International Journal of Science Academic Research
Vol. 06, Issue 03, pp.9591-9595, March, 2025
Available online at http://www.scienceijsar.com

ISSN: 2582-6425

Research Article

EXPANDING THE REACH: INTEGRATING AI-GENERATED AUTO CONTOURS VIA DEEP LEARNING SEGMENTATION INTO DIVERSE TREATMENT PLANNING SYSTEMS

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Received 15th January 2025; **Accepted** 17th February 2025; **Published online** 28th March 2025

Abstract

Aim: Contouring in treatment planning systems for radiation oncology plays a crucial role in ensuring accurate and effective treatment. The integration of AI-generated auto-contouring with other planning systems, particularly in remote areas, is essential for achieving optimal contouring. This study explores the incorporation of deep learning-based auto-contouring into various treatment planning systems to enhance precision and accessibility. **Methods:** The study utilized the Ray Station planning system 12A (Ray Search Laboratories, Sweden), renowned for its GPU-powered algorithm capable of generating AI-generated contours through deep learning segmentation. The research encompassed a group of hospitals distributed across various locations in India. **Results:** The OAR contours generated through deep learning segmentation in Ray Station were seamlessly transferred to both Monaco and Eclipse TPS via cloud connectivity. The average time required for any auto contour was less than two minutes and the maximum time it took to implement auto contour and exporting and start planning through other planning systems at any remote site is less than one hour. **Conclusion:** By Integrating, we could able to come down the contour time three days to one hour even for remotest areas where there is no contour expert available. This method not only translates to significant time savings to start planning and treatment but also ensure uniformity of contours across all our units. This consistency fosters enhanced quality in treatment planning, facilitates research endeavour, and ultimately contributes to improved patient care especially in developing countries where the budget for dedicated treatment planning systems are not adequate.

Keywords: AI, Auto Contours, Ray Station, Treatment Planning Systems (TPS), Deep Learning Segmentation, Cloud Connectivity.

INTRODUCTION

In India, one out of every nine individuals is expected to develop cancer during their lifetime. In 2022, the estimated number of cancer cases in India was 1,461,427, with a crude rate of 100.4 per 100,000 people. By 2025, cancer cases are anticipated to increase by 12.8% compared to 2020 [1]. More than 50% of cancer patients require radiotherapy as part of their treatment, and it is commonly used for prevalent types like breast, cervical, Colo-rectal, and lung cancers. However, access to radiotherapy remains limited, especially in low- and middle-income countries. According to IAEA data, around one-third of countries still lack access to radiotherapy, with 28 of these nations located in Africa. Many of these countries could greatly benefit from improved access to radiotherapy services. The key lies in adapting radiation oncology solutions to local conditions, supported by proper safety infrastructure. The WHO/IAEA publication [2] is intended for medical physicists, biomedical and clinical engineers, radiation oncologists, oncologists and anyone else with responsibility for manufacturing, planning, selecting, procuring, regulating, installing or using radiotherapy equipment. In radiation oncology planning is a vital part. For best planning contour is the soul. Contour of structures required high skilled man power (radiation oncologists) and time and proper planning systems with contour application. In developing countries, there are several challenges in delivery of quality radiation therapy, which include lack of adequate infrastructure and availability of adequate radiation professionals [3]. Despite these challenges, there are ongoing efforts geared toward improvement of radiation therapy.

