Generating High-Quality Lymph Node Clinical Target Volumes for Head and Neck Cancer Radiation Therapy Using a Fully Automated Deep Learning-Based Approach

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Abstract

**Purpose:** To develop a deep learning model that generates consistent, high-quality lymph node clinical target volumes (CTV) contours for head and neck cancer (HNC) patients, as an integral part of a fully automated radiation treatment planning workflow.

**Methods and Materials:** Computed tomography (CT) scans from 71 HNC patients were retrospectively collected and split into training (n = 51), cross-validation (n = 10), and test (n = 10) data sets. All had target volume delineations covering lymph node levels Ia through V (Ia-V), Ib through V (Ib-V), II through IV (II-IV), and retropharyngeal (RP) nodes, which were previously approved by a radiation oncologist specializing in HNC. Volumes of interest (VOIs) about nodal levels were automatically identified using computer vision techniques. The VOI (cropped CT image) and approved contours were used to train a U-Net autosegmentation model. Each lymph node level was trained independently, with model parameters optimized by assessing performance on the cross-validation data set. Once optimal model parameters were identified, overlap and distance metrics were calculated between ground truth and autosegmentations on the test set. Lastly, this final model was used on 32 additional patient scans (not included in original 71 cases) and autosegmentations visually rated by 3 radiation oncologists as being “clinically acceptable without requiring edits,” “requiring minor edits,” or “requiring major edits.”

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Research data are not available at this time.
**Results:** When comparing ground truths to autosegmentations on the test data set, median Dice Similarity Coefficients were 0.90, 0.90, 0.89, and 0.81, and median mean surface distance values were 1.0 mm, 1.0 mm, 1.1 mm, and 1.3 mm for node levels Ia-V, Ib-V, II-IV, and RP nodes, respectively. Qualitative scoring varied among physicians. Overall, 99% of autosegmented target volumes were either scored as being clinically acceptable or requiring minor edits (i.e., stylistic recommendations, <2 minutes).

**Conclusions:** We developed a fully automated artificial intelligence approach to autodelinate nodal CTVs for patients with intact HNC. Most autosegmentations were found to be clinically acceptable after qualitative review when considering recommended stylistic edits. This promising work automatically delineates nodal CTVs in a robust and consistent manner, this approach can be implemented in ongoing efforts for fully automated radiation treatment planning.

**Introduction**

The use of intensity modulated radiation therapy (IMRT) techniques provides the ability to conform radiation dose distributions to the targets while sparing nearby normal tissues. Since clinical implementation, IMRT has required practitioners to manually define clinical target volumes (CTVs) and normal tissue organs at risk (OARs); these are both necessary to optimize dose distributions. This manual process is time-consuming and subject to significant inter- and intraobserver variabilities\(^1,2\) with reports suggesting that head and neck cancers (HNC) target delineation is both the most time-consuming anatomic site (taking physicians up to 2–3 hours) and subject to the largest variabilities.\(^3\)–\(^5\) Several consensus delineation guidelines have emerged to reduce this variability\(^6\)–\(^8\); yet significant variability persists, especially when delineating the head and neck lymph node levels and low-risk target volumes.

Automatic segmentation of HNC CTVs has been proposed as a solution for expediting the delineation process, promising improved efficiency and consistency in target delineations. Researchers have studied atlas-based autosegmentation, which takes advantage of deformable image registration to map well-defined delineations on 1 atlas to a new patient’s image for autosegmentation.\(^9\)–\(^14\) A challenge with atlas-based autosegmentation is that it relies on the algorithm’s ability to accurately register different patients’ anatomies (a single atlas to a new patient), which can result in inaccuracies due to variable anatomy and low contrast of lymph node regions on computed tomography (CT) scans. To address these inaccuracies, authors proposed that multiatlas-based autosegmentation captures a wider range of anatomic variations resulting in an improvement in the resulting segmentations.\(^11\),\(^12\),\(^15\)–\(^18\) Multiatlas-based autosegmentation typically uses 8 to 14 patients (atlases) with consensus or peer-reviewed manual contours. A limitation to the number of atlases is that each must be registered to the new patient, resulting in a computationally expensive process. In addition, whereas multiatlas-based autosegmentation provides more reference patient scans than single-atlas autosegmentation algorithms do, it only captures anatomic differences for a small sample of patients (atlases).

