

SCARF: Auto-Segmentation Clinical Acceptability & Reproducibility Framework for Benchmarking Essential Radiation Therapy Targets in Head and Neck Cancer

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Highlights:

- Our study highlights the significance of both quantitative and qualitative controls for benchmarking new auto-segmentation systems effectively, promoting a more robust evaluation process of AI tools.
- We address the lack of baseline models for medical image segmentation benchmarking by presenting SCARF, a comprehensive and reproducible six-stage framework, which serves as a valuable resource for advancing auto-segmentation research and contributing to the foundation of AI tools in radiation therapy planning.
- SCARF enables benchmarking of 11 open-source convolutional neural networks (CNN) against 19 essential organs-at-risk (OARs) for radiation therapy in head and neck cancer, fostering transparency and facilitating external validation.
- To accurately assess the performance of auto-segmentation models, we introduce a clinical assessment toolkit based on the open-source QUANNOTATE platform, further promoting the use of external validation tools and expert assessment.
- Our study emphasises the importance of clinical acceptability testing and advocates its integration into developing validated AI tools for radiation therapy planning and beyond, bridging the gap between AI research and clinical practice.

Abstract

Background and Purpose: Auto-segmentation of organs at risk (OAR) in cancer patients is essential for enhancing radiotherapy planning efficacy and reducing inter-observer variability. Deep learning auto-segmentation models have shown promise, but their lack of transparency and reproducibility hinders their generalizability and clinical acceptability, limiting their use in clinical settings. **Materials and Methods:** This study introduces SCARF (auto-Segmentation Clinical Acceptability & Reproducibility Framework), a comprehensive six-stage reproducible framework designed to benchmark open-source convolutional neural networks for auto-segmentation of 19 essential OARs in head and neck cancer (HNC). **Results:** SCARF offers an easily implementable framework for designing and reproducibly benchmarking auto-segmentation tools, along with thorough expert assessment capabilities. Expert assessment labelled 16/19 AI-generated OAR categories as acceptable with minor revisions. Boundary

distance metrics, such as 95th Percentile Hausdorff Distance (95HD), were found to be 2x more correlated to Mean Acceptability Rating (MAR) than volumetric overlap metrics (DICE).

Conclusions: The introduction of SCARF, our auto-Segmentation Clinical Acceptability & Reproducibility Framework, represents a significant step forward in systematically assessing the performance of AI models for auto-segmentation in radiation therapy planning. By providing a comprehensive and reproducible framework, SCARF facilitates benchmarking and expert assessment of AI-driven auto-segmentation tools, addressing the need for transparency and reproducibility in this domain. The robust foundation laid by SCARF enables the progression towards the creation of usable AI tools in the field of radiation therapy. Through its emphasis on clinical acceptability and expert assessment, SCARF fosters the integration of AI models into clinical environments, paving the way for more randomised clinical trials to evaluate their real-world impact.

Introduction

In recent years, deep-learning based architectures have dominated the field of automated segmentation of organs at risk (OAR) in the head and neck region [1–13]. However, the lack of transparency in publishing auto-segmentation methods, particularly regarding the release of code and data used for model training, has been a persistent issue [14]. While some studies have demonstrated the potential of deep learning-based auto-segmentation (DLAS) methods for optimising clinical contouring workflows, there remains a gap in understanding whether predicted contours gain clinician approval [8,12]. Some studies have placed an emphasis on clinical assessment of contours produced by these auto segmentation models without providing insight into whether the predicted contours actually receive clinician approval. Studies publishing auto-segmentation solutions across a wide range of medical image segmentation tasks have a tendency to disregard both reproducibility of their methods and the subsequent evaluation of their methods in a clinical setting to validate their findings. There have been a large number of guidelines and other papers describing requirements for publishing sufficient information to assess model performance [15,16]. However, these guidelines rarely provide a ready-made infrastructure or systematic code-base to realise the intent of the guidelines.

To address these challenges and promote both reproducibility and clinical evaluation of segmentation methods, we developed the auto-Segmentation Clinical Acceptability & Reproducibility Framework (SCARF). This six-step framework empowers researchers and clinicians to build and robustly evaluate open-source networks for various segmentation tasks

related to radiation therapy and beyond. SCARF's steps can be easily adapted to improve existing open-source segmentation repositories and checklists focused on leveraging artificial intelligence modelling for clinical applications [15,17].

Emphasising transparency through reproducibility of data, code, and tools, SCARF provides an intuitive framework for packaging research outputs, ensuring transparency, reproducibility, and reusability of medical imaging models. Moreover, it offers a collection of published auto-segmentation models and their corresponding training and evaluation protocols, facilitating robust benchmarking of baseline performance for medical segmentation tasks. To address the critical aspect of clinical acceptability, SCARF leverages the open-source QUANNOTATE platform [18], enabling internal and external evaluation of segmentation methods by clinical experts.

We demonstrate the application of SCARF in the development of deep learning models for the delineation of 19 essential OARs in head and neck cancer radiation therapy. In summary, SCARF, with its compendium of open-source and reproducible auto-segmentation models, curated datasets, and clinical acceptability testing toolkit, lays a strong foundation for the advancement and benchmarking of the next generation of deep learning models in medical imaging segmentation.

Materials and Methods

Dataset Curation

Radiological and clinical data extracted from institutional databases or public repositories, such as The Cancer Imaging Archive (TCIA) [19], often requires a high level of curation to harmonise the data and make them ready for deep learning. In this study, we used a large institutional imaging dataset of 3211 HNC patients whose radiological and clinical data were available (<https://doi.org/10.7937/J47W-NM11>) [20]. A UHN institutional review board approved our study (REB 17-5871); we performed all experiments in accordance with relevant guidelines and ethical regulations of Princess Margaret Cancer Centre (PM). The associated clinical data have been collected prospectively as part of the PM Anthology of Outcomes [21]. We used Med-ImageTools [22] to collect the meta-data and curate the radiation therapy structure files (RT-STRUCT).