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Our Institute and this task is one of that. With minimal planning systems and licenses, and by integrating with multiple existing systems while leveraging cloud-based virtual connectivity across locations, we have significantly improved efficiency in delivering high-quality contours across all our units. This innovation has reduced the time required for planning radiation oncology patients from several days to just a few hours. This advancement has been particularly beneficial in locations where there is a shortage of radiation oncologists and a lack of specialized expertise. Additionally, it has enabled us to maintain uniform protocols across all our units in different regions of India, ensuring consistency in treatment planning. Moreover, the standardized contours facilitate better tracking of patient outcomes post-treatment and provide a robust database for future research, ultimately contributing to improved patient care and advancements in radiation oncology. Manual contouring is associated with several challenges. Firstly, contouring is time-consuming; previous studies have reported that each patient may take several hours of clinician's time to delineate all OARs [4]. This could affect the treatment outcomes due to the delay in the start of the treatment. Secondly, manual contouring is subjective, as a radiation oncologist or dosimerist performs the delineation of OARs based on their previous experience and knowledge, which is a source of inconsistency. Several studies have shown high inter-operator variability in contouring, which may lead to inappropriately treating normal areas [5-6]. Accordingly, there is great demand in the field of RT for auto segmentation to standardize and enhance the quality of contours and make the process more efficient by streamlining the clinical workflow and reducing staff workload. In the last decade, computing in RT has helped address manual contouring challenges through the development of auto segmentation algorithms. Deep learning based auto-segmentation entered the field of RT after it was demonstrated that the convolutional neural networks (CNNs) could considerably improve image classification and recognition task predictions [7]. Since then, there have been a considerable number of studies published on the performance of deep-learning auto-segmentation for delineation of OARs, which demonstrate that it is outperforming traditional auto-segmentation methods. The most popular method for medical images delineation is the U-net architecture, which was established by Ronneberger et al. For MR-only RT treatment planning, instead of traditional CT, the needed electron density information is obtained through a synthetic-CT (sCT) produced from the MRI scan [8]. This study explores the Integrating AI-Generated Auto Contours via Ray Station V13.1 (Ray search Laboratories, Sweden) Deep Learning Segmentation into Diverse Treatment Planning Systems at various locations for all kinds of diagnosis.

METHODS

The study utilized the Ray Station planning system 12A (Ray Search Laboratories, Sweden), renowned for its GPU-powered algorithm capable of generating AI-generated contours through deep learning segmentation. The research encompassed a group of hospitals comprising five facilities equipped with Eclipse V16.1 (Varian Medical Systems, USA) and Monaco V6.1.2 (Elekta Medical Systems, Crawley, UK) treatment planning systems, distributed across various locations in India. Additionally, a central planning system utilizing Ray Station V13.1 (Ray search Laboratories, Sweden) was deployed at a distinct location. Simulated CT images for radiation oncology (RO) planning were transmitted to the cloud from Local Radiation Oncology centers and subsequently imported into the Ray Station platform which is located in the Cloud [Figure-1]. Auto contours were then generated on these CT images and exported back to the respective TPS via cloud connectivity. Importantly, this process enabled the seamless transfer of auto contoured images from the cloud to both Eclipse and Monaco contour stations, ensuring consistency and interoperability across diverse treatment planning environments. The study analyzed over 1000 cases across these five units, encompassing various diagnoses, to assess the efficacy of this approach.

Connecting other TPS and OIS through cloud

The research encompassed a group of hospitals comprising five facilities equipped with Eclipse V16.1 (Varian Medical Systems, USA) and Monaco V6.1.2 (Elekta Medical Systems, Crawley, UK) treatment planning systems, distributed across various locations in India. Additionally, a central planning system utilizing Ray Station TPS was deployed at a distinct location. Raystation is integrated with various Oncology information systems (Mosaiq in three locations, Crystal in one location, ARIA in one location). All these are integrated in the Azure cloud system.

Architecture of the this program

Microsoft Azure provides the foundation for a robust and secure environment [Figure 2]. Application and data servers are isolated, communicating only through private IP addresses within the Azure network. Secure, encrypted site-to-site (IPsec) tunnels connect hospitals to the Azure cloud. Additionally, high-performance Nvidia resources (GPUs) on Microsoft Azure ensure smooth operation of the Ray-station TPS. Radiation Oncology department CT Simulated images are securely transferred directly from the CT scanners at respective distributed network sites to the Ray-station TPS setuplocated in the cloud. The transfer leverages DICOM protocol over dedicated site-to-site IPsec tunnels within Microsoft Azure. Once transferred, the images are stored securely in Azure cloud storage. The Ray-station TPS system then processes the images on Microsoft Azure, allowing the Physics team to load them for auto contouring and treatment planning.