Deep learning-based autosegmentation algorithms have achieved impressive success in medical imaging segmentation tasks, with convolutional neural networks (CNNs) being the
most popular algorithms used in deep learning.\textsuperscript{19,20} Researchers have used these networks to autosegment many anatomic sites using computed tomography, magnetic resonance imaging, positron emission tomography, x-rays, and ultrasound images resulting in rapid development and quick translation to the field of radiation oncology. Several studies have focused on normal tissue\textsuperscript{21–36} and CTV\textsuperscript{37–40} autosegmentation for HNC radiation therapy. In previous deep learning-based CTV autosegmentation work, researchers developed algorithms to autodelineate targets based on their risk (high-risk\textsuperscript{37,38} or low-risk\textsuperscript{37,39,40} CTVs) but lacked the ability to autodelineate individual lymph node levels. Therefore, in the present study, we developed a deep learning model to automatically segment targets based on lymph node level combinations commonly used in HNC radiation therapy. Our model’s architecture uses an ensemble of models and test-time augmentations to improve its generalizability for new patients. To the best of our knowledge, this is the first deep learning-based autosegmentation model for use with individual lymph node level target volumes for radiation treatment planning for HNCs. Unique to this work is that the resulting automatic segmentations can be implemented to administer radiation therapy for HNC at a large majority of subsites. Our hypothesis is that a vast majority of autosegmented lymph node target volumes can be used for radiation therapy treatment planning without user edits.

**Methods and Materials**

**Patient data**

Radiation therapy simulation CT scans and clinically approved contours for 71 patients with HNC previously treated at The University of Texas MD Anderson Cancer Center were used in this study under an institutional review board-approved protocol. Each patient had lymph node level Ia-V, Ib-V, and II-IV and retropharyngeal (RP) node level target volume contours (CTV_LN_II_IV, CTV_LN_Ia_V, CTV_LN_Ib_V, and CTV_LN_RP, respectively). These lymph node levels were previously contoured manually or autosegmented using an in-house multiatlas-based algorithm, visually inspected, and approved (as “clinically acceptable without requiring edits”) by a radiation oncologist specializing in HNC. This patient cohort included a variety of HNC disease scenarios, including different primary sites, lymph node statuses (negative vs positive), and lymph node locations (none vs ipsilateral vs bilateral).

**Generation of ground-truth contours**

In a previous study,\textsuperscript{17} a multiatlas-based autosegmentation tool was developed by our group using 2 separate atlases that independently autosegmented structures in the left and right lymph node levels. A radiation oncologist (B.M.B.) with more than 10 years of experience treating HNC manually delineated each individual lymph node level target volume on 20 patients’ radiation therapy simulation CT scans. In this previous analysis, manually delineated target volumes consisted of a combination of lymph node levels, except for the retropharyngeal node target volumes, which were delineated according to our clinical practice. These atlases were then used to autosegment the target volumes for 115 HNC patients who subsequently presented to our institution for radiation therapy. The resulting autosegmentations were scored by the same radiation oncologist on a 5-point scale (5: perfect, indistinguishable from physician-drawn contours for dose-volume histogram-based planning; 4: within acceptable interphysician variation for planning purposes; 3: good, needs
minor edits to be used for planning purposes; 2: fair, needs significant edits to be used for planning purposes; and 1: poor, large areas need minor or major edits, is unusable for planning purposes). For the present study, 51 of the 115 cases with scores of 4 or 5 for all autosegmented target volumes were collected and combined with the 20 manually contoured cases scored by a radiation oncologist as clinically acceptable without requiring edits to generate a well-curated high-quality ground truth contour data set.

