Medical X-ray images enhancement based on super resolution convolution neural network

Sharda Rani, Navdeep Kaur
Department of Computer Science, Sri Guru Granth Sahib World University, Fatehgarh Sahib, Punjab, India

Article Info

Article history:

Received Dec 12, 2023
Revised Mar 31, 2024
Accepted Apr 30, 2024

Keywords:

CLAHE
CXR
HR
PSNR
SRCNN

ABSTRACT

Pneumonia is a severe lung infection, chest X-ray (CXR) image preferred to find infection. Real images lost its quality, resolution and other feature due to transmission. So good qualitative datasets are very limited. Quality enhancement in medical images is challenging task for researchers. And quality in clinical diagnosis of any disease in deep learning play a very important role. So, this paper presents an aspect with importance of quality in medical images CXR of a particular dataset and how to enhance and create new images with high quality resolution, that is re-used for classification in deep learning. Super resolution convolutional neural netwok (SRCNN) is deep learning based method, which is used for improving resolution in image. Super resolution means low resolution (LR) images from dataset is to be reconstructed or magnified into high resolution (HR). The objective behind this study is to measure the effect of super resolution with quality index, peak signal-to-noise ratio (PSNR), mean squared error (MSE), and structural similarity index measure (SSIM). This experinment performed on 200 images with 10 batches, each batch has 20 images from Kermany dataset, select LR images and converted into HR with SRCNN. Then we find PSNR value of image is increase upto 2 to 5 DB, and MSE of qood quality images is near to zero and MSE decrease up to 20-25, SSIM value have little variation due to same pattern is found in input and output images. Enhancement means highlight or improve the region of interest of pneumonic images. Main goal of this study is to preapare a modified dataset which is further used for classification.

Corresponding Author:

Sharda Rani
Department of Computer Science, Sri Guru Granth Sahib World University
Fatehgarh Sahib, Punjab, India
Email: duhan.sharda@gmail.com

1. INTRODUCTION

Pneumonia is a disease of lungs, in the small air sacs (alveoli) is affected. In this air sacs fill with fluid (pus) which leads cough, high fever, breathing problems and sometime death. And pneumonia can be very dangerous for children and the elder with weak immunity [1]. Mostly the chest X-ray (CXR) is being used all over the world for detection of this infection due to hardware, bandwidth, storage space limitation, under exposure, over exposure, transmitted image degrades their quality and resolution, due to noise and compression techniques Figure 1 shows low quality images (Figures 1(a)-1(f)) and Figure 2 shows high quality images of Kermany dataset (Figures 2(a)-2(f)). Visual observation clearly shows the difference between low quality and high quality.

No doubt deep learning method has great success in the field of medical images diagnosis. But this requires training on large number of images with good quality. Mostly available datasets have low quality and it became cause of poor performance in deep learning. Çallı *et al.* [2] provide a detailed survey on publicly available dataset of CXR, and suggest that for deep learning more focus on clinical needs in CXR interpretion. Kieu *et al.* [3] describe four main issues in deep learning w.r.t datasets; i) data imbalance, ii) limited availability, iii) size of image, and iv) high correlation error. And suggested some potential future direction like, use of cloud computing, more datasets availability and more variety of features. Using super convolution neural network (SRCNN) proposed by Dong *et al.* [4], we construct high resolution (HR) from low resolution (LR) CXR to enhance the quality of dataset. Chaudhari *et al.* [5] and Park *et al.* [6] applied super resolution method in medical domain. Rahimi *et al.* [7] suggested that LR can be converted into high quality. Study involved SR approaches including SRCNN, SR generative adversarial network (SRGAN), U-net and presented that all approaches showed significant improvement in mean opinion score (MOS). Ulhaq *et al.* [8] recommended that small (less no of images) dataset is barrier and their quality became challenging in healthcare imaging domain.

Author [9]-[11] presented research on chest radiograph with deep learning. Rani *et al.* [12] compared SRCNN technique with other enhancement method like histogram equalization; contrast limited adaptive histogram equalization (CLAHE), Gamma correction, and other filter techniques. And find this approach is better then other, so it gives an idea to reconstruct a dataset from LR (low quality) to HR (high quality) of CRX images. In the field of super resolution, Zhang *et al.* [13], Kin *et al.* [14], Lim *et al.* [15], Zang *et al.* [16], provide super restoration of images between LR to HR images.