Curation of Auto-Segmentation Models

We have identified a set of auto-segmentation models that have been published between 2016 and 2020 for which sufficient data, code and documentation have been released to allow re-implementation. A literature search was conducted from January 2016 to April 2020 to find medical image segmentation studies using deep learning-based modelling approaches. We reviewed 75 studies with a medical image segmentation theme in the conducted literary search to augment networks we could test during our analysis. We refactored all tested models into a Pytorch Lightning framework [23] to increase readability, reusability and shareability of the re-implementation code.

Training of Auto-Segmentation Models

Models were trained using a combined loss scheme to address the heavy pixel-wise class imbalance present within our dataset between the individual classes of OARs. For each experiment we used the same 80%/10%/10% split, corresponding to 479, 44, and 59 scans for training, tuning, and testing, respectively. Each model was trained on 4 NVIDIA Tesla P100 GPUs for 3 days or until convergence. Early stopping was implemented if no significant change (0.1 decrease in loss magnitude) was made in tuning loss minimization after 50 epochs. More information regarding specifics in configuring our training pipeline can be found in Appendix A.

Performance Evaluation

The performance of each model was estimated by averaging volumetric overlap indices (Dice similarity coefficient - DICE, jaccard index) with boundary distance metric (95th% Hausdorff Distance - 95HD) on the independent testing set of patients (**Supplementary Figure 1**) [24]. Taking this into consideration, after fine tuning the winning model in a second round of training, four other quantitative performance metrics were calculated. Additional metrics calculated include boundary metrics (Surface Distance [SD], Added path length [APL]), and false negative metrics (False Negative Volume and False Negative Length) [25]. Multiple metrics are essential during validation of any segmentation task as overlap-based metrics such as DICE do not take the correctness (or complexity) of an object's boundaries into account. Additionally, properties of the target structure need to be considered when evaluating the scores for each OAR. For example, a small pixel deviation in a low volume OAR like the chiasm, can have a substantial effect on DICE and other volumetric based overlap metrics that are calculated for it [26]. More information regarding model finetuning and selection can be found in Appendix A.

Clinical Evaluation

We employed an enhanced QUANNOTATE interface to facilitate the review and evaluation of clinical acceptability by multiple physician observers. They rated AI-generated and Ground Truth OAR contour pairs while remaining blinded to the source of origin for each contour. (Supplementary Figure 2) [24]. Mean Acceptability Rating (MAR) was calculated for each contour examined by averaging ratings across all observers. After inference, segmentation network performance was assessed by calculating six different performance metrics listed in **Performance Evaluation**. These metrics were extracted for each OAR contour. To determine the weight each metric should have when assessing acceptability, we computed the correlation between each performance metric and MAR using Pearson to identify which metrics best align with clinical acceptability [27–29]. Overlap metrics were considered ‘more clinically acceptable’ if they showed significantly positive correlation with MAR, while boundary distance metrics were considered ‘more clinically acceptable’ if they showed significantly negative correlation with MAR. Suggestions will be made as to how these metrics can be used to optimise a network’s segmentations for clinical acceptability.

Statistical Analysis

To evaluate the statistical power of our study, a continuous endpoint, two independent sample study power analysis was conducted for each OAR group. The MAR from each of the 4 observers can be averaged and separated into two distinct study groups for each OAR category. (Group A: MAR of Ground-Truth contours; Group B: MAR of AI-Generated contours). Because no analysis has been conducted to this effect for each OAR category previously, the MAR and standard deviation for each OAR category were taken from the final calculated MAR after clinical acceptability testing was completed. Post-hoc power (PHP) analysis was also conducted for each OAR category. We will use these preliminary acceptability testing results to further refine sample size in future clinical acceptability testing experiments.

Generalizability Assessment

Our model was trained using RADCURE as the primary dataset. Due to the inevitable biases intrinsic to demographics of patients treated at our centre, we tested whether our model performed accurately on data collected at external institutions with varying patient populations. A model’s generalizability, in this context, is the ability of a model to perform as trained when applied to external data collected at different institutions. To assess model generalizability, seven publically available datasets were collected and curated (Supplementary Table 1).

Data Availability

Raw imaging data and corresponding contours are available on The Cancer Imaging Archive (TCIA) [19] (Supplementary Table 1). Processed external datasets and predictions using our model on those datasets are publicly available via the ptl-oar-segmentation GitHub repository (<https://github.com/bhkclab/ptl-oar-segmentation>).

Code Availability

The computer code for the reimplementation and evaluation of all the auto-segmentation models reimplemented in this study is available via <https://github.com/bhkclab/ptl-oar-segmentation>. The code for the QUANNOTATE clinical acceptability testing interface is available via the Quannotate GitHub repository (<https://github.com/bhkclab/quannotate>).

Model Availability

The weights for each trained auto segmentation model trained, and processed versions of each external dataset, were saved and made available on the project's github page. All auto segmentation models have been uploaded to mhub.ai to maximise reusability.

Research Reproducibility

Tutorials were generated for easy re-implementation using [Google Collab](#). Users can use these collaborative notebooks provided to get started with easy re-implementation. Users can also clone the github repositories, set-up a local anaconda environment based on the one provided, set their local variables and train each network using internal resources. Templates have also been provided to integrate their own networks and training protocols if desired.

Results

Auto-Segmentation Clinical Acceptability & Reproducibility Framework (SCARF)

To improve the development of auto-segmentation models and their potential clinical impact, we propose a framework composed of six main steps: (1) Dataset Curation, (2) Model Selection, (3) Model Training, (4) Quantitative Performance Evaluation, (5) Clinical Assessment, and (6) Generalizability Assessment. (Figure 1). Successful implementation of this new framework requires a reproducible way to extract and curate medical imaging data and metadata. Furthermore, providing a reproducible architecture for selection, training and evaluation of open-

source models can help the community curate “baseline” data for a wide range of segmentation tasks. Finally, placing a strong emphasis on clinical acceptance, and providing open-source tools to conduct these assessments will help optimise these systems for increased clinical benefit, which translates to greater adoption and use of these models by clinicians at large. SCARF’s goal is to build a community resource that allows collection, standardisation, testing and validation of various segmentation methods made available by the open-source community with the intent of establishing baseline quantitative and qualitative data for each region of interest being segmented (**Figure 1**).

