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ORIGINAL ARTICLE

Fully automated radiological analysis of spinal disorders and deformities: a deep learning approach

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Abstract

Purpose We present an automated method for extracting anatomical parameters from biplanar radiographs of the spine, which is able to deal with a wide scenario of conditions, including sagittal and coronal deformities, degenerative phenomena as well as images acquired with different fields of view.

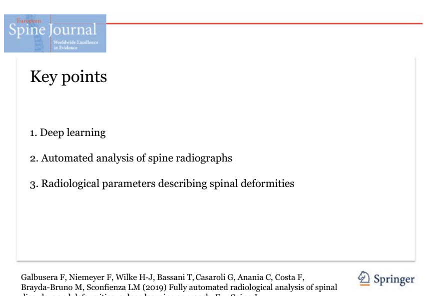
Methods The location of 78 landmarks (end plate centers, hip joint centers, and margins of the S1 end plate) was extracted from three-dimensional reconstructions of 493 spines of patients suffering from various disorders, including adolescent idiopathic scoliosis, adult deformities, and spinal stenosis. A fully convolutional neural network featuring an additional differentiable spatial to numerical (DSNT) layer was trained to predict the location of each landmark. The values of some parameters (T4–T12 kyphosis, L1–L5 lordosis, Cobb angle of scoliosis, pelvic incidence, sacral slope, and pelvic tilt) were then calculated based on the landmarks' locations. A quantitative comparison between the predicted parameters and the ground truth was performed on a set of 50 patients.

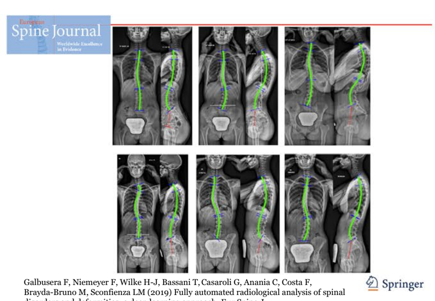
Results The spine shape predicted by the models was perceptually convincing in all cases. All predicted parameters were strongly correlated with the ground truth. However, the standard errors of the estimated parameters ranged from 2.7° (for the pelvic tilt) to 11.5° (for the L1–L5 lordosis).

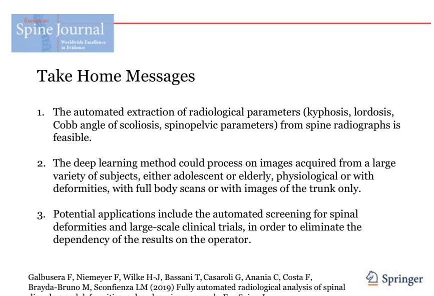
Conclusions The proposed method is able to automatically determine the spine shape in biplanar radiographs and calculate anatomical and posture parameters in a wide scenario of clinical conditions with a very good visual performance, despite limitations highlighted by the statistical analysis of the results.

Graphical abstract

These slides can be retrieved under Electronic Supplementary Material.







Keywords Deep learning · Spine deformities · Automated analysis · Coordinate regression · Biplanar radiographs

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Introduction

Various quantities, typically angles and distances, describing anatomical and posture features of the spine, have a huge clinical relevance for the diagnosis, treatment, and follow-up of spinal disorders, especially deformities. Determining those parameters reliably gained even higher relevance in the last decade with the growing importance of sagittal balance and spinopelvic parameters [1] for planning surgeries that aim to restore a correct sagittal alignment of the spine in elderly patients [2, 3].

For several decades, different methods for manually measuring those quantities have been developed. The Ferguson method for the study of scoliosis was first described in 1930 [4], and the Cobb method, which is still considered the state of the art, was introduced in 1948 [5]. Until recently, such measurements were performed directly on X-ray films using protractors, entailing non-negligible intra- and inter-observer variabilities [6]. The introduction of computer-aided tools further improved the quality of the measurements [7]. Currently, an increasing interest toward the development of fully automated software tools, which would completely eliminate the issue of reproducibility, while likely improving the accuracy of the outputs, is emerging.

Recent studies [8, 9] suggest that a fully automated radiological analysis of the spine shape is technically feasible, considering the rapid development of novel machine learning methods for image processing and the easily accessible compute power offered by modern graphics processing units (GPU). Nevertheless, all available studies focused on specific groups of patients or pathologies, mostly adolescent idiopathic scoliosis [8, 10, 11]. In this paper, we present a method for the automatic extraction of clinically relevant anatomical parameters from biplanar radiographs of the spine that is able to deal with a wide scenario of clinical conditions, including both young and elderly subjects, sagittal and coronal deformities, degenerative and compensatory phenomena, as well as images acquired with different fields of view.

