Automatic urinary bladder detection from medical computed tomography scans using convolutional neural network

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ABSTRACT

This paper introduces a system for detecting and evaluating an algorithm that segments the urinary bladder in medical images obtained from contrast-less computed tomography (CT) scans of patients with bladder tumors. Multiple segmentation methods are needed in situations where tumors in the bladder cause structural changes that appear as irregularities in images, complicating the slicing process. The segmentation process begins with viewing the urinary bladder DICOM in three different perspectives, and then enhancing the image to expand the dataset. Next, the areas of the urinary bladder are pinpointed, with the urinary bladder dataset being split into 70% for training and 30% for testing to distinguish it from the nearby tissues, organs, and bones. The suggested system was evaluated on eight 3D CT images obtained from the cancer imaging archive (TCIA). Results from the experiment show that the designed system is effective in identifying and delineating the urinary bladder.

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1. INTRODUCTION

Bladder cancer ranks as the ninth most prevalent cancer globally, with highest incidence in men in Western and Southern Europe, North America, North Africa, and Western Asia. Additionally, women consistently have lower rates of infection compared to men, although gender disparities differ across countries [1]. Based on the latest data, The American Cancer Society predicts that bladder cancer will result in 25,870 fatalities (19,240 among males and 6,630 among females) in the US in 2026 [2], with 76,030 new diagnoses (60,490 in males and 18,540 in females) [3]. Even with this data, urinary bladder cancer remains one of the most treatable types of cancer. If cancer is detected early and remains only in the bladder, 94% of patients have been effectively treated and survived. Nonetheless, if diagnosed late, the chances of survival drop significantly to just 6% [4]. This distinct variation necessitates a precise and thorough review of all instances in which hemorrhagic bleeding is the sole typical and visible sign [5], in order to identify tumors prior to them infiltrating nearby structures or giving rise to a malignant tumor, thereby maximizing the patient's chances of survival [6]. During this competition with the clock, the bladder examination is standard and typically mandatory [7]-[9].

Identifying bladder boundaries in computed tomography (CT) scans poses various difficulties. Contrast material injected intravenously can fill the bladder, leading to partial or complete opacity. Distinguishing between wall of bladder and surrounding soft tissue is difficult due to the very low contrast, presenting a challenge in clear definition. Additionally, bladders may present themselves in different sizes and shapes during imaging.

Nonetheless, it comes with several drawbacks as it is highly restricted, requires a lot of time, causes discomfort, and is intrusive. Imaging techniques are now taking the place of it [10]. CT and magnetic resonance imaging (MRI) are commonly selected options. MRI is most commonly utilized in the creation of computer-aided diagnostic systems for the urinary bladder due to its ability to provide detailed imaging and align soft tissues, making it easier to distinguish between them [11]. Nevertheless, doctors frequently utilize CT scans for manual diagnosis and staging due to their reduced expenses, quicker processing times, and increased patient comfort [12].

In these cases, the training sets were usually limited, typically containing fewer than 500 examples. With the increase in computational power, it becomes feasible to utilize convolutional neural networks (CNNs) with intricate structures that need to be trained with extensive datasets. The deep learning convolutional neural network (DL-CNN), powered by graphics processing units (GPUs), has demonstrated the ability to categorize real-life images with high accuracy when trained on a large dataset. Dheman *et al*. [13] Demonstrated in their study that the use of DL-CNN resulted in lower error rates and accurate classification on Image Net ILSVRC-2011 and ILSVRC-2013 data sets as well as the CIFAR-10 data set [14]. Our research focuses on implementing DL-CNN for bladder segmentation. DL-CNN was learned on identifying patterns in and around bladder, producing a map indicating the likelihood of the bladder to assist in level set segmentation [15]-[17]. To compare, we also created a map showing the probability of a bladder using Haar features to distinguish the bladder area from nearby structures identified by a random forest classifier [18]. The efficiency of template-based approach was evaluated by comparing their performances with our previous class using the local contour refinement (LCR) technique [19]-[21].

In this research, we investigated the use of DL-CNN for segmenting bladders. The DL-CNN was learned to identify bladder patterns and create a bladder probability map to assist in level set segmentation. The paper's outline is as follows. Firstly, the method for constructing the bladder using CNN is explained. Following that, the results of the segmentation method using CNN are presented. Finally, the conclusion is investigated.

2. METHOD

The study's design consists of three stages. The initial step involves preprocessing, which relies on data augmentation techniques; following that, 70% of dataset is used for training while 30% for test. Second step involves preparing the model using a complex CNN, and the third step involves implementing the process on the prepared model. Figure 1 depicts these three stages.