The 71 cases were randomly placed in 3 groups: training (51), cross-validation (10), and final test (10) sets. The training and cross-validation sets were used for training and optimal hyperparameter selection as well as identifying the most favorable postprocessing strategy. Postprocessing strategy was defined by using the trained model and predicting on cross-validation set cases to determine postprocessing steps, including morphology operations such as erosion/dilation with varying filter sizes and dimensionality (ie, 2D vs 3D). The final test set was held until the best model parameters and strategies were identified.

**Deep learning-based autosegmentation**

Due to the limited number of well-curated training cases available for this study, a model was designed that could predict lymph node target volumes regardless of neck laterality, essentially doubling our training data. Our approach to autosegment HNC lymph node target volumes is described in detail in the following subsections.

**Data preparation**

Our model’s input generation is depicted in Figure 1. Similar to our previous work, the CT scan field of view was reduced in the craniocaudal direction by identifying (1) the most caudal extent of the fusion of the sphenoid bone and basilar part of the occipital bone as the CT scan’s field of view’s most cranial CT slice and (2) the most cranial extent of the sternum as the field of view’s most caudal CT slice. Normalizing the field of view across patients is performed automatically by training the Xception model in Keras using a TensorFlow backend to classify individual CT slices. This is described in more detail in our previous work.

Once the craniocaudal field of view is identified, the body contour is defined automatically using previously developed in-house software. The body contour is then used to reduce the input volume by identifying a bounding box about the most cranial slice to extract the CT image’s input volumes for both the left and right lymph node regions. The resulting CT image volume of interest (VOI) and its corresponding target volume masks are resized using bilinear interpolation to a predefined volume size (64 x 128 x 64) for use as inputs in our deep learning model. Lastly, image intensities were transformed using our clinic’s head and neck CT window/level settings (−350, 350 Hounsfield Units) to have values from 0 to 1 (ie, −350 = 0 and 350 = 1) as was done in our previous work.

**Architecture and training parameters**

A hyperparameter search was performed to identify the optimal parameters (eg, resolution steps, kernel size) on a modified 3D U-Net architecture. Our U-Net model uses a residual function (short-connections) similar to that described by Milletari et al and uses
batch normalization \(^{43}\) after each 3D convolutional layer. The same architecture is used to train 5 separate model weights (random initialization of weights) focused on identifying patterns to autosegment each individual target volume (CTV\_LN\_II\_IV, CTV\_LN\_Ia\_V, CTV\_LN\_Ib\_V, and CTV\_LN\_RP) using the same input volume (preprocessed CT scan as previously described in the Data Preparation section). These models are used in an ensemble approach to further improve the confidence in the resulting segmentation.

The model was trained using the Adam optimizer with a learning rate of 0.001 and early stopping regularization to avoid overfitting of the models. Typical data augmentations (eg, translation, rotation) were used during training. Herein a new overlap loss is introduced that incorporates the Dice similarity coefficient (DSC) loss and false-negative Dice (FND) loss to penalize missed target volumes during training. The generalized “DSC + FND” loss is defined as

\[
DSC + FND \text{ loss} = \frac{1}{C} \sum_{c=0}^{C} \sum_{i=0}^{N} \frac{2 \sum_{i=0}^{N} p_i g_i}{\sum_{i=0}^{N} p_i^2 + \sum_{i=0}^{N} g_i^2} + \mu \frac{1}{C-1} \sum_{c=1}^{C} \sum_{i=0}^{N} \frac{2 \sum_{i=0}^{N} p_i' g_i}{\sum_{i=0}^{N} p_i'^2 + \sum_{i=0}^{N} g_i^2}
\]

in which the first term is the multiclass (C) DSC loss described by Milletari et al.\(^{42}\) and the second term is the multiclass FND component introduced herein. For the DSC loss, the sums run over N voxels of the predicted probabilities \(p_i \in P\) and the ground truth binary volume \(g_i \in G\) for all classes, whereas for the FND loss, the numerator calculates the sums over N voxels between the complement \((P' = 1 - P)\) of the predicted probabilities \(p_i' \in P'\) and the ground truth binary volume \(g_i \in G\) are only calculated for nonbackground classes (here, background is defined by \(C = 0\)). The rationale for introducing this loss function is that the DSC loss leads to systematic underestimation of the predicted volumes compared with the cross-validation ground-truth volumes.