Materials and methods

Overview

This study is based on a supervised learning approach, which consists of training models to provide an output (i.e., coordinates of landmarks) based on a large series of images for which the ground truth (i.e., the actual landmark coordinates for each image, determined either manually or with a state-of-the-art method) is known. The next paragraphs describe the collection and preparation of the images and ground truth data used to train the models, the creation and training of the models themselves, the extraction of radiological parameters from the landmark coordinates, and the evaluation of the accuracy of the models conducted with standard statistical methods.

Dataset

Written informed consent for using the data for research purposes was obtained from all patients. Ethical committee approval for this retrospective study has been obtained, and patients' informed consent was waived. A database of biplanar radiographs from 493 patients acquired with the EOS imaging system (EOS Imaging, Paris, France) has been created from the archives of IRCCS Istituto Ortopedico Galeazzi. The database comprises images from subjects suffering from various pathologies such as adolescent idiopathic scoliosis, adult scoliosis, degenerative disorders including sagittal imbalance, and spinal stenosis. Forty-eight patients had spinal instrumentation implanted prior to the scan with the EOS system, which thus is visible on the images. A full-body scan was performed on 138 subjects, whereas the images of the other patients ranged from the head to the proximal femurs. For all patients, the three-dimensional (3D) spinal anatomy was reconstructed manually using the sterEOS commercial software (EOS Imaging, Paris, France).

Preparation of the training and testing data

A custom C++ program automatically extracted the 3D coordinates of 39 landmarks from each of the reconstructed spinal anatomies. The anatomical landmarks included the center of the end plates of all thoracolumbar vertebrae, the center of the upper sacral end plate as well as its anterior and posterior margins, and the centers of the hip joints (Fig. 1).

For all patients, the two planar radiographs were combined into a single image with a fixed size of 512 × 512, in which the left half consisted of the anteroposterior radiographic projection (resized to 256 × 512), whereas the right half included the sagittal projection (Fig. 1). It should be noted that resizing changes the aspect ratio of the images and alters the value of the radiological parameters of interest; therefore, this issue needs to be compensated in the successive steps. The set of 493 combined images were used as training ($N = 443$) and testing ($N = 50$) datasets for the deep learning models; to ensure an unbiased evaluation of the performance, training and testing datasets did not overlap. Augmentation techniques involving randomized horizontal flipping, rotations, and changes to brightness and contrast were used to extend the size of the training dataset.

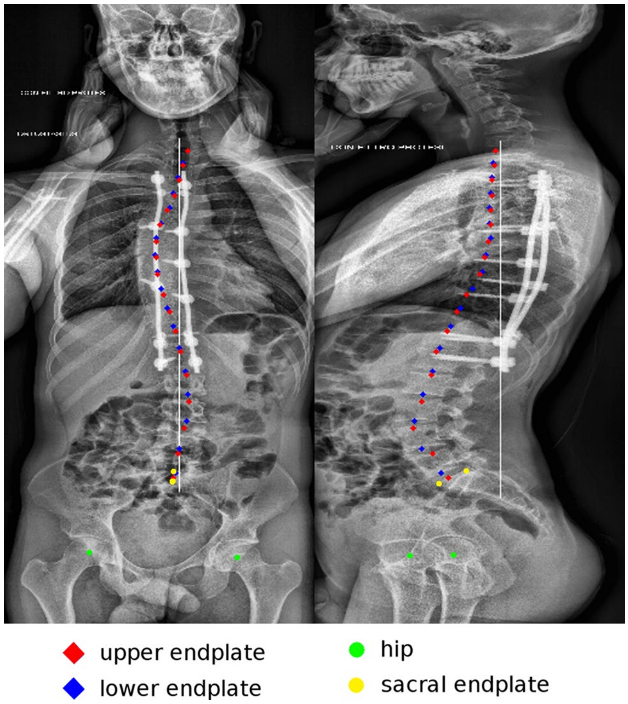

Fig. 1 Representative scaled biplanar radiographs showing the 78 landmarks, which included the center of the upper (red) and lower (blue) end plates of the thoracolumbar spine, the center of the hip joints (green), and the anterior and posterior margins of the S1 end plate (yellow)