Image quality specifications

CT Image data sets of 1000 cases with clinical simulation protocols were selected from a retrospective clinical cohort from the past 2 years used to build auto-segmentation models. All the cases were chosen to enable careful quality assurance of the contours. CT scans for various sites were acquired using the following acquisition parameters for five institutes having different CT and TPS facilities. The details (KVp, FOV, Plane resolution, slice thickness, scan type) of the each CT image acquisition and each unit CT, TPS and OIS etc detils were given in the below Tables 1 and Table-2.

Deep learning Segmentation

Deep Learning auto Segmentation can be used to rapidly delineate organ structures in CT, CBCT and MR image sets, depending on what data they have been trained on. In this algorithm each voxel in the image is classified as belonging either to background or a specific structure. To learn how to classify voxels, the algorithm is trained using non-linear optimization methods on a large number of previously segmented data sets. The result from the training is called a network and can be looked upon as a non-linear function taking a three-dimensional image as input and producing a labeled (segmented) image as output [9]. A commercially available treatment planning system (Ray Station V13.1, RaySearch Laboratories AB, Stockholm, Sweden)) using 3D U-net (Çiçek *et al.,* 2016) was used to train all the autosegmentation models [10-12].

Deep learning statemented auto contours for clinic- quality assurance (QA)

All the auto contoured images were reviewed in-terms of Image quality, contour accuracy. OAR labeling was reviewed and found it is in consistent with AAPM TG-263 [13]. The clinical contours were reviewed in all cases and edited in few cases where necessary .For MRI Fusion, the the original clinical contours were copied and then edited based on the rigidly registered T1-weighted MRI images and then reviewed and edited as necessary based on the MRI anatomy [14-16].

RESULTS

The OAR contours generated through deep learning segmentation in Ray Station were seamlessly transferred to both Monaco and Eclipse TPS via cloud connectivity. Analysis revealed that most of the contours were deemed perfect and utilized in clinical planning. Our Institute successfully establishes RayStation on Secure Microsoft Azure for Central Radiotherapy Planning in Distributed Cancer Care Network. Our organization is pioneering a new era of distributed cancer care with a cutting-edge cloud-based solution.

Table 1. Details of CT in five institutes

Institute	CT Scan	TPS	OIS
Bhopal	Siemens Shanghai Medical Equipment Ltd : SOMATOM go. Now	Monaco 6.1.2.0	Mosaiq 3.1.3.2
Nandyala	Siemens Healthcare Pvt Ltd, India: Somatom go. Now	Monaco 6.1.2.0	Mosaiq 3.1.3.2
Imphal	WIPRO GE : Revolution Maxima..	Raystation v13.1.0.144	Krystal 4.0.0
Jalna	Wipro GE : Optima CT 520	Monaco and Oncentra 5.11.03 and 4.6.0.16	Mosaiq 2.4.1.1
Kolakata	Wipro GE : OPTIMA CT 520	Eclipse 6.1.2.0	ARIA 6.1.2.0

Table 2. CT Parameters for five units (Range of values)

Site	KVP	mAs	FOV(cm)	Resolution	Slice Thickness (mm)	Scan type (Helical/ Axial)
Brain	120-130	140-279	35x 35 to 50x50	512x512	1.0 to 3.0	Helical
Head and Neck	120-130	80-277	50x50	512x512	2 to 3	Helical
Breast	120-130	80-349	38.8x38.8 to 70x70	512x512	2 to 3	Helical
Thorax (Lung and liver)	120-130	71-349	38.8x38.8 to 50x50	512x512	2 to 3	Helical
Pelvis	120-130	106-300	45x45 to 70x70	512x512	2 to 3	Helical

