Glottic lesion segmentation of computed tomography images using deep learning

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ABSTRACT

The larynx, a common site for head and neck cancers, is often overlooked in automated contouring due to its small size and anatomically complex nature. More than 75% of laryngeal tumors originate in the glottis. This paper proposes a method to automatically delineate the glottic tumors present contrast computed tomography (CT) images of the head and neck. A novel dataset of 340 images with glottic tumors was acquired and pre-processed, and a senior radiologist created a detailed, manual slice-by-slice tumor annotation. An efficient deep-learning architecture, the U-Net, was modified and trained on our novel dataset to segment the glottic tumor automatically. The tumor was then visualized with the corresponding ground truth. Using a combined metric of dice score and binary cross-entropy, we obtained an overlap of 86.68% for the train set and 82.67% for the test set. The results are comparable to the limited work done in this area. This paper's novelty lies in the compiled dataset and impressive results obtained with the size of the data. Limited research has been done on the automated detection and diagnosis of laryngeal cancers. Automating the segmentation process while ensuring malignancies are not overlooked is essential to saving the clinician's time.

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1. INTRODUCTION

The larynx, also known as the voice box, is a 5 cm long organ extending from the tongue's base to the tracheal cartilage. Laryngeal cancer, also known as cancer of the throat, is a common site of Head and Neck cancer. A significant portion of the population is affected by laryngeal cancer, with over 184,000 new cases detected every year, and annually, 99,000 patients die of laryngeal cancer worldwide [1]. The significant risk factors for laryngeal cancer are smoking tobacco and consumption of alcohol [2].

The larynx comprises three sub-sites: the supra-glottis, glottis, and sub-glottis. The incidence of cancers across these sub-sites is not uniform. The incidence of glottic cancers is much higher at 60% to 70% of the cases of laryngeal cancer [3]. The glottis is a minor larynx component, yet most laryngeal cancer originates in this region. The glottic larynx includes the true vocal cords. Small lesions on the vocal cords can cause noticeable changes, such as hoarseness in the voice. Larger lesions can restrict mobility and cause vocal cord fixation [4]. When detected early, the five-year survival rate of glottic cancer is 83%. However, if cancer spreads to surrounding tissue and lymph nodes, the five-year survival drops to 48%. If not detected by the time cancer metastasizes, the number further decreases to 42% [5]. In this paper, we focus on glottic cancers.

Medical image segmentation is the process of detecting boundaries within a medical image. These boundaries can be 2D or 3D in nature. The segmentation of the larynx into the sub-anatomical structures and the lesion detected in the imaging play a role in deciding the course of treatment of laryngeal cancer. Segmenting the suspicious lesions that could be missed and the anatomical structures to indicate the areas of the larynx affected can help develop an accurate treatment plan while reducing the time taken on analysis. Automated segmentation could diminish the possibility of overlooking a malignancy, and under-staging could be reduced and lead to the development of a better treatment plan in a time-efficient manner. Automatic segmentation is the process of automatically assigning a label to every pixel present in the medical image. This saves time and effort for the clinician and provides secondary support in cases of missed areas of concern in a scan. Segmentation of laryngeal anatomies in a computed tomography (CT) scan requires ground-truth creation. A clear reference protocol must be consistently followed for delineating various laryngeal sub-anatomies. This did not exist until 2014 when a paper defined a standard method for larynx contouring [6]. The size of the tumor and the anatomies affected are crucial pieces of information that determine the stage, which determines the treatment course. Table 1 illustrates the impact of the tumor's size, location, and subsite involvement on the T stage of the tumor [5], [6].

Table 1. T stages of glottic tumor

Stage	Relevance
T1	The extent is limited to the vocal cord involvement without affecting mobility.
T2	Extends to the supra-glottis above and the sub-glottis below with the possibility of vocal cord mobility impairment.
T3	The extent of the tumor is limited to the larynx, with paralysis of either or both of the vocal cords.
T4	The extent of tumor spread is beyond the larynx organ.

A symptomatic individual undergoes imaging tests that are carried out to assess the extent and spread of glottic cancer. Contrast-enhanced CT imaging is a standard diagnostic test performed for detecting and diagnosing glottic cancer. CT scanning is painless, non-invasive, and accurate. A significant advantage of CT is its ability to image bone, soft tissue, and blood vessels simultaneously. Unlike conventional X-rays, CT scanning provides detailed images of many types of tissue, bones, and blood vessels. They are relatively quick to acquire, efficient in cost and computational power required, and tolerant to slight movements during acquisition. Glottic anatomy on a contrast CT image is shown in Figure 1.