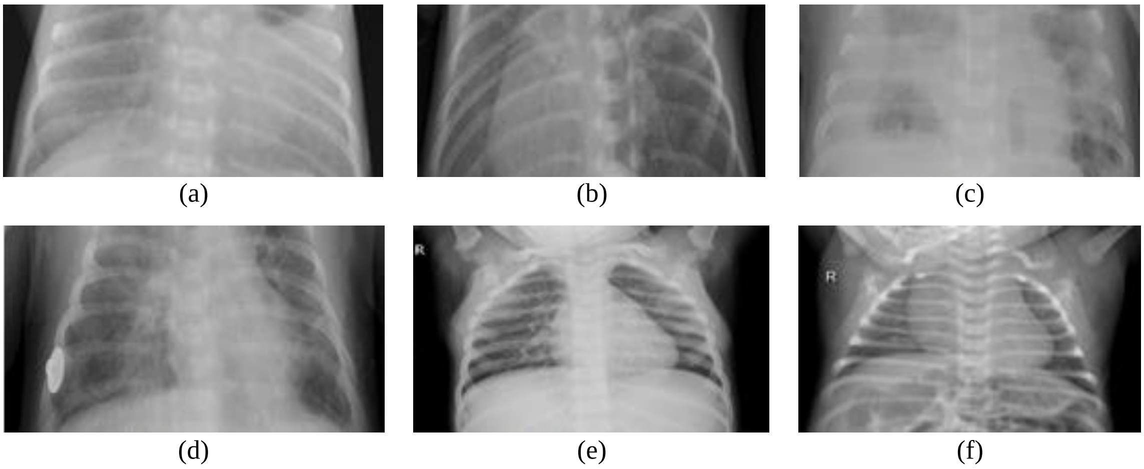

Figure 1. Low quality images, (a)-(b) virus, (c)-(d) bacterial, (e)-(f) normal

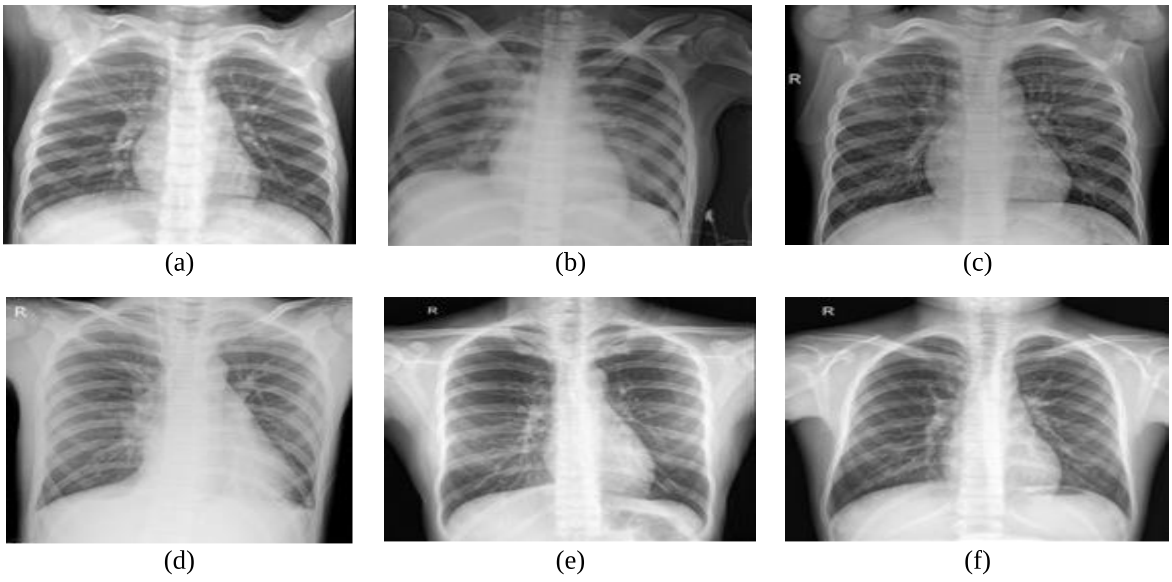

Figure 2. High quality images, (a)-(b) virus, (c)-(d) bacterial, (e)-(f) normal

Dataset description, pediatric CXRs (PP) labeled pediatric CXRs from the Guangzhou Woman and Children Medical Centre (Guangzhou, China) Kermany *et al.* [17], which contains 5,856 CXR images from pediatric patients aged 1-5 years. Table 1 shows the distrubtion of total images for training and testing. In table we observe that pneumonia-based images are more than double as compare to normal images. As we know that for binary classification equal number of images is desirable for deep neural network, especially for medical imaging domain for specific.

Table 1. Distrubtion of images in Kermany dataset

Partition	Class	images	Total images
Training	Normal	1341	5216
	Pneumonia	3875	
Testing	Normal	234	624
	Pneumonia	390	

In Kermany dataset pneumonia images is further divided into two types viral and bacterial. Table 2 describe the second important factor that is quality, the resolution (width and height) of each category normal, viral and bacterial. Explain low and HR with file size.

Table 2. Resolution description with minimum to maximum

S. No	Type	Minimum resolution with file size	Maximum resolution with file size
1.	Viral	400 × 138 (5.31 KB)	1896 × 1752 (668.5 KB)
2.	Bacterial	460 × 157 (5.51 KB)	2334 × 1956 (400 KB)
3.	Normal	1416 × 992 (152 KB)	2482 × 2570 (2.04 MB)

In table we observe there is big difference in resolution of pneumonic and normal images. Thousand of pneumonic images are less then 50 KB. So, need of reconstruction of low images to increase structural details.

2. RELATED WORK

