Artificial Intelligence Detection of Bladder Tumors under Endoscopy

Study Protocol

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1. Research Background

Bladder cancer is the ninth most common malignancy worldwide, with an estimated 430,000 new cases diagnosed annually [1]. The standard diagnosis and monitoring of bladder cancer rely on white light cystoscopy (WLC), with over 2 million cystoscopies performed annually in the United States and Europe [2]. Due to the high recurrence rate of bladder cancer, frequent monitoring and intervention are necessary.

Early detection and complete resection of non-muscle invasive bladder cancer can reduce recurrence and progression. However, up to 40% of patients with multifocal disease do not achieve complete resection during the initial transurethral resection of bladder tumor (TURBT) [3]. Many papillary tumors and flat lesions are difficult to identify through WLC [4]. There is an urgent need for cost-effective, non-invasive, and user-friendly adjunct imaging technologies to address the diagnostic deficiencies of WLC.

Recent advancements in deep learning-based automated image processing may provide new solutions to the limitations of cystoscopy [5]. Convolutional neural networks (CNNs) possess the ability to learn complex relationships and integrate existing knowledge into models, showing potential applications across various fields, including bladder tumor diagnosis [6]. We employed the HRNet algorithm, a convolutional neural network, for enhanced bladder tumor detection.

2. Research Objectives

We aim to explore the potential application of AI in urological tumors by collecting cystoscopy videos from patients undergoing cystoscopy. These videos including bladder tumors will be annotated manually by urologists, these annotated videos will then be used to train the AI algorithm to recognize the bladder tumors. We will compare the effect of AI algorithm with urologists.

3. Research Methods

This is a multicenter, retrospective, observational study.

4. Research Process

4.1 Patient enrollment

Inclusion criteria: 1. The patients who had bladder tumor and received WLC or TURBT, and the full-length surgery video is available.

Exclusion criteria:

1. The video is too blurry to distinguish the normal bladder wall and bladder tumor.
2. Lack of the appearance of bladder tumor before resection.
3. Lack of informed consent.

Patient personal information in the videos will not be shown.

Videos from the initially recruited 200 bladder tumor patients will be used for algorithm training and validation. Then, we compare the urologist and algorithm capability of detecting bladder tumor.

4.2 Data Preprocessing

To reduce the data volume, we extract the frame at a ratio of 1:4. Two urologists outline the boundary of bladder tumors in each frame separately and check for each other. AI algorithm is used to contour the same bladder tumors. The outlines of bladder tumor annotated by urologists and algorithm are compared, the IOU value, precision, sensitivity and false negative rate are analyzed.

4.3 Algorithm Development

This study uses semantic segmentation to identify bladder tumors in WLC. The D-LinkNet network structure uses a pre-trained ResNet34 on the ImageNet dataset as its encoder, with the central part utilizing dilated convolutions with different dilation rates in a cascaded manner, and upsampling performed using deconvolution [7]. The original resolution of all images is 1920×1080, downsampled by 2 to 960×540, and zero-padded in the width direction to obtain the image with a resolution of 960×544. The RGB images of this size are normalized, mean-subtracted, and variance-divided before being input into the network. The images undergo five encoding processes, dilated convolutions, and five decoding processes, ultimately producing a prediction result of 960×544, which is further post-processed. In this research, the parameter settings are as follows: batch size of 8, Adam optimizer, a learning rate of 0.001. The training environment is an NVIDIA TITAN Xp GPU.

4.4 Results Interpretation

The intersection over union (IOU) is a crucial standard for evaluating single-frame image recognition capability in image recognition [8]. When IOU is above the threshold, it suggests that the algorithm detects the object successfully, indicating a true positive. When IOU cannot reach the threshold, it suggests that the algorithm fails to detect the object, and indicating a false negative. If a prediction appears without ground truth in the image, it is considered a false positive. We calculate the algorithm's sensitivity and precision in the test set. The Dice coefficient measures the similarity between two samples. A higher average Dice coefficient indicates a better detection performance of the algorithm.

4.5 Indicators

① We classify the videos in test and validation groups according to the discernibility of bladder tumors in the video;

② We observe the algorithm's sensitivity, precision, false negative rate, false positive rate, and average Dice coefficient at IOU thresholds of 0.1 and 0.5 in the test set under different discernibility groups.

4.6 Statistical Methods

Analysis will be analyzed by R 4.0.2 software; the data will be expressed as absolute numbers or percentages.

5. Data Management and Confidentiality

All data in this study is properly stored to ensure security without loss or leakage. Sensitive information and patient information will not be uploaded to public platforms. During data processing, patients' personal information will be anonymized, and patient identification codes will be used to replace patient names and IDs. If technical services are needed, data will be appropriately encrypted, and a confidentiality agreement will be signed.

Reference:

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