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Clinical Study

An algorithm for using deep learning convolutional neural networks with three dimensional depth sensor imaging in scoliosis detection

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Abstract

BACKGROUND CONTEXT: Timely intervention in growing individuals, such as brace treatment, relies on early detection of adolescent idiopathic scoliosis (AIS). To this end, several screening methods have been implemented. However, these methods have limitations in predicting the Cobb angle.

PURPOSE: This study aimed to evaluate the performance of a three-dimensional depth sensor imaging system with a deep learning algorithm, in predicting the Cobb angle in AIS.

STUDY DESIGN: Retrospective analysis of prospectively collected, consecutive, nonrandomized series of patients at five scoliosis centers in Japan.

PATIENT SAMPLE: One hundred and-sixty human subjects suspected to have AIS were included.

OUTCOME MEASURES: Patient demographics, radiographic measurements, and predicted Cobb angle derived from the deep learning algorithm were the outcome measures for this study.

METHODS: One hundred and sixty data files were shuffled into five datasets with 32 data files at random (dataset 1, 2, 3, 4, and 5) and five-fold cross validation was performed. The relationships between the actual and predicted Cobb angles were calculated using Pearson's correlation coefficient analyses. The prediction performances of the network models were evaluated using mean absolute error and root mean square error between the actual and predicted Cobb angles. The shuffling into five datasets and five-fold cross validation was conducted ten times. There were no study-specific biases related to conflicts of interest.

RESULTS: The correlation between the actual and the mean predicted Cobb angles was 0.91. The mean absolute error and root mean square error were 4.0° and 5.4°, respectively. The accuracy of the mean predicted Cobb angle was 94% for identifying a Cobb angle of ≥10° and 89% for that of ≥20°.

FDA device/drug status: Not approved (SCOLIOMAP).

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CONCLUSIONS: The three-dimensional depth sensor imaging system with its newly innovated convolutional neural network for regression is objective and has significant ability to predict the Cobb angle in children and adolescents. This system is expected to be used for screening scoliosis in clinics or physical examination at schools.

Keywords: Accuracy; Adolescent idiopathic scoliosis; Cobb angle; Convolutional neural network for regression; Correlation coefficient analyses; Deep learning algorithm; Mean absolute error; Noncontact and noninvasive system; Three-dimensional depth sensor

Introduction

Adolescent idiopathic scoliosis (AIS) is most the common musculoskeletal disease in children of school-going age. It is defined as a curvature of the spine ≥10° without an underlying condition [1]. Timely intervention in growing individuals, such as brace treatment, relies on early detection of AIS. To this end, several screening methods have been implemented. Adam's forward bend test using a scoliometer has relatively high sensitivity (83.3%) and specificity (86.8%) to detect scoliosis [2, 3]. However, the scoliometer must be manually positioned on the subject's back, which is laborious for the examiner who must carefully observe many subjects in a limited time [4]. In addition, the correlation coefficient between scoliometer values and Cobb angles is not satisfactory (r=0.677) [5]. Moiré topography has been used to detect scoliosis by projecting contour lines onto a human's back. However, the direction of the light source should be vertical to the back [4] and is not designed to be shot with a forward bend of the trunk, resulting in high false positive rates (32%−60%) [6−9]. To overcome these limitations, we developed a system consisting of a three-dimensional (3D) depth sensor and an algorithm installed in a laptop computer [4, 10]. With this system, Cobb angle can be automatically predicted from the degree of asymmetry on the surface of the back within 1.5 seconds [4, 10]. This noncontact and noninvasive system has been approved as a medical device by the national agency in Japan (Fig. 1, SCOLIOMAP®; Robert-Leid, Tokyo, Japan).

Deep learning is a branch of machine learning that has the ability to identify highly complex patterns in large datasets [11]. In particular, convolutional neural networks (CNNs) are designed to learn the features from data through back-propagation by using multiple building blocks, such as convolution layers, pooling layers, and fully-connected layers [12,13]. In the spine field, CNNs have been applied for detection, classification or segmentation of diseases such as differentiation of intradural extramedullary tumors [13] and spinal metastases [14]. Using deep learning algorithms (DLAs) with CNNs to detect AIS, some systems have been developed using 2D photographs [15] or Moiré topography shot from human back [16−18]. Although these systems can classify scoliosis or estimate the position of vertebrae, there are still significant limitations with predicting the Cobb angle. We have modified our system [4, 10] to accurately predict Cobb angle using CNN for regression analysis. The purpose of this study was to evaluate the performance of the new algorithm in predicting Cobb angle.