Dataset Curation

SCARF provides an open-source methodology to rapid dataset curation, model benchmarking and clinical performance assessment for radiation oncology specific segmentation tasks. For this analysis, we selected 19 OARs that were consistently delineated in a subset of 582 head and neck cancer patients in RADCURE (**Supplementary Figure 3**). Seven external datasets, spanning a total of 587 patients [12,55–59], were also collected and curated to assess the generalizability of the best auto-segmentation models with variability of overlapping OARs (**Supplementary Tables 1 and 2**).

Model Curation & Training

SCARF’s codebase enables rapid integration and training of open-source models coded in Pytorch to benchmark these networks on your segmentation task. We selected 11 open-source CNNs to train on the segmentation of the 19 OARs of interest [7,30–39] (**Supplementary Figure 4, Supplementary Table 3**).

Performance Evaluation

SCARF enables the comparison and performance validation using multiple metrics which are necessary for accurately representing model performance. For initial performance evaluation, we use volumetric overlap metrics (DICE) and boundary distance metrics, which assess the error at the boundary of two overlapping contours (95HD, SD) for the combined set of OARs being segmented [5,10,13]. When analysing the mean performance metrics of all OARs for each open source model trained, the top three segmentation models were UNET variants. WOLNET (a simple implementation of the standard 3D-UNET) [40,41] performed best among the 11 models and achieved the highest average DICE (0.765 ± 0.10) (**Figure 2A**) and lowest average HD (2.63 ± 2.61) (**Figure 2B**). Altered 3D versions of UNet3+DEEPSUP [34,42] (DICE

0.74±0.10; HD 2.98±2.63) and UNet++ [35,42] (DICE 0.73±0.10; HD 3.10±2.83) were the second and third top-performing segmentation models, respectively (**Supplementary Figure 5**).

Performance Evaluation of the Best Model After Fine Tuning

SCARF allows for optimisation and versioning of networks, which make tracking improvements made by hyperparameter or architecture changes easy. The training scheme of the best performing open source network, WOLNET, was further tuned resulting in a final average test DICE of (0.77± 0.09) and a 95HD of (3.42± 4.05) across all OAR(s). (**Supplementary Figure 6 A-C**).

Clinical Evaluation

In addition to quantitative benchmarking of segmentation methods, SCARF implements an open-source web-based toolkit for rating clinical acceptability of contours generated for each region of interest being automatically delineated. In our experiment, four experienced oncologists from our centre used the QUANNOTATE interface to complete the blinded questionnaire defined above for the “Ground Truth” (human) and “AI-Generated” sets of contours for each OAR. When comparing MAR for all OARs, 78% of Ground-Truth contours are considered acceptable (**Figure 3A**) compared with 52% for AI-generated contours (**Figure 3B**). When analysing individual OAR categories, Ground-Truth contours were considered more acceptable than AI-generated contours for 15 out of the 19 OARs assessed. Experts rated 16/19 AI-Generated OARs as acceptable for planning with minor edits ($3 < \text{MAR} < 3.5$) (**Table 1**). Only three OAR categories (brainstem, larynx, and the right optic nerve) were shown to be rated more clinically acceptable than their paired deep learning contour with sufficient post-hoc power (PHP > 80%). Ten OAR categories had no significant differences in MAR (PHP < 20%) indicating that the WOLNET network can currently delineate these OARs with human level accuracy. The MAR between the remaining six OAR categories ($20\% < \text{PHP} < 80\%$) may be significantly different if more samples are analysed for each group (**Table 1**). Mean acceptability rating correlation with 6 common segmentation metrics was extracted. Mean acceptability rating showed significant negative correlation with boundary distance metrics like 95HD and Surface distances. (~ -0.26 for 95HD and ~ -0.30 for Surface Distance). A less significant positive correlation with DICE was also observed (~ 0.14) (**Appendix B, Supplementary Figure 7**).

Generalizability Assessment

To assess the generalizability of the WOLNET model, we used 7 external datasets that have been generated in different institutions (Figure 1, Supplementary Table 1). While external datasets are valuable to assess generalizability of AI methods, these datasets released by external centres had variable labels of OARs that overlapped with our analysis (Supplementary Table 2). In addition to this, the quality of the "Ground-Truth" labels for each dataset are only as good as the observer generating the labels, and therefore it is important to note that there may exist variability within contouring protocols for multiple OARs generated at these independent centres. We found extensive variability of ground truth information extracted from each external dataset and only a subset of OARs segmented in this study overlapped with any given dataset (Supplementary Table 2). One dataset Radiomics-HN1 (RHN1) had the most overlapping OAR categories with our RADCURE dataset (17 out of 19 OARs successfully overlapped). TCIA-HNSCC (TCHN) had the least overlapping categories (5 out of 19 OARs). Results for each external dataset can be found in Appendix B (Supplementary Figure 8, Supplementary Tables 4 and 5) [5,20,43–52].

Discussion

In this study, we introduce SCARF, a six-step benchmarking framework for evaluating open-source AI models' performance and clinical acceptability in auto-segmentation of essential radiation therapy targets for head and neck cancer treatment. Our results show the majority of OARs generated by the best model tested required only minor edits for use in radiation therapy plans. SCARF proves to be a valuable framework for open-source resources' curation, model training, performance evaluation, and clinical acceptability testing, providing a protocol for recording baseline results for each OAR category's segmentation performance.

SCARF, with its focus on easy and reproducible benchmarking of auto-segmentation systems, can significantly improve the AI evidence pyramid in the context of radiation therapy planning. By providing open access to all data and methods used in the analysis, SCARF addresses some of the key challenges faced in the field of radiation therapy and AI integration. In the context of the AI evidence pyramid [16], SCARF can play a vital role in the external validation of AI models for auto-segmentation in radiation therapy as shown in the context of OAR segmentation for HNC. The availability of preprocessed datasets and open access to all relevant information ensures that AI models can be rigorously evaluated using different patient

populations and clinical scenarios. This process enhances the reliability and generalizability of AI models, moving them closer to the third step of the AI evidence pyramid.

