AN UPDATE VIEW IN MEDICAL IMAGES ANALYSIS

C.N.M. da Silva [1,2], F. Bossio [1,2], P.S. de Souza [2], T.S. Cabral [1,2].

[1] Instituto de Radioproteção e Dosimetria/CNEN - DIMET, Rio de Janeiro, Brazil
[2] Universidade Federal do Rio de Janeiro, COPPE/PEN, Rio de Janeiro, Brazil.

Abstract— **In this paper is made a collection of the latest published works on the quality of medical image formation using Convolutional neural networks. Convolutional neural networks have recently achieved impressive results in pattern recognition, moreover, various studies have successfully applied them in medical images analysis, such as image segmentation, artifacts removal, image denoising, resolution improvement and contrast saliency detection. We have divided into sections for better visualization of the impact on the several areas that influence the reconstruction of the image.**

Keywords— **deep learning, image quality, convolutional neural networks.**

I. INTRODUCTION

From the earliest moments of computer history, scientists have been dreaming about the idea of creating an "electronic brain." Among all modern technological research, this search for artificially intelligent computer systems has been one of the most ambitious. Doctors were also captivated by the potential that this might have when applied in medicine.

The first information on neuro computation dates back to 1943, in articles by McCulloch and Pitts, which suggested the construction of a machine based on the human brain. Donald Hebb, in 1949, was the first to propose a specific learning law for neuron synapses.

In 1957, Rosenblatt conceived the "perceptron", which was a neural network of two layers, used for the recognition of characters.

The artificial neural network is a system of neurons connected by synaptic connections divided into incoming neurons, which receive stimuli from the external environment, internal or hidden neurons, and output neurons, which communicate with the outside. The way to arrange layered perceptrons is called Multilayer Perceptron. The multilayer perceptron was designed to solve more complex problems, which could not be solved by the basic neuron model. The internal neurons are of great importance in the neural network, since it has proved that without these it becomes impossible to solve linearly non-separable problems. In other words, it can be said that a network is composed of several processing units, whose operation is quite simple. These units are usually connected by communication channels that are associated with certain weights. The intelligent behavior of an Artificial Neural Network comes from the interactions between the network processing units.

Most neural network models have some training rules, where the weights of their connections are adjusted according to the presented patterns. In other words, they learn through examples. Neural architectures are typically layered, with units that can be connected to the back-layer units.

The neural network undergoes a training process from the known real cases, acquiring, from there, the systematic necessary to properly execute the desired process of the data provided. Thus, the neural network is capable of extracting basic rules from actual data, differing from programmed computation, where a set of rigid rules is required and algorithms.

The most important property of neural networks is the ability to learn from their environment and thereby improve their performance. This is done through an iterative process of adjustments applied to their weights, training. Learning occurs when the neural network reaches a generalized solution to a class of problems.

A learning algorithm is defined as a set of well-defined rules for solving a given problem. There are many types of learning algorithms specific to particular neural network models, these algorithms differ mainly by the way weights are modified.

The neural network relies on the data to extract a general model. Therefore, the learning phase must be rigorous and true, in order to avoid spurious models. All knowledge of a neural network is stored in the synapses that are, in the weights assigned to the connections between the neurons. About 50% to 90% of the total data must be separated for neural network training, randomly chosen data, in order for the network to learn the rules. The rest of the data is only presented to the neural network in the test phase, so that it can correctly deduce the relationship between the data.

Neural Networks are a family of computationally biologically inspired brain models, forming a series of processing units, called neurons, which program nonlinear functions of their inputs. Neurons are organized in layers, which are interconnected with each other. The processing of an input through a neural network occurs through the passage through several layers of neurons, to the output layer that provides the final response. In general, the greater the number of layers, the greater the power of the network, and the greater the computational cost.

