Turkish Journal of Pediatric Surgery 2024;38(1):22-26
Doi: 10.62114/JTAPS.2024.19

Turkish Journal of Pediatric Surgery

Original Article

OPEN ACCESS

Development of a deep learning algorithm for the detection of renal image and luminal emptying in diuretic renography

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Abstract

Objectives: This study aimed to determine the accuracy of deep learning (DL) in kidney detection and differentiation of luminal emptying in pediatric diuretic renography.

Patients and methods: In the retrospective study, labeling was performed on 1,260 diuretic renography images of 36 children with unilateral or bilateral hydronephrosis between January 2020 and December 2020. The Tensorflow Object Detection API was used to deploy object detection models. Sensitivity, precision, and F1 score were determined for the detection of the right or left kidney as an object. Supervised training was applied for the differentiation of filled and empty renal pelvis and calyxes.

Results: In 1,260 labeled renal images, the left or right kidney was detected by the machine with 94% sensitivity, 96% precision, and 95% F1 score. The accuracy for differentiation was 88% for filled renal pelvis and calyxes and 66% for empty renal pelvis and calyxes.

Conclusion: The machine using DL algorithms with a large data set training may differentiate the kidney, its location, and the contrast-filled lumen. Low contrast and unclear boundaries in an empty lumen may affect the quality of annotation. The DL model used in this study could be adapted to other urinary system pathologies in medical scans.

Keywords: Artificial intelligence, children, deep learning, diuretic renography, nuclear medicine.

Deep learning (DL), as one of the main subsets of artificial intelligence (AI), uses ultrafast computing to rapidly optimize large multilayered datasets.[1] Image recognition is one of the cognitive functions of DL, and DL algorithms could help interpret images of surgical cases, including diagnostic medical scans, images of open surgery and endoscopic procedures, and pathology slides.[2-5]

In pediatric urology, urinary tract luminal pathologies such as obstruction, perforation, and reflux mostly need a radiological study with contrast material. Depending on the pathology, nuclear scans, X-ray studies, and computed tomography (CT) or magnetic resonance imaging (MRI) with contrast might be preferred. A well-demonstrated filling and emptying phase of the radionuclide or radiocontrast agent, location, and duration of the contrast stasis may affect the diagnostic process in urinary tract luminal pathologies.

Routine prenatal ultrasound screening of hydronephrosis increased the number of patients who have postnatal follow-up for differentiation of simple renal dilation from a more severe flow impairment related to the obstruction. A diagnostic tool is needed for interpretation of dilatation and the drainage problem to answer the question of whether the dilated luminal structure of the kidney is due to a significant obstruction or just due to a reservoir effect of the dilated cavity.

Received: January 15, 2024
Accepted: April 01, 2024
Published online: April 17, 2024

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Citation:

Tokar B, Celik O, Cetin N, Abbasov T, Ak Sivrikoz I. Development of a deep learning algorithm for the detection of renal image and luminal emptying in diuretic renography. Turk J Pediatr Surg 2024;38(1):22-26. doi: 10.62114/JTAPS.2024.19.

In the urinary system, diuretic renography is the method preferred to detect upper urinary tract obstruction associated with hydronephrosis. Injected radioisotope produces dynamic images of the kidneys. Renography is a noninvasive investigation of upper urinary tract obstruction, and it was first studied during the 1970s.[6] Conventionally, the diagnosis of the obstruction using renography is based on a visual interpretation of renograms.[7,8] This conventional method depends on the readers' experience and needs a more accurate quantitative approach to differentiate upper urinary tract obstruction.[8] To prevent discordant interpretations, the method should be improved with the support of a quantitative technique that may also determine the severity level of the obstruction.

A DL model for radiological image recognition could be built for a specific surgical pathology. If the dataset continues to accumulate, this model continues to learn and progresses gradually. A well-constructed DL model that has a dynamic training process with new data supports the decision-making process of a physician, and this may prevent misinterpretation caused by interobserver and intraobserver variabilities in the assessment of a radiological investigation.

This study aimed to construct a DL model that could detect the kidney as an image, locate its anatomic position, and would be able to understand whether the lumen is empty or filled with a contrast agent. Accordingly, diuretic renography was preferred to evaluate the model's ability to detect the kidney as the organ, differentiate the side as right or left, and differentiate empty or filled renal pelvis and calyxes (RPCs).

PATIENTS AND METHODS

Patients who were admitted to the pediatric urology clinic of the Eskişehir Osmangazi University Faculty of Medicine with unilateral or bilateral hydronephrosis between January 2020 and December 2020 were included in the retrospective study. A diuretic renography was required for the differential diagnosis of ureteropelvic junction obstruction to distinguish dilated, nonobstructed systems from those with significant obstruction. A total of 2,088 renogram images of 36 patients were received from the Department of Nuclear Medicine. The renography was performed with the F+20 protocol. Patients were hydrated and positioned supine with a gamma camera placed under the table. Following the radioisotope injection with 10 mCi of DTPA (diethylenetriamine pentaacetate), data acquisition started. Twenty minutes after the administration of the tracer, the furosemide was injected. Serial 1-min images as a 64×64 matrix were obtained for 29 min beginning from the start.