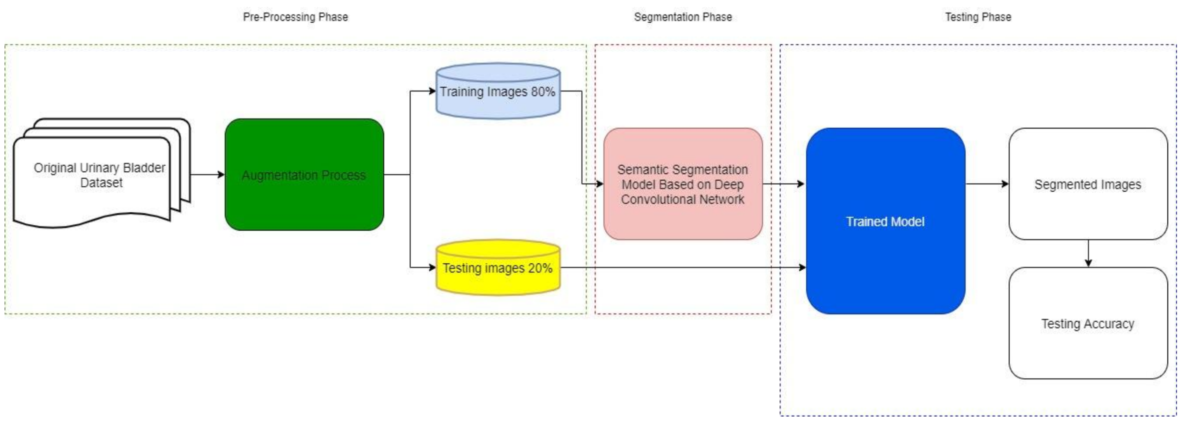


Figure 1. Suggested design for semantic segmentation model

2.1. Preprocessing phase

In order to prevent and combat overfitting, images are enlarged using label-preserving transformations [22]. Data augmentation is used on the training set in order to make the resulting model more resilient and resistant to any transformation that may occur during the medical scanning process. The rotation technique adopted in this study involves angles of 35, 65, 95, 125, 155, 185, 215, 245, 275, 305, and 335 [23]. In (1) and (2) are utilized to calculate image transformation through rotation.

$$I2 = cos(\theta) * (I1 - I0) + sin(\theta) * (J1 - J0) \quad (1)$$

$$J2 = -sin(\theta) * (I1 - I0) + cos(\theta) * (J1 - J0) \quad (2)$$

where the coordinates of a point (I1, J1), when rotated by an angle θ around (I0, J0), become (I2, J2) in the augmented image [24].

The implemented augmentation method increased the dataset size to 11 times its original size. This collection now contains 9110 images that will be utilized in both the training and testing stages. This will greatly enhance the testing accuracy of CNNs and increase the robustness of the proposed model against various rotation scenarios [25]. Figure 2 shows different rotation angles for images within dataset.

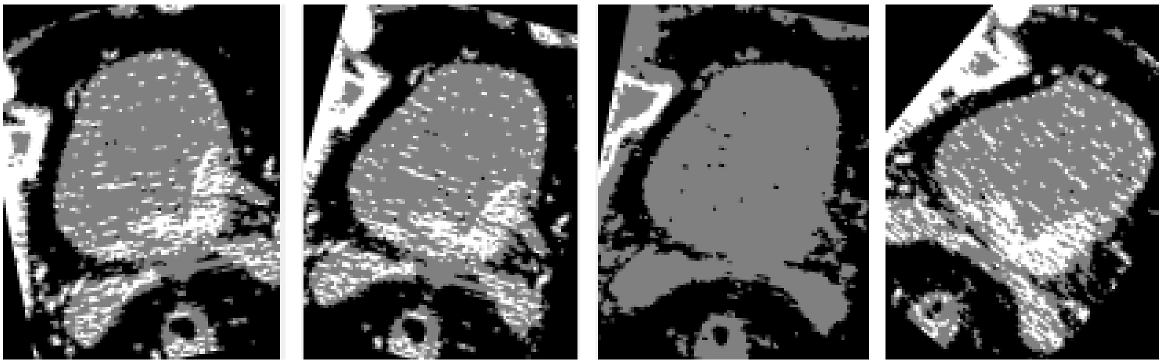


Figure 2. The dataset images rotated at angles of 35, 65, ..., 275 degrees for a sample image