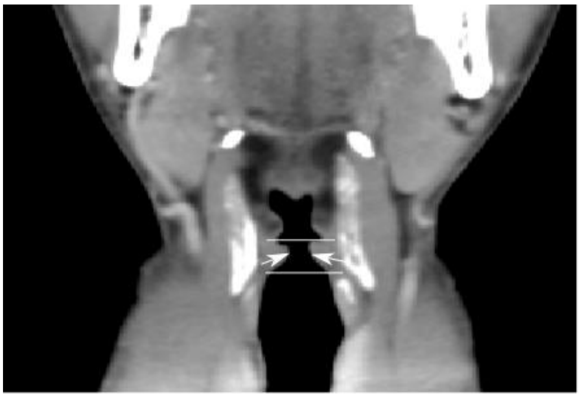


Figure 1. Coronally reformatted contrast CT image shows the region of the glottis with pointers to the vocal cords

There have been a few papers that have expressed interest in this domain. The first approaches included using multi-atlas-based registration techniques [5], [7]–[9]. In this technique, an atlas is a prelabelled segmentation image that serves as a ground truth. The new images are superimposed on the atlas image, and the algorithm segments the region of interest based on the overlap similarities. However, this technique for lesion segmentation requires an extensive ground truth database. The highest Dice score coefficient obtained for the glottis was 64% in a work that used a dataset of 10 images [10].

Ibragimov and Xing [11] were the first to use deep learning for larynx segmentation in Head and Neck CT images. They used a convolutional neural network (CNN) approach to auto-segment the larynx. A CNN is a machine learning technique that takes an input image to differentiate one from the other and assigns importance to various aspects/objects in the image, learning from the dataset as it goes along [12]. Dijk *et al.* [13] used multiple CNNs to label the input voxel by voxel. With the largest dataset of all laryngeal tumor studies (311 volumes), they reached a segmentation accuracy of 71% for the entire larynx segmentation. Rooij *et al.* [14] used the 3D U-Net architecture to segment the larynx automatically. A 3D U-Net is a CNN architecture, a deep learning approach that performs segmentation of larynx volume from the sparse annotation of datasets [15]. This paper obtained a Dice score of 78% for the entire larynx. Wu *et al.* [16] used fuzzy models that figured the hierarchy based on relationships between detected objects and a delineation algorithm to contour the substructures of the head and neck. Fuzzy models are designed to model data that can be vague or uncertain by recognizing patterns and utilizing relevant information [17]. They obtained a dice score overlap of 75%.

Work done on automated larynx segmentation on CT images is primarily focused on segmenting the entire larynx volume of interest. Automated segmentation of tumors in the glottis on contrast CT images is a relatively unexplored area. Of the papers compiled and studied, the dice score overlap of the entire larynx using the CNN method is 83% [11], 85% [18] and 87% [19], respectively. We aim to extend the previous research by exploring automated segmentation of laryngeal tumors on contrast CT images. The goal is to identify and delineate the malignant tissue using a 2D binary classification deep learning technique. This paper proposes a method to extract glottic tumor segmentations from contrast CT images using a modified U-Net. Our study aimed to see how well a deep learning model would perform on our novel custom dataset of 90 patients.

2. METHOD

2.1. Image acquisition

This study used head and neck contrast CT images of 90 individuals. Data was acquired using a Philips CT scanner, with a resolution of 512×512 pixels and a 3mm distance between the slices. The grayscale image obtained in 16-bit DICOM format [20] was converted to NIfTI file format [21]. The image acquisition stage consisted of a total of 99 CT image series collected. The radiology, histopathology and clinical information of these patients were accessed. The distribution of the dataset across T stages is represented in Table 2. The T stages represent tumors on different sub anatomies of the glottis. The size of the tumor increases with the T-number as more anatomies are affected. Image acquisition was a crucial highlight of this study as the datasets containing glottic tumor segmentation on CT images are not publicly available.

Table 2. Distribution of T-stage across glottic tumor dataset collected

T Stage	No. of Studies
T1	37
T2	13
T3	24
T4	16
Unknown	9
Total	99

2.2. Dataset creation

Once the images once obtained, the groundwork is established to make these images usable. The steps involved in creating the dataset are illustrated in Figure 2. The dataset was divided into test and train sets using an 80:20 split. Only CT slices with segmentations present in them were used for training.