In area of super resolution, author [18] provides an approach to improve resolution in chest X-ray images. Xu *et al.* [19] proposed supervised generative adversarial net approach to construct HR images from LR. Khishigdelger *et al.* [20] proposed advance SR approach with residual-in-residual (RIR) structure to diagnostic potential of CXR imaging. Method shows superior performance, delivering enhanced accuracy with visual improvenment. Monday *et al.* [21] proposed a enhanced fast super resolution convolution neural network (EFSRCNN) and obtained peak-signal-to-noise ratio (PSNR) and structural similarity index measure (SSIM) values 32.24 DB and 0.9341 for region of interest. Ahmadian and Alikhani [22] presented X-ray image enhancement based on self organizing neural network, performance, accuracy and quality measurement index like PSNR (38.42), SSIM (0.98) gives good result as compared to other medical images enhancement methods. Umehara *et al.* [23] applied super resolution convolution network on chest CT, high quality images were constructed from low quality images, and obtained 41.79± 2.49 DB values of PSNR and 0.947± 0.029 value of SSIM for 2X magnification. The super resolution schemes yielded higher image quality than linear interpolation.

3. RESEARCH METHOD

The dataset used for this study is available on Kaggle, Kermany dataset have 5856 images of two categories, normal and pneumonia (bacterial and viral). This study is performed on Tesla K80 GPU, paid Google Collab platform with sufficant RAM, with extra computing units. Python language is used to implement SRCNN and SciPy open-source scientific computing library is used for statistical analysis. Sequence of steps performed in this experiment is shown in Figure 3 by flow diagram.

With SRCNN technique, construct HR images from LR images to improve spatial resolution of CXR. This experinment is performed on 200 images of mix resolution; with batch size of 20 images. This paper shows the result of one batch. Figure 4 shows the low-resolution input images of each type.