2.2. Semantic segmentation method

Recommended semantic segmentation model utilizes deep CNNs. It includes 10 convolutional layers, 15 ReLU activation layers, 6 max-pooling layers, 6 de-convolution layers, 1 soft-max activation layer, and an output layer for pixel classification. First step of the model takes in a 256*256-pixel medical image, and additional layers are included in the order specified. The 1st and 2nd convolutional layers contain 128 filters each, 3rd and 4th have 256, 5th and 6th have 512, the 7th and 8th have 1024, and the 9th and 10th have 2,048 filters, all with a window size of 5*5. A ReLU activation layer comes before every convolutional layer. Also, there are max pooling layers following each 2 convolutional layers that reduce image's dimensions by 0.5. Deconvolutional part is composed of 4 layers: 2,048 filters in the first, 1,024 in the second, 512 in the third, and 256 in the fourth. A ReLU activation layer follows each deconvolutional layer. The model concludes with two ultimate layers: pixel classification layer and soft-max layer. Figure 3 shows suggested structure.

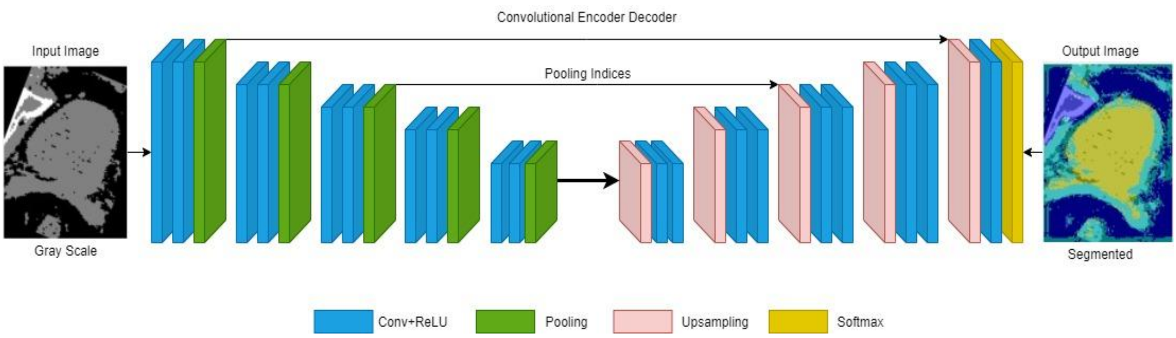


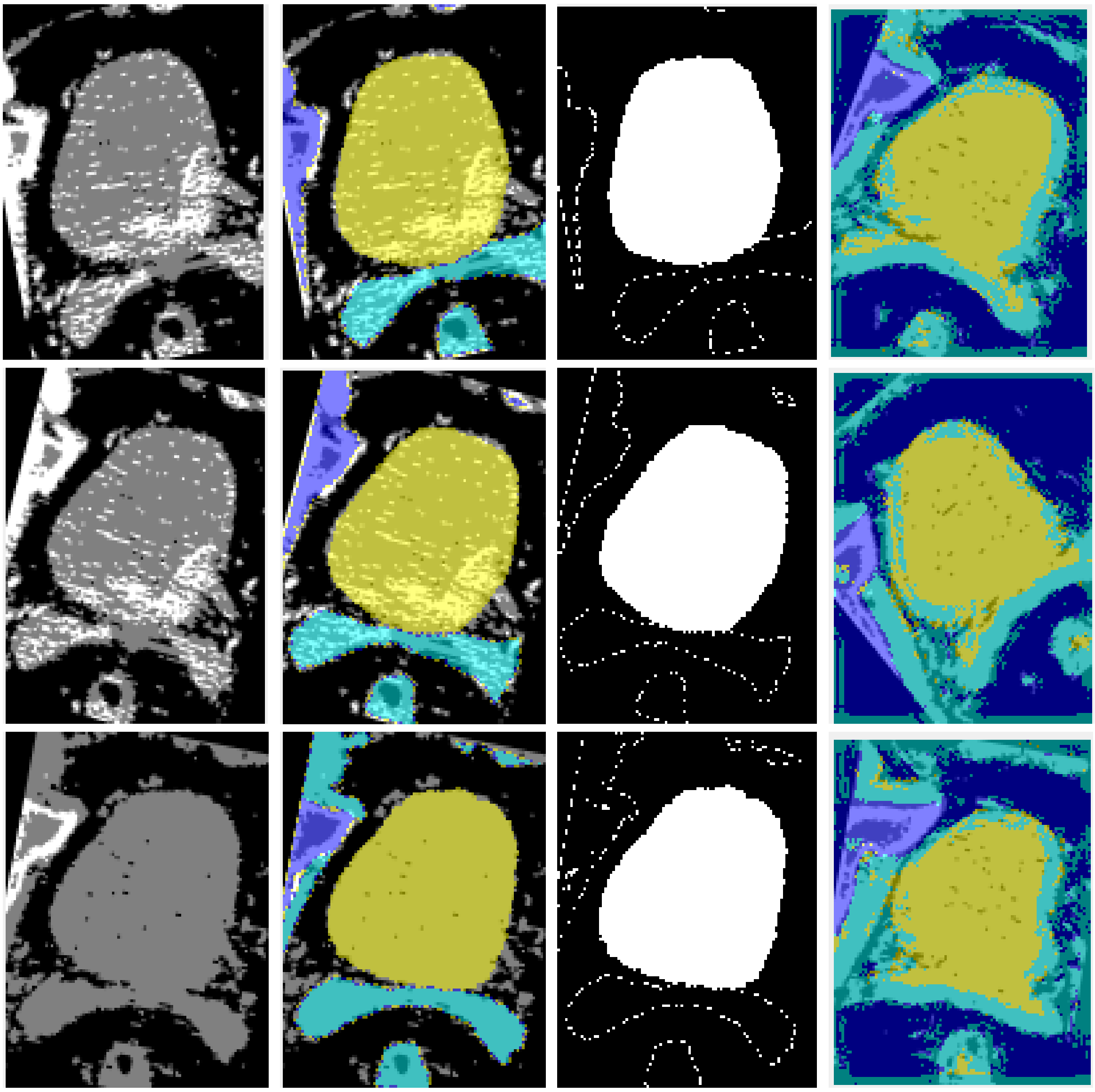
Figure 3. Visual representation of the semantic segmentation model