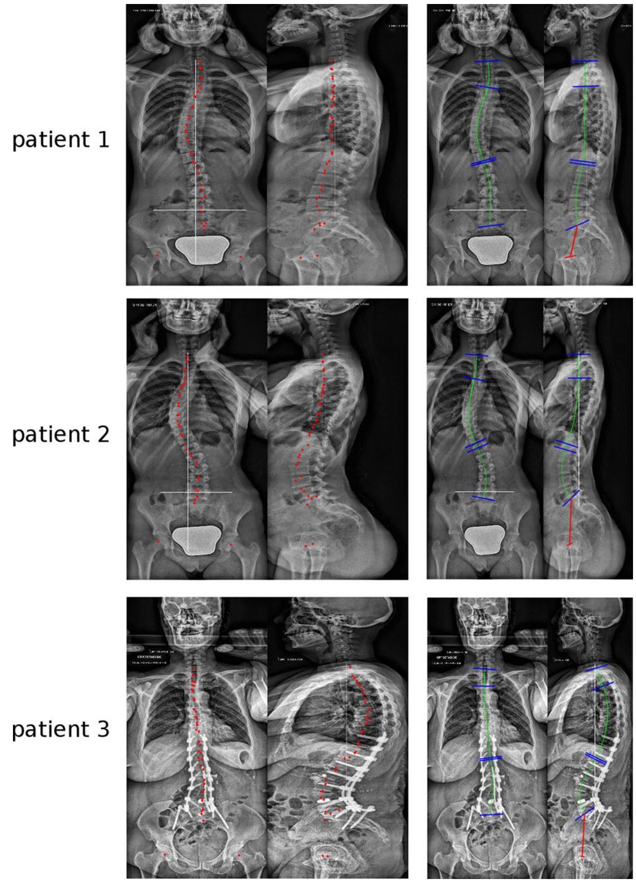

Fig. 2 Predicted location of the 78 markers (left) and their polynomial interpolation (right, in green) in three representative patients. The line connecting the hip centers to the S1 end plate, used for the calculation of the spinopelvic parameters, is also shown (in red), as well as the orientation of the end plates of relevant vertebrae (T1, T4, T12, L1, S1 in blue)

Coordinate regression with deep learning

The dataset was used to train and test 78 distinct regression models aimed at the determination of the location of the anatomical landmarks. Indeed, each landmark, which has three spatial coordinates, was considered twice, i.e., separately in the coronal and in the sagittal planes. Therefore, one regression model (named "localizer" in the following text) was trained to predict the position of the landmark projected onto the coronal plane, thus belonging to the left half of the image, whereas an independent localizer calculated its location in the sagittal plane, corresponding to the right half of the image. The localizers themselves were based on the state-of-the-art differentiable spatial to numerical transform (DSNT), which was shown to outperform the other most common approaches for image-based coordinate regression while preserving desirable properties such as spatial generalization and end-to-end differentiability [12]. In brief, the method combines a standard fully convolutional network (FCN) with a DSNT layer as its output layer, which converts the spatial heatmap generated by the FCN to numerical coordinates. In contrast to other methods, the DSNT layer has no trainable parameters and generalizes spatially. The localizer is trained to minimize the Euclidean distance between the predicted coordinates and the ground truth. A complete description of the method is reported elsewhere [12]. In this work, we used a simple seven-layer FCN implemented with Keras [13] using the TensorFlow backend [14]. A Linux workstation featuring a NVIDIA Titan Xp GPU was used for training and testing the localizers.

Determination of the spine shape and the spinopelvic parameters

From the coordinates of the 78 landmarks localized by the models, we derived several anatomical and posture parameters widely used in clinics. First, all coordinates were readjusted to match the original aspect ratio of the images (Fig. 2). Then, using least squares as implemented by a freely available C++ code [15], two sixth-order polynomials [16] were fitted to the coordinates of the points representing the center of the upper and lower end plates, independently of the coronal and sagittal projections (Fig. 2). With the exception of the sacral slope, the orientation of each end plate, both in the coronal and in the sagittal projection, was then geometrically determined as the slope of the line orthogonal to the fitting polynomial calculated so that the distance between the corresponding landmark as predicted by the localizer and the intersection between the orthogonal line and the polynomial is minimized. In order to increase the accuracy of the spinopelvic parameters, the sagittal orientation of the S1 end plate, which corresponds to the sacral slope (SS), was calculated as the slope of the straight line best fitting the relevant markers (the center of the end plate and its anterior and posterior margins). Pelvic tilt and incidence were determined based on their geometrical definitions [1].

Testing and statistical analysis

In order to quantitatively compare the results obtained for the testing set with the original reconstructions obtained with sterEOS (considered as "ground truth"), linear regression and Bland–Altman analysis [17] were conducted on several clinically relevant parameters: T4–T12 kyphosis angle, L1–L5 lordosis angle, Cobb angle (if the spine was scoliotic), pelvic incidence (PI), SS, and pelvic tilt (PT). In case of a scoliotic spine, the Cobb angle of the most severe curve was considered. The same end vertebrae determined automatically by sterEOS were also used for the calculation of the Cobb angle based on the deep learning approach. Statistical analysis was performed using the Python libraries SciPy [18] and StatsModels [19].

