Artificial Neural Network: A Primer for Radiologists

Mayur Pankhania[1]

ABSTRACT

Artificial Intelligence (AI) and Deep Learning (DL) have swiftly advanced in various fields within the past few years and have recently gained attention in the radiology community. An artificial neural network (ANN) is an artificial intelligence algorithm that presents remarkable competence for image analysis. They are information processing systems that automatically develop capabilities in response to information presented to them. This article describes the fundamental concept of Artificial Neural Networks along with its application, limitation, challenges, future trends and their potential implication for radiologic imaging. This article may be helpful for radiologists planning research in the field of radiologic image analysis using artificial neural networks.

Keywords: Radiology, Artificial Neural Network, Artificial Intelligence, Deep Learning

INTRODUCTION

While both the medical and IT is evolving every day and only time can demonstrate the real influence of AI, we must understand the evolution and current scenario of ML and DL in radiology in order to keep up with the changing tide. Familiarity with the concepts, strengths, and limitations of computer-assisted techniques based on ML and DL is critical to ensure optimal patient care. We live in a rapidly evolving world today. Science in general, information technology (IT) and computing power, in particular, has spurred the emergence of Artificial Intelligence (AI) and its applications in our day to day life.

In its most straightforward structure, an artificial neural network (ANN) is an impersonation of the human mind. A characteristic cerebrum can learn new things; adjust to new and evolving condition. The mind has the most incredible ability to break down secondary and muddled, fluffy data, and make its judgment out of it.[1] For instance, we can peruse other's penmanship; however, how they compose might be unique concerning how we compose. A kid can distinguish that the state of a ball and orange are both a circle. Indeed, even a couple of days old child can perceive its mom from the touch, voice and smell. We can recognize a realized individual even from a foggy photo.

With the introduction of IT, medical sciences have seen a paradigm change in the way diseases are identified, diagnosed, and patients treated. AI and its branches like Deep learning (DL) and Artificial Neural Network (ANN) are emerging as one of the most crucial parts of health care provision. Of all the medical fields, radiological sciences influenced the most.

OVERVIEW OF DEEP LEARNING & ARTIFICIAL NEURAL NETWORKS

ML generally categorized into two types, supervised and unsupervised. The first uses handcrafted engineered features that are defined in terms of mathematical equations (such as tumour texture) and can thus be quantified using computer programs. The second method, of which deep learning is a part, can automatically learn feature representations from data without the need for prior definition by human experts (Figure 1).

It is the evolution of the second type what presently called as the third era of IT, which has led to DL. Here the artificial neuronal networks that resemble the human neurons in complexity and function are created. These networks have nodes that are similar to the synopses in the human brain and would work in multiple layers. We still do not know how some of these layers work, and that is why these layers called hidden layers. These systems and neurons are self-improving and can work with unlabelled raw data and can draw their inferences over time without the need of human command.

When joining at least two artificial neurons, we are getting an artificial neural network. On the off chance that solitary artificial neuron has practically no convenience in taking care of genuine issues, the artificial neural networks have it. Truth be told artificial neural networks are equipped for illuminating complex genuine issues by preparing data in their fundamental structure squares (artificial neurons) in a non-direct, conveyed, equal and nearby way.[3]

How individual artificial neurons are interconnected is called geography, engineering or on the other hand, diagram of an artificial neural network. The way that interconnection should be possible in various ways brings about various potential geographies that partitioned into two fundamental classes.[4] These two geographies; the left half of the figure speak to direct feed-forward geography (non-cyclic diagram) where data streams from contributions to yields in as it were one heading and the right side of the figure speak to basic intermittent geography (semi- cyclic chart) where a portion of the data streams, not just one way from contribution to

[1]Sahyog Imaging Center, Department of Radiodiagnosis, PDU Medical College& Government Hospital, Rajkot, Gujarat, India

Corresponding author: Dr Mayur Pankhania, C702, Haridwar Heights, Nana Mauva Main Road, Near Shastrinagar, Opposite Gandhi School, Rajkot 360005, Gujarat, India

How to cite this article: Pankhania M. Artificial neural network: a primer for radiologists. International Journal of Contemporary Medical Research 2020;7(11):K1-K6.