Moreover, the transparency provided by SCARF enables better assessment and benchmarking of segmentation systems, which is crucial in moving towards the creation of usable AI tools (the fourth step of the pyramid) in radiation therapy planning. Researchers and clinicians can examine the methods and results of the study, enabling them to build upon the findings and implement the technology in clinical practice more confidently. Furthermore, SCARF's emphasis on clinical acceptability testing aligns with the notion of optimising networks not only for model performance but also for their practicality in a clinical environment. This focus is in line with the goal of increasing the number of randomised clinical trials (the penultimate step of the pyramid) to evaluate the true impact of AI-driven auto-segmentation systems in real-world radiation therapy scenarios. By ensuring that AI models are not only accurate but also meet the requirements of clinical experts, SCARF facilitates the integration of AI technology into routine clinical workflows and can be used as an introductory code base to facilitate compliance with the checklists governing proposing AI interventions for auto-segmentation in radiation therapy of head and neck cancer (Table 2) providing an allotted time savings of over 450 developer hours.

This study has several limitations. The open-source repositories used in the analysis were collected and trained up to April 2020, missing potential newer models and opportunities for further analysis. The primary focus was on proposing a reproducible training framework for auto-segmentation pipelines, not on quantitative superiority. The clinical assessment step involved only four radiation oncologists due to resource constraints, limiting statistical significance. Acceptability ratings showed significant differences in only three out of thirteen organ-at-risk categories, suggesting the need for further analysis with more clinicians. The Quannotate clinical testing interface provided valuable insights but may benefit from exploring other assessment methods. The models trained were restricted to datasets with complete ground truth labels, limiting their usability with datasets containing partial labels. Future work should address this limitation and explore improvement opportunities using SCARF as a benchmark for effectiveness.

Conclusion

In conclusion, SCARF, our open-source and reproducibility framework for auto-segmentation in radiation therapy planning, significantly enhances the AI evidence pyramid in this medical

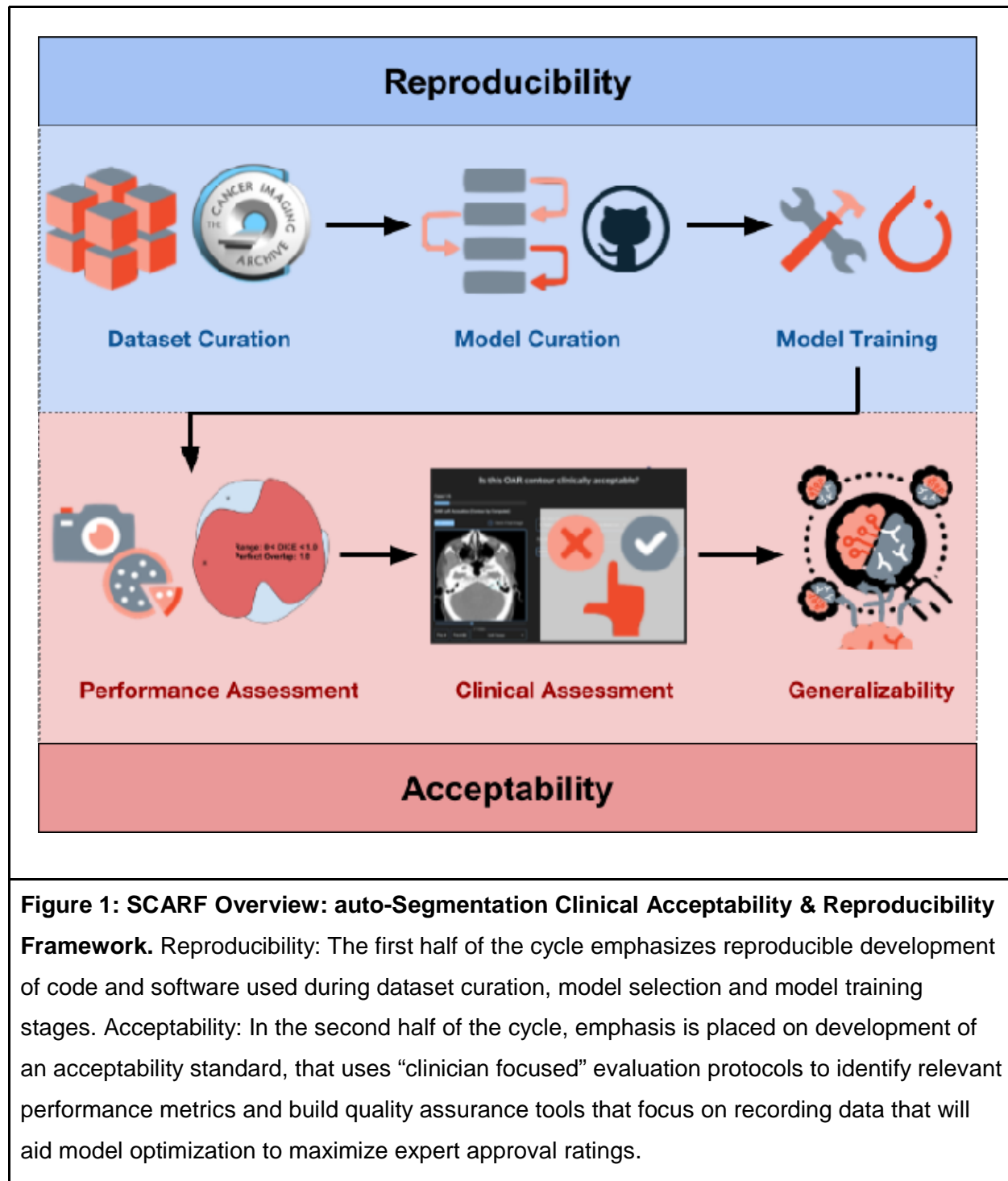
domain. By promoting transparency, facilitating external validation, and emphasising clinical acceptability, SCARF enables robust validation studies by multidisciplinary teams, bridging the gap between AI research and clinical practice. This advancement can lead to improved standards of care for radiation therapy patients and open up new avenues for research and advancements in the field. Our study also highlights the importance of incorporating both quantitative and qualitative controls in benchmarking auto-segmentation systems. With SCARF, we provide a comprehensive six-stage framework that enables benchmarking state-of-the-art convolutional neural networks against essential organs-at-risk in head and neck cancer. The availability of SCARF and the clinical assessment toolkit fosters transparency, reproducibility, and acceptance of auto-segmentation systems in clinical practice, accelerating the adoption of reliable and efficient models in radiation therapy planning and beyond.