Materials and methods

Subjects

We retrospectively analyzed data which were collected prospectively from a nonrandomized series of participants in five scoliosis centers in Japan [4, 10]. Institutional review board approval was obtained from all participating centers. Subjects were referred to our hospitals due to suspected AIS. The inclusion criteria were as follows [4, 10]: (1) Age 7 to 18 years; (2) Referral with a confirmed diagnosis using X-rays; (3) No prior treatment with a brace; (4) The intention and ability to provide written informed consent or assent. Informed consent was obtained from high school students and assent was obtained from elementary/junior high school students. In addition, the informed consent of all guardians was obtained. Exclusion criteria were the presence of syndromic, neuromuscular, or congenital scoliosis. One hundred and-sixty subjects (23 males and 137 females) participated in this study. Information about age, gender, and Cobb angle measured from digital radiographs was obtained. The assessors of the radiographic Cobb angles were blinded to the results of the CNN.

3D depth sensor imaging

The system comprised a 3D depth sensor (Xtion Pro Live, ASUSTeK Computer Inc. Taipei, Republic of China) and a laptop computer (Core-i5, 7200U-4 GB HP pavilion-15-au105tu, HP Inc, CA, USA) [4, 10]. The subjects were instructed to assume the posture for the Adam's forward bend test [2, 3] with their upper bodies exposed. A three-dimensional point cloud of the subject's back was then captured by the sensor [4, 10].

Prediction of Cobb angle using the previously developed algorithm

Our fully developed algorithm for detecting asymmetry on the back has been previously documented in detail [4]. Briefly, the algorithm contained the following steps (Fig. 1) [4, 10]:

