Journal of Clinical and
Medical Images

Review Article

ISSN: 2640-9615 | Volume 8

AGI In Radiation Oncology - The Dawn of New Era

Sheenu Priya[1], Navik Goyal[2]

[1]Guru Gobind Singh medical college and hospital, Faridkot, Punjab, India

[2]Guru Gobind Singh medical college and hospital, Faridkot, Punjab, India

***Corresponding author:**

Sheenu Priya,
Guru Gobind Singh medical college and hospital,
Faridkot, Punjab, India

Received: 26 Sep 2024
Accepted: 26 Oct 2024
Published: 31 Oct 2024
J Short Name: JCMI

Citation:

Sheenu Priya, AGI In Radiation Oncology - The Dawnof New Era. J Clin Med Img. 2024; V8 (4): 1-4

1. Review

Artificial General Intelligence has kept its footsteps in the field of Radiation Oncology. Radiation delivery consists of 5 major steps (Figure 1), i.e a) Patient assessment which includes Radiation Decision and consultation ,b) Simulation consisting of Image Registration and Reconstruction and Contouring , c) Treatment Planning which includes Dosimetry and plan review, d) Quality Assurance and Treatment Delivery comprising of image review,-set up verification ,daily imaging ,e) Patient follow up [1]. Rapid advancement in Radiotherapy has generated the 'big data'concept which means massive amount of data accumulated due to complexity of Radiotherapy processes that includes; Volume (data intensive imaging systems) ,Velocity (growing archives), Veracity (subjective interpretation of data) and Variety (diversity of imaging modalities) . An innovative branch of Information Technology is required to analyse and process this Data [2]. In Machine Learning, a branch of Artificial Intelligence, computer algorithms are developed which mimic Human Intelligence. Intensive programming and soft coding allow these algorithms to become better and better through repetition [3]. In patient assessment, CADe is Computer aided detection which allows computer to give its second opinion in diagnosis and assessment of images [3]. Several ML based models are proposed like Lung nodules in CT using ANN (Artificial neural network) [4], and CNN (convolutional neural network) in mammography [5]. Superlative results are seen in regard to detection of Brain lesions via deep learning [6]. This ML can significantly contribute in enhancing Clinician and Radiologist's assessment of Disease as well as predict Risk Benefit ratio in treatment modalities [7]. Treatment simulation involves minute details of the patient from Kidney function test, fasting of bladder filling, rectal contrast, immobilisation,image registration , reconstruction etc. All this process is carefully registered and assessed by Machine Learning Algorithms [7]. In this regard, Global respiratory motion model developed by ML method based on PCA(principal component analysis) was demonstrated in a study [8]. Image reconstruction studies [9-12] demonstrated models which can transform CT images into MRI. Chen et al. [12]. Investigated the dosimetric accuracy on the dose-volume histogram (DVH) parameters and found that discrepancy was less than 0.87% with the maximum point dose discrepancy within PTV (planning target volume) less than 1.01% with respect to the prescription on prostate intensity modulated radiotherapy (IMRT) planning. Deformable image registration (DIR) is widely being incorporated nowadays in radiotherapy processes. It is a method for detecting the mapping between points in one image and the corresponding points in another image.Intrafractional and Interfractional Registration are 2 types of image registration in IGRT.Combining two images after registration is called Data Fusion[13,14]. Studied On line adaptive radiotherapy in Head and neck cancers, wherein they compared manual contouring with that of automatic contouring. Using automatic image segmentation, Computed tomography images were delineated. Manually drawn contours were data-fed as references. Quantitative validation was done with similarity coefficient index which was approximately 0.8. also distance transformation was studied between manually and automatically delineated ROI surfaces which were almost within 3mm.

International Commission on Radiation Units and Measurements (ICRU) Reports No. 50, 62, 71 and 83 are used to define specific Target volumes and Organ at Risk [15]. Various Machine learning models have been proposed for Auto Contouring [16-19]. Used Support vector machines as machine learning approach to develop two algorithms for Glioma tumor segmentation and patient's Overall survival prediction. This included noise removal, extraction of image intensity data, segmentation using 'Gaussian kernal' and post processing to enhance segmentation morphology. Knowledge Based Treatment Planning is a new concept. Here, prior treatment plans and archived patient information is used to plan further treatment such as limiting DVHs within accepted ranges. Thereafter Automated plan generation is done [20]. Technology selection and resource allocation are areas of major concern where the patient's doubts reagrding which Radiation modality out of the plethora available out there, is most suitable for him/her that will neither be a financial burden nor will it cause dissatisfaction related to results. Value of DVH has been effectively proven in improving population-based treatment and plan quality with simultaneous detection of outliers. However, there are limitations to DVH prediction within accepted ranges in this approach. Various studies [21,22] have been done to improve Quality Assurance, detect minute errors in Dosimetry and Radiation Protection issues via Artificial Intelligence. Deep Learning is the domain which provide complex software for Adaptive Radiotherapy (Tumor Replanning post shrinkage). Deep learning includes computational models which consist of multiple processing channels which are fed with enormous data memory and it also has the ability of abstraction at various levels. These very methods have transformed traditional ways in speech and visual object recognition, and also drug discovery and genomics. Deep learning identifies the complex structure in heavy data sets by backpropagation and further indicates peculiarities about areas requiring modifications layer by layer. Deep convolutional nets have shown splendid results in processing images, video, speech etc. And recurrent nets have been useful in areas of text and speech [23]. Radiomic Biomarkers [24] are now used to assist decisions in treatment with precision medicine. These Biomarkers contain information about Cancer traits and phenotypes. GPT 4, PaLM 2, LLM (Large language models) and SAM (Segment anything models) are some of the models of AGI which can transform Radiation Oncology in near future. In Precision Oncology [Figure 2], we use patient specific data to facilitate management tailored to meet personalised targets of radical cure. Precision refers to areas of molecular resolution, mechanistic specificity, therapeutic accuracy that is accompanied by genomics [25]. This area of discussion is subject in itself and is widely expanding in research.