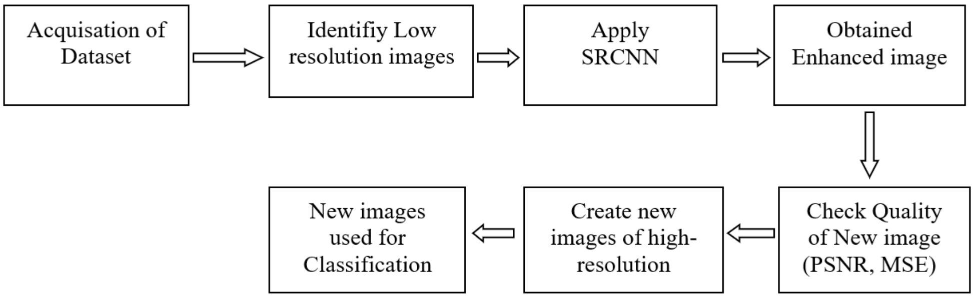

Figure 3. Flow diagram of the methodology used in this study

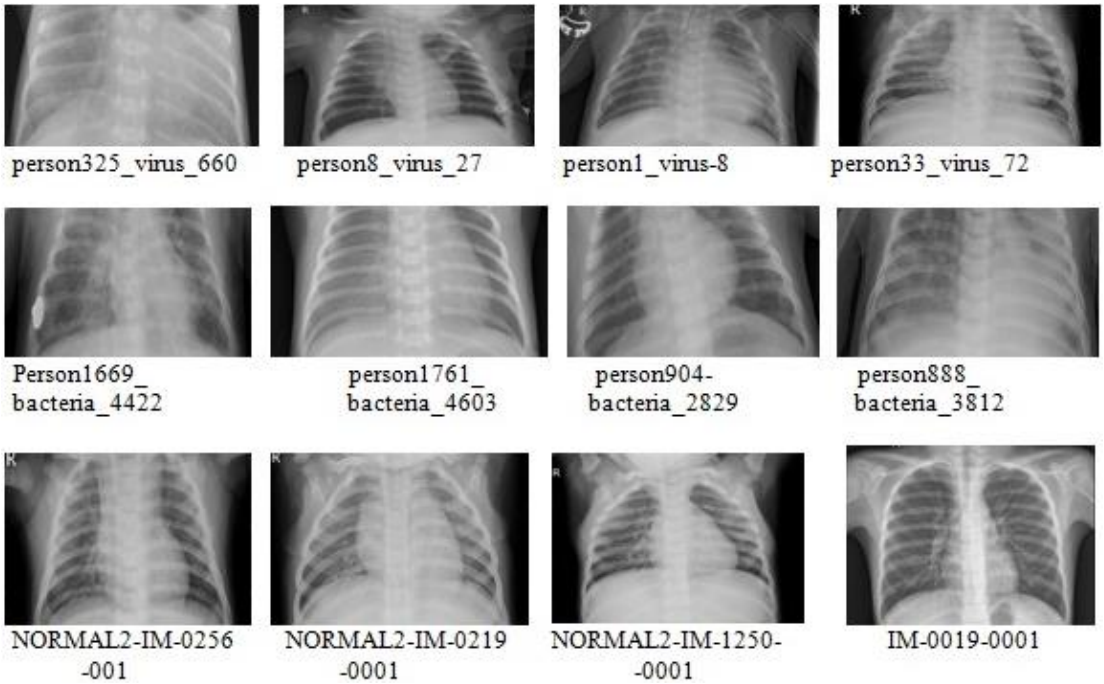

Figure 4. Input image (Virus, Bacteria, and normal)

Image quality assessment: Mean squared error (MSE), PSNR, and SSIM are popular and widely used metric for quality assessment.

MSE: this is most common and widely used full reference method, where reference image is available for measurenment. It is calculated by squared intensity difference of distorted and reference image pixels and averaging them. It measures the average of the square of the error. And values closer to zero, are better output.

$$MSE = \frac{\sum(y_i - \hat{y}_i)^2}{\mathrm{n}}$$

PSNR: commonly used to measure quality of reconstructed images, it is ratio of maximum possible signal power (original image) to the power of noise (reconstruct image) which affects the quality [24]. Ratio between two images is measured in decibel (dB), PSNR value varies from 30 to 50 dB for 8-bit representation and 60 to 80 Db for 16-bit data. In 8-bit unsigned integer data type peakval is 255. Higher PSNR value means better image quality and less distortion.

$$\mathrm{PSNR} = 10\ \mathrm{Log}_{10}\ (\mathrm{peakval}^2)\ /\ \mathrm{MSE}$$

Where peakval is the maximum possible pixel value in the image.