DOI: http://dx.doi.org/10.21276/ijcmr.2020.7.11.3

yield yet additionally inverse way. While watching Figure 2, we have to refer to that for more straightforward taking care of and scientific depicting of an artificial neural network us gathering singular neurons in layers.

At the point when we pick and manufacture geography of the artificial neural network, we just completed a portion of the undertaking before we can utilize this artificial neural network for taking care of the given issue. Similarly, as natural neural networks need to get familiar with their appropriate reactions to the given contributions from the condition, the artificial neural networks need to do likewise. So, the following stage is to learn the legitimate reaction of an artificial neural network, and this can be accomplished through learning (directed, un-regulated or fortification learning). Regardless of which strategy we use, the errand of learning is to set the estimations of weight and inclinations on the premise of learning information to limit the picked cost work.

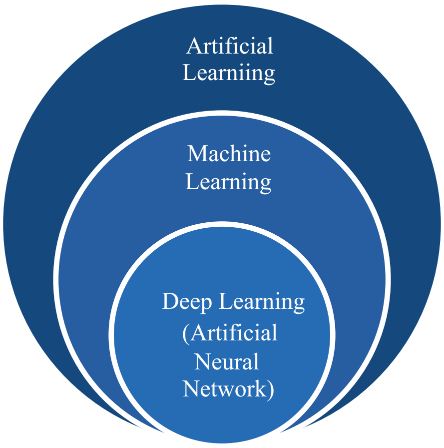

Figure-1: Venn diagram representation of Artificial neural networks in the artificial intelligence hierarchic terminology.

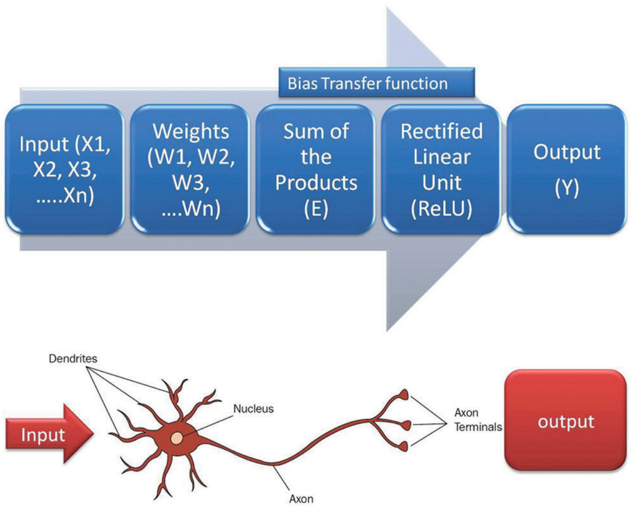

Figure-2: Diagrammatic representation of an artificial neuron and biologic neuron. Input of data is received through the dendrites, which are usually termed weights in the artificial neuron. Each input (X) is multiplied by its corresponding weight (W), and all the multiplications are summed (E). A nonlinear mathematical formula, rectified linear unit function is performed on the result. The output of the neuron serves as an input in the next layer of neurons.

TYPES OF ARTIFICIAL NEURAL NETWORKS

Feed-forward Artificial Neural Networks

An artificial neural network with feed-forward geography is called Feed-Forward artificial neural network and as such has just one condition: data must spill out of contribution to yield just a single way with no back-circles. There are no restrictions on the number of layers, kind of move work utilized in individual artificial neuron or number of associations between individual artificial neurons. The most straightforward feed-forward artificial neural network is a solitary perceptron that equipped for learning direct distinguishable issues.[6,7]

Recurrent Artificial Neural Networks

An artificial neural network with the intermittent geography is called Recurrent artificial neural network. It is like a feed-forward neural network without any constraints in regards to back-circles. In these cases, data is not, at this point sent distinctly one way yet it additionally communicated in reverse, which makes an inner condition of the network which permits it to display fleeting dynamic conduct. Repetitive artificial neural networks can utilize their internal memory to process any grouping of information sources.[8] The most basic geography of a repetitive artificial neural network is the entirely intermittent artificial network where each essential structure square (artificial neuron) is straightforwardly associated with each other essential structure obstruct toward all path. Other intermittent artificial neural networks, for example, Hopfield, Elman, Jordan, bi-directional and different networks are uncommon instances of redundant artificial neural networks.

