# Auto-Segmentation of Elective Nodal Clinical Target Volumes for Anal Cancer Using Artificial Intelligence

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## Purpose

The application of artificial intelligence (AI) for automatically segmenting organs at risk and target volumes in radiation therapy planning is rapidly developing. We aim to develop a model for automatically segmenting elective nodal clinical target volumes (nCTV) in anal cancer as a template for pelvic nodal auto-segmentation in general, and as a model for similar efforts in other pelvic and abdominal disease sites. The primary aim of this investigation is to improve the efficiency, accuracy, and consistency of contouring for physicians by refining the data pool to utilize fewer cases for AI training while maintaining accuracy.

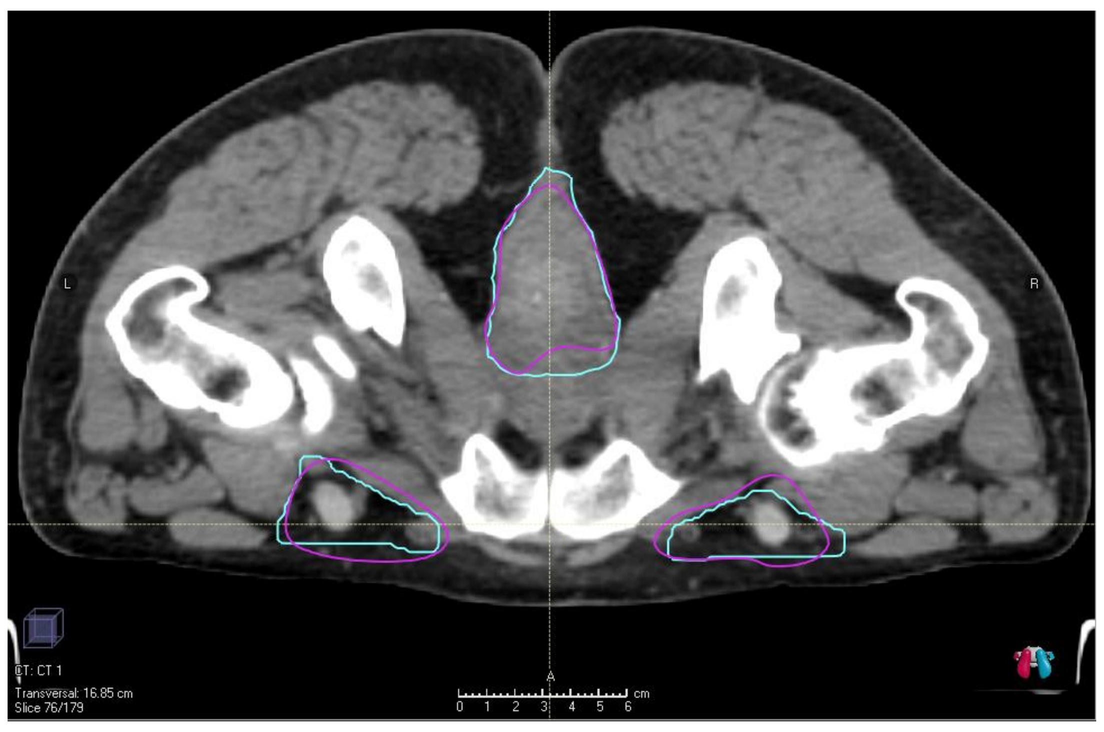
## Materials/Methods:

We retrospectively identified 70 anal cancer patients that were contoured between 12/20/2010 and 12/1/2022. To be included, patients had to have undergone CT simulation. The CTV elective nodal volumes were edited using commercial radiation therapy planning software to align with the anorectal elective nodal contouring guidelines from NRG Oncology, a radiation therapy oncology group consensus panel atlas. We also recorded various scan and patient characteristics, such as gender, the number of scans performed with IV and oral contrast, and the number of scans done in a supine or prone position. Of the 70 cases, 40 cases were assigned to the training group, and 30 cases were assigned to the testing group. Thirty seven of 40 training cases were used to train an artificial intelligence (AI) and the 30 testing cases were contoured by the AI. Three training cases were excluded due to incomplete data. The differences in the AI generated and the CTVs manually contoured based on NRG Oncology contouring guidelines were quantitatively evaluated using newly developed scripts for the median, mean and range of (1) Hausdorff distance 100th and 95th, (2) volumetric differences, and (3) dice similarity index measures.

