down sampling through pooling layer. This layer also reduces the number of parameter within that activation.

- The fully connected layer get the total scores from the activation and given into classifier for classification. In between these layers LeakyReLu is used for better performance in the image denoising.

The complexity of the model is significantly reduced by convolution layer with the optimization of output. There are three parameters such as depth; stride and zero-padding are used to optimize this model.

Depth: Filters are used and it for different characteristics.

Stride: It is used to find out filtering process across the input. It is not allowed to slide more than three pixels at a time.

Zero padding: It determines the number of pixels filled with zero around the border.

Pooling/subsampling layers: This layer will helpful to reduce the feature resolution. It renders the respective characteristics of anti-noise and warp. There are two categories of pooling: maximum pooling and average pooling. The following figure illustrates the example of pooling:

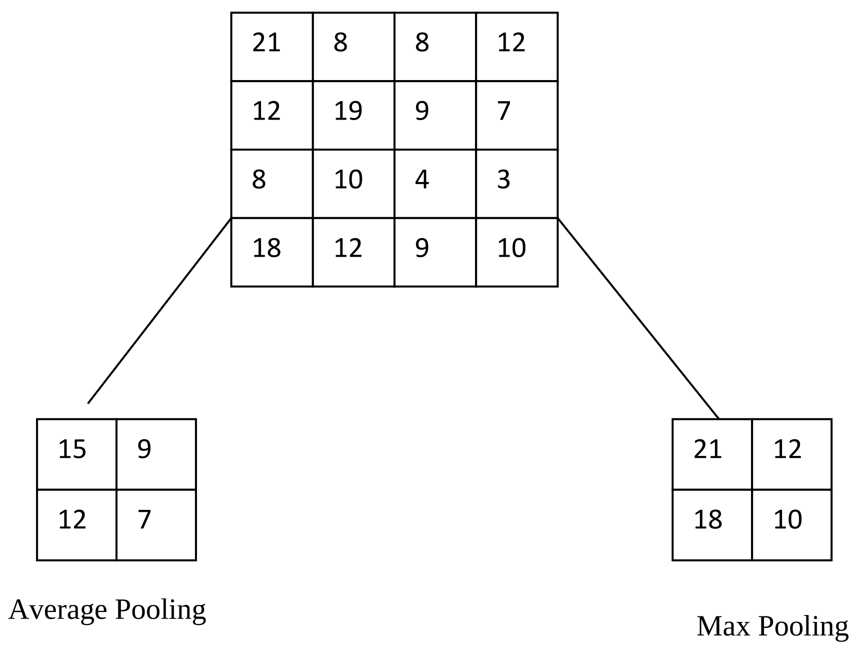


Figure 2: example of Pooling

Fully connected layer: The output of the final convolution is generally flattened, or transformed into a single-dimensional array of numbers, then joined into fully connected layers. The thick layers are those in which each input is coupled with each output by the learning weight. Clustering layers are used to sample the properties extracted by the convolution layer. Finally, the probabilities of each class in the classification task are passed to final output by a subset of fully connected layers. This layer has the same number of outputs and classes as the preceding layer. The LeakyReLU activation function is applied to every layer of the end result.

Batch normalization: In the formation of deep neural networks, it is recommended to reduce the offset of internal covariates and prevent dispersion of gradients. By combining standardization, scale-up and job transformation, it was applied to each CNN layer. It is used to accelerate convergence and prevent gradient explosion, as well as to prevent overflow. The CNN layer is then applied by means of a LeakyReLU.

Leaky Rectified Linear Unit: This activation function is first introduced by **(Maas et al., 2013).** This function is mathematically expressed by:

$$\boldsymbol{y_i} = \begin{cases} \boldsymbol{y_i \; if \; y_i \; \geq 0} \\ \dfrac{\boldsymbol{y_i}}{\boldsymbol{a_i}} \; \boldsymbol{if \; y_i} < 0 \end{cases}$$

Where y_i represents the input of ith channel and a_i denotes the fixed parameter in the range of $(1, +\infty)$.