**Postprocessing and ensemble approach**

When generating a prediction on a new patient, an ensemble approach and test-time augmentations are used to further improve the resulting segmentations. Our ensemble approach uses the 5 trained model weights for each region of interest and applies random shifts (total, 13) about the center of the input image to generate 13 probability maps for each trained model. These shifts ranged from ±3, ±10, and ±5 for the z-, y-, and x-directions, respectively. The probability maps for all models and their corresponding test-time augmentations (total, 65) are then shifted back to the original input space and averaged on a per-voxel basis. The resulting averaged probability map for the target volume is then converted into a binary mask by thresholding individual voxels’ probabilities to have a value greater than or equal to 0.5. The resulting binary mask then goes through a postprocessing step to ensure the removal of holes and/or keep the largest autosegmented volume.
Quantitative and qualitative evaluation

During our quantitative evaluation of our model’s autosegmentations, the ground-truth contours are compared with the autosegmented target volumes using overlap and distance metrics, as overlap metrics alone can be less sensitive to larger volumes. These metrics include the DSC, FND, false-positive Dice, volumetric similarity (VS), mean surface distance (MSD), and Hausdorff distance (HD), which are defined in Equations 2 to 7:

\[
DSC = \frac{2 \times TP}{2 \times TP + FN + FP}
\]

\[
FND = \frac{2 \times FN}{2 \times TP + FN + FP}
\]

\[
FPD = \frac{2 \times FP}{2 \times TP + FN + FP}
\]

\[
VS = \frac{2 \times (FN - FP)}{2 \times TP + FN + FP}
\]

\[
MSD = \frac{1}{2}(d_{Auto, Truth} + d_{Truth, Auto})
\]

\[
HD = \max(d_{DNN, G} \cup d_{G, DNN})
\]

in which TP, FN, and FP are the numbers of true-positive, false-negative, and false-positive voxels, respectively; Auto and Truth represent the autosegmentation and ground-truth contours, respectively, and \(d_{a,b}\) is a vector with all the minimum Euclidean distances from each surface point in volume “a” to volume “b.” The FND and FPD are good metrics that help quantify potential near misses and overtreatment, respectively. Because the target volumes used to train the model were generated as a combination of lymph node levels, our quantitative analysis focuses on the target volume as a whole and not explicitly on individual lymph node levels.

To confirm our quantitative analysis results, we conducted a multi-institutional qualitative review of the proposed model’s autosegmentations using a separate set of HNC patient scans (32 new cases) from the 71 cases used to train, cross-validate, and test our models. In this analysis, 3 radiation oncologists (BMB, ASG, and HDS, ordered alphabetically) each with more than 10 years of experience treating HNC visually inspected each target volume on a slice-by-slice basis for each patient. Each individual target volume was scored using a 3-point scale (clinically acceptable without requiring edits, requiring minor edits, and requiring major edits). Acceptable autosegmentations are those that do not require any edits and can be used “as is.” Autosegmentations requiring minor edits are contours that can be manually edited and corrected quicker than 2 minutes and/or are acceptable for clinical use.
if a CTV-to-planning target volume margin of 5 mm is used suggesting that the edits are stylistic in nature. Autosegmentations requiring major edits are those that are not acceptable for clinical use and are believed to clinically affect the likelihood of cure, adverse events, or locoregional control.