SSIM: SSIM is also type of FR perception-based metric by Wang *et al.* [25], where it finds how much similarities between perfect reference image and a test image based on factor luminance, contrast, and structure. Structural inform about strongly inter-dependent pixel or spatially closed pixel. Luminance masking is a term which measured by mean intensity of signals, where distortion part of an image is less visible in the edges of an image. Contrast masking is term calculate by using standared deviation, where distortions less visible in texture of an image. Range of SSIM varies -1 to 1, and perfect value is 1.

$$SSIM\ (x,y) = ((\ 2\ \mu x \mu y + C1)\ (\ 2\ \sigma x \sigma y + C2))/((\ 2\ \mu 2x \mu 2y + C1)\ (\ 2\ \sigma 2x \sigma 2y + C2))$$

Where µx, µy, σx, σy are local means, standard deviations and cross-covariance for image.

4. RESULT

In this section Table 3 represent experimental results of 12 images out of 20 images, of each category. Quality enhancement evaluated by PSNR, MSE, and SSIM. Table 3 also compare the effect of super resolution in CXR befor and after apply SRCNN. PSNR value is increase up to 2-5 DB. MSE value is decrease with good ratio. For SSIM, there is little variation, means same pattern is in input and output images. Figure 5 show some screen shot during runtime, first we have to save 20 images then find quality evaluation parameter before apply SRCNN. Figure 6 show output of high resolutiom with quality index after SRCNN.

Table 3. Comparisons of LR and HR

Image type	Source image with LR Input				SRCNN images with HR Output			
Viral	PSNR	MSE	SSIM	File size	PSNR	MSE	SSIM	File size
Person325_virus_660	43.28	9.15	0.97	5.3 KB	45.13	5.97	0.98	10.3 KB
Person8_virus_27	38.57	27.07	0.97	49 KB	43.38	8.94	0.98	120 KB
Person1_virus_8	36.64	42.26	0.96	44 KB	41.32	14.36	0.97	99 KB
Person33_virus_72	36.79	40.78	0.95	47 KB	41.20	14.76	0.95	98 KB
Person1669_bacteria_4422	41.20	14.79	0.96	8.3 KB	42.47	11.04	0.97	16 KB
Person1761_bacteria_4603	42.99	9.79	0.97	9.5 KB	43.98	7.79	0.98	20 KB
Person904_bacteria_2829	43.10	9.54	0.97	11 KB	44.52	6.88	0.97	21 KB
Person888_bacteria_2812	41.38	14.17	0.96	11 KB	42.59	10.73	0.97	23 KB
NORMAL2-IM-0256-0001	36.38	44.85	0.94	45 KB	39.93	19.79	0.95	92 KB
NORMAL-IM-0219-0001	38.01	30.78	0.96	67 KB	42.01	12.27	0.96	147 KB
NORMAL-IM-1250-0001	36.59	42.69	0.95	153 KB	41.30	14.45	0.95	224 KB
IM-0019-0001	38.06	30.49	0.92	280 KB	40.25	18.39	0.93	568 KB

