An Algorithm for Creating the Imitate Myelography CT from the Plain CT of Lumbar Spine Using Generative Adversarial Networks

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INTRODUCTION:

The MRI is golden standard for diagnosing the lumbar spine diseases. However, there are certain patients who can't undergo the MRI scan due to some reasons such as heart diseases requiring pacemaker and claustrophobia. To evaluate lumbar spine of these patients, other modalities are necessary. The myelography CT is one of the alternative methods, however, this method is high invasive because of injection of a contrast medium into the intradural space. While, the plain CT has too low visualization to assess the spinal canal, in spite of lower invasion than the myelography CT. The Cycle-consistent generative adversarial networks (Cycle GAN) can learn the relationship between two image datasets and translate the images in one dataset into similar images based on the other dataset. The purpose of this study is to develop an algorithm for creating the imitate myelography CT from the plain CT of lumbar spine using Cycle GAN and validate the translating algorithm.

METHODS: Data from 33 patients who underwent myelography CT and the plain CT of lumbar spine between January 2015 to December 2023 was included. The exclusion criteria are as follows; (1) Injection of a contrast medium into the inappropriate space; (2) Inserting implant into vertebrae; (3) Patients with bone metastasis and intradural tumor. We obtained each 489 images of the myelography CT and the plain CT from 15 patients. The paired images between the myelography CT and the plain CT were almost same level. Each 389 images were used for training by Cycle GAN and the other 100 images from the plain CT were translate to the imitate myelography CT using trained Cycle GAN model. To evaluate the performance of translating to the myelography CT from the plain CT, the other evaluation deep learning algorithm (eDLA) to determine the presence of spinal canal stenosis from each myelography CT slice was created. Binary cross entropy was utilized as output layer in the eDLA, where a spine specialist labeled the actual myelography CT images of 389 as 1 for the presence of spinal canal stenosis and as 0 for its absence. The actual myelography CT images and the imitate myelography CT images were validated using the eDLA. Finally, thin slice plain CT images from another patient were translate into the imitate myelography CT images to conduct the reconstruction. The study flow was shown in Figure 1.

RESULTS:

The examples of the plain CT, the actual myelography CT and the imitate myelography CT are demonstrated in Figure 2. In 100 images of the imitate myelography CT, there are 3 images (3%) which trained cycle GAN model couldn't stain from the plain CT. In internal validation to create the trained eDLA model, the model had accuracy of 91%, true positive rate (TPR) of 92% and true negative rate (TNR) of 91%. In the external validation using 100 actual myelography CT images to confirmed the performance of the trained eDLA model, accuracy, TPR and TNR were 92%, 92% and 92%, respectively (confusion matrix 1, Table 1). When the trained eDLA model validated the imitate myelography CT images, accuracy, TPR and TNR were 78%, 77% and 78%, respectively (confusion matrix 2, Table 1). Although there are 7 false positive images in the actual myelography CT and 19 false positive images in the imitate myelography CT, 4 images were paired same level images. The reconstruction using thin slice images is illustrated in Figure 3.

DISCUSSION AND CONCLUSION: The present study suggests that Cycle GAN can translate the plain CT into the imitate myelography CT. Not only is this new technology not yet in practical use, but there are no articles about creating the imitate myelography using Cycle GAN. Meanwhile, there are some problems that we must solve based on the results of this study. First, the imitate myelography CT didn't had enough visualization accuracy compared to actual myelography CT. Second, the imitate myelography can be underestimated, because eDLA is incomplete for determining the presence of canal stenosis. Finally, a considerable portion on coronal and sagittal reconstruction using thin slice images is not delineated. To solve these problems, it is considered that thin slice images from many cases are essential to improve not only the visualization accuracy of imitate myelography CT but also the performance of eDLA.

Confusion matrix

1. The eDLA validated actual myelography CT

	label'=0	label'=1	Recall
label=0	80	7	0.9195
label=1	1	12	0.923
Precision	0.9876	0.6315	
F-Measures	0.9523	0.7499	
Accuracy	0.92		
Avg.Precision	0.8096		
Avg.Recall	0.9213		
Avg.F-Measures	0.8511		

2. The eDLA validated imitated myelography CT

	label'=0	label'=1	Recall
label=0	68	19	0.7816
label=1	3	10	0.7692
Precision	0.9577	0.3448	
F-Measures	0.8607	0.4761	
Accuracy	0.78		
Avg.Precision	0.6512		
Avg.Recall	0.7754		
Avg.F-Measures	0.6684		

Figure 1 study flow

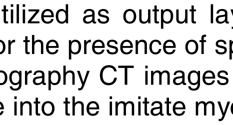

Figure 2 example of each images

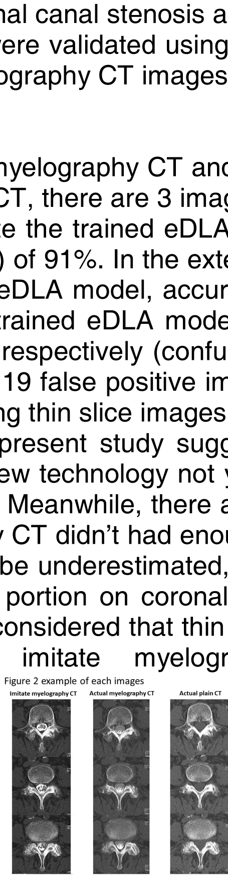

Figure 3 reconstructed images from thin slice images

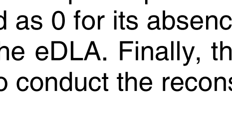

Table 1. Experimental indicators for detecting canal stenosis using eDLA.

	AUC	Sensitivity	Specificity	PPV	NPV	Accuracy	PLR	NLR
Actual myelography CT (N=100)	0.94	0.92	0.92	0.63	0.99	92%	11.47	0.08
Imitate myelography CT (N=100)	0.85	0.77	0.78	0.35	0.96	78%	3.52	0.30

AUC= area under the curve, PPV= positive predictive value, NPV= negative predictive value, PLR= positive likelihood ratio, NLR= negative likelihood ratio