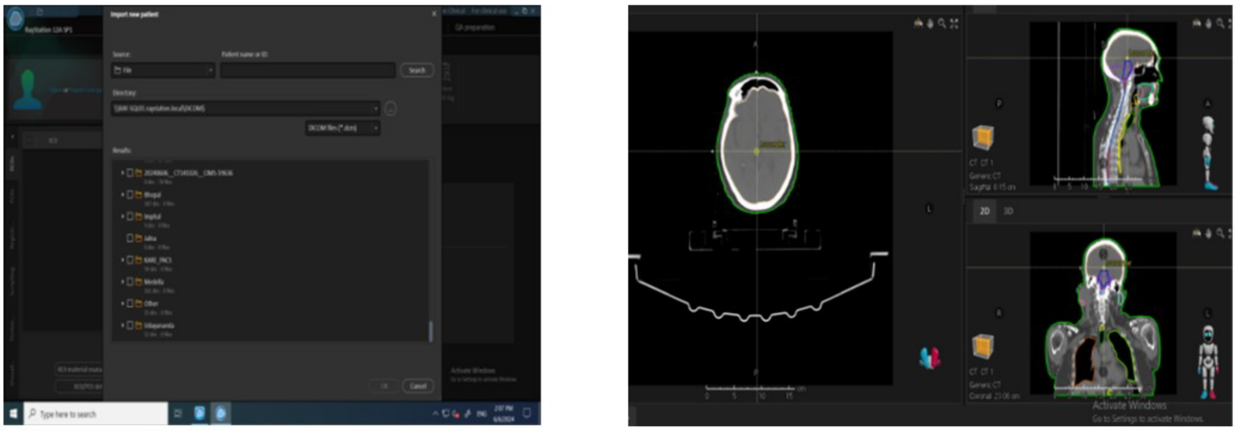

Figure 1 A. Importing of CT images from the dedicated folder of a given Institute to Ray station TPS in cloud. B. Auto contour through deep segmentation technique.

This innovative network leverages the power of Microsoft Azure, a secure and scalable cloud platform, to host the industry-leading RayStation (from RaySearch) treatment planning system. Managed by Central Physics and IT team DevOps team, this system empowers our Physics team to deliver seamless radiation therapy planning support to hospitals across the network, 24/7.

1. Enhanced Security and Performance on Microsoft Azure: Microsoft Azure provides the foundation for a robust and secure environment. Application and data servers are isolated, communicating only through private IP addresses within the Azure network. Secure, encrypted site-to-site (IPsec) tunnels connect hospitals to the Azure cloud. Additionally, high-performance Nvidia resources (GPUs) on Microsoft Azure ensure smooth operation of the Ray-station TPS.
2. Automated Workflows for Network-Wide Efficiency: Our IT team has automated the entire system within Microsoft Azure, allowing the Physics team to power on and off resources on-demand with a simple process. This enables them to support Auto Contour and Remote plan creation from the central Azure cloud resources, maximizing efficiency for the entire distributed network.
3. Restricted Access Ensures Secure Communication: When the Physics team connects to the Azure resources, they utilize our Institute VPN with restricted access protocols within Microsoft Azure. This ensures only authorized users and IP addresses can connect, guaranteeing secure communication between all sites and the cloud-hosted Ray-station system.
4. Seamless Image Transfer and Processing: RT planning images are securely transferred directly from the CT scanners at respective distributed network sites to the TPS setup. The transfer leverages DICOM protocol over dedicated site-to-site IPsec tunnels within Microsoft Azure. Once transferred, the images are stored securely in Azure cloud storage. The Ray-station TPS system then processes the images on Microsoft Azure, allowing the Physics team to load them for contouring and treatment planning [Figure-3].
5. Integrated Workflow for Centralized Treatment Delivery: Following Auto contour and treatment planning, the RT plan and DICOM images are transferred back to the hospital's OIS (Oncology Information System) for the next steps. This includes utilizing the "Patient Positioning System" and "Control Console" to manage the radiation workflow efficiently. By leveraging Microsoft Azure's secure cloud infrastructure and the power of Ray-station, our Institute has established a centralized, efficient radiation therapy planning system for its distributed cancer care network. This empowers our Medical Physics team to deliver uniform auto contours and state-of-the-art radiotherapy plans to patients across various hospitals, regardless of location.