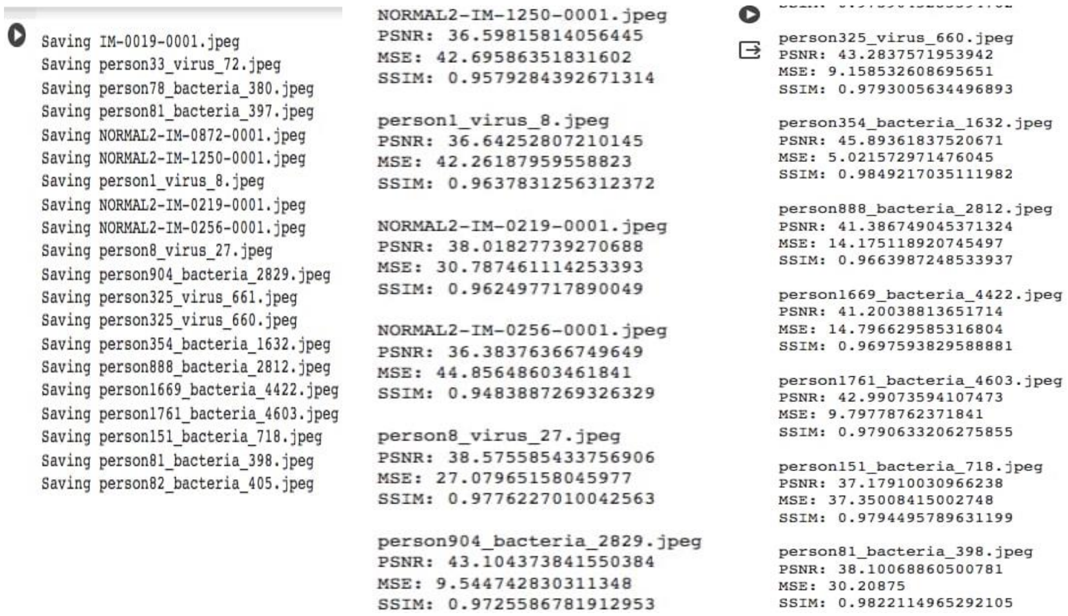

Figure 5. Input image (virus, bacteria, and normal)

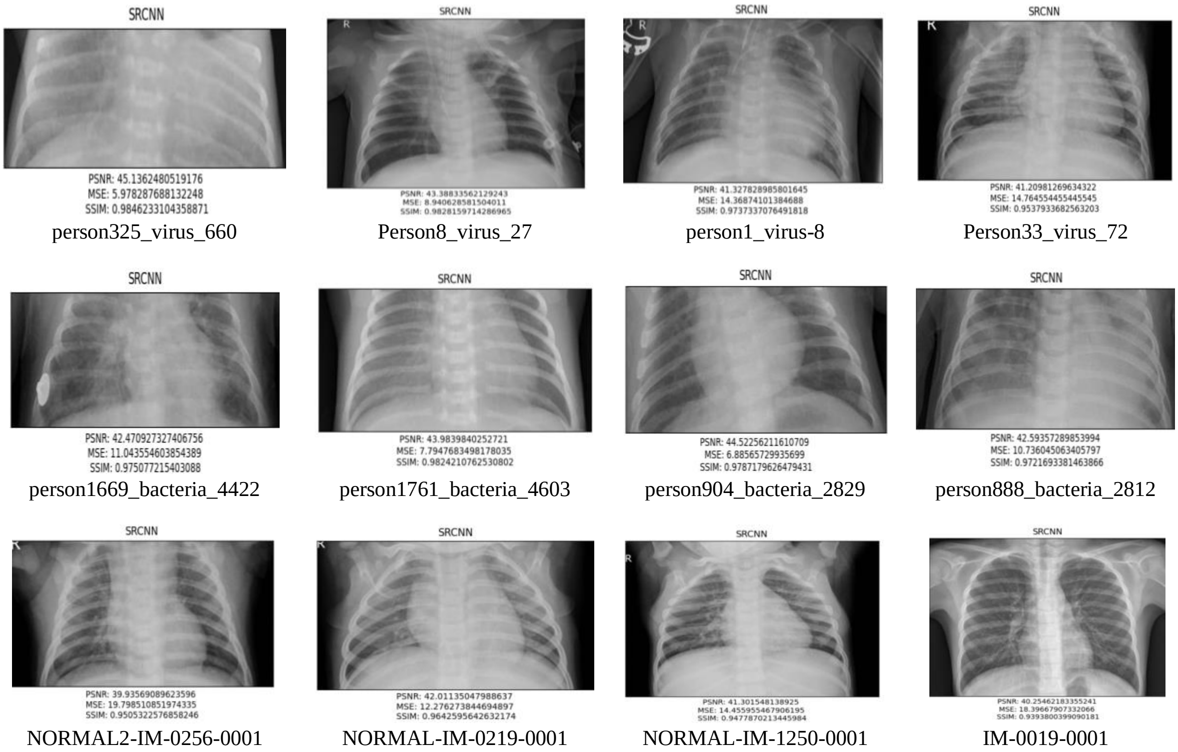

Figure 6. Quality assessment index after SRCNN

5. CONCLUSION

Objective of the researchers is to create superior quality of clinical images. In this paper, we present compasion of super resolution images HR with LR. Experimental result shows outperformed enhancement factor like PSNR and MSE. LR images rebuild into HR images; it helps us to increase number of images. We create modified dataset which will be used for classification of normal and pneumonia disease in deep learning.

