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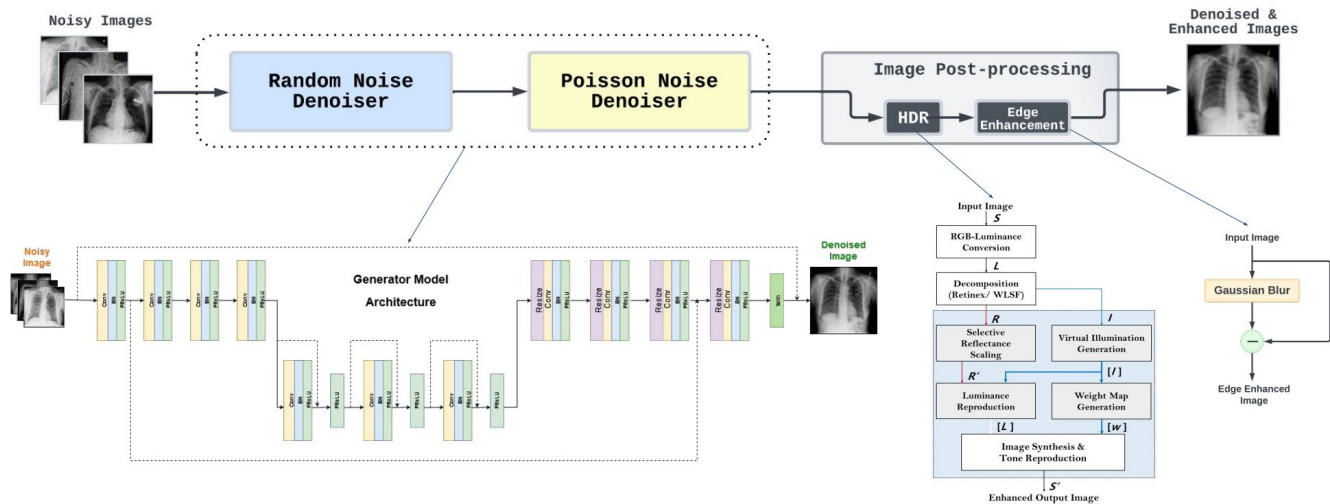
Motivation

- Medical procedures rely on radiation to produce the images required for diagnosing diseases or checking the body's internal structure.
- Heavy radiations adversely affect the human body but produce images with less noise.
- There is a trade-off between the image quality and the amount of radiation so radiographers struggle to find a balance between the two.
- Radiations from diagnostic machines have random fluctuation of photons. Hence, obtained images have spatial and temporal randomness. This type of noise is called Poisson noise and is dominant in medical imaging[6]
- We saw this as an opportunity to develop a pipeline which, given a noisy x-ray image, constructs a denoised and visually similar image. This will help the patients being faced with a reduced amount of radiation.

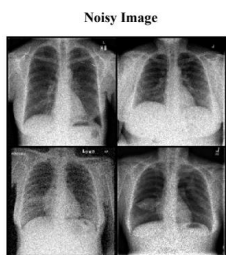
Related Work

- Various attempts have been made at denoising medical images using techniques like spatial domain filters (gaussian, median, bilateral) and NLM[4][5], but these tend to blur the necessary details.
- Prior work in denoising with U-Net and ResNets has also been done on natural images[3]
- Similarly, neural network architectures have been used for natural images[1]
- Single-shot HDR using selective reflectance scaling and virtual illumination generation has been done to generate enhanced images[2]

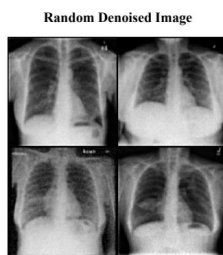
Approach and Methodology



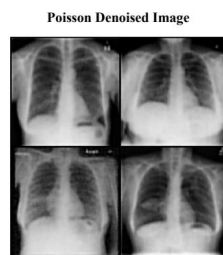
Experimental Results



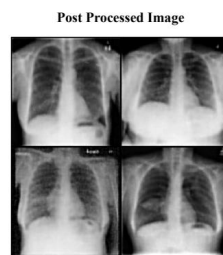
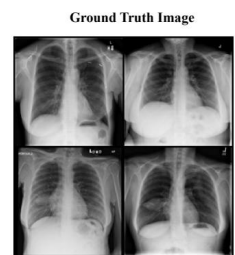
PSNR: 26.18
SSIM: 69.90



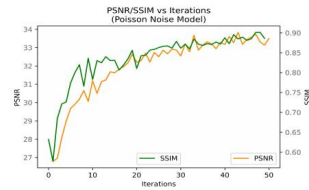
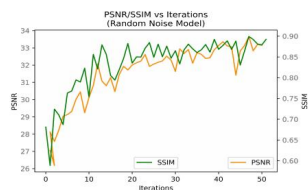
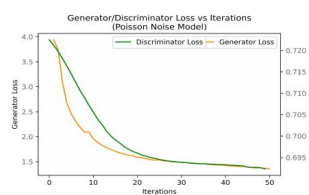
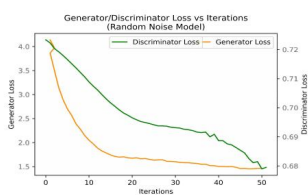
PSNR: 32.15
SSIM: 89.55



PSNR: 32.55
SSIM: 92.48

PSNR: 29.75
SSIM: 93.05

Ground Truth Image



Method	PSNR	SSIM
Noisy Image	25.88	0.68
Gaussian ($\sigma=0.5$)	29.59	0.82
Median Filter (size=7)	26.79	0.81
Bilateral ($\sigma=1, \sigma_{\text{intensity}}=0.5$)	30.79	0.89
NLM ($\sigma=3, \text{window}=2$)	28.15	0.84
ADMM + DnCNN solver	30.14	0.91
ADMM + TV	28.73	0.89
GANs (Random Noise)	31.92	0.893
GANs (Random + Poisson)	32.27	0.926
GANs + Edge Enhancer	29.36	0.933

References

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- [4] Fan L., Zhang F., Fan H., Zhang C. Brief review of image denoising techniques. *Vis Comput Ind Biomed Art*. 2019 Jul 8;2(1):7. doi: 10.1186/s42492-019-0016-7. PMID: 32204414; PMCID: PMC7099553.
- [5] Sagheer, Samera V. Mohd, and Sudshini N. George, "A review on medical image denoising algorithms," *Biomedical signal processing and control* 61 (2020): 102036.
- [6] Boyat, A. K., & Joshi, B. K. (2015). A Review Paper: Noise Models in Digital Image Processing. <https://doi.org/10.48550/ARXIV.1505.03489>