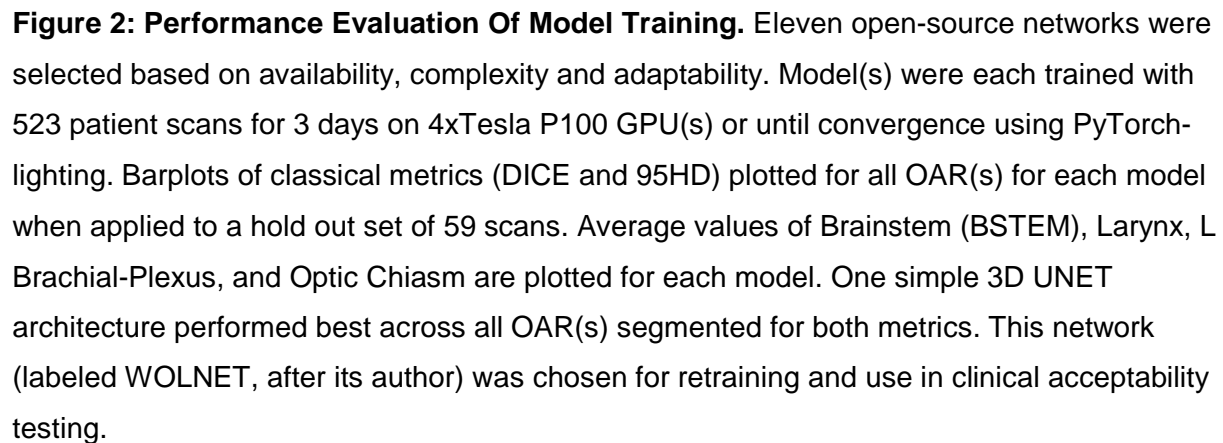
References

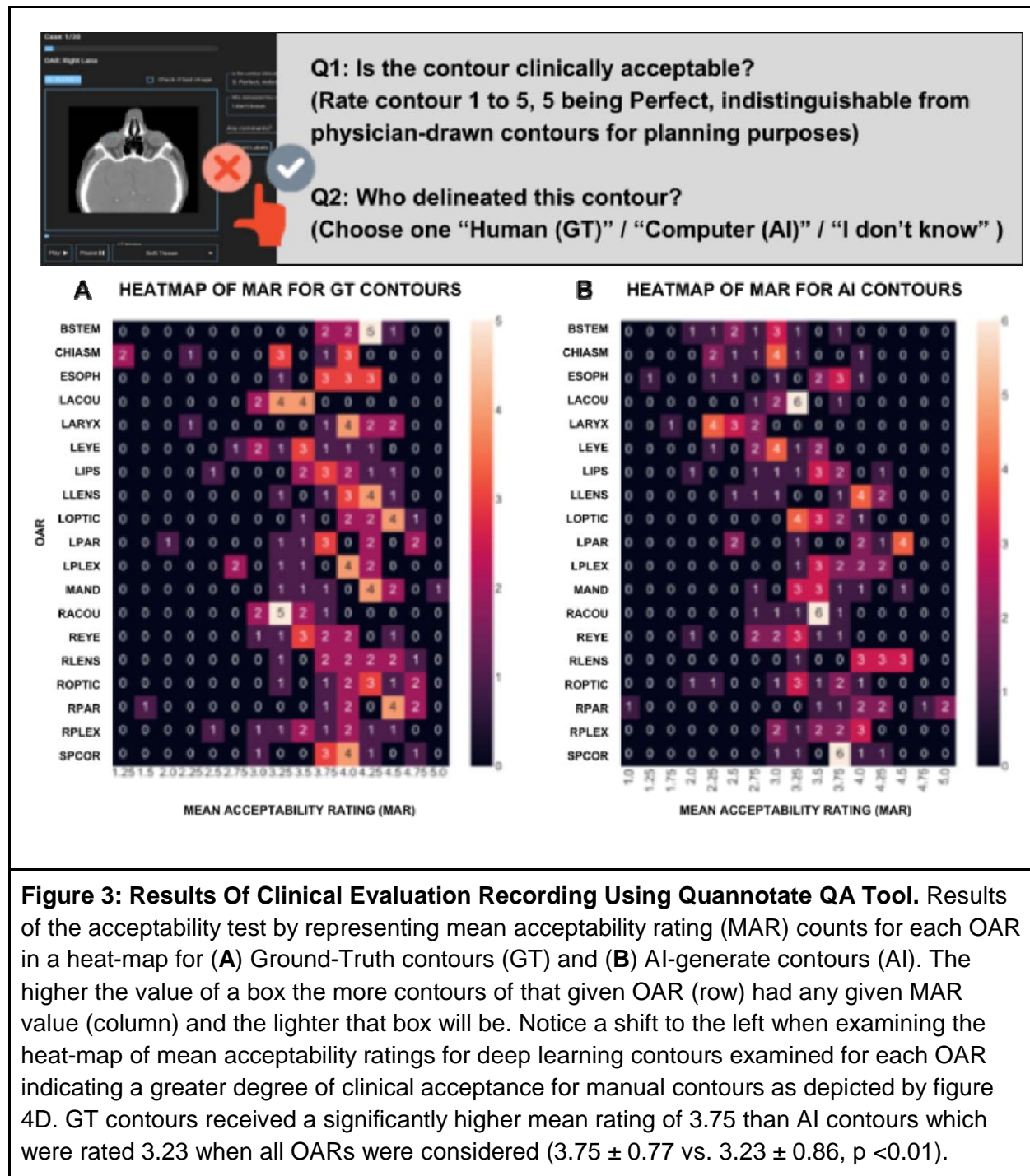
- [1] Fritscher K, Raudaschl P, Zaffino P, Spadea MF, Sharp GC, Schubert R. Deep Neural Networks for Fast Segmentation of 3D Medical Images. Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016, Springer International Publishing; 2016, p. 158–65.
- [2] Ibragimov B, Xing L. Segmentation of organs-at-risks in head and neck CT images using convolutional neural networks. Medical Physics 2017;44:547–57. <https://doi.org/10.1002/mp.12045>.
- [3] Močnik D, Ibragimov B, Xing L, Strojani P, Likar B, Pernuš F, et al. Segmentation of parotid glands from registered CT and MR images. Phys Med 2018;52:33–41.
- [4] Ren X, Xiang L, Nie D, Shao Y, Zhang H, Shen D, et al. Interleaved 3D-CNNs for joint segmentation of small-volume structures in head and neck CT images. Medical Physics 2018;45:2063–75. <https://doi.org/10.1002/mp.12837>.
- [5] Nikolov S, Blackwell S, Zverovitch A, Mendes R, Livne M, De Fauw J, et al. Deep learning to achieve clinically applicable segmentation of head and neck anatomy for radiotherapy. arXiv [csCV] 2018.
- [6] Tappeiner E, Pröll S, Hönig M, Raudaschl PF, Zaffino P, Spadea MF, et al. Multi-organ segmentation of the head and neck area: an efficient hierarchical neural networks approach. Int J Comput Assist Radiol Surg 2019;14:745–54.
- [7] Zhu W, Huang Y, Zeng L, Chen X, Liu Y, Qian Z, et al. AnatomyNet: Deep learning for fast and fully automated whole-volume segmentation of head and neck anatomy. Med Phys 2019;46:576–89.
- [8] van Rooij W, Dahele M, Ribeiro Brandao H, Delaney AR, Slotman BJ, Verbakel WF. Deep Learning-Based Delineation of Head and Neck Organs at Risk: Geometric and Dosimetric Evaluation. Int J Radiat Oncol Biol Phys 2019;104:677–84.
- [9] Zhong T, Huang X, Tang F, Liang S, Deng X, Zhang Y. Boosting-based Cascaded Convolutional Neural Networks for the Segmentation of CT Organs-at-risk in Nasopharyngeal Carcinoma. Med Phys 2019;46:5602–11.
- [10] Tang H, Chen X, Liu Y, Lu Z, You J, Yang M, et al. Clinically applicable deep learning framework for organs at risk delineation in CT images. Nature Machine Intelligence 2019;1:480–91.
- [11] Rhee DJ, Cardenas CE, Elhalawani H, McCarroll R, Zhang L, Yang J, et al. Automatic detection of contouring errors using convolutional neural networks. Med Phys 2019;46:5086–97.
- [12] van Dijk LV, Van den Bosch L, Aljabar P, Peressutti D, Both S, J H M Steenbakkers R, et al. Improving automatic delineation for head and neck organs at risk by Deep Learning Contouring. Radiother Oncol 2020;142:115–23.
- [13] Guo D, Jin D, Zhu Z, Ho T-Y, Harrison AP, Chao C-H, et al. Organ at Risk Segmentation for Head and Neck Cancer using Stratified Learning and Neural Architecture Search. arXiv [csCV] 2020.
- [14] Haibe-Kains B, Adam GA, Hosny A, Khodakarami F, Massive Analysis Quality Control (MAQC) Society Board of Directors, Waldron L, et al. Transparency and reproducibility in artificial intelligence. Nature 2020;586:E14–6.
- [15] Liu X, Cruz Rivera S, Moher D, Calvert MJ, Denniston AK, SPIRIT-AI and CONSORT-AI Working Group. Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: the CONSORT-AI extension. Nat Med 2020;26:1364–74.
- [16] Bellini V, Cocolini F, Forfori F, Bignami E. The artificial intelligence evidence-based medicine pyramid. Pediatr Crit Care Med 2023;12:89–91.
- [17] Jorge Cardoso M, Li W, Brown R, Ma N, Kerfoot E, Wang Y, et al. MONAI: An open-source