Results

Quantitative evaluation

Quantitative results for our ensemble model segmentations are shown in Figure 2 and are summarized in Table 1. The mean (± standard deviation [SD]) DSC values between the final segmentations and the ground truth were 0.843 ± 0.030, 0.907 ± 0.013, 0.909 ± 0.013, and 0.897 ± 0.014 for CTV_LN_RP, CTV_LN_II_III, CTV_LN_Ib_V, and CTV_LN_Ia_V, respectively. The mean FND/FPD values for these 4 volumes were 0.234/0.099, 0.063/0.123, 0.062/0.120, and 0.053/0.154, respectively. The mean VS values were 0.135, −0.060, −0.057, and −0.101, respectively. The mean (±SD) MSD and HD values were 1.0 ± 0.2 mm and 5.5 ± 1.3 mm, 1.1 ± 0.2 mm and 8.4 ± 3.7 mm, 1.1 ± 0.2 mm and 8.1 ± 3.1 mm, and 1.3 ± 0.2 mm and 8.6 ± 3.1 mm, respectively. When comparing the ensemble model results with each individual model’s segmentations (ensemble - others), we noticed a mean (± SD) improvement of 0.01 ± 0.01 for the DSC. We observed similar slight improvements as demonstrated by mean (± SD) reductions in the MSD and HD across all volumes of −0.1 ± 0.2 mm and −0.7 ± 2.8 mm, respectively. A visual comparison of the ground-truth and autosegmented target volumes is shown in Figure 3.

The model generated all regions of interest with a mean (± SD) time of 6.0 ± 0.6 minutes using an NVIDIA RTX 2080 graphics processing unit and 32 cores. This time was significantly reduced when a user decided to only include both RP nodes and unique target combinations for both neck sides (mean [± SD] time of 3.2 ± 0.4 minutes when autosegmenting both RP nodes and targets for levels Ia-V and Ib-V for the right and left neck lymph nodes, respectively).

Qualitative evaluation

Physician slice-by-slice review and scoring of the autosegmentations are listed in Table 2. The 3 physicians reviewed 256 target volumes each (8 target volumes for each of the 32 cases). Seven (22%) of these patients previously underwent neck surgery, which included unilateral or bilateral dissection. Of the 768 target volumes reviewed, 438 (57%) were scored as acceptable as is, 323 (42%) were scored as requiring minor edits (ie, stylistic recommendations, <2 minutes), and 7 (1%) required major edits. When considering individual reviewer scores, reviewer 1 scored 96%, 4%, and 0% of autodelineated target volumes as acceptable, minor, and major, respectively, reviewer 2 scored 63%, 38%, and 0% of autodelineated target volumes as acceptable, minor, and major, respectively, and reviewer 3 scored 12%, 85%, and 3% of autodelineated target volumes as acceptable, minor, and major, respectively.
Discussion

In this study, we developed an ensemble model to automatically delineate nodal CTVs for patients with HNC undergoing radiation treatment planning using a novel deep learning-based approach. The metrics (DSC and HD) and clinical acceptability (based on clinician review of the lymph node target volume autosegmentations) demonstrated excellent performance and are promising for clinical usability, with greater than 99% of the autosegmentations scored as acceptable or requiring only stylistic edits. The resulting model can autosegment multiple CTV level options, allowing radiation oncologists to choose patient-specific target volumes based on lymph node level involvement and clinical history (Fig. 4).

Manual delineation of CTVs for HNC radiation therapy remains a challenging and time-consuming task for radiation oncologists. Researchers have proposed several atlas-based methods for head and neck lymph node autosegmentation. Teguh et al.\textsuperscript{44} developed a multiatlas-based approach that resulted in a mean DSC of 0.67 for lymph node levels. Similarly, Yang et al.\textsuperscript{17} reported a median DSC value of 0.778 using a multiatlas-based approach that used the Simultaneous Truth and Performance Level Estimation algorithm. More recently, investigators have developed deep learning models to autosegment lymph node CTVs.\textsuperscript{37,40,45} Also, Men et al.\textsuperscript{37} developed an end-to-end deep 2-dimensional deconvolutional neural network trained with 184 nasopharyngeal cancer patients who resulted in a mean DSC value of 0.826 for the low-risk CTV. Our group\textsuperscript{39} reported similar results (mean DSC value, 0.816 for 75 test cases) using a 3-dimensional fully convolutional neural network trained with 210 oropharyngeal cancer patients. More recently, Wong et al.\textsuperscript{40} reported a mean DSC value of 0.72 for neck CTVs using a commercial system (Limbus Contour) with a U-Net—based model. Our approach is different from previous work in that we developed a model that can provide a variety of target volumes for the same patient (ie, the radiation oncologist can choose lymph node level coverage). This makes comparison of our results with those of previously published studies of lymph node target volume autosegmentation difficult to interpret. Furthermore, the greatest benefit of our ensemble approach was a systematic reduction of the number of slices (mode of 1 slice vs 2 slices from the ground truth) in the caudal edges of the target volumes. We expect the caudal extent to exhibit the largest variability in our input data, so it is natural to expect for individual models to be more sensitive to larger deviations in these regions. Using this ensemble approach, our model can define this caudal edge with more confidence than single model autosegmentations, which leads to better generalization compared with ground truth contours.