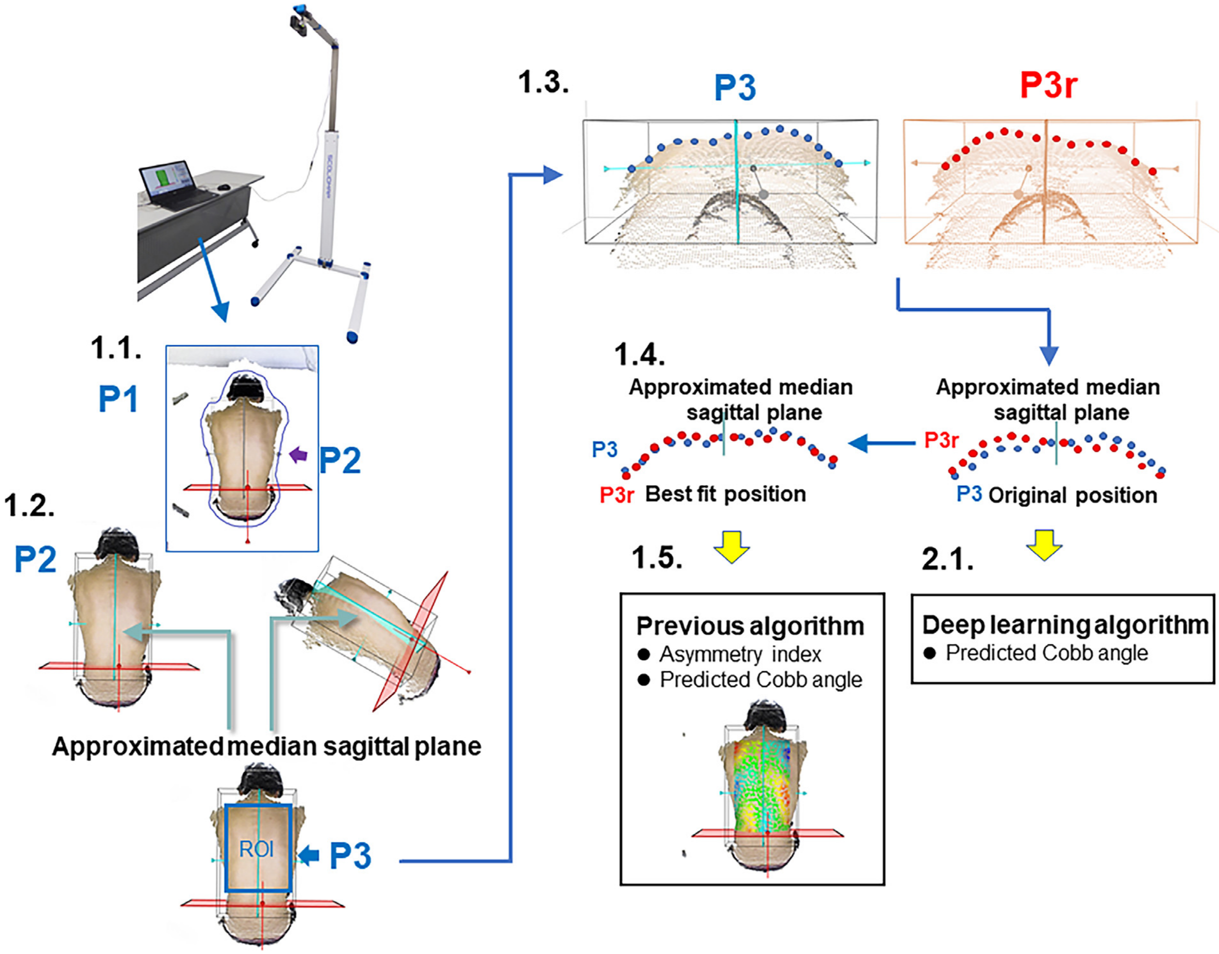

Fig. 1. **Previously developed algorithm for calculating the asymmetry index [4, 10] and input data used in the current deep learning algorithm (DLA).** The differences in the position of original P3r relative to original P3 were used as datasets of DLA with a convolutional neural network.

Identification of point clouds from the body surface

The patient's back surface was scanned with a depth sensor so that both left and right waist lines roughly match the recommended lines on the computer monitor. A 3D point cloud P1 was obtained [4, 10].

Estimation of approximated median sagittal plane and region of interest

Principal component analysis was used to obtain the pose-normalized point cloud P2 from P1 where the approximated median sagittal plane was arranged. The region of interest (ROI) was defined as a square box generated from the waist line to both shoulders, and the point cloud of the ROI was obtained as P3 [4, 10].

Generation of reflected point clouds

In order to perform asymmetry analysis, the reflection point group P3r was initially obtained from the mirror projection of P3 in relation to the sagittal plane [4, 10].

Best fitting between the original point cloud and the reflected point cloud

An iterative closest point method was used to determine the optimal position and orientation of P3r which was best fitted to P3 [4, 10].

Calculation of the asymmetry index and predict Cobb angle

The difference in the position of the best-fitted P3r relative to P3 was assessed, and the distribution of the difference was rendered as a color map. The asymmetry index was also calculated according to the mean deviation between the original point clouds and the corresponding best-fit reflection point clouds [4, 10]. Finally, we derived an approximation of the cubic function to predict the Cobb angle using scatter plots between the actual Cobb angle and the asymmetry index.

Prediction of Cobb angle using new DLA with a CNN

Input data

The differences in position of original P3r relative to original P3 (as in step 3 for using the previously developed algorithm) were used as datasets for the DLA with a CNN (Fig. 1). The difference value represented altitude difference between right and left sides based on the approximated median sagittal plane. The data were exported to a Comma Separated Value (CSV) file with 159 rows and columns, where zeros were filled into boxes without numbers