- framework for deep learning in healthcare. arXiv [csLG] 2022.
- [18] Marsilla J, Won Kim J, Kim S, Tkachuk D, Rey-McIntyre K, Patel T, et al. Evaluating clinical acceptability of organ-at-risk segmentation In head & neck cancer using a compendium of open-source 3D convolutional neural networks. bioRxiv 2022. <https://doi.org/10.1101/2022.01.15.22269276>.
- [19] 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;26:1045–57.
- [20] Bilello E. Computed tomography images from large head and neck cohort (RADCUR) - the cancer imaging archive (TCIA) public access - cancer imaging archive wiki n.d. <https://wiki.cancerimagingarchive.net/pages/viewpage.action?pageId=70226325> (accessed August 2, 2023).
- [21] Wong K, Huang SH, O'Sullivan B, Lockwood G, Dale D, Michaelson T, et al. Point-of-care outcome assessment in the cancer clinic: audit of data quality. Radiother Oncol 2010;95:339–43.
- [22] Kim S, Kazmierski M, Qu K, Peoples J, Nakano M, Ramanathan V, et al. Med-ImageTools: An open-source Python package for robust data processing pipelines and curating medical imaging data. F1000Res 2023;12:118.
- [23] Falcon W, Borovec J, Wälchli A, Eggert N, Schock J, Jordan J, et al. PyTorch Lightning: The lightweight PyTorch wrapper for high-performance AI research. 1.3.6 release. 2021. <https://doi.org/10.5281/zenodo.3828935>.
- [24] Kim JW, Marsilla J, Kazmierski M, Tkachuk D, Huang SH, Xu W, et al. Development of web-based quality-assurance tool for radiotherapy target delineation for head and neck cancer: quality evaluation of nasopharyngeal carcinoma n.d. <https://doi.org/10.1101/2021.02.24.21252123>.
- [25] Vaassen F, Hazelaar C, Vaniqui A, Gooding M, van der Heyden B, Canters R, et al. Evaluation of measures for assessing time-saving of automatic organ-at-risk segmentation in radiotherapy. Phys Imaging Radiat Oncol 2020;13:1–6.
- [26] Reinke A, Tizabi MD, Baumgartner M, Eisenmann M, Heckmann-Nötzel D, Kavur AE, et al. Understanding metric-related pitfalls in image analysis validation. ArXiv 2023. <https://doi.org/10.3115/1072064.1072067>.
- [27] Waskom ML. seaborn: statistical data visualization. Journal of Open Source Software 2021;6:3021.
- [28] Hunter JD. Matplotlib: A 2D Graphics Environment. Comput Sci Eng 2007;9:90–5.
- [29] The pandas development team. pandas-dev/pandas: Pandas. 2023. <https://doi.org/10.5281/zenodo.7857418>.
- [30] Çiçek Ö, Abdulkadir A, Lienkamp SS, Brox T, Ronneberger O. 3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation. Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016, Springer International Publishing; 2016, p. 424–32.
- [31] Lee K, Zung J, Li P, Jain V, Sebastian Seung H. Superhuman Accuracy on the SNEMI3D Connectomics Challenge. arXiv [csCV] 2017.
- [32] Li W, Wang G, Fidon L, Ourselin S, Jorge Cardoso M, Vercauteren T. On the Compactness, Efficiency, and Representation of 3D Convolutional Networks: Brain Parcellation as a Pretext Task. arXiv [csCV] 2017.
- [33] Fang X, Yan P. Multi-Organ Segmentation Over Partially Labeled Datasets With Multi-Scale Feature Abstraction. IEEE Trans Med Imaging 2020;39:3619–29.
- [34] Huang H, Lin L, Tong R, Hu H, Zhang Q, Iwamoto Y, et al. UNet 3+: A Full-Scale Connected UNet for Medical Image Segmentation. ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020, p. 1055–9.
- [35] Zhou Z, Siddiquee MMR, Tajbakhsh N, Liang J. UNet++: A Nested U-Net Architecture for