Although our autosegmentations and ground-truth volumes agreed well in most cases, we noticed that the deep learning model failed to produce acceptable target volumes for the patients who had prior neck surgery. Figure 5 shows CT images from 3 patients who underwent neck dissection. In these cases, physician review suggested minor or major edits at lymph node level II/III where the right neck contours failed to provide appropriate coverage posteriorly in all 3 cases (only CTV\_LN\_Ib\_V autosegmentation is shown in the figure, but we observed similar results for CTV\_LN\_Ia\_V and CTV\_LN\_II\_IV). After noticing consistent undercontouring in these regions during qualitative analysis, we reviewed
the cases used to train our models and found that none presented with large resections
as observed in these 3 cases. Clearly, when a patient underwent neck dissection, the
deep learning-based algorithm lacks the prior knowledge to confidently produce acceptable
delineations. Whether similar anatomic scenarios (ie, prior parotidectomy, glossectomy, oral
cavity resection) can have similar effects on the model’s ability to produce reliable target
volumes remains unknown, and further testing may be warranted to identify additional
failure modes in autosegmentations. Inclusion of outlier cases, such as those with prior
surgeries, during training of the model could help overcome deficiencies in these scenarios,
but this remains to be evaluated.

Qualitative evaluation showed that 99% of autosegmented target volumes were within
acceptable ranges by board-certified head and neck cancer radiation oncologists with either
no edits or only stylistic edits. Overall, this demonstrates the use (and safety) of these
autosegmented volumes; fundamentally, 99% of them could be used without risk by the
treating physicians. However, it also points out, again, that individual physicians have their
own contouring styles. Overall, reviewer 1 scored the autosegmentations more favorably
than reviewers 2 and 3. Because reviewer 1 generated the manual contours used to train
the autosegmentation model, it is not surprising that the autosegmentations were more
consistent with reviewer 1’s delineation style. Reviewers 2 and 3 scored the large majority
of volumes as “minor edits;” these were described as safe, acceptable in a typical peer
review QA of target volumes, and stylistic in nature. When asked for detailed feedback,
reviewers 2 and 3 considered the autodelineated target volumes to be slightly generous
toward the posterior digastric muscle, scalene muscle, sternocleidomastoid muscle, and/or,
ocasionally, adjacent parotid. The retropharyngeal node target volumes were scored as
having the most “acceptable” scores (72%) among the 3 reviewers; examples of “minor
edits” from reviewers 2 and 3 included deleting contours on the most caudal slice or
edits to the posterior border (<3 mm in size) of the volumes for some slices. Only 1
reviewer provided recommendations for “major” edits to some of the autosegmented target
volumes of 3 cases. Two of these patients had previously received neck dissections (both
shown in Fig. 5). For these cases, each individual reviewer provided different scores for the
target volumes (ie, these received scores of “acceptable,” “minor,” and “major”). The third
case’s contours that received “major edits” scores were scored as “acceptable” by the other
reviewers. This qualitative evaluation does highlight the stylistic preferences of different
treating physicians, which will be a significant challenge for any automated system.

