

An algorithm for using deep learning convolutional neural networks with three dimensional depth sensor imaging in scoliosis detection - In order to avoid the detection of extremely mild AIS patients and false positive cases -

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INTRODUCTION: Adolescent idiopathic scoliosis (AIS) is the most ordinary pediatric spinal disease. Timely intervention in growing individuals, such as brace treatment, relies on early detection of AIS. We developed a system consisting of a three-dimensional (3D) depth sensor and an algorithm installed in a laptop computer. In this system, the correlation between the actual Cobb angle and the predicted Cobb angle calculated from the asymmetry index was 0.85 ($P < 0.01$)¹. However, it could be excessive to detect patients with Cobb angle of 10° to 15° , which isn't an indication for brace treatment, because they would be exposed to unnecessary radiation. In addition, healthcare resources could be strained due to the examinations for extremely mild AIS patient and false positive cases. The purpose of this study is to create a deep learning algorithm (DLA) to distinguish between false-positive or minor cases and moderate to severe cases requiring the secondary screening using 3D depth sensor data of subjects detected in the school screening.

METHODS: This study was conducted retrospectively. Three hundred and thirty-four subjects detected using the 3D depth sensor system in school screening from April 2021 to March 2022 were included. The 3D images were used as input data for the DLA with Convolutional neural networks. The architecture of CNNs is described in Figure 1. We randomly separated the 334 subjects into an internal validation data of 250 and an external validation data of 84. To avoid the imbalanced dataset in the internal validation, binary classification was performed as 0 for images with Cobb angle of $< 12^\circ$ and 1 for images with Cobb angle of $\geq 12^\circ$ based on the average actual Cobb angle of 12.0° . Five-fold cross validation was conducted to evaluate the probability for Cobb angle of $\geq 12^\circ$. We set up a batch size 32, and 300 epochs were configured. The computer was equipped with a central processing unit of Core i7-9750H (Intel), graphics processing unit of GeForce RTX 2070 (NVIDIA) and random-access memory of 32GB. In the internal validation dataset with the highest performance, the minimum predicted probability in subjects with Cobb angle of $\geq 15^\circ$ was configured as the cut-off value to detect the second screening targets. In the external validation, 84 images were evaluated using trained DLA with the highest performance in the internal validation, and determined whether secondary screening is necessary or not, based on the cu-off value.

RESULTS: The range of Cobb angle was 0° to 34° in the internal validation and 0° to 32° in the external validation, respectively. In the internal validation, the number of subjects with Cobb angle of $\leq 12^\circ$ and $> 12^\circ$ were 132 and 118, respectively. The five-fold cross validation showed that the dataset 3 had the highest predicted performance (Table 1 and Figure 2). The minimum predicted probability in subjects with Cobb angle of $\geq 15^\circ$ was 0.47 in dataset 3. In the external validation, the number of subjects with Cobb angle of $< 10^\circ$ and $\leq 15^\circ$ were 36 and 62, respectively. Based on a cut-off value of 0.47, 39 (63%) subjects with Cobb angle of $\leq 15^\circ$ were judged as unnecessary for the second screening. The false positive cases with Cobb angle of $< 10^\circ$ reduced by 24 cases (67%). There was only one false negative case with Cobb angle of $< 20^\circ$.

DISCUSSION: This DLA reduced the number of extremely mild AIS patient and false positive cases in the external validation, indicating that this DLA can reduce the unnecessary medical care expenditures and the unnecessary radiation exposure for children and adolescents. We had reported that the performance for predicting Cobb angle was improved by incorporating the other DLA in the current system². It is believed that a high accurate AIS screening can be achieved through the combination of this DLA for identifying AIS patients requiring the secondary screening and the other DLA for predicting the Cobb angle.

SIGNIFICANCE: This AI algorithm can reduce unnecessary radiation exposure for children and medical care expenditures by reducing number of extremely mild AIS patient and false positive cases in school screening.

REFERENCE

1. Kokabu T, et al. Three-dimensional depth sensor imaging to identify adolescent idiopathic scoliosis: a prospective multicenter cohort study. Sci Rep. 2019 Jul 4;9(1):9678.
2. Kokabu T, et al. An algorithm for using deep learning convolutional neural networks with three dimensional depth sensor imaging in scoliosis detection. Spine J. 2021 Jun;21(6):980-987.

Figure 1. The architecture of CNNs

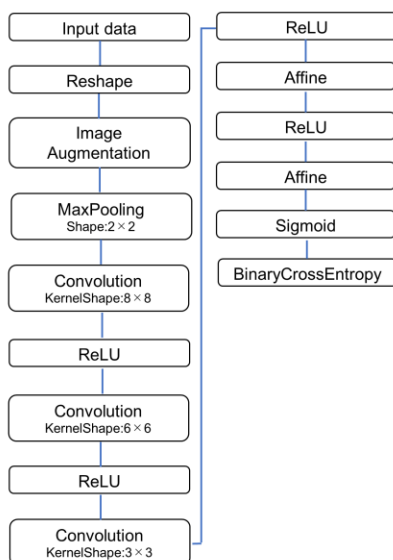


Figure 2. ROC curves for detecting scoliosis with a curve $\geq 15^\circ$ in five-fold cross validation

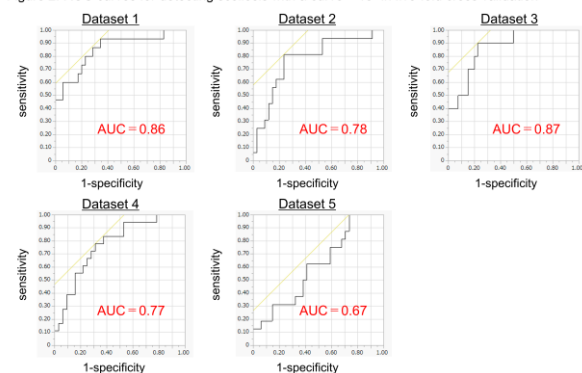


Table 1. Experimental indicators for detecting scoliosis with a curve $\geq 15^\circ$ in each dataset

Dataset	Sensitivity	Specificity	PPV	NPV	Accuracy	PLR	NLR
1	0.93	0.66	0.54	0.96	0.74	2.72	0.10
2	0.81	0.77	0.62	0.90	0.78	3.45	0.25
3	0.90	0.78	0.50	0.97	0.80	4.00	0.13
4	0.78	0.69	0.58	0.85	0.72	2.49	0.32
5	1.00	0.27	0.39	1.00	0.50	1.36	0.00

PPV= positive predictive value, NPV= negative predictive value,

PLR= positive likelihood ratio, NLR= negative likelihood ratio