A DL study was conducted on the renal images of 29 frames of the left and right kidneys of each patient. Renal images of the patients who were operated before, the images showing poor renal function and urinary stasis in the ureter, and the images with an uncertainty label were excluded. In the 2,088 images of 36 patients, prespecified 1,260 renal images were annotated as the left or right side and as a filled or empty RPC.

The dataset was used to evaluate two different competencies of the machine. In the first part of the study, the aim was to evaluate the ability of the machine in the differentiation of the right and left kidneys in the different renography phases. Sensitivity, precision, and F1 score were found for the detection of the right or left kidney as an object. In the second part of the study, the renal images were classified into two groups. The images with a filled RPC were included in Group 1, while the images of empty RPC were in Group 2. The image recognition and differentiation performance of the machine for filled and empty RPC were tested.

The open-source Python programming language (Python 3.6.1; Python Software Foundation, Wilmington, DE, USA), convolutional neural network, and the Tensorflow Object Detection API were used for the model development. The training was performed on a computer equipped with 16 gigabytes of RAM and an NVIDIA GeForce GTX 1060Ti graphics card (NVIDIA, Santa Clara, CA, USA). Supervised training was used for the differentiation of filled and empty renal collecting systems labeled by a nuclear medicine radiologist and a pediatric urologist. For data augmentation during training, multiple image transformations were applied. A self-training was not used.

RESULTS

In the first part of the study, the set with 1,260 annotated renal images was separated into datasets, including 1,134 images for training and validation

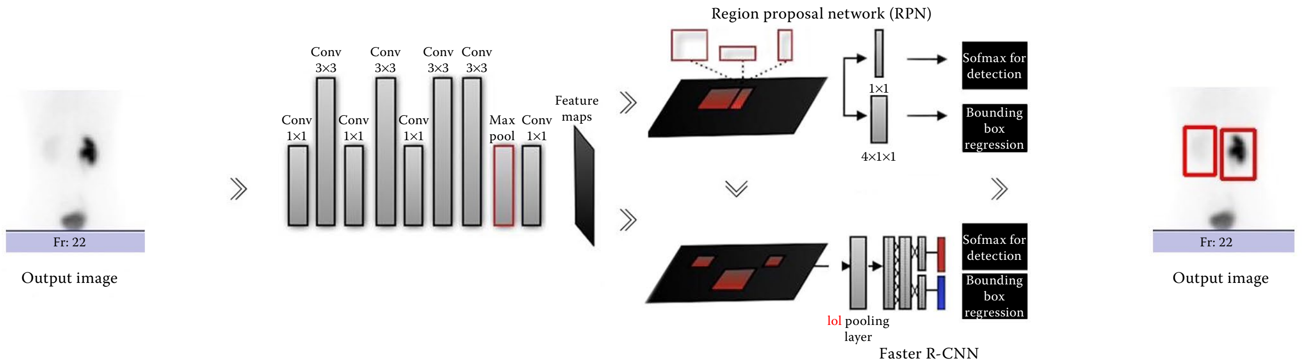

Figure 1. Tensorflow inception implementation.

and 126 for the test group. The Tensorflow Inception V2 Coco architecture with 85,000 epochs was applied (Figure 1). The kidney was detected by the machine with side differentiation as left or right kidney with 94% sensitivity, 96% precision, and 95% F1 score.

In the second part of the study, the number of the renal image labeled was 638 for Group 1 and 358 for Group 2. The set was separated into datasets for training and validation (600 images with 300 from each group) and for testing (116 images with 58 from each group). The learning rate was 0.01, the epoch was 20,000, the architecture was the Tensorflow Inception V3, and the batch size was 100. Following the training, the test groups with 116 images had 88% accuracy for Group 1 and 66% for Group 2.

DISCUSSION

Artificial neural networks (ANNs) are computational systems having a set of interconnected simple processing elements that take the input, respond dynamically, and process the information.[9,10] Data could be introduced to ANNs by supervised, unsupervised, or reinforced methods.[9,11] Training is needed to obtain good accuracy. Deep learning models are hierarchical ANNs with multiple layers and are able to learn representations of data with increasing levels of abstraction starting from the input data[12] The chance of overfitting due to the increased number of network layers in ANNs decreased with the implementation of DL algorithms. The basic DL architecture has an input layer, many hidden layers responding to different features of the image (e.g., shape or edges), and an output layer. Deep learning, compared to other subtypes of AI, has an autodidactic quality in image recognition that depends on the number of layers and is determined by the data itself.[1] In our study, we used convolutional neural network, which is a type of DL architecture.