Convolutional neural networks (CNNs) are neural networks where connections between layers are organized as in a convolution operation. All the neurons of a CNN are associated with a specific spatial position, and each neuron is connected only to the neurons of the anterior layer that are in a near spatial position. The layers of an CNN are organized in planes, which are called feature maps. All neurons on the same feature map share the same set of parameters. In this way, each feature map is equivalent to the application of a convolution operation on the result of the previous layer. These characteristics allow a reduction in the number of network parameters, which facilitates the training of very deep networks.

Neural networks have been applied to various problems in the area of medical image analysis, such as image classification, character recognition, object detection, noise removal and colorization of black and white images.

"Deep Learning" technology is based on the concept of neural networks where this technology can be used from digital diagnostics through image recognition to retrieval of unstructured information from patients' medical records.

II. Deep learning applied to medical images

In the last four years there has been a huge expansion in the usage of deep learning algorithms for medical images analysis. An increasing number of papers are being published on the topic and several of them have reached human expert-level performance [1]. The most explored tasks so far are image classification, object detection, segmentation and registration, but many more are being investigated. Compared to other computer algorithms, deep learning has the crucial advantage of finding the informative representations of the data by itself. Therefore, the complex and time-consuming step of manual features engineering can be avoided. Nowadays a major challenge in applying deep learning to medical images analysis is the limited amount of data available to researchers. This can lead to an over fitting of the training data with a final low performance in the test dataset. To treat this problem, several strategies are being investigated. Some of them artificially generate more data applying affine transformations to the initial dataset (data-augmentation), others attempt to reduce to total number of parameters of the models or initialize those with pre-trained models from non-medical images and then fine-tune them on the specific task. However, the data itself exists, as millions of medical images are stored in the hospital archives. Gaining access to those archives is the main problem nowadays because of the various regulations present. Each image is also generally stored with patient information, so a process of data anonymization is required as well before a study can be undertaken. In the last years several datasets have been made publicly available and this trend is expected to accelerate in the future. Convolutional neural networks (CNNs) are a type of deep neural networks and have recently achieved excellent results in several areas of knowledge. CNNs have drawn a great interest on the topic because of their intrinsic capability of accepting images as input. They can perform a classification or segmentation task and have proved to be the most successful type of artificial neural network for image analysis problems. Deep learning offers exciting solutions and perspectives for medical image analysis. There is room for improvements regarding both the algorithms and the way to acquire large training datasets. As this last challenge will be overcome, in the next years deep learning will really play a key role also in medical imaging.

III. Convolutional neural networks

Convolutional neural networks are a type of feed-forward artificial neural networks successfully employed today to tackle a wide range of problems. They are inspired by the animal visual cortex. Convolution is the name of the mathematical operation mainly employed by these networks. CNNs are very similar to common neural networks, but they make the important assumption that the input data is arranged in a grid-like topology. The most straightforward example of this kind of data are images, having pixels in a 2D grid. The architecture of CNNs takes advantage of this fact in order to optimize the learning. Convolutional neural networks are multi stage architectures, where each stage usually consists of a convolution layer, a nonlinearity layer and a pooling layer, see figure 1. CNNs use relatively little pre-processing, since the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage.

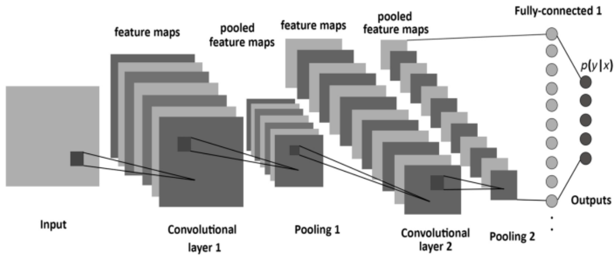

Fig. 1 Convolutional Neural Network.