Hopfield Artificial Neural Network

A Hopfield artificial neural network is a kind of repetitive artificial neural network that utilized to store at least one stable objective vectors. These steady vectors can be shown as recollections that the network reviews when furnished with comparative vectors that go about as a prompt to the network memory. These paired unit stake two distinct qualities for their states that are controlled by whether the units' information surpasses their limit. Paired units can take either estimation of 1 or - 1 or estimations of 1 or 0.[9]

Elman and Jordan Artificial Neural Network

Elman network likewise alluded as Simple Recurrent Network is an extraordinary instance of intermittent artificial neural networks. It varies from customary two-layer networks in that the primary layer has a repetitive association. It is a primary three-layer artificial neural network that has back-circle from shrouded layer to include layer trough alleged setting unit. This kind of artificial neural network has a memory that is permitting it to both identify and produce time-shifting examples.[10]

The Elman artificial neural network has commonly artificial sigmoid neurons in its concealed layer and straight artificial neurons in its yield layer. This mix of artificial neurons moves capacities can make inexact any capacity with discretionary exactness if there are sufficient artificial neurons in concealed layer. Having the option to store data Elman artificial neural network is fit for producing fleeting examples just as spatial examples and reacting on them. The main distinction is that setting units are taken care of from the yield layer rather than the shrouded layer.[11]

Long Short Term Memory

Long Short Term Memory is one of the intermittent artificial neural networks geographies. Conversely, with virtual intermittent artificial neural networks, it can gain from its experience to process, group and anticipate time arrangement with long delays of obscure size between significant occasions. This makes Long Short Term Memory to outflank other intermittent artificial neural networks, Hidden Markov Models and other grouping learning techniques. Long Short Term Memory artificial neural network is work from Long Short Term Memory hinders that equipped for recalling an incentive for any periods.[12]

Bi-directional Artificial Neural Networks (Bi-ANN)

Bi-directional artificial neural networks intended to foresee complex time arrangement. They comprise of two individual interconnected artificial neural (sub) networks that perform immediately and converse (bidirectional) change.[12] Interconnection of artificial neural subnetworks done through two unique artificial neurons that equipped for recollecting their interior states. This sort of interconnection among future and past estimations of the handled signs increment time arrangement expectation capacities. As such, these artificial neural networks anticipate future estimations of information as well as past qualities. That brings a requirement for two-stage learning; in the first stage, we show one artificial neural sub-network for anticipating future, and in the second stage, we show a second artificial neural sub-network for foreseeing past.[13]

Self-Organizing Map (SOM)

Self-sorting out guide is an artificial neural network that identified with feed-forward networks, yet it should inform that this kind of engineering is in a general sense distinctive in the game plan of neurons and inspiration. Regular course of action of neurons is in a hexagonal or rectangular matrix. Self-sorting out guide is distinctive in contrast with other artificial neural networks as in the utilize a local capacity to protect the topological properties of the information space.[13] They utilize unaided learning worldview to deliver a low-dimensional, discrete portrayal of the info space of the preparation tests, called a guide what makes them incredibly helpful for envisioning low-dimensional perspectives on high-dimensional information. Such networks can figure out how to recognize regularities and connections in their information and adjust their future reactions to that input as needs be.

Stochastic Artificial Neural Network

Stochastic artificial neural networks are a kind of an artificial knowledge apparatus. They worked by bringing arbitrary varieties into the network, either by giving the network's neurons stochastic exchange capacities or by giving them stochastic loads. This makes them valuable devices for improvement issues since the irregular changes assist it with getting away from nearby minima. Stochastic neural networks that worked by utilizing stochastic exchange capacities are frequently called Boltzmann machine.[14,15]

Physical Artificial Neural Network

The more significant part of the artificial neural networks today is programming based yet that does not prohibit the likelihood from making them with physical components which based on customizable electrical flow opposition materials. History of physical artificial neural networks returned in the 1960s when first physical artificial neural networks made with memory semiconductors called memristors. Memristors imitate neurotransmitters of artificial neurons. Even though these artificial neural networks marketed, they did not keep going for long because of their ineptitude for adaptability.[16] After this endeavour a few others followed, for example, endeavour to make physical artificial neural network dependent on nanotechnology or stage change material.