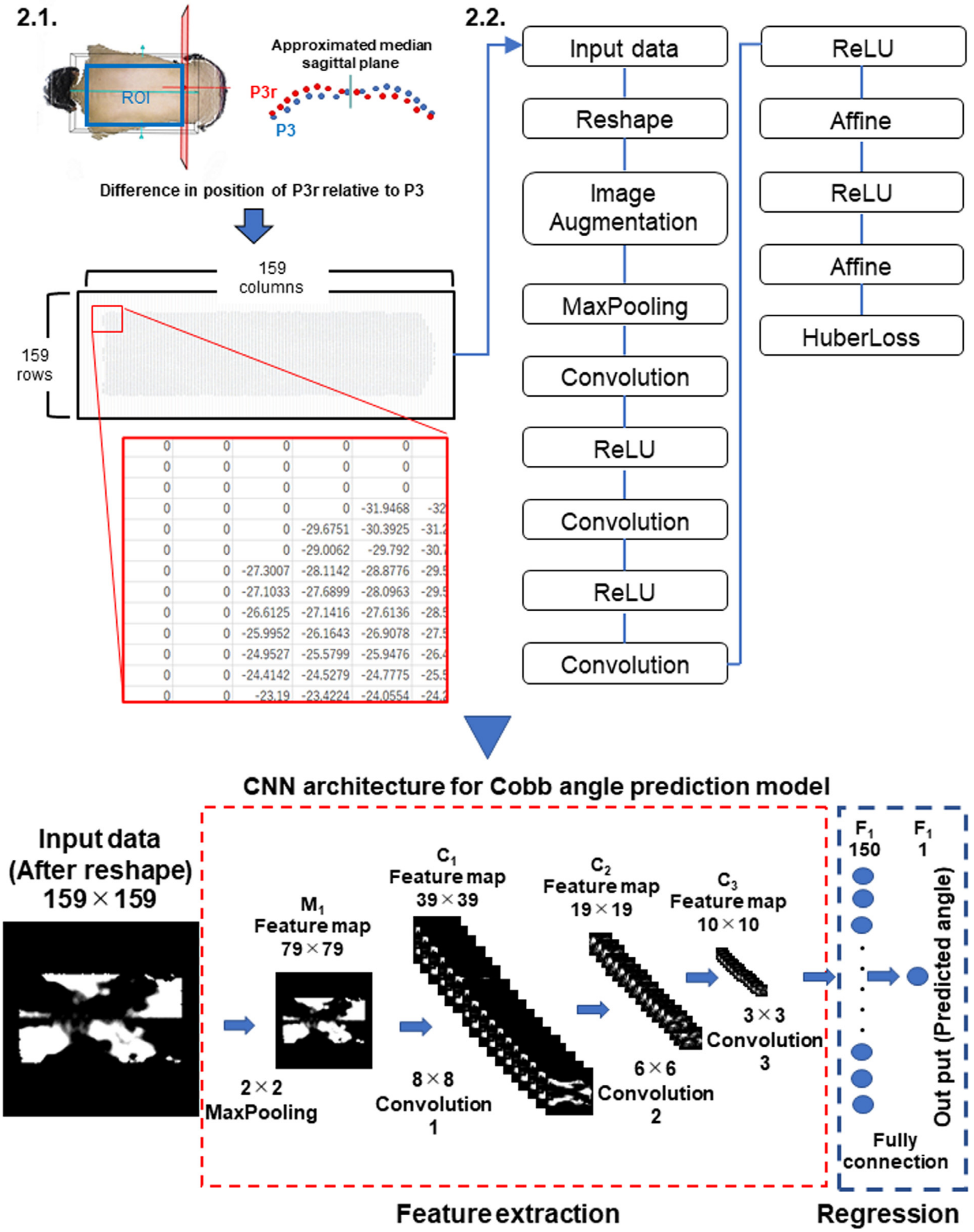

Fig. 2. **Input data from a Comma-Separated Value (CSV) file and the architecture of the convolutional neural networks.** The CSV files were generated by converting from the point clouds within the region of interest. The CSV files included 159 rows and 159 columns, where zeros were filled into boxes without a number.

(Fig. 2). Five-fold cross validation was performed to negate selection bias. One hundred and sixty CSV files were shuffled into five datasets with 32 CSV files at random (dataset 1, 2, 3, 4, and 5). One dataset was used as a validation dataset and the other four were used as training datasets. Training and validation were performed five times by exchanging five datasets.

Additionally, data augmentation was conducted on the training dataset to construct a more robust training network. The CSV files with different ROIs were generated by shifting the transverse line of the waist to upper limit, center, and lower limit within an allowance using the special application (3 CSV files per one original file). The training dataset included 384 files in total. All data in the validation dataset were independent of the files in the training dataset. The shuffling into five datasets and five-fold cross validation was conducted 10 times in this process [19].

CNN models

The architecture of CNNs is described in Fig. 2. A Neural Network Console (Sony Network Communications, Tokyo, Japan) was used to construct the DLA with a CNN, which was equipped with the original layer of "ImageAugmentation." This layer serves to create a robust training network by processing the images of training datasets in each epoch. Each image was randomly varied at each epoch by rotation from −0.1 rad to 0.1 rad, cropping after zooming in and out within 1.1-folds, horizontal inversion and vertical inversion. A combination of a MaxPooling layer and three Convolution layers was integrated after the ImageAugmentation layer. The HuberLoss layer, which was less sensitive to outliers in data, was selected as the output layer. The maximum Cobb angle of each subject was used as output data for training and validation. In addition, we evaluated whether the DLA/neural network could identify the location of the curve. Cobb angles of thoracic and thoracolumbar/lumbar curves were used as output data. In the case of a single thoracic curve, thoracolumbar/lumbar Cobb angle was set as 0°. Conversely, the thoracic Cobb angle was set as 0° in the single thoracolumbar/lumbar curve. In the case of double curve, both the Cobb angles of the thoracic and thoracolumbar/lumbar curves were included.

We set up a batch size 16 and an Adam Optimizer [20]. Five thousand epochs were configured, due to training datasets being slightly altered at each epoch by the ImageAugmentation layer. 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.

Statistical analysis

The relationships between the actual Cobb angles and predicted Cobb angles were calculated using Pearson's correlation coefficient analyses. The prediction performances of the network models were evaluated using mean absolute error (MAE) and root mean square error (RMSE) between actual Cobb angle and predicted angle. The one-way ANOVA was applied to assess the difference in absolute error (AE) among the 10 repeats. Sensitivity, specificity, positive predictive value, negative predictive value, accuracy, positive likelihood ratio, and negative likelihood ratio were estimated according to the actual Cobb angles at 10°, 15°, 20°, and 25°.