IV. CNNs for medical image segmentation

Image segmentation is the process of automatically or semi-automatically subdividing an image into significant regions. Image segmentation provides a more meaningful representation of the data and it is a crucial step for fully understanding the content of medical images. In the last years CNNs have been the most common technique applied to image segmentation. Convolutional neural networks (CNNs) take as input an image and give as output a vector containing the probabilities of the image to belong to each possible class. Those methods are called end-to-end training. Thus, end-to-end approaches reduce the human effort and they have achieved great results in medical imaging segmentation tasks [2, 3]. The CNN architectures can indeed be easily adapted for a segmentation task, where each single pixel or voxel is assigned to a class. In this approach, the network learns mostly local features, ignoring global patterns and the convolutions are computed redundantly. A different approach, proposed to overcome these limitations, employs the common CNN architecture replacing the fully connected layers with convolutions. The output of the network, however, ends up smaller than the input, due to the convolutions and pooling layers. To deal with this issue, Long et al. [4] introduces deconvolution operations to up sample the reduced size feature maps. This type of network, without fully-connected layers, is commonly referred to as fully-convolutional network. Ronneberger et al. [5] developed another architecture, called U-Net, for biomedical image segmentation. It consists of a contracting path, made of a common CNN, followed by an expanding part where deconvolution is used to restore the initial size of the image. Due to its structure, this type of network is also known as encoder-decoder. A recent study proposed a CNN for different segmentation tasks in images acquired with diverse modalities [6], where a single convolutional network which performed well in the segmentation of tissues in MR brain images, of the pectoral muscle in MR breast images and of the coronary arteries in cardiac CTA. Another study has described a CNN with a U-Net inspired architecture performing an automatic segmentation of the proximal femur from MR images [7].

V. CNN FOR IMAGE ARTIFACTS

Artifacts may be defined as any content or object of the image, which does not coincide with the arrangement of the scanned object or occasional noise, i.e., artifact, is an artificial feature appearing in an image that is not present in the original investigative objects. The most common sources of artifacts in medical image are movement artifact, caused by the movement of the patient during examination, including breathing, heartbeat, and blood flow. Artifacts can arise from the inherent physics of the image system: beam hardening, streak artifacts, chemical shift artifacts, susceptibility or metal artifact, black boundary artifacts, aliasing artifacts. In the presence of patients with metal implants, metal artifacts are introduced to x-ray CT images. There are a large number of metal artifact reduction techniques in the literature, but this is still a major problem in medical image. Recently the convolutional neural network (CNN) has been applied to medical imaging for low dose CT reconstruction and artifacts reduction [8–17], including application in metal artifact reduction [12–14], [35–39]. Zhang et al [20] proposed a convolutional neural network-based metal artifact reduction (CNN-MAR) framework that is able to distinguish tissue structures from artifacts and fuse the meaningful information to yield a CNN image. In x-ray computed tomography (CT) the use of sparse projection views is a recent approach to reduce the radiation dose. However, insufficient projection views in sparse-view CT produces severe streaking artifacts in filtered back projection reconstruction. To tackle this, very recently, Kang et al [23] provided the first systematic study of deep convolutional neural network (CNN) for low-dose CT and showed that deep CNN using directional wavelets is more efficient in removing low dose related CT noises. Since the streaking artifacts are globally distributed, CNN architecture with large receptive field network was shown essential in these works [24–25], and their empirical performance was significantly better than the existing approaches.

VI. DEEP NEURAL NETWORKS FOR IMAGE DENOISING

X-ray CT is a crucial medical imaging tool. However, the potential radiation risk is a critical issue. Lowering the radiation dose tends to significantly increase the noise and artifacts in the reconstructed images, which can compromise diagnostic information. Noise is a generally undesirable image characteristic that reduces the visibility of low contrast objects and structures. In x-ray CT is determined by the photon fluence. In the last years, deep neural networks have made great advances in CT imaging denoising. Dong et al. [26] developed a convolutional neural network for image super resolution and demonstrated a significant performance improvement compared with other traditional methods. At the same year Chen et al [27] published a paper using a CNN to low dose CT denoising with similar results. More recently Yang et al [28] propose a new method for CT image denoising by designing a perceptive deep CNN that relies on a perceptual loss as the objective function. Zhang et al [29] designed a deep convolutional neural network where the batch normalization [30] and residual learning are integrated to speed up the training process as well as boost the denoising performance.