Results

From a qualitative point of view, the spine shape reconstructed with the deep learning approach was perceptually convincing and rather accurate in most cases, both for patients in whom only the trunk was scanned (Fig. 3) and for patients in whom a full-body acquisition was

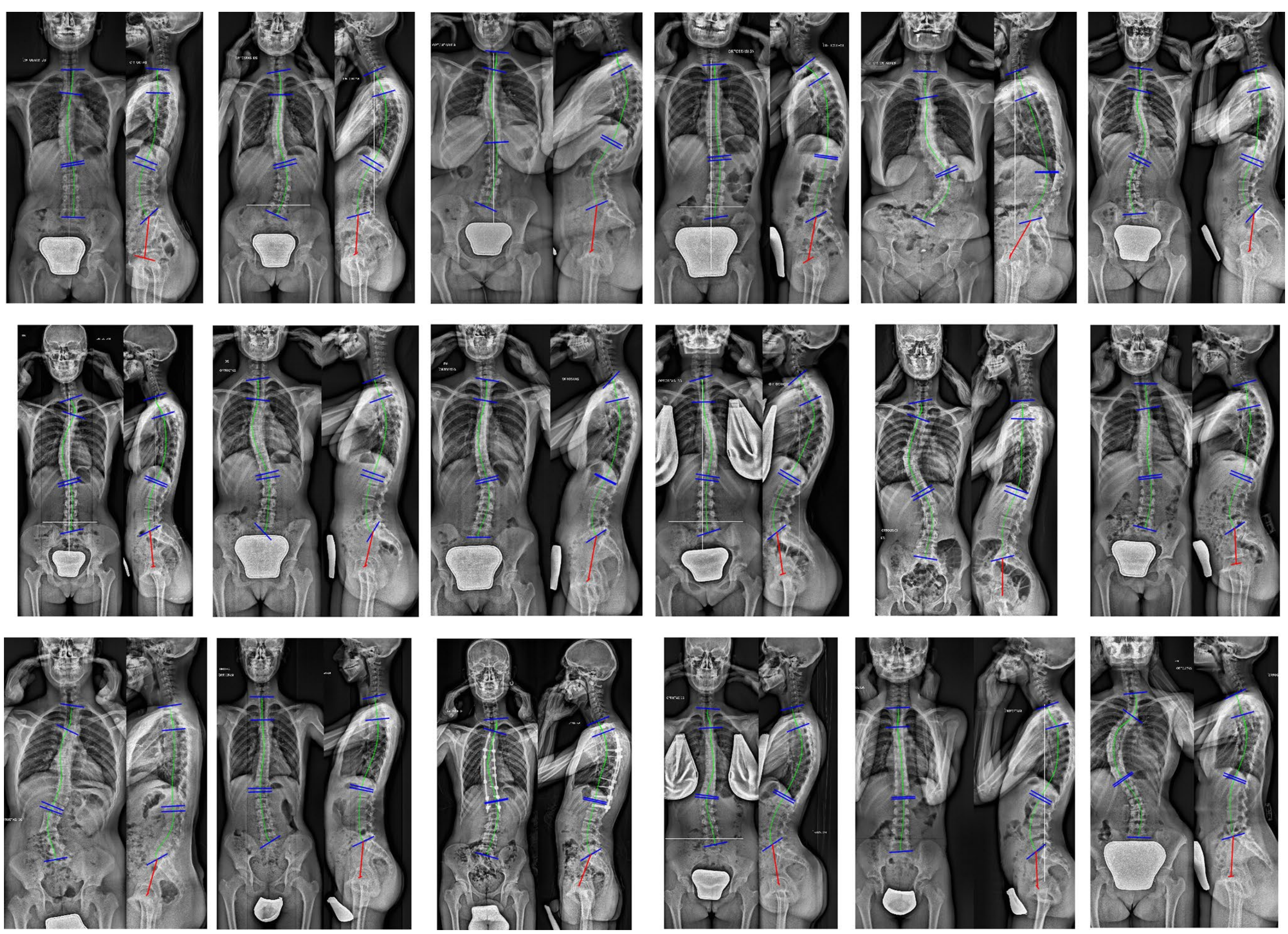

Fig. 3 Exemplary predicted spinal shapes (in green) for 18 subjects extracted from the testing set, in which the trunk only was scanned. The line connecting the hip centers to the S1 end plate is also shown (in red), as well as the orientation of the end plates of relevant vertebrae (T1, T4, T12, L1, S1 in blue)

performed (Fig. 4). It should be noted that the landmark localizers were able to deal with both types of scans, with no need for an a priori knowledge of the acquisition area. Most of the inaccuracies detectable visually in the outputs were located close to the ends of the fitting polynomial approximating the spinal shape, i.e., at the T1 and S1 end plates, especially in the coronal projection. In particular, gross errors in the coronal orientation of the S1 end plate were observed in a number of cases. Nevertheless, in most of the cases, the localizers were able to successfully capture the general shape of the thoracolumbar spine, even in patients with spinal instrumentation, clearly depicting pathological features such as scoliotic curves and thoracic hyperkyphosis as well as degenerative phenomena such