Data analyses were performed using JMP statistical software for Windows (version 14; SAS, Inc., Cary, NC, USA). $p<.05$ was considered statistically significant.

Results

The mean age was 14.7±2.4 years, and the average Cobb angle of the maximum curve was 30° (range, 0°−64°). The time from scanning to obtaining an analysis result was 2.4±

Table 1
Correlations and coefficients of determination in five-fold cross validation with 10 repeats

		Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 5	Total
1	r	0.94	0.78	0.85	0.88	0.95	0.89
	R^2	0.88	0.60	0.73	0.77	0.90	0.79
2	r	0.84	0.92	0.90	0.84	0.90	0.88
	R^2	0.71	0.84	0.81	0.71	0.81	0.77
3	r	0.94	0.92	0.90	0.77	0.88	0.89
	R^2	0.88	0.85	0.81	0.59	0.78	0.79
4	r	0.85	0.88	0.89	0.88	0.87	0.87
	R^2	0.72	0.78	0.80	0.78	0.76	0.76
5	r	0.91	0.87	0.83	0.91	0.88	0.88
	R^2	0.83	0.76	0.70	0.82	0.77	0.77
6	r	0.87	0.88	0.94	0.84	0.84	0.88
	R^2	0.75	0.78	0.89	0.71	0.70	0.77
7	r	0.89	0.78	0.95	0.92	0.85	0.89
	R^2	0.79	0.60	0.89	0.85	0.73	0.79
8	r	0.90	0.83	0.87	0.92	0.87	0.88
	R^2	0.81	0.70	0.76	0.84	0.76	0.78
9	r	0.84	0.89	0.80	0.93	0.84	0.87
	R^2	0.71	0.80	0.64	0.87	0.70	0.76
10	r	0.88	0.84	0.84	0.92	0.82	0.88
	R^2	0.77	0.70	0.71	0.85	0.67	0.78

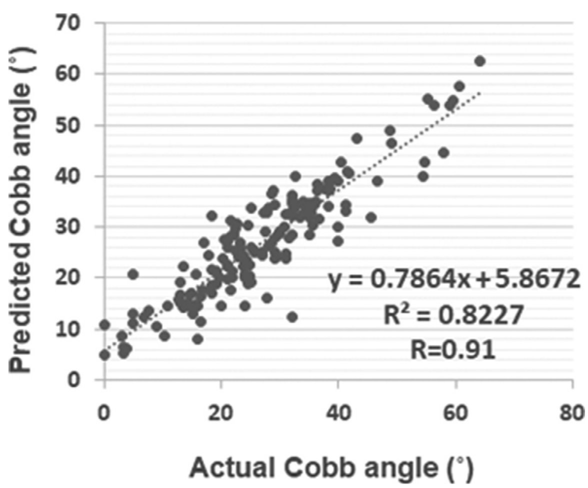

Fig. 3. Correlation in total number of subjects between the actual Cobb angle and the predicted Cobb angle.

0.4 seconds (range, 1−3 second). The correlations and the coefficients of determination were shown in Table 1. The range of correlation coefficients was 0.87 to 0.89. The range of coefficients of determination was 0.76 to 0.79. The correlation between the actual and the mean predicted Cobb angles with 10 repeats was 0.91 (Fig. 3).

The MAEs and RMSEs are summarized in Table 2. The range of MAEs was 4.4° to 4.7°. There was no significant difference in the AE among ten repeats (p=.43). The range of RMSEs was 5.8° to 6.3°. The MAE and RMSE between the actual Cobb angle and the mean predicted Cobb angles with 10 repeats were 4.0° and 5.4°, respectively.

The performance of predicted Cobb angles of 10°, 15°, 20°, and 25° is described in Table 3. The range of accuracy was 0.84 to 0.94. At a Cobb angle of 10°, which confirms a diagnosis of scoliosis, the mean predicted Cobb angle displayed a sensitivity of 0.99, a specificity of 0.42, positive predictive value of 0.95, negative predictive value of 0.71, accuracy of 0.94, positive likelihood ratio of 1.69, and a negative likelihood ratio of 0.03.

Finally, we evaluated whether the DLA/neural network identified the location of the curve based on location/apex of the curves (Table 4). In predicting thoracic Cobb angle, the range of the correlation between the actual thoracic Cobb angle and the predicted thoracic Cobb angle was 0.78 to 0.83 (the coefficients of determination; 0.61−0.70). The range of MAEs of the thoracic Cobb angle was 7.4° to 18.5°. In predicting the thoracolumbar/lumbar Cobb angle, the range of the correlation between the actual thoracolumbar/lumbar Cobb angle and the predicted thoracolumbar/lumbar Cobb angle was 0.50 to 0.66 (the coefficients of determination; 0.25−0.43). The range of the MAEs of the thoracolumbar/lumbar Cobb angle was 8.7° to 16.8°.