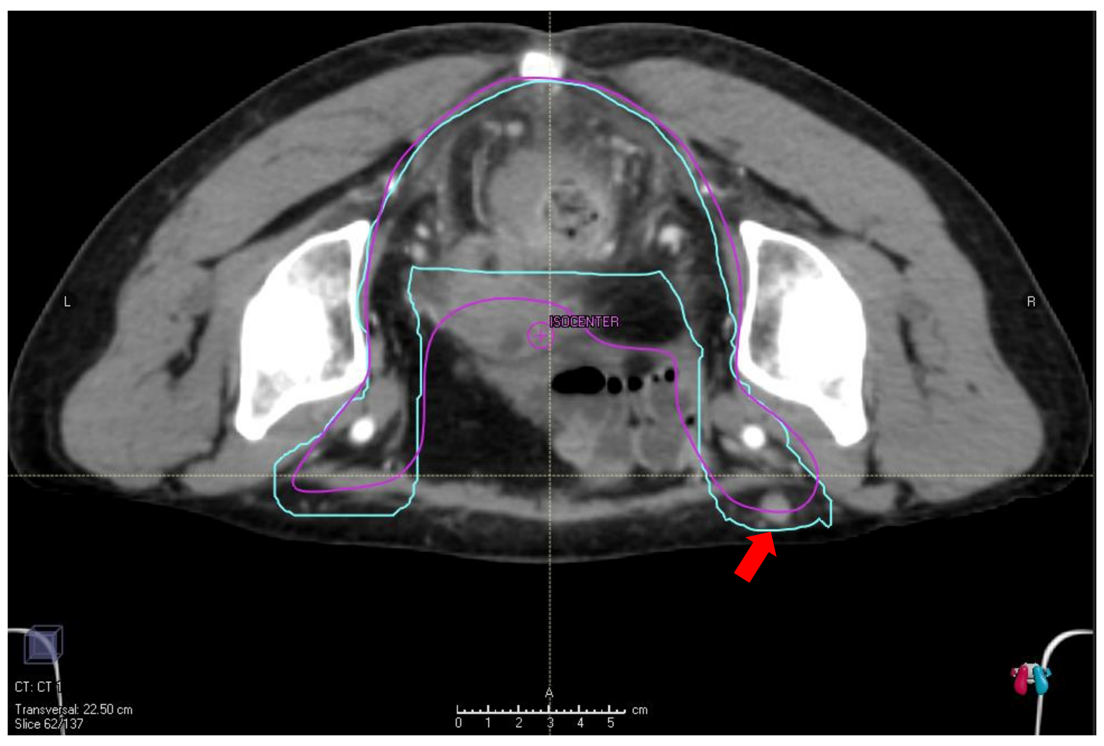
## Data Comparison of AI Contours vs. Human Contours