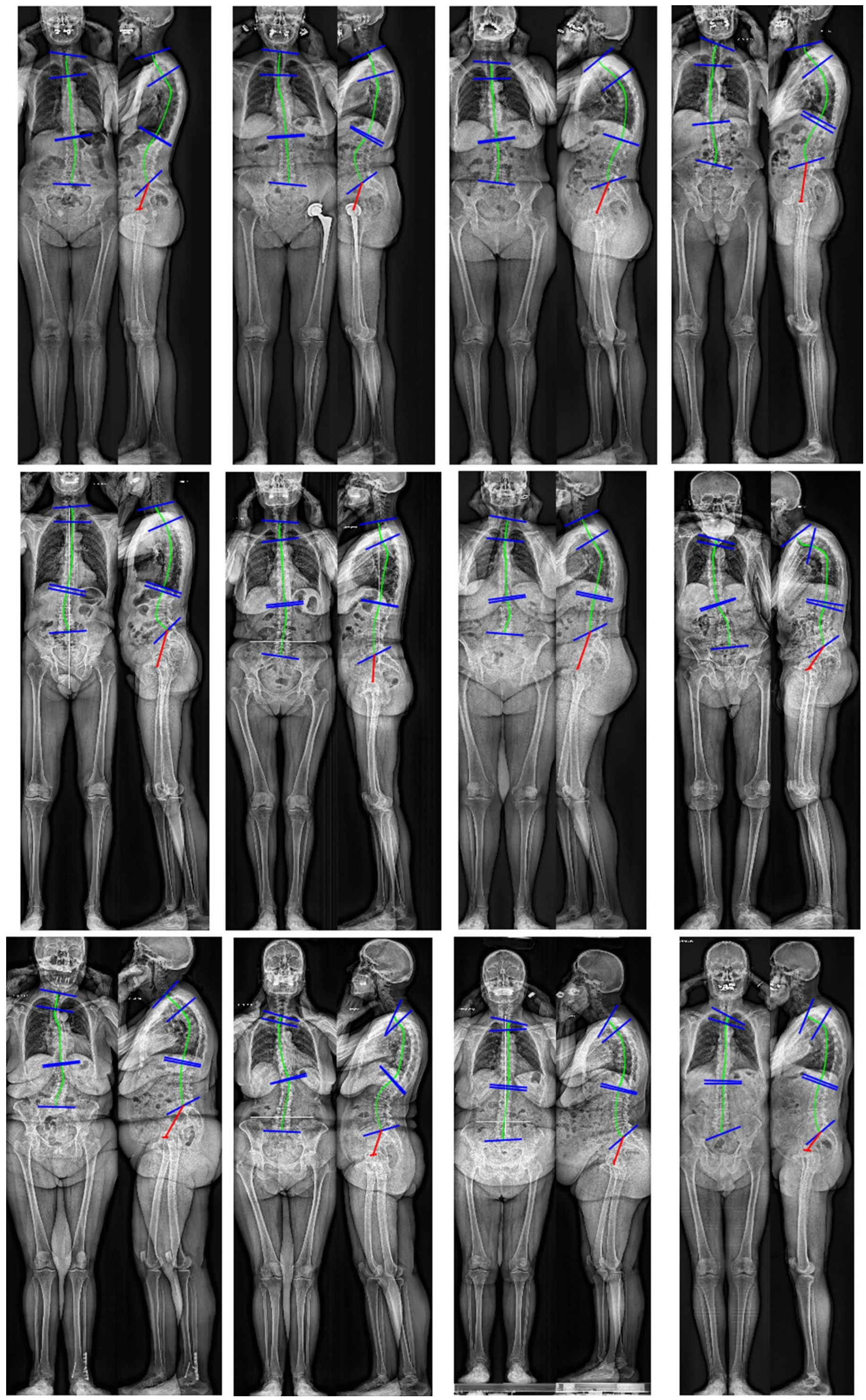

Fig. 4 Exemplary predicted spinal shapes (in green) for 12 subjects extracted from the testing set, subjected to a whole-body scan. The line connecting the hip centers to the S1 end plate is also shown (in red), as well as the orientation of the end plates of relevant vertebrae (T1, T4, T12, L1, S1 in blue)