Discussion

There have been some studies about predicting the Cobb angle using DLAs [15−18]. Choi et al. [16, 17] and Watanabe et al. [18] estimated the positions of vertebral bodies using a CNN. To develop the system, which could estimate the positions of 17 vertebral bodies on Moiré images, Moiré image-radiographic pairs from the same people were collected for machine learning by the CNN [16−18]. To measure the predicted Cobb angle, a curve was first fit to the 17 positions of vertebrae using a cubic B-spline, and the angles were calculated [16−18]. The authors reported that the

Table 2
MAE and RMSE in five-fold cross validation with 10 repeats

		Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 5	Total
1	MAE (degree)	3.3	5.0	5.0	4.7	3.7	4.4
	RMSE (degree)	4.6	6.4	6.6	6.4	4.6	5.8
2	MAE (degree)	4.5	4.2	3.6	6.1	4.1	4.5
	RMSE (degree)	5.9	5.3	4.8	8.1	5.8	6.1
3	MAE (degree)	4.2	4.4	4.1	5.2	4.3	4.4
	RMSE (degree)	5.2	5.5	6.0	6.7	5.8	5.9
4	MAE (degree)	4.5	4.4	4.2	5.3	4.3	4.5
	RMSE (degree)	5.9	5.9	6.3	6.8	6.0	6.2
5	MAE (degree)	4.5	4.5	5.1	4.0	5.0	4.6
	RMSE (degree)	5.7	6.2	6.7	4.8	7.0	6.1
6	MAE (degree)	5.6	4.1	3.6	4.7	5.1	4.6
	RMSE (degree)	7.2	5.4	4.6	6.3	6.8	6.1
7	MAE (degree)	5.0	4.6	3.2	4.3	5.2	4.4
	RMSE (degree)	6.0	5.7	4.2	5.6	7.3	5.8
8	MAE (degree)	4.4	4.4	5.4	4.8	4.5	4.6
	RMSE (degree)	5.7	6.0	6.4	6.2	6.0	6.0
9	MAE (degree)	5.1	5.3	5.5	4.0	4.3	4.7
	RMSE (degree)	6.5	6.8	7.3	5.3	6.2	6.3
10	MAE (degree)	4.5	5.6	4.0	4.9	4.4	4.4
	RMSE (degree)	5.9	7.7	5.4	6.2	5.9	5.9

MAE, Mean absolute error; RMSE, Root mean square error.

Table 3
Experimental indicators for detecting scoliosis

	Cobb angle	Sensitivity	Specificity	PPV	NPV	Accuracy	PLR	NLR
Mean predicted Cobb angle	10°	0.99	0.42	0.95	0.71	0.94	1.69	0.03
	15°	0.94	0.65	0.93	0.68	0.89	2.72	0.09
	20°	0.93	0.80	0.92	0.81	0.89	4.55	0.09
	25°	0.89	0.78	0.81	0.87	0.84	4.04	0.14

PPV, positive predictive value; NPV, negative predictive value; PLR, positive likelihood ratio; NLR, negative likelihood ratio.

Table 4
Location/apex of the curves

	Thoracic curve (n=71)	Thoracolumbar/ Lumbar curve (n=41)	Double curves (n=46)	
			Thoracic curve	Thoracolumbar/ Lumbar curve
T3	2	NA	0	NA
T4	2	NA	1	NA
T5	1	NA	1	NA
T6	0	NA	3	NA
T7	8	NA	10	NA
T8	22	NA	16	NA
T9	22	NA	13	NA
T10	13	NA	2	NA
T11	1	NA	0	NA
T12	NA	14	NA	4
L1	NA	17	NA	18
L2	NA	9	NA	21
L3	NA	1	NA	3

Data are presented as number. NA, Not applicable.

DLA displayed high performance in predicting the Cobb angle, however, data processes employed used a multi-stage procedure. This resulted in the MAEs varying from 2.7° to 10.6°. In addition, the correlation coefficient was unclear [16−18]. Yang et al. [15] developed DLAs for automated scoliosis detection using unclothed 2D back photographs. The accuracy of the algorithm for detecting scoliosis was 0.75 and 0.87 with curves of ≥10° and ≥20°, respectively [15]. However, the greatest limitation of this system was that their DLAs could not predict the Cobb angle, because they were based on the classification method [15].