REFERENCES

[1] WHO (http://www.who.int/news-room/fact-sheets/detail/pneumonia)

[2] E. Çallı, E. Sogancioglu, B. van Ginneken, K. G. van Leeuwen, and K. Murphy, "Deep learning for chest X-ray analysis: a survey," *Medical Image Analysis*, vol. 72, p. 102125, Aug. 2021, doi: 10.1016/j.media.2021.102125.

[3] S. T. H. Kieu, A. Bade, M. H. A. Hijazi, and H. Kolivand, "A survey of deep learning for lung disease detection on medical images: State-of-the-art, taxonomy, issues and future directions," *Journal of Imaging*, vol. 6, no. 12, p. 131, Dec. 2020, doi: 10.3390/jimaging6120131.

[4] C. Dong, C. C. Loy, K. He, and X. Tang, "Image super-resolution using deep convolutional networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 38, no. 2, pp. 295–307, Feb. 2016, doi: 10.1109/TPAMI.2015.2439281.

[5] A. S. Chaudhari *et al.*, "Super-resolution musculoskeletal MRI using deep learning," *Magnetic Resonance in Medicine*, vol. 80, no. 5, pp. 2139–2154, Nov. 2018, doi: 10.1002/mrm.27178.

[6] J. Park, D. Hwang, K. Y. Kim, S. K. Kang, Y. K. Kim, and J. S. Lee, "Computed tomography super-resolution using deep convolutional neural network," *Physics in Medicine and Biology*, vol. 63, no. 14, 2018, doi: 10.1088/1361-6560/aacdd4.

[7] H. M. Rahimi *et al.*, "Super-resolution of dental panoramic radiographs using deep learning: a pilot study," *Diagnostics*, vol. 13, no. 5, p. 996, Mar. 2023, doi: 10.3390/diagnostics13050996.

[8] A. Ulhaq, A. Khan, D. Gomes, and M. Paul, "Computer vision for COVID-19 control: a survey," *arXiv preprint*, 2020, [Online]. Available: http://arxiv.org/abs/2004.09420.

[9] P. Rajpurkar, *et al.*, "Deep learning for chest radiograph diagnosis: a retrospective comparison of the CheXNeXt Algorithm to Practicing Radiologists", *PLoS Med*, vol. 15, no. 11, 2018, doi: 10.1371/journal.pmed.1002686.

[10] O. Stephen, M. Sain, U.J. Daduh, D-U. Jeong, "An efficient deep learning approach to pneumonia classification in healthcare", *Journal of Healthcare Engineering*, 2019, doi:10.1155/2019/4180949.

[11] E. Ayan, H. M. Unver, "Diagnosis of pneumonia from Chest X-Ray images using deep learning", *Proc. IEEE Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT'09)*, Apr. 2019, doi: 10.1109/EBBT.2019.8741582

[12] S. Rani, "Investigation of different pre-processing quality enhancement techniques on X-ray images," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 11, no. 6, pp. 499–508, Jun. 2023, doi: 10.17762/ijritcc.v11i6.9685.

[13] Y. Zhang, K. Li, K. Li, L. Wang, B. Zhong, and Y. Fu, "Image super-resolution using very deep residual channel attention networks," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11211 LNCS, pp. 294–310, 2018, doi: 10.1007/978-3-030-01234-2_18.

[14] J. Kim, J. K. Lee, and K. M. Lee, "Accurate image super-resolution using very deep convolutional networks," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 2016-December, pp. 1646–1654, 2016, doi: 10.1109/CVPR.2016.182.

[15] B. Lim, S. Son, H. Kim, S. Nah, and K. M. Lee, "Enhanced deep residual networks for single image super-resolution," *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, vol. 2017-July, pp. 1132–1140, 2017, doi: 10.1109/CVPRW.2017.151.