Automating the delineation of target volumes in HNC radiation therapy has several potential
benefits. First, if automatically generated target volume delineations are consistent and
accurate, it could lead to the standardization of target volume delineations, which are
among the largest sources of uncertainty in radiation treatment planning. Second, consistent,
sequential target volume delineations using automated models could lead to increased
quality of clinical data. Authors have reported that noncompliant target volume delineations
in clinical trials can significantly affect patient outcomes and the quality of clinical trial data.
Third, if an autosegmentation model is clinically implemented and validated by positive
patient outcomes, it could be scaled to provide low-resource clinics around the world
with high-quality delineations. Several ongoing efforts are increasing access to high-quality
radiation therapy in low- and middle-income countries through automation. For example, the
Radiation Planning Assistant (RPA, https://rpa.mdanderson.org) is being developed at The University of Texas MD Anderson Cancer Center to fully automate the radiation treatment planning process with no or minimal user interventions.\textsuperscript{45-48} For such a system to be effective in reducing the workload at busy clinics with limited resources, including radiation oncologists, high-quality automatic contouring is essential.\textsuperscript{23} The present study showed that deep learning can achieve this, and we are integrating these tools to autosegment normal tissue and target volumes into the RAP system. Specifically, the RPA workflow is currently designed so that the radiation oncologist first identifies which lymph node levels should be contoured. After they are automatically contoured, the radiation oncologist contoursthe gross tumor volumes and reviews and, if necessary, edits the nodal level contours. The RPA then automatically generates a volume-modulated arc therapy plan. This is only reasonable with access to a very robust automated contouring solution such as that described herein. The target volume delineation model in the present work could be integrated into such systems to reliably and consistently generate high-quality lymph node clinical target volumes for HNC radiation therapy in the vast majority of cases.

Our study had a few limitations. First, a single radiation oncologist manually contoured the target volume delineations used to train our model. This individual is subspecialized in HNCs, with more than 10 years of clinical experience; however, practice pattern variations in target volume delineation may not be appreciated. Second, all cases evaluated (both quantitatively and qualitatively) were HNC patients previously given treatment at a single institution. Thus, our patients may not sufficiently represent the large variability in anatomic presentations for HNC observed across different populations. Another limitation is that the model was trained to autosegment target volumes that were a combination of lymph node levels (typically treated in head and neck cancers) and did not allow for individual lymph node level autosegmentation.

**Conclusion**

We developed a fully automated artificial intelligence approach to autodelineating nodal CTVs for patients with intact HNC. The vast majority of autosegmentations were clinically acceptable after qualitative review when considering recommended stylistic edits. This work is promising in that it automatically delineates high-quality CTVs in a robust and reliable manner. This approach can be implemented in ongoing efforts for fully automated radiation treatment planning for HNC.

**Supplementary Material**

Refer to Web version on PubMed Central for supplementary material.

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Fig. 1.
(A) Computed tomography scans of patients with head and neck cancer are normalized in the craniocaudal extent by automatically cropping out slices below and above predefined anatomic markers. (B) Identification of the left and right neck lymph node regions using computer vision techniques. Here the training data were doubled by performing a horizontal flip of the resulting input data. (C) Our deep learning model is trained using the unilateral input data to automatically segment individual lymph node target volumes.
Fig. 2.
Box plot of the distributions of overlap and distance metrics in a comparison of the ground-truth and autosegmented volumes for each neck lymph node target volume. The boxplots are representative of individual metric’s interquartile range, whereas the whiskers denote values within 1.5 interquartile range, and the outliers (circles) are values that are found outside of this range. Abbreviations: DSC = dice similarity coefficient; FND = false negative dice; FPD = false positive dice; HD = hausdorff distance; MSD = mean Surface distance; VS = volume similarity.
Fig. 3.
Visual comparison of the ground-truth and auto-segmented neck lymph node (LN) target volumes.
Fig. 4.
Example results from a randomly selected case from our test set. Twenty axial slices from a computed tomography scan of a 57-year-old male patient with base of tongue cancer show the auto-segmented lymph node target volumes. The axial slices are evenly sampled and distributed from the cranial extent of the retropharyngeal lymph nodes to the caudal extent of the level IV lymph node.
Fig. 5. Computed tomography images of 3 patients with auto-segmentations requiring minor edits. All 3 patients (1 per row) had their neck dissection before radiation therapy. In these cases, the auto-segmented volumes were undercontoured between lymph node levels II and III as shown in columns 2 and 3. Whereas target volumes for neck lymph node levels Ib-V are shown in this figure, auto-segmentations for levels II-IV and Ia-V were subject to similar undercontouring in these regions. RP node target volumes were unaffected in this clinical presentation.
Table 1