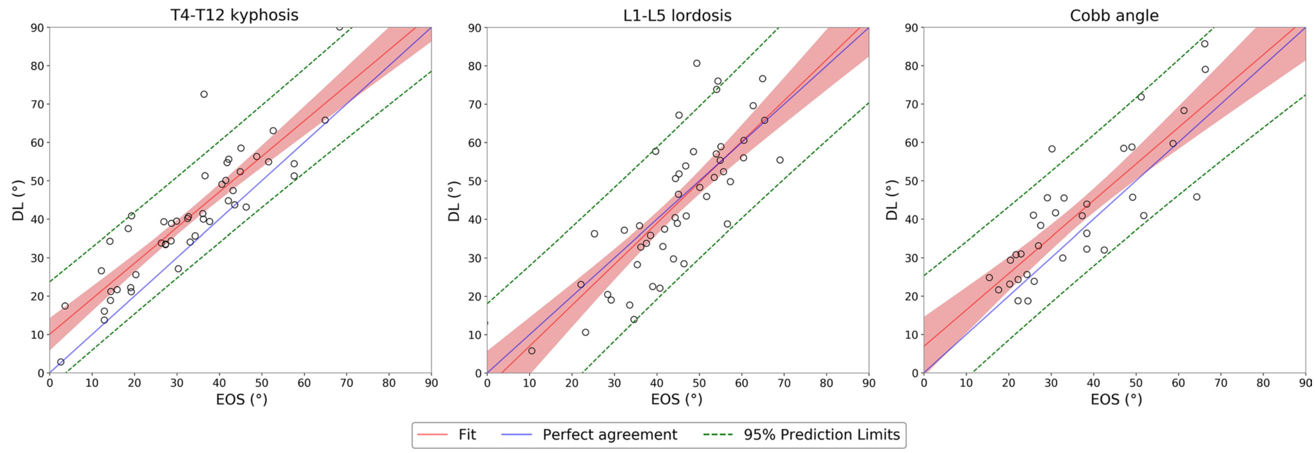

Fig. 5 Regression analysis of three parameters describing the curvature of the spine (from left to right: T4–T12 kyphosis, L1–L5 lordosis, and Cobb angle for scoliotic spines), showing the values predicted by the deep learning localizers ("DL") versus the ground truth calculated by sterEOS reconstruction software ("EOS"). The 95% confidence interval of the predictions (green dashed lines) and the 95% confidence limits of the regression line (rendered in solid light red) as well as the line indicating a perfect correspondence between deep learning and ground truth (in blue) are shown

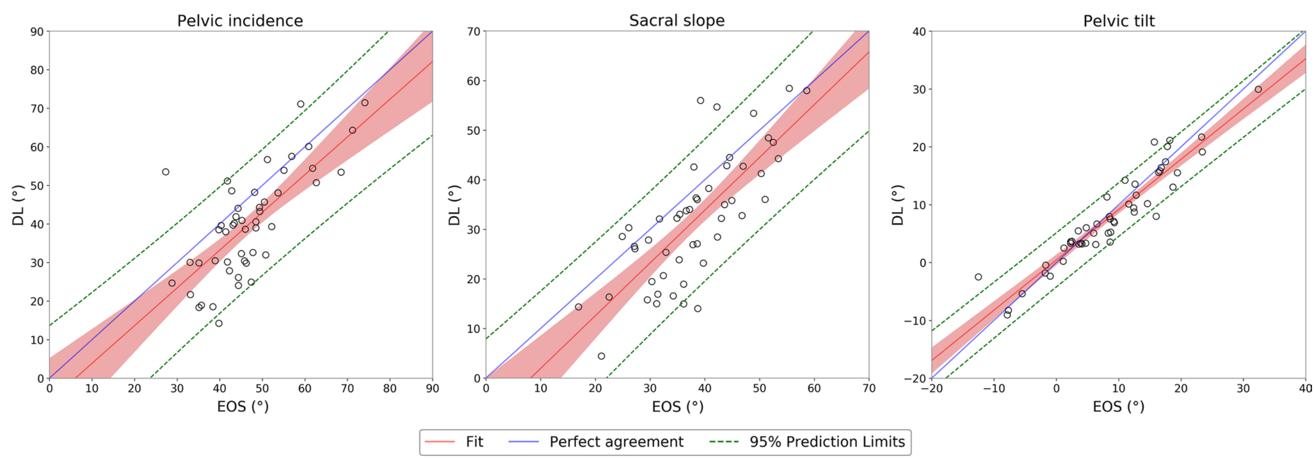

Fig. 6 Regression analysis of the spinopelvic parameters (from left to right: pelvic incidence, sacral slope, and pelvic tilt), showing the values predicted by the deep learning localizers ("DL") versus the ground truth calculated by sterEOS reconstruction software ("EOS"). The 95% confidence interval of the predictions (green dashed lines) and the 95% confidence limits of the regression line (rendered in solid light red) as well as the line indicating a perfect correspondence between deep learning and ground truth (in blue) are shown

as the loss of lumbar lordosis and compensatory pelvic retroversion.

