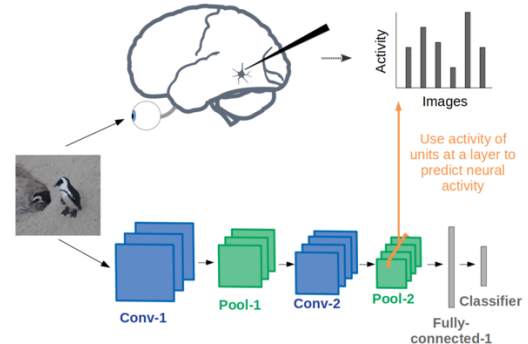
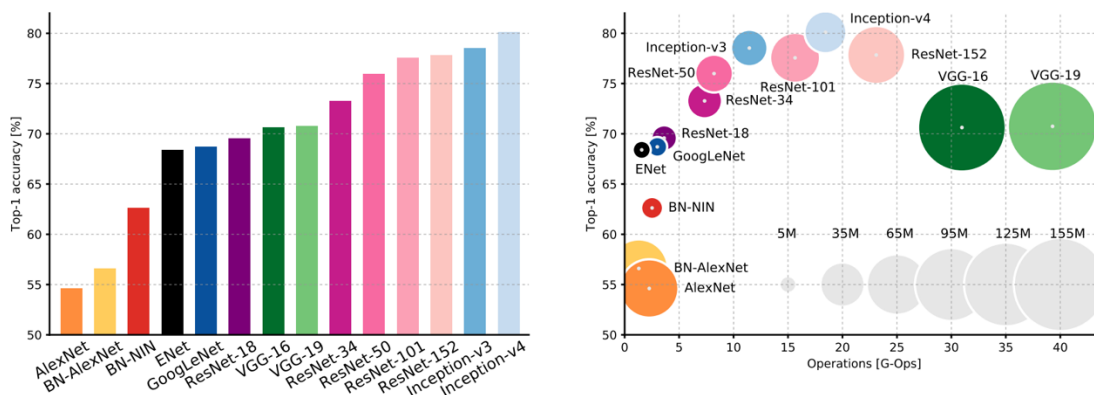


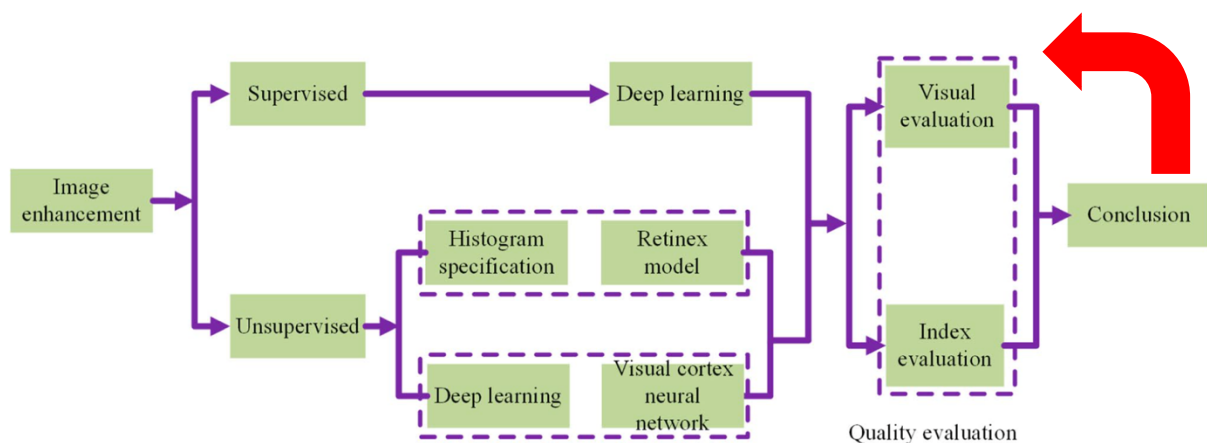
	Histogram Equalization	CNN
Pros	<ul style="list-style-type: none"> <li>Requires a few parameters</li> <li>Simple algorithms</li> <li>Requires modest CPU resources</li> </ul>	<ul style="list-style-type: none"> <li>It transforms image pixels into similar features used by the human brain [2][3]:</li> </ul>  <ul style="list-style-type: none"> <li>Can learn complex, non-linear patterns and textures</li> <li>Once trained due to the large size of the training set, it can generalize; and be applied to new image datasets with good performances.</li> </ul>
Cons	<ul style="list-style-type: none"> <li>Cannot learn complex patterns</li> <li>Does not handle non-linear mappings</li> <li>Can amplify noise and may distort fine details</li> </ul>	<ul style="list-style-type: none"> <li>Needs specialized hardware like GPU and could be computationally demanding [4]</li> <li>Many parameters to tune, for ex.: number of layers, type of activation gateways, normalization layers, number of dropouts, skip layers, learning rate, type of optimizers, kernel size, and many more.</li> <li>Is vulnerable to adversarial attacks which might lead to subtle image manipulation and failed diagnoses [5]</li> <li>Susceptible to biases present in the images</li> </ul>

Deep learning shows great potential for advancing medical image processing:

- There has been an explosion in the number of parameters of Deep Learning models, and as generative AI has shown, it may soon be possible to train neural networks on vast datasets of digitized medical images, achieving exceptional performance in image enhancement.



- In addition, there have been recent research to simulate the mammalian visual cortex through neural networks. For instance, the Pulse Coupled Neural Network (PCNN) mimics how neurons respond to visual stimuli. A time matrix generated by the PCNN captures areas of high pixel intensity by assigning them earlier "firing" times. By inverting and re-normalizing this matrix, image contrast is enhanced, with high-intensity pixels are more emphasized, leading to sharper and more distinct features.
- Human feedback could be incorporated through reinforcement learning loopback: in the figure below, reinforcement learning could be implemented as feedback from conclusion step to reannotate the images to retrain the Deep Learning models.



- Weakly supervised or unsupervised Deep Learning methodologies will be improved and will offer innovative image enhancement frameworks.

- There has been excessive research to make Deep Learning more robust to adversarial attacks and biases

- [1] What are the pros and cons of different image enhancement techniques?  
<https://www.linkedin.com/advice/3/what-pros-cons-different-image-enhancement-techniques#:~:text=Elevate%20the%20edges%2C%20textures%2C%20and%20shapes%20within,decision%2Dmaking%20for%20infrastructure%20development%20or%20disaster%20response>.
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doi:10.1162/jocn\_a\_01544
- [3] Pulkit Agrawal and AI, UC Berkeley, Convolutional Neural Networks Mimic the Hierarchy of Visual Representations in the Human Brain,
- [4] Canziani, A. et al. "An Analysis of Deep Neural Network Models for Practical Applications." *ArXiv* abs/1605.07678 (2016): n. pag.
- [5] Hirano, H., Minagi, A. & Takemoto, K. Universal adversarial attacks on deep neural networks for medical image classification. *BMC Med Imaging* **21**, 9 (2021).  
<https://doi.org/10.1186/s12880-020-00530-y>
- [6] Yunliang Qi et Al., A Comprehensive Overview of Image Enhancement Techniques Archives of Computational Methods in Engineering (2022) 29:583–607  
<https://doi.org/10.1007/s11831-021-09587-6>