APPLICATION TO RADIOLOGY

Designing an in-depth learning study entails a typical pattern that includes several steps, as shown in figure 3. There are many applications of Radiology[17]:-

Order scheduling and patient screening

One significant way radiologists can give extra esteem is by diminishing the number of patient flake-outs. Analysts are now taking a shot at utilizing AI to recognize patients who are at great danger of missing their radiology care or not going to arrangements, the creators clarified. These advancements additionally can help improve quiet screening.

Image acquisition

Both imaging suppliers and patients have a great deal to pick up from this one; it could mean more proficiency and snappier test times. "AI could make imaging frameworks shrewd," the creators composed. "AI-based information preparing techniques can diminish imaging time. Further, savvy imaging frameworks could decrease superfluous

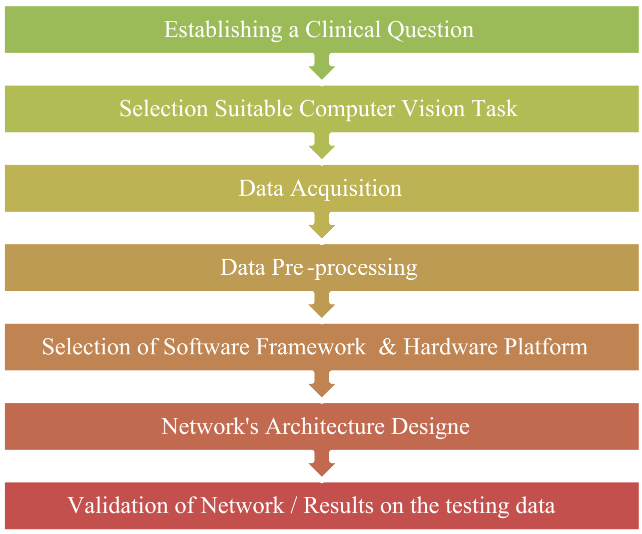

Figure-3: Diagram of the steps involved in constructing a deep learning study imaging, improve situating, and help improve the portrayal of the discoveries."[18]

Automated detection of findings

Choy and associates noticed this is one way AI can affect radiology immediately. AI can separate accidental discoveries, for instance, and it can help distinguish fundamental discoveries also. Different territories that could exploit AI, later on, are bosom malignant growth screening and the discovery and the board of pneumonic knobs. What is more, that is only the start.

Post processing: image segmentation, registration, quantification

Research has shown how machine learning can be used for image segmentation, Choy and colleagues observed. It also has the potential to assist radiologists with image synthesis, image registration and image quantification. On an example of this is a recent study from Wang et al. published in Computer Methods and Programs in Biomedicine that used a Convolutional neural network-based algorithm to segment adipose tissue volume on CT images.

Image quality analytics

Picture quality methods everything in radiology, and AI could affect here also. "Prepared human spectators (e.g., experienced radiologists) viewed as the reference for the task-based assessment of clinical picture quality," the creators composed. "Be that as it may, quite a while is required to assess an enormous number of pictures. For this issue, the AI numerical spectators (otherwise called model eyewitnesses) have created as a proxy for human onlookers for picture quality evaluation."[19]

Automated radiation dose estimation

AI calculations could support radiologists and technologists with making portion gauges before tests, the creators noted. This comes while presenting patients to the most reduced portion conceivable is all the more a concentration in clinical imaging than any time in recent memory.

Radiology reporting and analytics

By applying machine learning techniques to natural language processing, researchers can extract data from free-text radiology reports, extra findings and measurements from narrative radiology reports and even track recommendations made by radiologists to referring physicians.

This segment presents late applications inside radiology, which partitioned into the accompanying classes: characterization, division, discovery, and others.