[16] Y. Zhang, Y. Tian, Y. Kong, B. Zhong, and Y. Fu, "Residual dense network for image super-resolution," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 2472–2481, 2018, doi: 10.1109/CVPR.2018.00262.

[17] D. S. Kermany *et al.*, "Identifying medical diagnoses and treatable diseases by image-based deep learning," *Cell*, vol. 172, no. 5, pp. 1122-1131.e9, Feb. 2018, doi: 10.1016/j.cell.2018.02.010.

[18] K. Umehara, *et al.*, "Super-resolution convolution neural network for improvement of the image quality of magnified images in chest radiograph" proc. spie medical imaging 2017: Image processing, 10133, Orlando, 11-16 February, 101331P-1-101331P-7.

[19] L. Xu, X. Zeng, Z. Huang, W. Li, and H. Zhang, "Low-dose chest X-ray image super-resolution using generative adversarial nets with spectral normalization," *Biomedical Signal Processing and Control*, vol. 55, p. 101600, Jan. 2020, doi: 10.1016/j.bspc.2019.101600.

[20] A. Khishigdelger, A. Salem, and H. S. Kang, "Elevating chest X-ray image super-resolution with residual network enhancement," *Journal of Imaging*, vol. 10, no. 3, p. 64, Mar. 2024, doi: 10.3390/jimaging10030064.

[21] H. N. Monday *et al.*, "COVID-19 Diagnosis from chest X-ray images using a robust multi-resolution analysis siamese neural network with super-resolution convolutional neural network," *Diagnostics*, vol. 12, no. 3, p. 741, Mar. 2022, doi: 10.3390/diagnostics12030741.

[22] K. Ahmadian and H. R. Alikhani, "X-ray medical image super-resolution via self-organization neural networks and geometric directional gradient," *IET Image Processing*, vol. 16, no. 14, pp. 3910–3928, Dec. 2022, doi: 10.1049/ipr2.12603.

[23] K. Umehara *et al.*, "Performance evaluation of super-resolution methods using deep-learning and sparse-coding for improving the image quality of magnified images in chest radiographs," *Open Journal of Medical Imaging*, vol. 07, no. 03, pp. 100–111, 2017, doi: 10.4236/ojmi.2017.73010.

[24] Q. Huynh-Thu and M. Ghanbari, "Scope of validity of PSNR in image/video quality assessment," *Electronics Letters*, vol. 44, no. 13, pp. 800–801, 2008, doi: 10.1049/el:20080522.

[25] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," *IEEE Transactions on Image Processing*, vol. 13, no. 4, pp. 600–612, Apr. 2004, doi: 10.1109/TIP.2003.819861.

BIOGRAPHIES OF AUTHORS

Sharda Rani was born on 15-July-1981. She received her B.Sc. in Computer Science from Kurukshetra University Kurukshetra in 2001, MSc in Information Technology from Kurukshetra University in 2003, and M.Tech. in Computer Science from CDL University Sirsa, Haryana in 2007. She qualified UGC-NET (Computer Sc and Application) Exam in June 2014. She currently research scholar with the Department of Computer Science, Sri Guru Granth Sahib World University, and FatehgarhSahib (Punjab) India. Her research interests: intelligent systems/machine learning, and deep learning. She is a member of teaching staff at department of computer science and applications, A.S. College, Khanna (Punjab) India. She can be contacted at email: duhan.sharda@gmail.com.

Dr. Navdeep Kaur received her Ph.D. degree from IIT (Indian Institute of Technology) Roorkee, India in 2008. She has also Master degree M.Tech. (CSE) from Kurukshetra University, Kurukshetra, Haryana, in Dec 1998. B.E. degree from the NMU in 1997. She is currently professor and chairperson in the department of computer science at Sri Guru Granth Sahib World University, FatehgarhSahib (Punjab) India. Her main research interest's focus on machine learning, artificial intelligence, computer network, and software engineering. She has more than 25 years of teaching experience. She published moretha 30 research paper in international journal/National journals /Scopus/UGC Listed/SCI. She can be contacted at email: drnavdeep@sggswu.edu.in.