VII. DEEP NEURAL NETWORKS FOR RESOLUTION

Generative adversarial networks (GANs) are a class of unsupervised machine learning algorithms that can produce realistic images from randomly sampled vectors in a multi-dimensional space. GANs have been used to generate synthetic images of unprecedented realism and diversity [31]. Applications in imaging, including biomedical imaging, have flourished, but have been confined to relatively small image sizes [32]. Recently, Karras et al. devised a training scheme for GANs called progressive growing of GANs (PGGANs) that can create photorealistic images at high resolutions, with images up to 1024 × 1024 pixels [33]. This method (PGGAN) can be applied to two classes of medical images: retinal fundus photographs with retinopathy of prematurity (ROP), and two-dimensional magnetic resonance images taken from a publicly-available, multi-modality glioma dataset (BraTS). According to studies, its application will open new avenues for synthetic image generation in medical imaging, which has thus far been limited by an inability to synthesize images at native resolution.

VIII. Deep neural network for contrast saliency detection

Contrast is the ability to distinguish between differences in intensity in an image and visual saliency attracts the most attention of the human visual system. Recently, deep convolutional neural networks have emerged in this research field, which can generate high level image features from CNN. It can surpass human level performance on object recognition [34]. CNNs have been largely used in salient object detection [35–37] because of their powerful feature representations and have achieved substantially better performance than traditional methods. Deep convolutional neural networks methods are based on either patch-wise training and inference, which can be very time consuming, or fully convolutional networks [38–40] category that directly map an input image of arbitrary size to a saliency map with the same size. However, pixel-level correlation is not considered in such fully convolutional networks, which usually generates incomplete salient regions with blurry contours. To tackle these obstacles Guanbin Li and Yizhou Yu [41] proposed an end-to-end contrast-oriented deep neural network for localizing salient objects using multi scale contextual information. They incorporate a fully convolutional stream for dense prediction and a segment wise spatial pooling stream for sparse inference.

IX. Conclusions

This work provides an idea of the importance of the use of deep learning, specifically convolutional neural networks for medical image analysis. Feature extraction is feasible for the primary detection of any type of disease and its use is more than necessary to generate reliable data. Such data may be incorporated by some *Machine Learning* technique, which is capable of detecting and highlighting certain desired pixels with some learning technique, or even classifying the images as possessing or not certain agent.