| Identifier | AI Volume | Original Volume | Hausdorff Distance 100th | Hausdorff Distance 95th | DICE Similarity | Volume difference |
|---|---|---|---|---|---|---|
| ANON60471 | 1315.49 | 1497.33 | 3.97 | 1.51 | 0.80 | 181.84 |
| ANON64089 | 1216.84 | 1052.60 | 4.50 | 1.37 | 0.81 | 164.23 |
| ANON82002 | 1234.06 | 1404.69 | 2.95 | 1.27 | 0.84 | 170.63 |
| ANON32969 | 1180.48 | 1005.45 | 8.88 | 1.62 | 0.80 | 175.04 |
| ANON72213 | 1254.93 | 1500.67 | 3.55 | 1.37 | 0.83 | 245.75 |
| ANON30253 | 1044.76 | 1139.80 | 3.38 | 1.91 | 0.80 | 95.04 |
| ANON71735 | 1279.18 | 1900.92 | 5.12 | 2.52 | 0.76 | 621.73 |
| ANON67877 | 1367.73 | 1775.00 | 5.63 | 2.50 | 0.80 | 407.27 |
| ANON30605 | 1016.11 | 918.58 | 3.35 | 1.73 | 0.83 | 97.53 |
| ANON26494 | 1198.74 | 1229.63 | 2.82 | 1.21 | 0.84 | 30.89 |
| ANON35708 | 922.86 | 857.09 | 3.61 | 1.67 | 0.78 | 65.77 |
| ANON39062 | 1383.25 | 1156.73 | 2.70 | 1.20 | 0.84 | 226.52 |
| ANON73087 | 1586.55 | 1630.25 | 3.48 | 1.50 | 0.84 | 43.69 |
| ANON79628 | 1162.45 | 1221.51 | 3.36 | 1.50 | 0.81 | 59.06 |
| ANON75052 | 720.18 | 870.09 | 5.14 | 3.60 | 0.68 | 149.91 |
| ANON69820 | 731.55 | 641.31 | 4.58 | 2.70 | 0.75 | 90.25 |
| ANON83508 | 965.65 | 779.08 | 3.90 | 1.80 | 0.77 | 186.57 |
| ANON71771 | 1614.78 | 1285.67 | 6.90 | 1.53 | 0.80 | 329.11 |
| ANON78556 | 703.55 | 676.68 | 6.20 | 3.45 | 0.72 | 26.87 |
| ANON19095 | 1261.91 | 1141.86 | 6.00 | 1.37 | 0.82 | 120.05 |
| ANON85472 | 1019.78 | 988.28 | 5.70 | 2.40 | 0.73 | 31.50 |
| ANON80663 | 1123.21 | 993.80 | 4.50 | 1.48 | 0.80 | 129.41 |
| ANON83918 | 1064.96 | 986.44 | 2.44 | 1.20 | 0.83 | 78.52 |
| ANON54024 | 1229.21 | 1063.79 | 6.48 | 2.10 | 0.80 | 165.42 |
| ANON52846 | 895.72 | 691.83 | 6.62 | 2.10 | 0.79 | 203.89 |
| ANON33182 | 1096.06 | 938.83 | 4.80 | 2.48 | 0.78 | 157.23 |
| ANON48595 | 1032.28 | 1016.00 | 6.70 | 2.13 | 0.77 | 16.29 |
| ANON23899 | 1170.53 | 1121.53 | 8.40 | 2.70 | 0.78 | 49.00 |
| ANON71623 | 1309.47 | 1028.97 | 7.57 | 2.10 | 0.80 | 280.50 |
| ANON21558 | 1200.12 | 1140.50 | 4.80 | 2.21 | 0.77 | 59.62 |
| Mean | | | 4.93 | 1.94 | 0.79 | 155.30 |
| Median | | | 4.69 | 1.77 | 0.80 | 139.66 |
| Range Upper Limit | | | 8.88 | 3.60 | 0.84 | 621.73 |
| Range Lower Limit | | | 2.44 | 1.20 | 0.68 | 16.29 |

ANON79628
Slice 70/140
AI: Purple
Human: Turquoise



ANON60471
Slice 76/179
AI: Purple
Human: Turquoise



ANON83508
Slice 62/137
AI: Purple
Human: Turquoise

Missing a crucial lymph node included by physician (red arrow)

## Results

We re-contoured 70 cases. 53 cases used IV contrast. 64 cases used oral contrast. 64 patients were simulated in the prone position and 6 patients were simulated in the supine position. 21 patients were males, and 49 patients were females. The median, mean and range of Hausdorff distances 100th and 95th, volumetric differences, and dice similarity index were 4.69 cm (mean of 4.93 cm {2.44, 8.88}), 1.77 cm (mean of 1.94 cm {1.20, 3.60}), 139.66 cc (mean of 155.30 cc {16.29, 621.73}), and 0.80 (mean of 0.79 {0.68, 0.84}) respectively. These data points formed the initial/preliminary model for our nCTV of anal cancer.