Optimization and Loss function network:

In this system, MSE and Adam are worked as total loss and optimizer of the network to perform better optimization of the network. The mathematical expression of the network is given as:

$$L_{joint} = L_{MSE} + w_{t+1}$$

In the above equation L_{MSE} stands for the loss function of pixel-to-pixel comparison.

The corresponding loss function is given as:

$$L = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{W \times h}\sum_{j=1}^{w}\sum_{k=1}^{h}\|d_i(j,k) - I_i(j,k)\|^2\right)$$

In the above equation d represents the denoised image, I represent the original image, n gives the number of images used in the training, and w and h represent the width and height of the training image. In this framework residual learning is applied for train the residual projection through$R(Y) \approx N$. The loss function of MSE is calculated between residual image and predicated image is $X = Y - R(Y)$. The loss function of MSE is:

$$MSE(w, b, X_i, Y_i) = \frac{1}{2N}\sum_{i=1}^{N}\left\|R_{w,b}(Y_i) - (Y_i - X_i)\right\|_F^2$$

In the above equation, parameter w and b used to learn and update the neural network.

The optimization system:

The gradient descent algorithm such as Adam is applied in to w and b parameter to optimize the system. The Adam method is used to determine the learning rate of the parameters. And, like momentum, it preserves an exponentially declining average of ever m_t. The decaying average of gradients m_t and v_t is calculated as:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) gt$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

$m_t$and $v_t$used to calculate the first and second moment of the gradients. The m_t andv_t are initialized as zero in the time of small decaying rates.

The estimation of first and second moment is given as:

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

The updation of Adam is given as:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t$$

Table 1: Layers of proposed framework model: "sequential"

Layer (type)	Output shape	Param
Convd (conv2D)	(None, None, None, 32)	320
Leaky_re_lu (LeakyReLu)	(None, None, None, 32)	0
Conv2d_1 (conv2D)	(None, None, None, 64)	18496
Leaky_re_lu_1 (LeakyReLu)	(None, None, None, 64)	0
Conv2d_2 (conv2D)	(None, None, None, 128)	73856
Leaky_re_lu_2 (LeakyReLu)	(None, None, None, 128)	0
Conv2d_3 (conv2D)	(None, None, None, 64)	73792
Conv2d_4 (conv2D)	(None, None, None, 32)	18464
Batch_normalization (BatchNo)	(None, None, None, 32)	128
Conv2d_5 (conv2D)	(None, None, None, 1)	289

Total params: 185,345
Trainable params: 185,281
Non-trainable params: 64

III. Result and discussion

Experimental findings from the proposed framework are compared with other conventional denotation algorithms. The performance of the proposed framework is assessed using two measures, such as the PSSR and SSIM, which are indicated below:

$$PSNR = 20.log_{10}\left(\frac{MAX}{\sqrt{MSE}}\right)$$

In the above equation MAX represents the maximum gray value of the input image and MSE denotes the mean square error is given as:

$$MSE = \frac{1}{m \times n}\sum_{i=1}^{m}\sum_{j=1}^{n}\|I(i,j) - d(i,j)\|^2$$

In the above equation m and n represent the length and width of the input and denoised image. Here I denote the input image and d represents the denoised image.

The structural similarity (SSIM) is given as:

$$SSIM(I,d) = \frac{(2\mu_I\mu_d + C_1)(2\sigma_{Id} + C_2)}{(\mu_I^2 + \mu_d^2 + C_1)(\sigma_I^2 + \sigma_d^2 + C_2)}$$

In the above equation $\mu_I\mu_d$ represents the mean value of I and d images, C_1, C_2 represents the constants. σ_I, σ_d represents the standard deviation of I and d, σ_{Id} represents the covariance of image I and d.