References

1. Geert Litjens, Thijs Kooi, Babak Ehteshami Bejnordi, Arnaud Arindra Adiyoso Setio, Francesco Ciompi, Mohsen Ghafoorian, Jeroen AWM van der Laak, Bram van Ginneken, and Clara I Sánchez. A survey on deep learning in medical image analysis. arXiv preprint arXiv:1702.05747, 2017.
2. Fausto Milletari, Nassir Navab, and Seyed-Ahmad Ahmadi. V-net: Fully convolutional neural networks for volumetric medical image segmentation. arXiv preprint arXiv:1606.04797, 2016.
3. Alex Fedorov, Jeremy Johnson, Eswar Damaraju, Alexei Ozerin, Vince Calhoun, and Sergey Plis. End-to-end learning of brain tissue segmentation from imperfect labeling. In Neural Networks (IJCNN), 2017 International Joint Conference on, pages 3785– 3792. IEEE, 2017.
4. Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3431–3440, 2015.
5. Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical Image Computing and Computer-Assisted Intervention, pages 234–241. Springer, 2015.
6. Pim Moeskops, Jelmer M Wolterink, Bas HM van der Velden, Kenneth GA Gilhuijs, Tim Leiner, Max A Viergever, and Ivana Išgum. Deep learning for multi-task medical image segmentation in multiple modalities. In International Conference on Medical Image Computing and Computer-Assisted Intervention, pages 478–486. Springer, 2016.
7. Cem M Deniz, Spencer Hallyburton, Arakua Welbeck, Stephen Honig, Kyunghyun Cho, and Gregory Chang. Segmentation of the proximal femur from mr images using deep convolutional neural networks. arXiv preprint arXiv:1704.06176, 2017.
8. G. Wang, “A perspective on deep imaging,” IEEE Access, vol. 4, pp. 8914–8924, 2016.
9. K. H. Jin, M. T. McCann, E. Froustey, and M. Unser, “Deep convolutional neural network for inverse problems in imaging,” IEEE Transactions on Image Processing, vol. 26, no. 9, pp. 4509–4522, 2017.
10. H. Chen, Y. Zhang, M. K. Kalra, F. Lin, Y. Chen, P. Liao, J. Zhou, and G. Wang, “Low-dose CT with a residual encoder-decoder convolutional neural network,” IEEE transactions on medical imaging, vol. 36, no. 12, pp. 2524–2535, 2017.
11. J. M. Wolterink, T. Leiner, M. A. Viergever, and I. Iˇsgum, “Generative adversarial networks for noise reduction in low-dose CT,” IEEE Transactions on Medical Imaging, vol. 36, no. 12, pp. 2536–2545, 2017.
12. L. Gjesteby, Q. Yang, Y. Xi, Y. Zhou, J. Zhang, and G. Wang, “Deep learning methods to guide CT image reconstruction and reduce metal artifacts,” in SPIE Medical Imaging. International Society for Optics and Photonics, 2017, pp. 101 322W–101 322W–7.
13. H. Chen, Y. Zhang, W. Zhang, P. Liao, K. Li, J. Zhou, and G. Wang, “Low-dose CT via convolutional neural network,” Biomedical Optics Express, vol. 8, no. 2, pp. 679–694, 2017.
14. L. Gjesteby, Q. Yang, Y. Xi, B. Claus, Y. Jin, B. D. Man, and G. Wang, “Reducing metal streak artifacts in CT images via deep learning: Pilot results,” in The 14th International Meeting on Fully Three-Dimensional Image Reconstruction in Radiology and Nuclear Medicine, 2017, pp. 611–614.
15. W. Du, H. Chen, Z. Wu, H. Sun, P. Liao, and Y. Zhang, “Stacked competitive networks for noise reduction in low-dose CT,” PloS One, vol. 12, no. 12, p. e0190069, 2017.
16. H. Chen, Y. Zhang, Y. Chen, J. Zhang, W. Zhang, H. Sun, Y. Lv, P. Liao, J. Zhou, and G. Wang, “Learn: Learned experts assessment-based reconstruction network for sparse-data CT,” IEEE Transactions on Medical Imaging, 2018.
17. Y. Liu and Y. Zhang, “Low-dose CT restoration via stacked sparse denoising autoencoders,” Neurocomputing, vol. 284, pp. 80–89, 2018
18. L. Gjesteby, Q. Yang, Y. Xi, H. Shan, B. Claus, Y. Jin, B. D. Man, and G. Wang, “Deep learning methods for CT image-domain metal artifact reduction,” in SPIE Optical Engineering + Applications, vol. 10391. SPIE, 2017, p. 103910W.
19. Y. Zhang, Y. Chu, and H. Yu, “Reduction of metal artifacts in x-ray CT images using a convolutional neural network,” in SPIE Optical Engineering + Applications, vol. 10391, 2017, p. 103910V.
20. [20] Y. Zhang and H. Yu, “Convolutional neural network-based metal artifact reduction in x-ray computed tomography,” arXiv preprint arXiv: 1709.01581, 2017.
21. H. S. Park, Y. E. Chung, S. M. Lee, H. P. Kim, and J. K. Seo, “Sinogramconsistency learning in CT for metal artifact reduction,” arXiv preprint arXiv:1708.00607, 2017.
22. H. S. Park, S. M. Lee, H. P. Kim, and J. K. Seo, “Machine-learning-based nonlinear decomposition of CT images for metal artifact reduction,” arXiv preprint arXiv:1708.00244, 2017.