- Medical Image Segmentation. Deep Learn Med Image Anal Multimodal Learn Clin Decis Support (2018) 2018;11045:3–11.
- [36] Yu L, Cheng J-Z, Dou Q, Yang X, Chen H, Qin J, et al. Automatic 3D Cardiovascular MR Segmentation with Densely-Connected Volumetric ConvNets. arXiv [csCV] 2017.
 - [37] Jégou S, Drozdal M, Vazquez D, Romero A, Bengio Y. The One Hundred Layers Tiramisu: Fully Convolutional DenseNets for Semantic Segmentation. arXiv [csCV] 2016.
 - [38] Zhang H, Zhang J, Zhang Q, Kim J, Zhang S, Gauthier SA, et al. RSANet: Recurrent Slice-Wise Attention Network for Multiple Sclerosis Lesion Segmentation. Medical Image Computing and Computer Assisted Intervention – MICCAI 2019, Springer International Publishing; 2019, p. 411–9.
 - [39] Milletari F, Navab N, Ahmadi S-A. V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation. arXiv [csCV] 2016.
 - [40] Wolny A, Cerrone L, Vijayan A, Tofanelli R, Barro AV, Louveaux M, et al. Accurate and versatile 3D segmentation of plant tissues at cellular resolution. Elife 2020;9. <https://doi.org/10.7554/eLife.57613>.
 - [41] Wolny A. pytorch-3dunet: 3D U-Net model for volumetric semantic segmentation written in pytorch. Github; n.d.
 - [42] Ali H. UNet-3-Plus: A Full-Scale Connected UNet for Medical Image Segmentation. Github; n.d.
 - [43] Arrowsmith C, Reiazi R, Welch ML, Kazmierski M, Patel T, Rezaie A, et al. Automated detection of dental artifacts for large-scale radiomic analysis in radiation oncology. Phys Imaging Radiat Oncol 2021;18:41–7.
 - [44] Bejarano T, De Ornelas-Couto M, Mihaylov IB. Longitudinal fan-beam computed tomography dataset for head-and-neck squamous cell carcinoma patients. Med Phys 2019;46:2526–37.
 - [45] Nolan T. Head-and-neck squamous cell carcinoma patients with CT taken during pre-treatment, mid-treatment, and post-treatment (HNSCC-3DCT-RT) n.d. <https://wiki.cancerimagingarchive.net/pages/viewpage.action?pageId=39879146> (accessed August 17, 2023).
 - [46] Raudaschl PF, Zaffino P, Sharp GC, Spadea MF, Chen A, Dawant BM, et al. Evaluation of segmentation methods on head and neck CT: Auto-segmentation challenge 2015. Medical Physics 2017;44:2020–36. <https://doi.org/10.1002/mp.12197>.
 - [47] Aerts HJWL, Velazquez ER, Leijenaar RTH, Parmar C, Grossmann P, Carvalho S, et al. Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach. Nat Commun 2014;5:4006.
 - [48] Andrearczyk V, Oreiller V, Vallières M, Castelli J, Elhalawani H, Jreige M, et al. 3D Head and Neck Tumor Segmentation in PET/CT. 2020. <https://doi.org/10.5281/zenodo.3714957>.
 - [49] Li H, Chen M. Automatic Structure Segmentation for Radio Therapy Planning Challenge 2020. Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention, Lima, Peru, 2020, p. 4–8.
 - [50] Grossberg AJ, Mohamed ASR, Elhalawani H, Bennett WC, Smith KE, Nolan TS, et al. Imaging and clinical data archive for head and neck squamous cell carcinoma patients treated with radiotherapy. Sci Data 2018;5:180173.
 - [51] Nolan T. Data from head and neck cancer CT atlas (head-neck-CT-atlas) n.d. <https://wiki.cancerimagingarchive.net/pages/viewpage.action?pageId=24281354> (accessed August 17, 2023).
 - [52] Luo X, Liao W, Zhou M, Fu J, Zhang S, Wang G, et al. Segmentation of Organs-at-Risk and Gross Tumor Volume for Radiotherapy Planning of Nasopharyngeal Carcinoma Challenge 2023. 2023. <https://doi.org/10.5281/zenodo.7839896>.