In a nut shell, Machine learning is developed to function on its own and improve with time. It is made to complement human expertise and care. Studies have shown promising results with the use of AGI in Radiation Oncology. But the major limitation is Self critical assessment which is yet to be worked on.

Figure 1: The Radiotherapy Workflow.

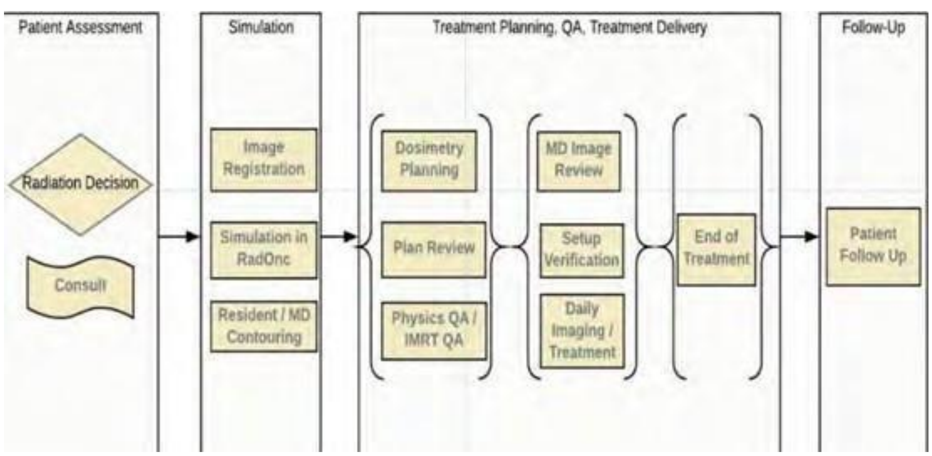
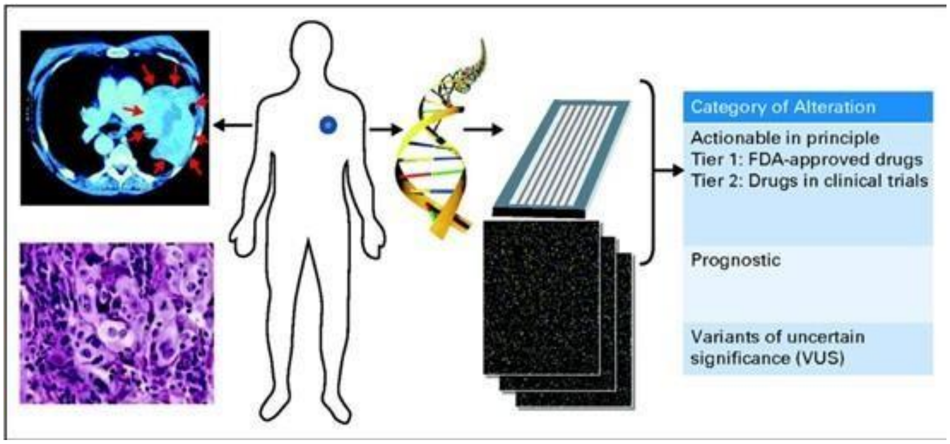


Figure 2: Precision Oncology- The Art of Genomics.