3. RESULTS AND DISCUSSION

The suggested model was put into effect using a software package (MATLAB). The GPU was explicitly used. All the tests were conducted on a computer equipped with Intel Core i7 processor operating at

4 GHz and RAM of 64 GB. As previously stated, the dataset contains 9,110 images following the augmentation process. Following the expansion process, dataset was divided into two parts: the first part for training and second portion for testing. The division is split into 70% for preparation and 30% for testing. The total number of images used for training is 6,377, and the total number of images used for testing is 2,733.

The proposed model achieved an overall testing accuracy of 97.86% based on the testing images. Figure 4 shows the results of suggested model for three distinct individuals. Figure 4(a) shows initial image, Figure 4(b) displays manual segmented image, Figure 4(c) illustrates segmented image from suggested model, and Figure 4(d) introduce discrepancy between ground truth image and segmented image, highlighting incorrect segmentation with a red pixel. The images show a cumulative error of 1.1% in all output segmented images due to a summation error. To test the strength and durability of the suggested model, a set of rotated medical images was chosen from testing dataset to confirm if model could accurately obtain and separate liver despite different angles of rotation. The model proposed was capable of accurately detecting liver, irrespective of its position, dimensions, and hue in image, achieving an average error rate of 1.1%.



(a) (b) (c) (d)

Figure 4. Images for 3 patients; (a) initial urinary bladder image, (b) identification of the urinary bladder, (c) accurate representation of the urinary bladder, and (d) segmented image created by proposed model on original image

4. CONCLUSION

In this research, we employed a deep semantic segmentation CNN to autonomously partition the urinary bladder in abdominal CT scans. Moreover, we created a deep semantic CNN model to generate CT scans displaying the urinary bladder. Furthermore, we acquired a likelihood map for the urinary bladder in order to start the segmentation procedure. The main benefit of our suggested approach is that it is easily usable by beginners as it does not need any input from users to start. Therefore, this method is appropriate for novices. Our suggested approach is one of the first attempts to utilize CNN and deep semantic segmentation for identifying the boundaries of the urinary bladder. The performance was assessed using the the cancer imaging archive (TCIA) and 3Dircadb1 public datasets in computer-assisted intervention and medical image computing. Our model has achieved a segmentation accuracy that exceeds the performance of the most advanced automated liver segmentation techniques. Suggested model reached a testing accuracy of 97.86% and is considered suitable for urinary bladder segmentation, supported by the close match between our segmentation findings and manual reference. In future research, it is essential to include lesions of bladder within the segmented bladder boundaries, and there are ongoing efforts to improve the segmentation process and accuracy. This project is a move towards developing a reliable bladder segmentation system, which is necessary for a CAD system to detect urothelial lesions found in CT urography images.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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