In our study, the correlation coefficient was 0.91, indicating that CNN for regression improved our previous system (r=0.85) [10]. In addition, the MAEs ranged from 4.4° to 4.7°. The accuracy for detecting scoliosis was 0.94 and 0.89 with curves of ≥10° and ≥20°, respectively. These results indicated that our developed DLA was the first to accurately predict the Cobb angle using CNN for regression analysis. Compared to the Moiré image and the back photograph in the standing position, the input data in our DLA consists of a 3D structure that includes more information to detect scoliosis. Our data regarding altitude difference on back surface are obtained from a 3D depth sensor and converted to numerical data. As a result, the Cobb angle can be estimated independent of recording conditions such as illumination of a room or human skin color. A DLA trained and tested for a certain category of samples may not work when it is generalized to different test samples [21]. In fact, the accuracy of the DLA by Yang et al. [15] was lower in the external data set than in the internal data set and the area under the curve in the receiver operating characteristic decreased from 0.95 to 0.81 when detecting scoliosis with a curve ≥10° [15].

The input data in our study were not used directly from the point clouds and were preliminarily processed as the ROI that is a square box generated from the waist line to both shoulders. Although the sample size of this study was small, this process as well as the quantification of the data contributed to efficient training and validation. Feature selection is frequently performed in deep learning to improve accuracy and reduce model complexity. It can remove tautological and irrelevant features that reduce the input dimensionality and helps in understanding the fundamental mechanism that links effective features [22]. The input data in our DLA were preprogramed to focus on the essential part of the human body with more feature quantity and to reduce the dimensionality of the data, resulting in high performance with a small sample size of training datasets.

Based on the data regarding the location/apex of the curves, we evaluated whether the DLA/neural network could identify the location of the curve. The results indicated that this system can identify the location of the curve. However, although this system has been mainly developed for screening scoliosis by predicting the maximum Cobb angle regardless of the curve type, there is a limitation in predicting each Cobb angle with high accuracy.

One of the strengths of the current study was its multicenter design. The fact that the system could be used at different institutions proved that it could be generalized [10]. A major limitation of the study was that an external validation dataset could not be prepared because the current study was retrospectively performed using previously corrected data [4,10]. A convoluted neural network uses a large amount of data and is computationally expensive. This disadvantage is not elaborate along with external validation. Although there are some reports without the external dataset [13, 19, 23, 24], the performance of our DLA should be assessed using an independent external validation dataset to validate our results in the future. Second, this cohort included only patients that were referred to the study center with suspected AIS [4,10]. This presents a possible selection bias as there were only 12 of 160 participants without scoliosis (Cobb angle <10°). Although this is acceptable when evaluating the correlation between Cobb measurements and the predicted Cobb angles, it may overrate the exact sensitivity/specificity when applied as a screening tool in a school where most children have no scoliosis [10]. Finally, the cross-validation was used to validate the performance to predict Cobb angle. Although the cross-validation helps to preclude overtraining of the algorithm, it does not completely eliminate biases implicit to the dataset, such as population-specific variance and data learning parameters [23]. The application of a hold-out set given the usable dataset significantly affects the availability of abnormal structures applied for training, resulting in obstruction of the learning process [23]. Since the outcomes in our DLA may be overfitted, further large-scale clinical trials targeting mass school scoliosis screening programs are anticipated [10].

From a clinical utility standpoint, this system is expected to be routinely used for screening scoliosis, which might otherwise be missed in clinics or physical examination at schools. However, this is also a possible surrogate for radiographs to monitor curve progression, preventing unnecessary X-rays for mild case of scoliosis.

Conclusions

The 3D depth sensor imaging system with its newly innovated CNN for regression is objective and has significant ability to predict the Cobb angle in children and adolescents. This system is expected to be used for screening scoliosis in clinics or physical examination at schools. In addition, this is also a possible surrogate for radiographs to monitor curve progression, preventing unnecessary X-rays for mild case of scoliosis.

References

[1] Dunn J, Henrikson NB, Morrison CC, Blasi PR, Nguyen M, Lin JS. Screening for adolescent idiopathic scoliosis: evidence report and systematic review for the US Preventive Services Task Force. JAMA 2018;319:173–87.

[2] Grivas TB, Vasiliadis ES, Mihas C, Triantafyllopoulos G, Kaspiris A. Trunk asymmetry in juveniles. Scoliosis 2008;3:13.

[3] Kotwicki T, Kinel E, Stryla W, Szulc A. Discrepancy in clinical versus radiological parameters describing deformity due to brace treatment for moderate idiopathic scoliosis. Scoliosis 2007;2:18.