Classification

In clinical picture investigation, arrangement with profound learning typically uses target sores portrayed in clinical pictures, and these injuries arranged into at least two classes. For example, profound learning regularly utilized for the arrangement of lung knobs on processed tomography (CT) pictures as amiable or harmful. As appeared, it is essential to set up an enormous number of preparing information with comparing names for productive grouping utilizing CNN. For lung knob arrangement, CT pictures of lung knobs and their marks (i.e., kindhearted or destructive) utilized as preparing information. Two instances of preparing information of lung knob classification between kindhearted lung knob and essential lung malignant growth; the preparation information where every datum incorporates a hub picture and its mark, and the preparation information where every datum incorporates three pictures (pivotal, coronal, what is more, sagittal pictures of a lung knob) and their names. After preparing CNN, the objective injuries of clinical pictures can be indicated in the arrangement stage by clinical specialists or PC supported identification (CADe) frameworks.[24]

Segmentation

Division of organs or anatomical structures is a fundamental picture handling strategy for clinical picture analysis, for example, quantitative assessment of clinical boundaries (organ volume and shape) and PC supported determination (CAD) framework. In the past segment, grouping relies upon the segmentation of sores of intrigue. Segmentation can be performed physically by radiologists or committed faculty, a tedious procedure. In any case, one can likewise apply CNN to this undertaking too. A delegate model of segmentation of the uterus with a threatening tumour on MRI.[25,26,27] By and large, a segmentation framework straightforwardly gets a whole picture and yields its segmentation result. Preparing information for the segmentation framework is comprises of the medical pictures containing the organ or structure of intrigue and the segmentation result; the last primarily gotten from recently performed manual segmentation—a delegated case of preparing information for the segmentation arrangement of a uterus with a threatening tumour. In contrast to the arrangement, because a whole picture inputted to the segmentation framework, the framework needs to catch the worldwide spatial setting of the whole picture for efficient segmentation.

Detection

A typical undertaking for radiologists is to identify variations from the norm inside clinical pictures. Variations from the norm can be uncommon, and they must identify among numerous typical cases. One past study explored the handiness of 2D-CNN for distinguishing tuberculosis on chest radiographs.[28] The examination used two unique sorts of 2D-CNN, AlexNet[29] and GoogLeNet[30], to identify aspiratory tuberculosis on chest radiographs. To build up the discovery framework and assess its execution, the dataset of 1007 chest radiographs utilized. As indicated by the outcomes, the best zone under the bend of recipient working trademark bends for distinguishing pulmonary tuberculosis from concrete cases was 0.99, which was gotten by a group of the AlexNet and GoogLeNet 2D-CNNs.

Others

Low-portion CT has progressively utilized in clinical circumstances. For instance, low-portion CT demonstrated to be helpful for lung disease screening.[31] Since boisterous pictures of low-portion CT ruined the dependable assessment of CT pictures, numerous techniques of picture preparing were utilized for denoising low-portion CT pictures. Two past investigations indicated that low-portion and ultra-low-portion CT pictures could be adequately denoised, utilizing profound learning.[32,33] Their frameworks separated the loud CT picture into picture patches, and denoised the picture patches, at that point reproduced another CT picture from the denoised picture patches. Profound learning with the encoder-decoder design utilized for their frameworks to denoise picture patches. They were preparing information for the denoising frameworks comprised of sets of picture patches, which gotten from standard-portion CT and low-portion CT.

HOW TO OVERCOME CHALLENGES

We can overcome the challenges of artificial neural network by following ways[21]:-

Neural Network Opacity

Picking up straightforwardness into profound learning networks is a big test that lays on the progression of different methods that help to imagine the highlights spoke to by singular neurons. There have been a few advancements in neural network innovation, which have empowered the making of neural networks that can account for themselves.

Ensuring Data Quality

AI and profound learning models are information ravenous, which means they need heaps of great information to get proficient at performing assignments like picture acknowledgment.

While an association or venture hoping to prepare and run an AI model underway clearly would not deliberately present information that can darken execution, unmistakably utilizing low quality preparing information can unexpectedly hamper the value of these advances.[22]

Plugging the Talent Gap

Organizations keen on stopping the ability hole need to expand their perspectives if they need to utilize AI arrangements that take care of issues. Besides, instructive foundations, for example, schools and colleges must comprehend the need to build information among understudies concerning the different AI advancements by presenting devoted modules and exercises concentrating on AI strategies, algorithmic factual demonstrating, and then some.