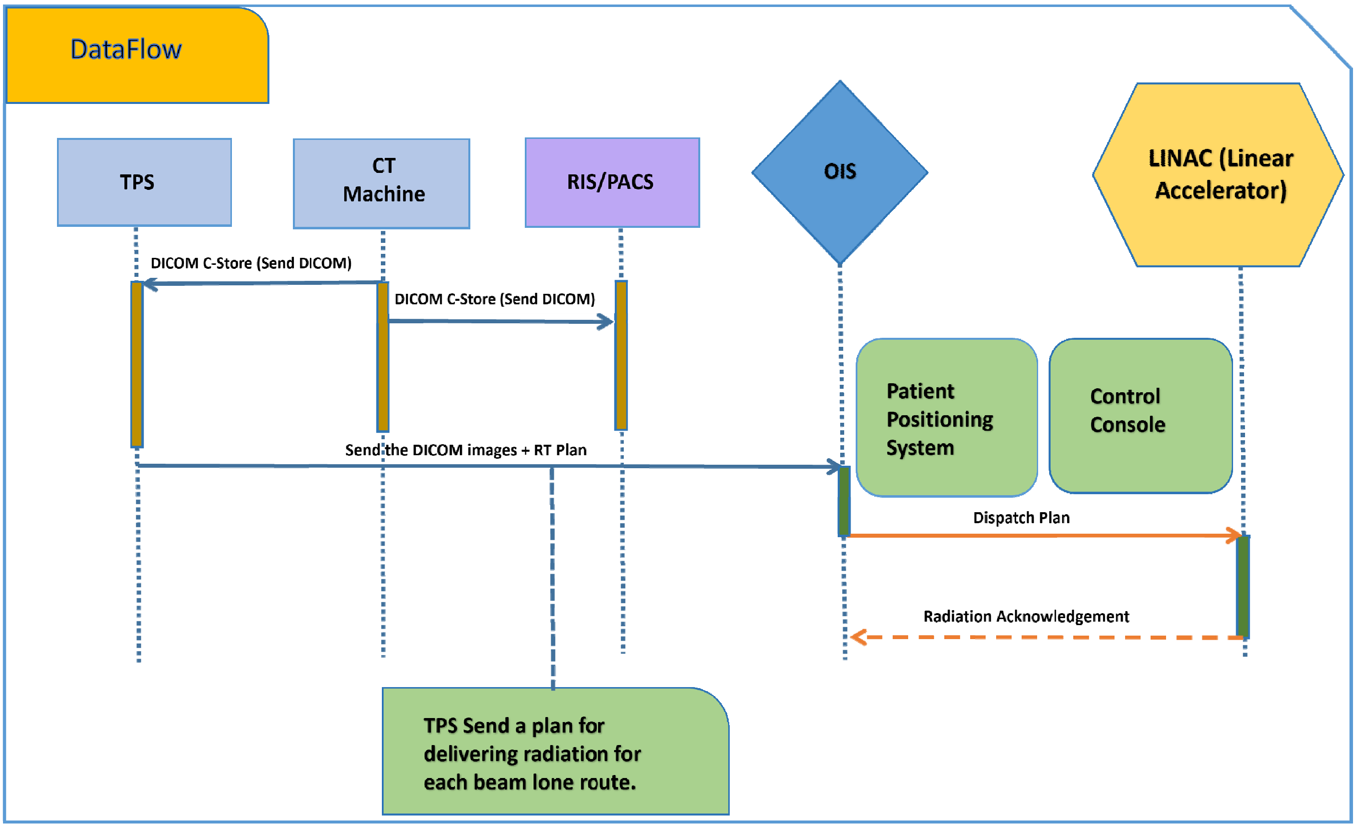

Figure 2. Integrating AI Generated Auto Contours via Ray Stations Deep Learning Segmentation into Diverse Treatment Planning Systems - Architecture