## Conclusions

A new model for auto-segmentation of nCTV has been developed that may be employed commercially and is based on the NRG Oncology anorectal contouring atlas for clinical trials. This model employed far fewer cases than other studies when creating AI models and created results similar to human models for standardized contours, showcasing that refining the training data to optimize the data pool can create a quality AI. Strategies for improving the similarity metrics employed in the study will be further investigated .This tool may significantly reduce physician effort required to contour pelvic lymph node CTVs but physician editing and oversight of each case is still required to account for inter-patient heterogeneity in volumes. Workflows are expected to improve with further streamlining of the model.

## References

Chung, Seung Yeun, et al. “Clinical Feasibility of Deep Learning-Based Auto-Segmentation of Target Volumes and Organs-At-Risk in Breast Cancer Patients after Breast-Conserving Surgery.” *Radiation Oncology*, vol. 16, no. 1, 25 Feb. 2021, 10.1186/s13014-021-01771-z. Accessed 31 May 2022.

Groendahl, Aurora Rosvoll, et al. “Deep Learning-Based Automatic Delineation of Anal Cancer Gross Tumour Volume: A Multimodality Comparison of CT, PET and MRI.” *Acta Oncologica (Stockholm, Sweden)*, vol. 61, no. 1, 1 Jan. 2022, pp. 89–96, pubmed.ncbi.nlm.nih.gov/34783610/, 10.1080/0284186X.2021.1994645. Accessed 28 Jan. 2023.

Guo, Zhe, et al. “Gross Tumor Volume Segmentation for Head and Neck Cancer Radiotherapy Using Deep Dense Multi-Modality Network.” *Physics in Medicine & Biology*, vol. 64, no. 20, 16 Oct. 2019, p. 205015, 10.1088/1361-6560/ab440d. Accessed 25 Nov. 2020.

Ren, Jintao, et al. “Comparing Different CT, PET and MRI Multi-Modality Image Combinations for Deep Learning-Based Head and Neck Tumor Segmentation.” *Acta Oncologica (Stockholm, Sweden)*, vol. 60, no. 11, 1 Nov. 2021, pp. 1399–1406, pubmed.ncbi.nlm.nih.gov/34264157/, 10.1080/0284186X.2021.1949034. Accessed 28 Jan. 2023.

Rigaud, Bastien, et al. “Automatic Segmentation Using Deep Learning to Enable Online Dose Optimization during Adaptive Radiation Therapy of Cervical Cancer.” *International Journal of Radiation Oncology, Biology, Physics*, vol. 109, no. 4, 15 Mar. 2021, pp. 1096–1110, pubmed.ncbi.nlm.nih.gov/33181248/, 10.1016/j.ijrobp.2020.10.038. Accessed 28 Jan. 2023.

Wong, Jordan, et al. “Implementation of Deep Learning-Based Auto-Segmentation for Radiotherapy Planning Structures: A Workflow Study at Two Cancer Centers.” *Radiation Oncology*, vol. 16, no. 1, 8 June 2021, 10.1186/s13014-021-01831-4. Accessed 17 May 2022.

Yang, Chongze, et al. “Deep Learning in CT Image Segmentation of Cervical Cancer: A Systematic Review and Meta-Analysis.” *Radiation Oncology (London, England)*, vol. 17, no. 1, 7 Nov. 2022, p. 175, pubmed.ncbi.nlm.nih.gov/36344989/, 10.1186/s13014-022-02148-6. Accessed 28 Jan. 2023.