Data Security

Data security is a colossal test with regards to understanding the business use instances of artificial knowledge procedures. Meeting this test involves guaranteeing all partners around educated on data security strategies, including encryption, confirmation, and consistence necessities. Different components can help, for example, performing danger displaying and practising great data security cleanliness.

Production-Grade AI

Production-grade AI arrangements must execute through sufficient interest in framework, including both equipment and programming. Necessary frameworks should be solid with insignificant vacation, especially if they are cloud-based.[23] Different concerns previously talked about, including guaranteeing information security and employing the correct ability, can additionally improve the acknowledgment of production-grade AI frameworks that take care of real business issues.

CONCLUSION

Recent advancement in artificial intelligence, data processing, computing hardware and network architectures, has enabled rapid development of deep learning algorithms. It has pointed out that the pattern recognition ability of artificial neural networks holds out the promise of extracting useful information has immense potential in imaging. Artificial Neural Network technique can competently solve image detection, recognition, and classification tasks that previously required human intelligence. The introduction of deep learning techniques in radiology will likely assist radiologists in a variety of diagnostic tasks. At present, the application of ANNs to the clinical field is limited mostly to research but has potentially proved to be a stepping stone for advancing imaging practice for radiologists.

REFERENCES

1. Petriu E M. Neural Networks: Basics [Internet]. Ottawa:School of Electrical Engineering and Computer Science, University of Ottawa, Canada – [cited 2020 Nov 10].Available from: http://www.site.uottawa.ca/~petriu/NN_basics-tutorial.pdf
2. Gershenson C. Artificial Neural Networks for Beginners. arXiv: cs/0308031 [Preprint]. 2003[cited 2020 Nov 10]. Available from: https://arxiv.org/abs/cs/0308031
3. Kuldeep S, Anitha GS. Neural Network Approach for Processing Substation Alarms.Int J Power Electron Controll Convert. 2015;1:21-28
4. Shukla M, Abdelrahman M. Artificial neural networks based steady state security analysis of power systems. In: Proceedings of the Thirty-Sixth Southeastern Symposium on System Theory; 2004; Atlanta, USA. New York: IEEE; 2004, p. 266-269.
5. Lee KY, Cha YT,Park JH. Short-term load forecasting using an artificial neural network.IEEE Trans Power Syst.1992;7:124-132
6. Gurney K. An Introduction to Neural Networks. London: UCL Press; 1997.
7. Krenker A,Volk M,Sedlar U, Bešter J, Kos A, et al. Bidirectional artificial neural networks for mobile-phone fraud detection. ETRI J.2009;31:92-94
8. Kröse B,Smagt P. An Introduction to Neural Networks.8th ed. Amsterdam: University of Amsterdam; 1996.
9. Pavešić N. Razpoznavanjevzorcev, uvod v analizo in razumevanjevidnih in slušnihsignalov.3rd ed.Ljubljana: Fakulteta za elektrotehniko; 2000.
10. Rojas R. Neural networks: a systematic introduction. New York: Springer-Verlag; 1996.
11. Beris R. Deep Learning/AI Challenges in 2019 and How to Work Around Them. 2019 Jun 12 [cited 2020 Nov 10]. In: Rebecca Beris[Internet]. San Francisco: Medium.Available from: https://medium.com/@rebeccab_16699/deep-learning-ai-challenges-in-2019-and-how-to-work-around-them-dfb3744ef9fd
12. Austin J. ADAM: A distributed associative memory