References

1. Osman, Alexander. Radiation Oncology in the Era of Big Data and Machine Learning for Precision Medicine. 2019; 10.
2. Kansagra AP, Yu JP, Chatterjee AR, Lenchik L, Chow DS. Big data and the future of radiology informatics. Academic Radiology. 2016; 23(1): 30-42.
3. El Naqa I, Li R, Murphy M. Machine Learning in Radiation Oncology: Theory and Applications. Cham: Springer. 2015; 336.
4. Suzuki K, Armato SG, Li F, Sone S, Doi K. Massive training artiicial neural network (MTANN) for reduction 64 Artificial Intelligence - Applications in Medicine and Biology of false positives in computerized detection of lung nodules in lowdose computed tomography. Medical Physics. 2003; 30(7): 1602-1617.
5. Chan HP, Lo SC, Sahiner B, Lam KL, Helvie MA. Computer-aided detection of mammographic microcalcifications: Pattern recognition with an artificial neural network. Medical Physics. 1995; 22(10): 1555-1567.
6. Rezaei M, Yang H, Meinel C. Deep neural network with l2-norm unit for brain lesions detection. In: Liu D, Xie S, Li Y, Zhao D, El-Alfy ES, editors. Neural Information Processing. ICONIP 2017. Cham: Springer. 2017; 798-807.
7. Chen S, Qin A, Zhou D, Yan D. Technical note: U-net-generated synthetic CT images for magnetic resonance imaging-only prostate intensity-modulated radiation therapy treatment planning. Medical Physics. 2018; 45(12): 5659-5665.
8. Steiner E, Shieh C, Caillet V, O'Brien R. WE-HI-KDBRB1-10: 4DCT and 4DCBCT under-predict intrafraction lung target motion during radiotherapy. Medical Physics. 2018; 45(6): e646-e647.
9. Nie D, Cao X, Gao Y, Wang L, Shen D. Estimating CT image from MRI data using 3D fully convolutional networks. In: Carneiro G et al., editors. Deep Learning and Data Labeling for Medical Applications. DLMIA 2016, LABELS 2016. LNCS.Vol. 10008. Cham: Springer; 2016; 170-178.
10. Bayisa F, Liu X, Garpebring A, Yu J. Statistical learning in computed tomography image estimation. Medical Physics. 2018; 45(12): 5450-5460.
11. Huynh T, Gao Y, Kang J. Estimating CT image from MRI data using structured random forest and auto-context model. IEEE Transactions on Medical Imaging. 2016; 35(1): 174-183.
12. Chen S, Qin A, Zhou D, Yan D. Technical note: U-net-generated synthetic CT images for magnetic resonance imaging-only prostate intensity-modulated radiation therapy treatment planning. Medical Physics. 2018; 45(12): 5659-5665.
13. Guerrero T, Zhang G, Huang TC, Lin KP. Intrathoracic tumour motion estimation from CT imaging using the 3D optical flow method. Physics in Medicine and Biology. 2004; 49(17): 4147-4161.
14. Zhang T, Chi Y, Meldolesi E, Yan D. Automatic delineation of on-line head-and-neck computed tomography images: Toward on-line adaptive radiotherapy. International Journal of Radiation Oncology, Biology, Physics. 2007; 68(2): 522-530.
15. Suzuki K, Armato SG 3rd, Li F, Sone S, Doi K. Massive training artiicial neural network (MTANN) for reduction of false positives in computerized detection of lung nodules in lowdose computed tomography. Medical Physics. 2003; 30(7): 1602-1617.
16. Osman AFI. Automated brain tumor segmentation on magnetic resonance images and patient's overall survival prediction using support vector machines. In: Crimi A, Bakas S, Kuijf H, Menze B, Reyes M, editors. Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries. Cham: Springer. 2018; 435-449.
17. Kamnitsas K, Bai W, Ferrante E. Ensembles of multiple models and architectures for robust brain tumour segmentation. In: Crimi A, Bakas S, Kuijf H, Menze B, Reyes M, editors. Brain Les. 2017. LNCS. Vol. 10670. Cham: Springer. 2018; 450-462.
18. Kamnitsas K, Ledig C, Newcombe VF. Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. Medical Image Analysis. 2017; 36: 61-78.
19. Pereira S, Pinto A, Alves V, Silva CA. Brain tumor segmentation using convolutional neural networks in MRI images. IEEE Transactions on Medical Imaging. 2016; 35(5): 1240-1251.
20. Feng M, Valdes G, Dixit N, Solberg TD. Machine learning in radiation oncology: Opportunities, requirements, and needs. Frontiers in Oncology. 2018; 8: 110.

21. Li Q, Chan MF. Predictive timeseries modeling using artificial neural networks for Linac beam symmetry: An empirical study. Annals of the New York Academy of Sciences. 2017; 1387(1): 84-94.

22. El Naqa I. SU-E-J-69: An anomaly detector for radiotherapy quality assurance using machine learning. Medical Physics. 2011; 38: 3458.

23. Le Cun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015; 521(7553): 436-444.

24. Arimura H, Soufi M, Kamezawa H, Ninomiya K, Yamada M. Radiomics with artificial intelligence for precision medicine in radiation therapy. Journal of Radiation Research. 2018; 60(1): 150-157.

25. Garraway LA, Verweij J, Ballman KV. Precision oncology: an overview. J Clin Oncol. 2013; 31(15): 1803-5.