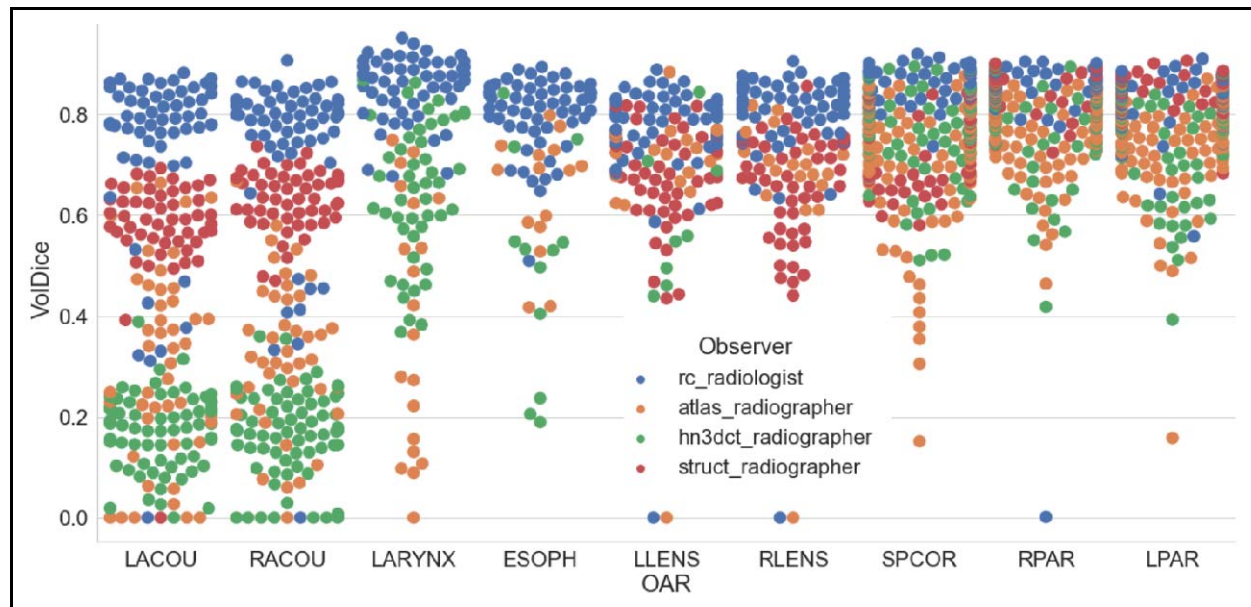


Figure 4: Performance differences of WOLNET ensemble for select OARs on external datasets. Beeplot to show variation of 3D Volumetric DICE performance of WOLNET ensemble for select OARs (L/R Acoustics, Larynx, Oesophagus, L/R Lens, Spinal Cord, L/R Parotids) across different datasets. Broad spectrum in contouring protocols of the acoustics across different centers.

Table 1: MC v. DLC Acceptability Ratings For Each OAR Category

ROI	MAR (GT)	MAR (AI)	Pn80	PHP %	ROI	MAR (GT)	MAR (AI)	Pn80	PHP %
MAND	4.15±0.89	3.53±1.13	32	27.5					
LEYE	3.45±0.71	3.00±0.78	39	27.1	RLENS	4.10±0.78	4.15±0.70	3820	3.5
REYE	3.68±0.62	3.05±0.68	15	58.1	LACOU	3.30±0.91	3.20±0.97	1300	4.3
BSTEM	4.13±0.69	2.8±0.91	4	95.8	RACOU	3.30±0.72	3.38±0.74	1272	4.3
LARYNX	3.95±0.85	2.38±0.90	5	98	LPLEX	3.68±0.76	3.78±0.58	907	5.2
SPCOR	3.93±0.76	3.70±0.56	171	11.7	RPLEX	3.63±0.84*	3.58±0.81	4431	3.4
LPAR	3.80±0.99	3.85±1.02	6154	3.2	LIPS	3.75±0.71	3.33±0.80	45	23.6
RPAR	4.08±1.02*	3.95±1.23	966	4.4	LOPTIC	4.28±0.68	3.50±0.78	12	66.47
ESOPH	3.93±0.80	3.13±0.97	16	52.1	ROPTIC	4.18±0.68	3.20±0.79	8	84.5
LLENS	4.05±0.68	3.65±0.92	45	19.6	CHIASM	3.03±1.27*	2.90±1.06	1498	4.3

Table 1: MC v. DLC Acceptability Ratings For Each OAR Category

Pn80 is defined as the minimum power required (number of paired samples) to have a significantly different rating between Ground-Truth and AI contours. For example, for our analysis of the sample size When assessing whether certain OAR categories passed the mean acceptability cutoff of 3.5, 15 manually delineated OARs on average were considered clinically acceptable, requiring no edits for planning purposes, compared with 9 OARs generated by deep learning. When analyzing categories of OARs requiring minor edits for their contours to be accepted into radiation therapy plans ($3.0 < \text{MAR} < 3.5$), 7 deep learning generated OARs compared with 4 manually contoured OARs met this criteria.

Table 2: SCARF's toolkit can be used to facilitate compliance to checklists like that provided by CONSORT-AI [15]				
SCARF Step	SCARF Tool	Facilitates CONSORT-AI Compliance		Time Savings (Dev. Hours)
Data Curation	1 Medlmg-Tools package allows for consistent processing of internal/external datasets	Allows standardization and processing of data, can be used to facilitate compliance to section:	5.ii - 5.iv	240
Model Curation	2 Suite of open-source CNN's modified to train 3D auto-segmentation models using pyTorch lightning. Weights of best model used in Clinical Acceptability and generalizability assessment provided	Systematic approach to model versioning and training supervised auto-segmentation modes proposed	5.i, 5.v	80
Model Training	3 Streamlined PyTorch Lightning boilerplate allows for easy model integration, training & inference in less than 10 lines of code			
Performance Assessment	4 Collection of easy to use scripts/notebooks that makes performance assessment of model easy	[5.v] Assessment of contours generated for 19 OAR(s) used in radiation therapy planning of HNC. [19] Quantitative metrics can be associated with qualitative metrics to discuss harms/limitations of method	5.v, 19	10

			when segmenting specific organs at risk		
Clinical Assessment	5	Quannotate platform enables web-based blinded clinical assessment of contours	Clinical assessment of contours allows experts to rate quality of predictions, and can be used for bias assessment (How would the expert rating change when seeded with the name of contour generator?)	5.vi , 19-20	100
Method Generalizability	6	Collection of scripts and notebooks that makes generalizability assessment (inference) on external datasets using both cpus/gpus easy	Collection and processing of 6 external datasets allows for external validity of best model performance, can be used to assess similarities/discrepancies of contouring methods used across centers	21-22	20