for scene analysis. In:Proceedings of the IEEE First International Conference on Neural Networks, vol. IV;1987; San Diego, USA. New York: IEEE;1987; p. 285-92
13. Battiti R. First- and second-order methods for learning: between steepest descent and Newton's method. Neural Comput.1992;4:141-166.
14. Bledsoe WW, Browning I. Pattern recognition and reading by machines. In: Papers Presented at the December 1-3, 1959, Eastern Joint IRE-AIEE-ACM Computer Conference; 1959 Dec 1-3; Boston, USA. New York: Association for Computing Machinery; 1959. p. 225-32.
15. Walter M. 8 key clinical applications of machine learning in radiology.2018 June 26 [cited 2020 November 10]. In: Radiology Business – Artificial Intelligence [Internet]. Providence: TriMed Media Group. Available from: https://www.radiologybusiness.com/topics/artificial-intelligence/8-key-clinical-applications-machine-learning-radiology
16. Bullock TH, Orkand R, Grinnell A. Introduction to nervous systems. San Francisco: WH Freeman& Co; 1977.
17. Caudell TP, Smith SDG, Escobedo R, Anderson M. NIRS - Large-scale ART-1 neural architectures for engineering design retrieval. Neural Netw.1994;7:1339-1350.
18. ConnollyM, Van Essen D.The representation of the visual field in parvocellular and magnocellular layers of the lateral geniculate nucleus in the macaque monkey. J Comp Neurol. 1984; 226:544-64.
19. Eluyode OS, Akomolafe DT. Comparative Study of Biological and Artificial Neural Networks. Eur J ApplEng Sci Res. 2013;2:36-46.
20. Fletcher R, Reeves CM. Function Minimization by Conjugate Gradients.Comput J. 1964;7:149-154.
21. Aleksander I, Thomas WV, Bowden PA. WISARD: A radical step forward in image recognition. Sens Rev. 1984; 4:120-124.
22. Grossberg S. Contour enhancement, short-term memory, and constancies in reverberating neural networks. Stud Appl Math.1973; 52:217-57.
23. Gullapalli V.A stochastic reinforcement learning algorithm for learning real-valued functions. Neural Netw.1990; 3:671-92.
24. Liang M, Tang W, Xu DM,Jirapatnakul AC, Reeves AP, Henschke CI, et al. Low-dose CT screening for lung cancer: computer-aided detection of missed lung cancers. Radiology. 2016;281:279-288
25. Clark K, Vendt B, Smith K, Freymann J, Kirby J, Koppel P, et al. The Cancer Imaging Archive (TCIA): maintaining and operating a public information repository. J Digit Imaging. 2013; 26:1045-1057.
26. LucchesiFR, Aredes ND. Radiology Data from The Cancer Genome Atlas Cervical Squamous Cell Carcinoma and Endocervical Adenocarcinoma [TCGA-CESC] collection. The Cancer Imaging Archive. 2016.
27. Kurata Y, Nishio M, Kido A, Fujimoto K, Yakami M, Isoda H, et al. Automatic segmentation of the uterus on MRI using a convolutional neural network. Comput Biol Med. 2019; 114:103438.
28. Lakhani P, Sundaram B. Deep Learning at Chest Radiography: Automated Classification of Pulmonary Tuberculosis by Using Convolutional Neural Networks. Radiology. 2017;284:574-582.
29. Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. In: Proceedings of the Twenty-Sixth Annual Conference on Neural Information Processing Systems; 2012 Dec 3-8; Lake Tahoe, USA. San Diego: Neural Information Processing Systems; 2012. P.1-9.
30. Huang G,Liu Z, Van Der Maaten L, Weinberger KQ. Densely Connected Convolutional Networks. In: Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition; 2017 Jul 21-26; Honolulu, USA. New York: IEEE; 2017. p. 2261-2269.
31. National Lung Screening Trial Research Team, Aberle DR, Adams AM, Berg CD, Black WC, Clapp JD, et al. Reduced lung-cancer mortality with low-dose computed tomographic screening. N Engl J Med. 2011; 365:395-409.
32. Chen H, Zhang Y, Zhang W, et al. Low-dose CT via convolutional neural network. Biomed Opt Express. 2017; 8:679-694.
33. Nishio M, Nagashima C, Hirabayashi S, Ohnishi A, Sasaki K, Sagawa T, et al. Convolutional auto-encoder for image denoising of ultra-low-dose CT. Heliyon. 2017;3:e00393.

Source of Support: Nil; **Conflict of Interest:** None

Submitted: 12-08-2020; **Accepted:** 09-09-2020; **Published:** 20-11-2020