Table 2: PSNR and SSIM of proposed framework for Noise Level 25

Epoch	Noise Level	Padding	Stride	PSNR	SSIM
10	25	50	5	25.57	0.79
10	25	60	5	26.16	0.75
10	25	70	4	27.99	0.77
10	25	40	4	28.62	0.77
10	25	60	3	26.24	0.76
10	25	10	3	28.38	0.75
10	25	10	1	28.65	0.74
10	25	30	1	28.88	0.80

Table 3: PSNR and SSIM of proposed framework for Noise Level 50

Noise Level	Patch Size	Strides	PSNR	SSIM
50	50.	5	25.16	0.65
50	60	5	25.74	0.68
50	70	5	26.23	0.71
50	40	10	24.94	0.64

Table 3: PSNR value by different methods on different images corrupted by impulse noise of different levels from 10% to 50% noise

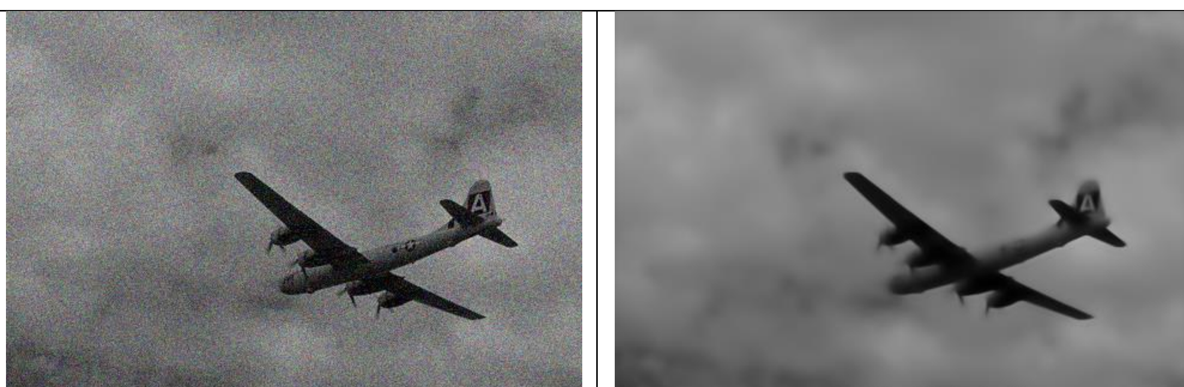
Methods	PSNR				
	10	20	30	40	50

VMF	29.38	23.10	18.75	18.34	17.89
AVMF	29.77	24.15	22.89	19.30	16.45
FPGF	30.29	24.21	22.06	19.78	16.40
LSM-NLR	29.27	26.59	22.79	20.23	18.47
ALOHA	31.57	27.35	23.96	19.12	15.04
ANN-EPR	28.04	26.11	25.45	23.05	21.53
DnCNNc	40.72	37.45	27.23	25.48	23.88
Proposed	**41.87**	**39.89**	**28.88**	**26.59**	**24.90**

The tables 2 and 3 shows the average PSNR and SSIM obtained for various padding size and strides for 25% and 50% noise. Here, a minimum epoch with lesser random noise is used. From the result, it shows that with the minimum Stride and increased Padding will helps to achieve maximum accuracy in image denoising.

Table 3 shows that the proposed strategy delivers excellent results on the PSPP and clearly exceeds other methods of comparison. Deep CNN methods, such as DnCNN and our suggested CNN method with an optimization strategy, surpass other approaches and dramatically improve PSNR. Moreover, DnCNN approach has consistently demonstrated a strong capacity to report low to high noise contamination. For low and high noise levels, the alternative method in this comparison table gives good results. Following these findings, DnCNN denouncing the methods appear to be promising.

From the table also observed that LSM-NLR method provides good results for Gaussian-impulse noise and provides very low results for impulse and random noise. ALOHA provides good PSNR value in low level noise. The method ANN-EPR provides good results compared to LSM-NLR and ALOHA in high level noise. The method VMF, AVMF and FPGF provides very low results in high level noise and give better results in high level noise. Overall from the table observed that proposed method of CNN with optimization techniques provides good results in both low and high level of noise.