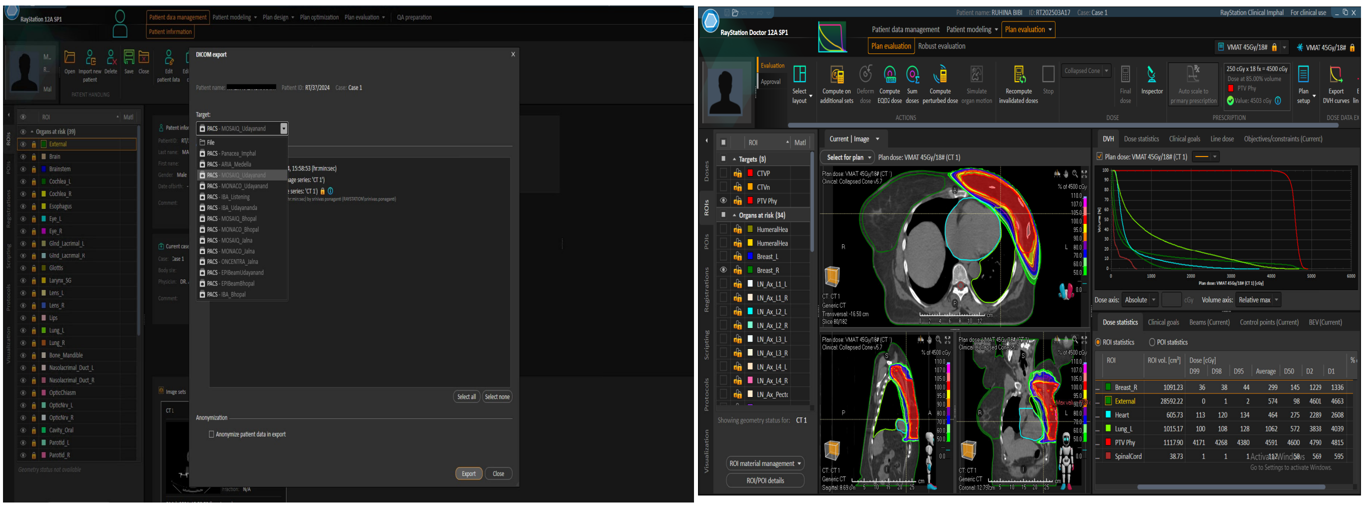

Figure 3. DICOM Export of Auto contours and RT plans to the Remote location hospital TPS OIS or QA device using dedicated filter

DISCUSSION

In this study, we developed a solution that enables both developed and developing countries to access the best treatments through AI and cloud technology. Using deep learning, we created an auto-contouring system that generates contours in the cloud, making them accessible to all centers, regardless of their contouring systems, treatment planning systems (TPS), Oncology Information Systems (OIS), or delivery systems. Contouring is a critical component of cancer treatment. However, outside of developed countries, it can be challenging to find skilled experts or trained professionals in radiation oncology, particularly for contouring. Drawing key contours manually typically takes 2 to 3 days, and the accuracy of these contours can sometimes be questionable.

To address this and and for better treatments, the goal of implementing auto-contouring system for radiation oncology centers using various planning systems and contouring stations at various locations was successfully achieved through cloud-based infrastructure and advanced IT network configurations. The AI-generated auto-contours, produced through deep segmentation, are highly accurate and can be generated in just 2 minutes. These contours can be fully integrated into treatment plans within an hour, including necessary adjustments such as table insertion and isocenter positioning. In contrast, manual contouring takes 2 to 3 days, meaning that treatment planning cannot begin until after this time. This demonstrates the significant advantage of using this AI-driven technique. Additionally, the system can be deployed in remote areas where expert personnel are unavailable for manual contouring, providing valuable support for undeserved regions.

Conclusion

By Integrating AI-Generated Auto Contours via Ray Station's Deep Learning Segmentation into Diverse Treatment Planning Systems, we could able to come down the contour time three days to one hour even for remotest areas where there is no contour expert available. This method not only translate to significant time savings to start planning and treatment but also ensure uniformity of contours across all our units. This consistency fosters enhanced quality in treatment planning, facilitates research endeavour, and ultimately contributes to improved patient care especially in developing countries where the budget for dedicated treatment planning systems are not adequate.

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