[4] Sudo H, Kokabu T, Abe Y, Iwata A, Yamada K, Ito YM, et al. Automated noninvasive detection of idiopathic scoliosis in children and adolescents: A principle validation study. Sci Rep 2018;8:17714.

[5] Sapkas G, Papagelopoulos PJ, Kateros K, Koundis GL, Boscainos PJ, Koukou UI, et al. Prediction of Cobb angle in idiopathic adolescent scoliosis. Clin Orthop Relat Res 2003;411:32–9.

[6] Daruwalla JS, Balasubramaniam P. Moiré topography in scoliosis. Its accuracy in detecting the site and size of the curve. J Bone Joint Surg Br 1985;67:211–3.

[7] Patias P, Grivas TB, Kaspiris A, Aggouris C, Drakoutos E. A review of the trunk surface metrics used as Scoliosis and other deformities evaluation indices. Scoliosis 2010;5:12.

[8] Ueno M, Takaso M, Nakazawa T, Imura T, Saito W, Shintani R, et al. A 5-year epidemiological study on the prevalence rate of idiopathic scoliosis in Tokyo: school screening of more than 250,000 children. J Orthop Sci 2011;16:1–6.

[9] Chowanska J, Kotwicki T, Rosadzinski K, Sliwinski Z. School screening for scoliosis: can surface topography replace examination with scoliometer? Scoliosis 2012;7:9.

[10] Kokabu T, Kawakami N, Uno K, Kotani T, Suzuki T, Abe Y, et al. Three-dimensional depth sensor imaging to identify adolescent idiopathic scoliosis: a prospective multicenter cohort study. Sci Rep 2019;9:9678.

[11] Zou J, Huss M, Abid A, Mohammadi P, Torkamani A, Telenti A. A primer on deep learning in genomics. Nat Genet 2019;51:12–8.

[12] Yamashita R, Nishio M, Do RKG, Togashi K. Convolutional neural networks: an overview and application in radiology. Insights Imaging 2018;9:611–29.

[13] Maki S, Furuya T, Horikoshi T, Yokota H, Mori Y, Ota J, et al. A deep convolutional neural network with performance comparable to radiologists for differentiating between spinal schwannoma and meningioma. Spine 2020;45:694–700.

[14] Chmelik J, Jakubicek R, Walek P, Jan J, Ourednicek P, Lambert L, et al. Deep convolutional neural network-based segmentation and classification of difficult to define metastatic spinal lesions in 3D CT data. Med Image Anal 2018;49:76–88.

[15] Yang J, Zhang K, Fan H, Huang Z, Xiang Y, Yang J, et al. Development and validation of deep learning algorithms for scoliosis screening using back images. Commun Biol 2019;2:390.

[16] Choi R, Watanabe K, Jinguji H, Fujita N, Ogura Y, Demura S, et al. CNN-based spine and Cobb angle estimator using moire images. IIEE Trans Image Electron Vis Comput 2017;5:135–44.

[17] Choi R, Watanabe K, Fujita N, Ogura Y, Matsumoto M, Demura S, et al. Measurement of vertebral rotation from moire image for screening of adolescent idiopathic scoliosis. IIEE Trans Image Electron Vis Comput 2018;6:56–64.

[18] Watanabe K, Aoki Y, Matsumoto M. An application of artificial intelligence to diagnostic imaging of spine disease: estimating spinal alignment from Moiré images. Neurospine 2019;16:697–702.

[19] Kautzky A, Vanicek T, Philippe C, Kranz GS, Wadsak W, Mitterhauser M, et al. Machine learning classification of ADHD and HC by multimodal serotonergic data. Transl Psychiatry 2020;10 (1):104.

[20] Cornell University Library. Adam: a method for stochastic optimization. https://arxiv.org/pdf/1412.6980.pdf. [accessed 13 June 2020].

[21] Jiao S, Gao Y, Feng J, Lei T, Yuan X. Does deep learning always outperform simple linear regression in optical imaging? Opt Express 2020;28:3717–31.

[22] Lee SH, Han P, Hales R, Voong KR, Noro K, Sugiyama S, et al. Multi-view radiomics and dosiomics analysis with machine learning for predicting acute-phase weight loss in lung cancer patients treated with radiotherapy. Phys Med Biol 2020. [Epub ahead of print].

[23] Ceschin R, Zahner A, Reynolds W, Gaesser J, Zuccoli G, Lo CW, et al. A computational framework for the detection of subcortical brain dysmaturation in neonatal MRI using 3D convolutional neural networks. Neuroimage 2018;178:183–97.

[24] Deepak S, P M Ameer PM. Brain tumor classification using deep CNN features via transfer learning. Comput Biol Med 2019;111:103345.