(a) (b)

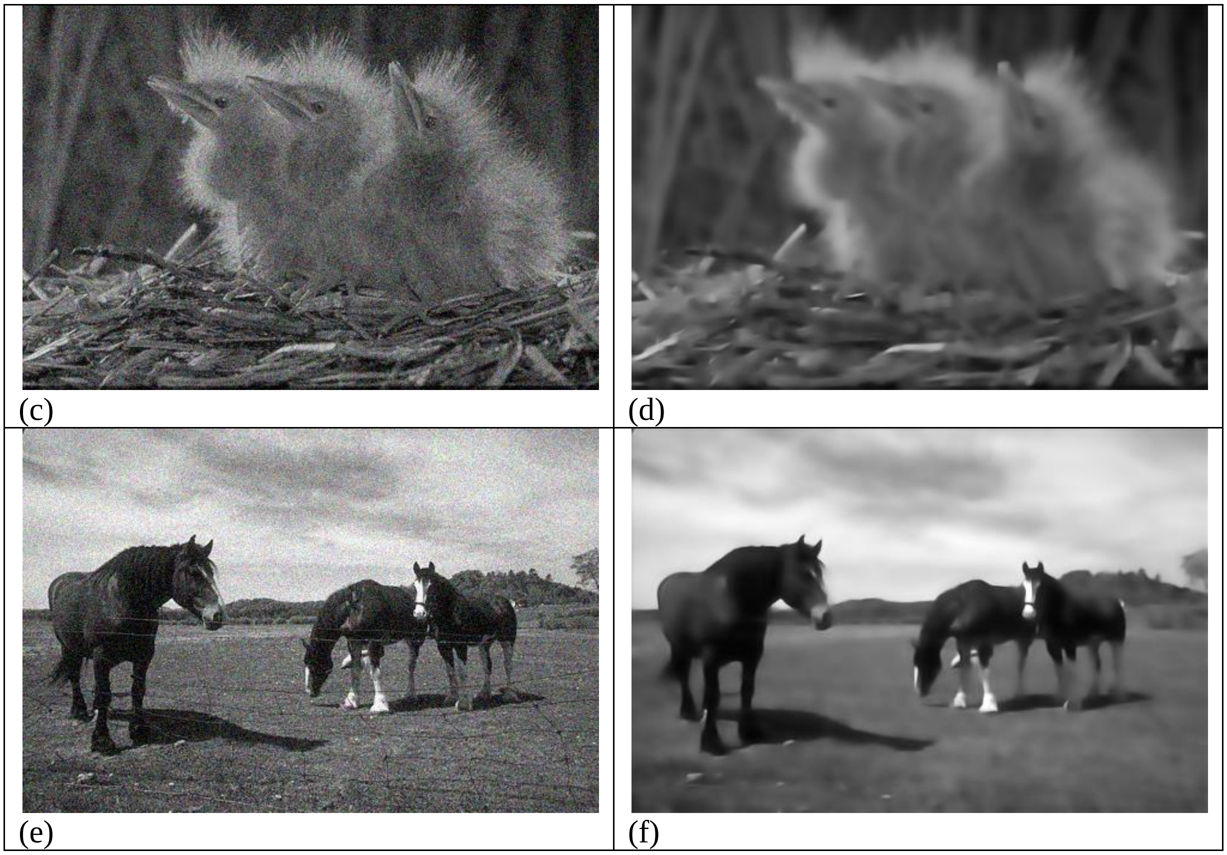


Fig. 5. Denoised results on various image: a,c,fis noisy image with random noise of 50%, and (b) (d) (f) are the denoised images

Fig. 5show the denoised images by proposed method on aero plane, sparrow and horse with random noise of 50%. From the figure observed that the proposed method effectively reduce the noise and at the same time it preserve the image edges and textures.

IV. CONCLUSION

This research provides a convolution neural network-based denoting approach that combines a joint function with an optimization algorithm. The image specifications are maintained in this document using the Leaky ReLU and ADAM optimization algorithms. Results from the experiments indicate that the proposed approach surpasses the existing naming algorithm. Randomized noise is central to the proposed approach. Increased CNN algorithm with optimisation technique suppresses random noise, resulting in improved performance. Another approach consists of developing the proposed algorithm for sound level 50. The results are taken for different padding and stride level in which minimum strides with maximum padding level provides high PSNR value.