23. E. Kang, J. Min, and J. C. Ye, "A deep convolutional neural network using directional wavelets for low-dose x-ray CT reconstruction," Medical Physics, vol. 44, no. 10, pp.360–375, 2017.
24. K. H. Jin, M. T. McCann, E. Froustey, and M. Unser, "Deep convolutional neural network for inverse problems in imaging," IEEE Trans. On Image Processing, vol. 26, no. 9, pp. 4509–4522, 2017.
25. Y. Han, J. Yoo, and J. C. Ye, "Deep residual learning for compressed sensing CT reconstruction via persistent homology analysis," arXiv preprint arXiv:1611.06391, 2016.
26. Dong, C., Loy, C.C., He, K., Tang, X.: Image super-resolution using deep convolutional networks. IEEE Trans. Pattern Anal. Mach. Intell. 38(2), 295-307 (2016).
27. Chen, H., Zhang, Y., Zhang, W., Liao, P., Li, K., Zhou, J., Wang, G.: Low-dose CT denoising with convolutional neural network (2016), arXiv:1610.00321.
28. Yang, Qingsong, Pingkun Yan, Mannudeep K. Kalra and Ge Wang. "CT Image Denoising with Perceptive Deep Neural Networks." CoRR abs/1702.07019 (2017): n. pag.
29. Zhang K, Zuo W, Chen Y, Meng D, Zhang L. Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising. IEEE Trans Image Process. 2017 Jul;26(7):3142-3155. doi: 10.1109/TIP.2017.2662206. Epub 2017 Feb 1.
30. S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," in International Conference on Machine Learning, 2015, pp. 448–456.
31. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y.: Generative adversarial nets. In: Advances in neural information processing systems. (2014) 2672–2680.
32. Marchesi, M.: Megapixel size image creation using generative adversarial networks. arXiv preprint arXiv:1706.00082 (2017).
33. Karras, T., Aila, T., Laine, S., Lehtinen, J.: Progressive growing of gans for improved quality, stability, and variation. arXiv preprint arXiv:1710.10196 (2017).
34. He K, Zhang X, Ren S, Sun J (2015) Delving deep into rectifiers: surpassing human level performance on imagenet classification, In: Proceedings of IEEE international conference on computer vision, pp 1026–1034.
35. G. Li and Y. Yu, "Visual saliency based on multiscale deep features," in Proc. IEEE Conf. CVPR, June 2015.
36. R. Zhao, W. Ouyang, H. Li, and X. Wang, "Saliency detection by multicontext deep learning," in Proc. IEEE Conf. CVPR, 2015, pp. 1265– 1274.
37. L. Wang, H. Lu, X. Ruan, and M.-H. Yang, "Deep networks for saliency detection via local estimation and global search," in Proc. IEEE Conf. CVPR, 2015, pp. 3183–3192.
38. J. Long, E. Shelhamer, and T. Darrell, "Fully convolutional networks for semantic segmentation," Proc. IEEE Conf. CVPR, 2015.
39. L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, "Semantic image segmentation with deep convolutional nets and fully connected crfs," arXiv preprint arXiv:1412.7062, 2014.
40. S. Xie and Z. Tu, "Holistically-nested edge detection," Proc. IEEE Conf. ICCV, 2015.
41. Li, G., & Yu, Y. (2018). Contrast-Oriented Deep Neural Networks for Salient Object Detection. CoRR, abs/1803.11395.

Contacts of the corresponding author:

Author: Cosme N. Mello da Silva
Institute: Instituto de Radioproteção e Dosimetria
Street: Av. Salvador Allende s/n – Barra da tijuca
City: Rio de Janeiro
Country: Brazil
Email: cosme@ird.gov.br