2.3. Data augmentation

Data augmentation is a technique that is used for training deep learning models. Our dataset contained 384 slices and trained our model with the given data as it would overfit the deep learning model. Therefore, we used data augmentation to generate synthetic data generated by applying certain transformations to available data to synthesize new data. Thus, this step acted as a regularize and helped reduce overfitting. The train data was augmented with transforms using the sci-kit-learn Python library [22]. The various transformations applied, and values are illustrated in Table 3. Augmentation was applied at run-time during model training.

2.4. Model building

The original U-Net [23] was trained with augmented data. After modifying the input and output layers of the U-Net to fit our requirements: input 128×128 dimensions, we observed that an additional layer prefacing the U-Net was giving us better results. The proposed model shown in Figure 3 uses the entire image as output, not a patch. The number of layers and activations are equal. Batches were shuffled during every iteration, and the batch size was selected as 30 considering memory requirements. The model's parameters that gave us the best output were binary cross-entropy, maximizing the dice coefficient, and using the Adam optimizer [24]. The resulting model developed, the modified U-Net, has a 128×128 input and generates a 128×128 output. The input to the model was an h5 file containing 3D train and test image vectors with corresponding tumor segmentations.

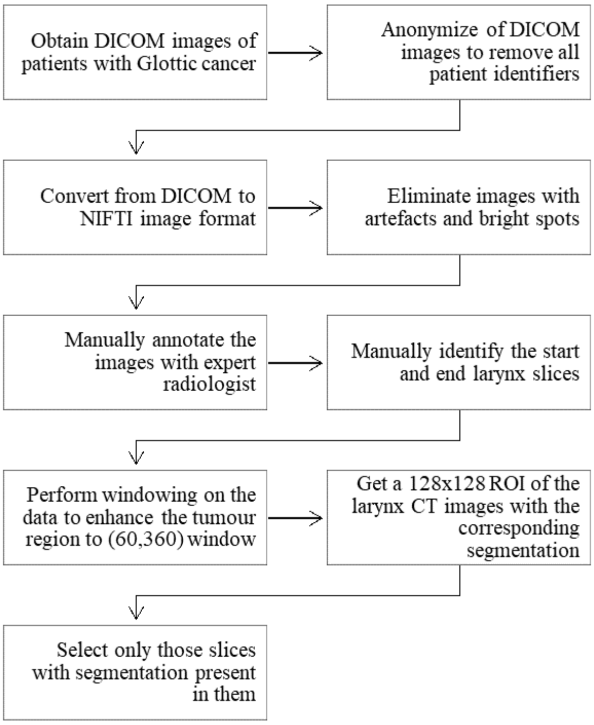


Figure 2. Steps involved in creating the glottic tumor dataset for the study

Table 3. Data augmentation applied and their table values

Augmentation Type	Range
Rotation	[-5◦, +5◦]
Shear	[0.1]
Zoom	[0.8,1,1]
Flip	1

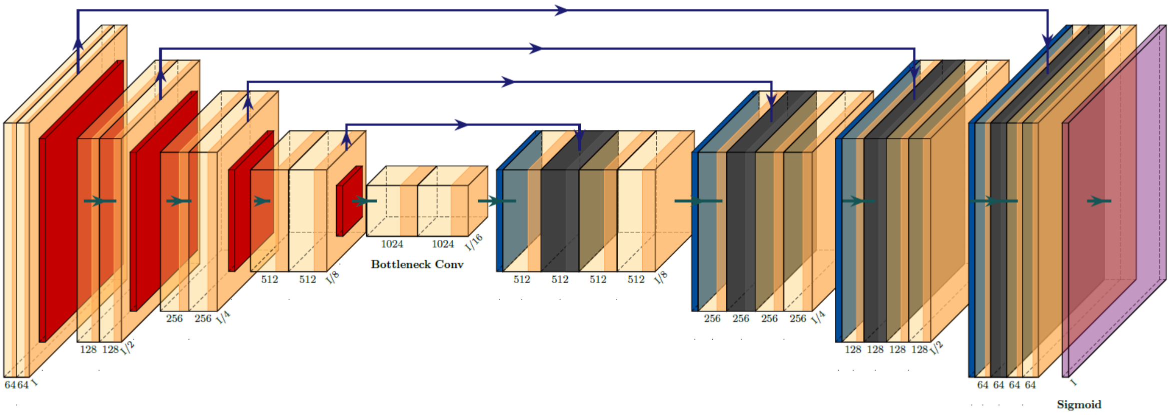


Figure 3. Proposed modified U-net architecture

2.5. Evaluation metrics

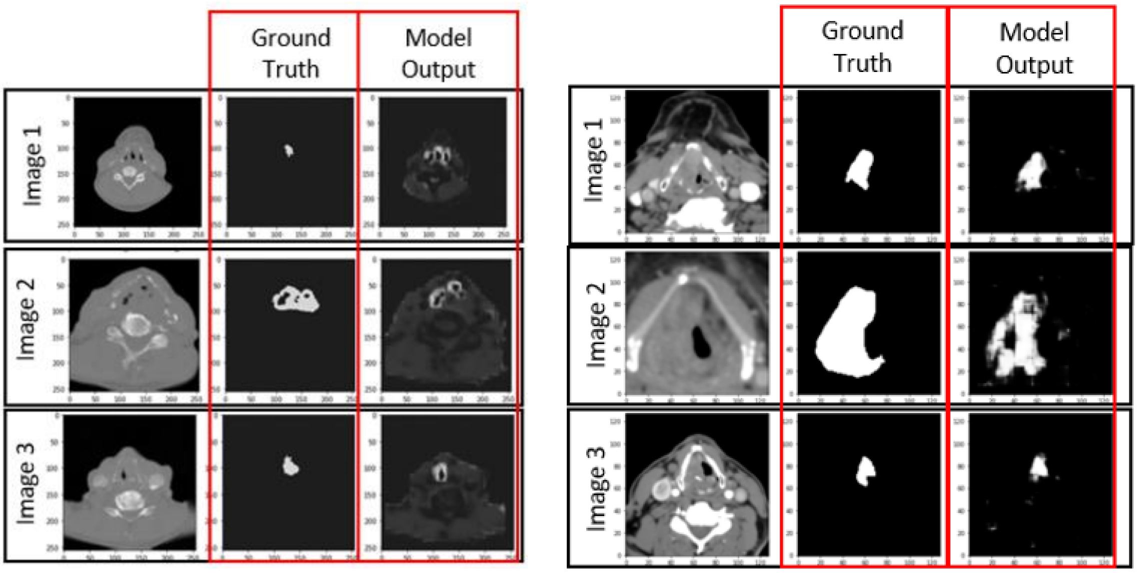
To analyze the efficiency of our model, we want to maximize the overlap between the expected segmentation versus obtained results. Therefore, we use the Dice similarity coefficient [25], [26]. In (1), if y is the desired segmentation pixel and $\tilde{y}$ is the segmentation output of our modified U-Net, using set theory notations, the Dice score D is (1).