Summary of quantitative evaluation between auto-segmented and ground-truth target volumes

|        | DSC      | FND      | FPD      | VS       | HD (mm)  | MSD (mm) |
|--------|----------|----------|----------|----------|----------|----------|
| RP     | 0.834 ± 0.030 | 0.234 ± 0.064 | 0.099 ± 0.033 | 0.135 ± 0.082 | 5.5 ± 1.3 | 1.0 ± 0.2 |
| Level II-IV | 0.907 ± 0.013 | 0.063 ± 0.023 | 0.123 ± 0.023 | -0.060 ± 0.038 | 8.4 ± 3.7 | 1.1 ± 0.2 |
| Level Ib-V | 0.909 ± 0.013 | 0.062 ± 0.021 | 0.120 ± 0.023 | -0.057 ± 0.036 | 8.1 ± 3.1 | 1.1 ± 0.2 |
| Level Ia-V | 0.897 ± 0.014 | 0.053 ± 0.019 | 0.154 ± 0.027 | -0.101 ± 0.037 | 8.6 ± 3.1 | 1.3 ± 0.2 |

Abbreviations: DSC = dice similarity coefficient; FND = false negative dice; FPD = false positive dice; HD = hausdorff distance; MSD = mean Surface distance; RP = retropharyngeal; VS = volume similarity.
Table 2
Qualitative scores for 32 cases separated by postoperative status

|                | Nonpostoperative (n = 25) | Postoperative (n = 7) |
|----------------|---------------------------|----------------------|
|                | Scores                    | Scores               |
|                | 1 | 2 | 3 | 1 | 2 | 3 |
| Reviewer 1     |               |               |               |               |               |               |
| Ia-V right     | 25 | 0 | 0 | 4 | 3 | 0 |
| Ia-V left      | 25 | 0 | 0 | 7 | 0 | 0 |
| Ib-V right     | 25 | 0 | 0 | 4 | 3 | 0 |
| Ib-V left      | 25 | 0 | 0 | 7 | 0 | 0 |
| II-IV right    | 25 | 0 | 0 | 4 | 3 | 0 |
| II-IV left     | 25 | 0 | 0 | 7 | 0 | 0 |
| RP right       | 25 | 0 | 0 | 7 | 0 | 0 |
| Reviewer 2     |               |               |               |               |               |               |
| Ia-V right     | 14 | 11 | 0 | 4 | 3 | 0 |
| Ia-V left      | 14 | 11 | 0 | 4 | 3 | 0 |
| Ib-V right     | 14 | 11 | 0 | 4 | 3 | 0 |
| Ib-V left      | 14 | 11 | 0 | 4 | 3 | 0 |
| II-IV right    | 14 | 11 | 0 | 4 | 3 | 0 |
| II-IV left     | 14 | 11 | 0 | 4 | 3 | 0 |
| RP right       | 21 | 4 | 0 | 5 | 2 | 0 |
| RP left        | 21 | 4 | 0 | 5 | 2 | 0 |
| Reviewer 3     |               |               |               |               |               |               |
| Ia-V right     | 0  | 25 | 0 | 0 | 5 | 2 |
| Ia-V left      | 0  | 24 | 1 | 0 | 7 | 0 |
| Ib-V right     | 0  | 25 | 0 | 0 | 5 | 2 |
| Ib-V left      | 1  | 23 | 1 | 0 | 7 | 0 |
| II-IV right    | 2  | 23 | 0 | 0 | 6 | 1 |
| II-IV left     | 4  | 21 | 0 | 1 | 6 | 0 |
| RP right       | 9  | 16 | 0 | 1 | 6 | 0 |
| RP left        | 11 | 14 | 0 | 2 | 5 | 0 |

Individual cases were reviewed on a slice-by-slice basis by 3 radiation oncologists each having more than 10 years of HNC experience.

Auto-segmentation scores: 1 = clinically acceptable without requiring edits; 2 = requiring minor edits (ie, stylistic recommendations, <2 minutes); 3 = requiring major edits.

Abbreviation: HNC = head and neck cancer.