The statistical analysis of the results confirmed the general validity of the deep learning approach, but also highlighted some differences between the outputs of the localizers and the ground truth calculated by sterEOS software, which were not apparent in the qualitative visual evaluation. In general, the results of the deep learning tool were strongly correlated with the ground truth, with $p < 0.001$ in all cases (Figs. 5, 6, Table 1). However, standard errors of the estimate (S), defined as the standard deviation of the differences between the deep learning estimations and the ground truth, were non-negligible and ranged between 2.7° and 11.5°.

Table 1 Regression analysis for the correlation between the values of the anatomical parameters evaluated with sterEOS software (ground truth) and those calculated with the deep learning models

Parameter	R^2	*p* value	Slope of the regression line	Standard error of the measurement (S)
T4–T12 kyphosis	0.79	< 0.001	43°	8.6°
L1–L5 lordosis	0.62	< 0.001	47°	11.5°
Cobb angle	0.69	< 0.001	44°	9.9°
Pelvic incidence	0.52	< 0.001	44°	9.5°
Sacral slope	0.58	< 0.001	47°	8.5°
Pelvic tilt	0.89	< 0.001	41°	2.7°

The slope of the regression line was relatively similar to the ideal value of 45° in all cases (range 41–47°), whereas the value of the intercept was positive for some parameters (T4–T12 kyphosis, Cobb angle, PI, SS) and negative for others (L1–L5 lordosis, PT). Specifically, the greatest standard error of the estimate (11.5°) was determined for L1–L5 lordosis (Table 1). However, Bland–Altman analysis showed a low mean difference between the ground truth and the predictions for this parameter, equal to 0.8°, thus demonstrating no consistent bias between the two methods (Fig. 7). T4–T12 kyphosis showed a stronger correlation and a lower standard error (8.6°), but a mean difference between ground truth and predictions of − 7.6° (Fig. 7). A similar behavior was observed for the Cobb angle (standard error 9.9°, mean difference − 5.1°).

Regarding the spinopelvic parameters (Figs. 6, 8), an excellent agreement between the results and the ground truth was found for PT, which showed a low standard error of the estimate (2.7°) and a mean difference between ground truth and predictions of 0.7° (Fig. 8). Reflecting the linear dependence between the three spinopelvic angles, PI and SS performed similarly, with standard errors of 9.5° and 8.5° (Table 1), and mean difference of 6.9° and 6.2° (Fig. 8), respectively.

As demonstrated by Bland–Altman plots (Figs. 7, 8), the estimation errors for all parameters showed negligible dependency on the magnitude of the parameters themselves. Nevertheless, the large amplitude of the 95% confidence intervals precludes the possibility of a direct clinical use of these deep learning models at the current state of development, with the notable exception of PT which could be reliably estimated.

Discussion

This paper presents a deep learning method for the fully automated evaluation of the spine shape and spinopelvic parameters based on biplanar radiographs. The novel localizers can be used on images acquired from a large variety of subjects, either adolescent or elderly, with physiological spinal alignment or with sagittal or coronal spinal deformities, with full-body scans or with images depicting only the trunk. Potential applications include the automated screening for

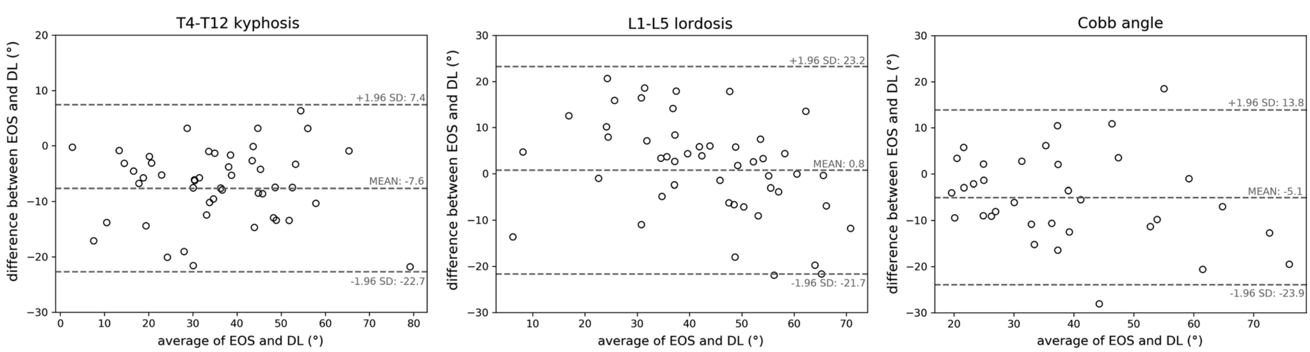

Fig. 7 Bland–Altman plots comparing the value of the parameters describing the spine shape from the ground truth calculated by sterEOS reconstruction software ("EOS") and those predicted by the deep learning localizers ("DL"). From left to right: T4–T12 kyphosis, L1–L5 lordosis, and Cobb angle for scoliotic spines