$$D\ (y, \tilde{y}) = \frac{2|y \cap \tilde{y}|}{|y| + |\tilde{y}|} \tag{1}$$

All processing for data analysis was done using Keras and Python. All computations for learning were performed on a Z230 Station from NVIDIA running Linux operating system with an Intel(R) Core(TM) i7-4790 CPU @ 3.60 GHz GPU NVIDIA QUADRO K420 with 4 GB RAM. The network architecture implemented a deep learning framework, Tensorflow [27] version 3.7.

3. RESULTS AND DISCUSSION

This section contains visual assessment findings for segmenting the laryngeal tumor on CT images using the 2D U-Net models. Out of the 99 collected cases of glottic laryngeal cancer, 90 cases were included in the study. A curated 70:30 train: test split was carried out. Figure 4(a) shows how the model worked with images of 256×256 size and without applying thresholding for the images. The model was not able to detect the tumor with acceptable accuracy. The method of pre-processing has had a significant impact on the results exhibited by the segmentation model. Setting the thresholding parameters to increase the contrast enhancement of the tumor was necessary to get outputs comparable to other studies conducted in this area. Creating the region of interest (RoI) for the larynx also helped the model train quicker and locate the region of tumor segmentation. Once done, the segmentations tremendously improved in quality and usefulness. Figure 4 shows the segmentation of glottic tumors by the original vanilla U-Net [23] on our glottic tumor dataset before preprocessing of data in Figure 4(a) and the improvement after preprocessing of data, in Figure 4(b). A side-by-side comparison shows the improvement of the Dice score from 34% in the original 256×256 dataset to 45% in the pre-processed dataset. The tumor enhancement and overall image quality can be observed in the first column of Figure 4(b). The images were cropped to 128×128 pixels, the contrast settings were changed to a 60,360 window, and the CT images were normalized with their Hounsfield unit conversion to highlight the larynx tumor.