A DL model for image recognition may use supervised learning with labeled input data or unsupervised learning without labeled data. In medical studies, unsupervised learning has been rarely applied, and most of the DL models for image recognition have used supervised learning. This study also used supervised learning. In our DL model, the nuclear renogram images were annotated as the left or right side and as a filled or an empty RPC, and then the model was trained.

Several factors cause difficulties in the radiological and nuclear medicine investigations and the interpretation of the medical scans in children. Difficulties in cooperation and immobilization, problems of ergonomics due to the age and size of the patient, need for radiation protection, and the variation in uptake and excretion of radiopharmaceuticals are the challenges in children. Those limitations may cause misinterpretation in the evaluation of medical scans in children. Advances in AI and DL can help reduce diagnostic and management errors and malpractice that are inevitable in human clinical practice. Deep learning models may improve and enhance the efficiency of the assessment of medical scans and support the clinical decision process by developing better image recognition and object detection.

The DTPA renogram images of the patients who had hydronephrosis were used to train our DL model. Diuretic renography was required to differentiate hydronephrosis with obstruction from nonobstructive hydronephrosis. This diagnostic modality was selected to test the performance of DL on image recognition of luminal organs and test the potential and limitations of the machine in the detection of a filled or empty lumen. In the first part of the study, following the training with 1,134 images, the model was able to find the kidney and differentiate the side as left or right kidney with 96% precision. The model was able to detect the kidney with high accuracy regardless of whether the RPC lumen was empty or filled with the radiolabeled agent. This finding may suggest that following the annotation by experienced physicians and training with a good number of input images, DL algorithms may detect and define the side and location of the organ. If the model was trained well, regardless of whether RPC has contrast or is empty, the kidney could be detected by the machine. The present DL model was successful in determining the lumen of RPC filled with the radiolabeled agent with 88% accuracy and was able to catch a filled lumen in different phases of the renogram series having 29 images.

The accuracy of describing an empty RPC lumen was 66% in our study. This was the weakness of the model, which will need to be improved by future research. Medical images are often rendered in grayscale, which may cause difficulty in interpretation[13] Medical image quality is normally characterized in terms of contrast, noise, and resolution[14] The images having blur, brightness, defect in detail visibility, and missing pixels may have a significant influence on the DL model performance. Detail visibility is not observed appropriately in some of the radiological and nuclear medicine studies. In our model, 66% accuracy in the prediction of an empty RPC may suggest that defining and labeling the variations of images showing an empty RPC was not good enough with the conventional annotation method we used.

In our study, empty RPC lumens had low tissue contrast and unclear boundaries. As an image, if the target organ has location variance, low tissue contrast, and unclear boundaries, the quality of annotation decreases. Manual segmentation or object detection performed on such images is prone to errors due to the low quality of the images, difficulty in hand-eye coordination, and operator interpretation. These errors directly affect the success of the model. Noval manual annotation methods have been reported. As one of these methods, the patch-based annotation extracts sequential patches with four or six strides along 16 rays extending from the inside of the object to the outside[15] A sequence of patches along a certain ray is viewed as a single training sample. This approach may provide better labeling compared to the image-based method for medical images with low tissue contrast and unclear boundaries. Automatic image annotation platforms could be developed for better labeling in such challenging medical images.[16,17]

Although DL algorithms for image recognition have been shown to surpass the human accuracy rate in several reports and show some promise in the evaluation of medical scans.[1,2,18] However, they are still far from demonstrating very high and reproducible machine accuracy in medicine. Physicians who need AI as an assistant to interpret medical scans and other visual medical data should learn the basic principles of DL and be involved in DL studies on medical image recognition. There are still few studies that have clinical implications. Medical doctors, engineers, and data scientists should work together to develop efficient DL models that could be accepted and adopted in the real-world clinical environment.

There are a few limitations in this study. The first is that it is a single-center study. Secondly, it is not a follow-up study and does not provide information about the long-term results of the patients.

In conclusion, the machine using DL algorithms with a large data set training may differentiate the kidney, its location, and the contrast-filled lumen. Low contrast and unclear boundaries in an empty lumen may affect the quality of annotation. The DL model used in this study could be adapted to other urinary system pathologies in medical scans.

Ethics Committee Approval: The study protocol was approved by the Eskişehir Osmangazi University Non-Interventional Clinical Studies Institutional Review Board (no: 241/2021). The study was conducted in accordance with the principles of the Declaration of Helsinki.

Patient Consent for Publication: A written informed consent was obtained from the parents and/or legal guardians of the patients.

Data Sharing Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Author Contributions: Project development, data collection, andlabeling, manuscript writing/editing: B.T.; Project development, data management, manuscript writing: O.C.; Project development, manuscript writing: N.C.; Data collection: T.A.; Project development, data collection and labeling, manuscript writing/editing: I.A.

Conflict of Interest: The authors declared no conflicts of interest with respect to the authorship and/or publication of this article.

Funding: The authors received no financial support for the research and/or authorship of this article.

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