REFERENCES

1. M. EminYüksel and AlperBaştürk, "Efficient Removal of Impulse Noise from Highly Corrupted Digital Images by a Simple Neuro-Fuzzy Operator", AEU - International Journal of Electronics and Communications Volume 57, Issue 3, 2003, Pages 214-219.
2. Rui Zhang, "Noise Removal in Color Images Based on Image Gradient Information",
    a. Advances in Mechanical Engineering, volume 6, 2015.
3. Qin Xu , Qiang Zhang, Duo Hu,and Jinpei Liu, "Removal of Salt and Pepper Noise in Corrupted Image Based on Multilevel Weighted Graphs and IGOWA Operator", Mathematical Problems in Engineering Volume 2018, Article ID 7975248, 11 pages.
4. Ren S, et al. Faster r-cnn: towards real-time object detection with region proposal networks. In: Advances in neural information processing systems; 2015.
5. Dai J, et al. R-fcn: Object detection via region-based fully convolutional networks. In: Advances in neural information processing systems; 2016.
6. Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. In: Advances in neural information processing systems; 2012.
7. CireşAn D, et al. Multi-column deep neural network for traffic sign classification. Neural networks. 2012;32:333–8.
8. Long J, Shelhamer E, Darrell T. Fully convolutional networks for semantic segmentation. in Proceedings of the IEEE conference on computer vision and pattern recognition; 2015.
9. Noh H, Hong S, Han B. Learning deconvolution network for semantic segmentation. in Proceedings of the IEEE international conference on computer vision; 2015.
10. Hannun, A., et al., Deep speech: scaling up end-to-end speech recognition. arXiv preprint arXiv:1412.5567, 2014.
11. Schwenck J, et al. Comparison of 68Ga-labelled PSMA-11 and 11C-choline in the detection of prostate cancer metastases by PET/CT. European journal of nuclear medicine and molecular imaging. 2017;44(1):92–101.
12. Ledig, C., et al. Photo-realistic single image super-resolution using a generative adversarial network. in Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.
13. Ronneberger, O., P. Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. in International Conference on Medical image computing and computer-assisted intervention. 2015. Springer.
14. Milletari, F., N. Navab, and S.-A. Ahmadi. V-net: Fully convolutional neural networks for volumetric medical image segmentation. in 2016 Fourth International Conference on 3D Vision (3DV). 2016. IEEE.
15. Wang, S., et al. Accelerating magnetic resonance imaging via deep learning. in 2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI). 2016. IEEE.
16. Kang E, Min J, Ye JC. A deep convolutional neural network using directional wavelets for low-dose X-ray CT reconstruction. Medical physics. 2017;44(10): e360 –75.
17. Chen H, et al. Low-dose CT via convolutional neural network. Biomedical optics express. 2017;8(2):679 –94.
18. Cireşan DC, et al. Mitosis detection in breast cancer histology images with deep neural networks. in International Conference on Medical Image Computing and Computer-assisted Intervention. Springer: Berlin, Heidelberg. 2013;411–18.
19. Jose Luis Hidalgo et al. Enhancement and Cleaning of Handwritten Data by Using Neural Networks. Camí de Vera, s/n, 46022 València, Spain, 2005.

20. Maas, Andrew L, Hannun, Awni Y, and Ng, Andrew Y. Rectifier nonlinearities improve neural network acoustic models. In ICML, volume 30, 2013.
21. K.N. Plataniotis, A.N. Venetsanopoulos, Color Image Processing and Applications, Springer- Verlag, Berlin, 2000.
22. R. Lukac, Adaptive vector median filtering, Pattern Recognit. Lett. 24 (12) (2003) 1889–1899.
23. B. Smolka, A. Chydzinski, Fast detection and impulsive noise removal in color images, Real-Time Imag. 11 (5/6) (2005) 389–402.
24. K.H. Jin, J.C. Ye, Sparse and low rank decomposition of a Hankel structured matrix for impulse noise removal, IEEE Trans. Image Process. 27 (3) (2018) 1448–1461.
25. T. Huang, W. Dong, X. Xie, G. Shi, X. Bai, Mixed noise removal via Laplacian scale mixture modeling and nonlocal low-rank approximation, IEEE Trans. Image Process. 26 (7) (2017) 3171–3186.
26. I. Turkmen, The ANN based detector to remove random-valued impulse noise in images, J. Vis. Commun. Image Represent. 34 (2016) 28–36.
27. K. Zhang, W. Zuo, S. Gu, L. Zhang, Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising, IEEE Trans. Image Process. 26 (7) (2017) 3142–3155.