(a) (b)

Figure 4. Vanilla U-Net segmentation results (a) before and (b) after data preprocessing

The original U-Net was modified to include batch normalization with a batch size of 30 and an additional input layer to accept our input images of 128×128. Runtime augmentation of the training data was carried out to increase the generalizability of the glottic tumor dataset. In the proposed U-Net, optimization was performed to minimize the loss functions. The performance of Dice score as a metric was compared with the performance of a combined metric of Dice score and binary cross entropy [28] as performed in a related research work [29]. The comparison of the metrics is shown in Table 4.

Table 4. Evaluation of U-Net variations

Deep Learning Architecture	Dataset	Loss Function Metric Used	Train Score	Test Score
Vanilla U-Net without	Before Preprocessing	DSC	48.82	34.73
Batch normalization	After Preprocessing	DSC	56.15	45.33
Proposed U-Net with batch normalization	After Preprocessing	DSC	79.43	65.50
(Batch size=30)		DSC + Binary Cross Entropy	86.68	82.67

Our proposed model worked best with a combined loss function metric of the dice score and binary cross entropy [28] method succeeded in segmentation with a Dice coefficient of 82.67% on a test set and 86.68% on the train set. The results of our model visualized on the test data are shown in Figure 5. The tumor was then visualized with the corresponding ground truth. Sensitivity and Specificity are not included as they were found to be highly correlated with the obtained Dice score metric. The vanilla U-Net performed the poorest on our dataset when there was no augmentation of data. However, it was an excellent point to start with and work on improving the performance of the segmentation model. The performance of our model improved considerably with preprocessing and fractionally with data augmentation.

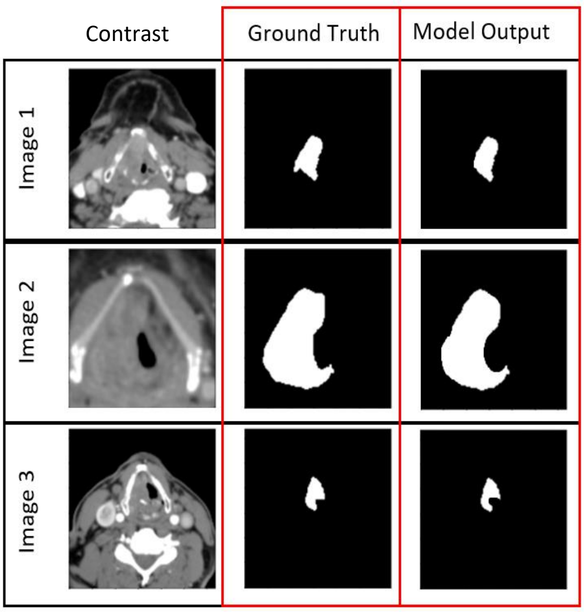


Figure 5. Proposed 2D U-net glottic tumor segmentation results

4. CONCLUSION AND FUTURE WORK

This paper proposes a modified version of the U-Net for automated 2D laryngeal glottic tumor segmentation in contrast-enhanced Head and Neck CT images. The small size and the inherent complexity of the anatomy make the larynx a challenging organ to segment compared to other anatomies such as the brain or lung. In smaller tumors, i.e., T1 tumors, there is a possibility of a CT scan missing the tumor entirely. In such cases, the tumors can only be detected by a laryngoscope as the tumor is only superficially visible and is minuscule.

Future research would entail working on a larger multicentric dataset. In terms of the model architecture, 3D CNNs can be employed to exploit the spatial nature of the data and construct a 3D segmentation model. The prediction accuracy can be improved further as the possibility of a tumor extending to the nearby slices is more likely than anywhere else randomly. This semantic information on a well-designed model is bound to give promising results. 3D networks will significantly improve efficiency as the spatial volume information is retained in such scenarios.

Therefore, we conclude that this is a significant initial step in automating the glottic tumor detection and delineation process. Automated tumor segmentation can save hundreds of clinicians' manual annotation hours and have applications in detection, diagnosis, and treatment planning. A user interface designed and integrated to showcase this annotated dataset can be used as a teaching tool for medical trainees. It can be used to visualize tumor spread, especially in extreme cases where the tumor is either too small to be observable or large enough to distort the larynx and its anatomy completely.

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