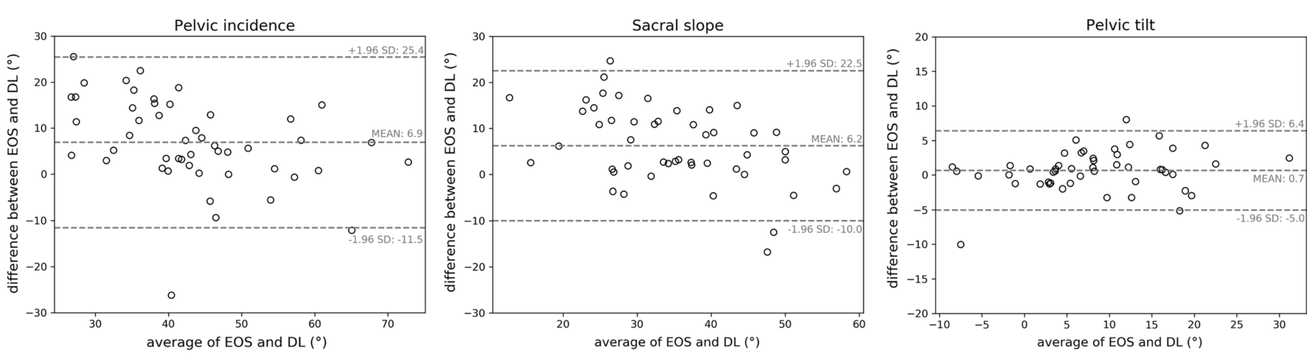

Fig. 8 Bland–Altman plots comparing the value of the spinopelvic parameters from the ground truth calculated by sterEOS reconstruction software ("EOS") and those predicted by the deep learning localizers ("DL"). From left to right: pelvic incidence, sacral slope, and pelvic tilt

spinal deformities, for example in adolescent subjects when scoliosis is suspected, and large-scale clinical trials, in order to eliminate the dependency of the results on the operator.

The qualitative analysis of the results showed an excellent visual performance of the method; however, the quantitative comparison with the ground truth, i.e., anatomical parameters extracted from the 3D reconstructions obtained with sterEOS, showed discrepancies, which would have an impact if the method was used in clinical practice. Nevertheless, even the current results clearly highlighted the remarkable potential of artificial intelligence techniques for the study of spinal deformities.

Following the increasing use of machine learning methods in several fields of medical research, the automated assessment of radiological parameters in patients suffering from spinal disorders is currently a subject of active research. Recent papers promoted the use of modern convolutional architectures to detect spinal landmarks and then calculate the value of Cobb angles in adolescent patients suffering from idiopathic scoliosis [8, 10]. Other papers used more conventional machine learning techniques [20] or methods relying on classical image analysis, such as active contours [21], charged particle models [22], and fuzzy Hough transform [11, 23]. To our knowledge, the current paper represents the first attempt to create a method able to perform a fully automated biplanar analysis of the spine shape, including spinopelvic parameters, which can be generally applied to any subject, independently of age and spinal pathology. Existing methods, on the other hand, focused on specific disorders, such as adolescent idiopathic scoliosis. Although a direct quantitative comparison with the previous literature cannot be made due to differences in the nature of the reported results, the quality of the predicted position of the landmarks seems to be comparable to that shown in other studies [8, 10].

In this paper, we did not propose a novel deep learning method for the estimation of the anatomical parameters, but we rather preferred to select, among the currently available methods, the one, which was likely to perform the best at the tasks of interest. Although a complete technical discussion of DSNT with respect to alternative solutions is out of the scope of this paper, its main advantages with respect to the alternative solutions are worthy of mention. In brief, DSNT inherently possesses the property of spatial generalization, which is particularly relevant in cases in which the location of a specific landmark may be anywhere in the whole image [12]. For example, a method with poor spatial generalization would be less suitable to deal with different types of images and thus landmark location patterns, such as the full-body scans versus images of the trunk only, or with images from patients with distinctly different spinal anatomies, such as commonly seen in severe deformities. In comparison with the heatmap matching method, which is spatially general, DSNT directly outputs the point location and thus allows calculating a loss function straight from the predicted coordinates, whereas in heatmap matching the loss function is not directly connected to the metric of interest (i.e., the distance between the predicted point location and the ground truth). Previous research showed that this advantage permits a consistent improvement in the accuracy [12].

Despite the good qualitative performance of the new method, the differences between the ground truth and the current predictions preclude a direct successful introduction into clinical practice. As a comparison, regarding the manual measurement of the sagittal angles, mean absolute difference values between the measurements ranging from 1.5° [24] to 7.3° [25] were reported [7], whereas the current method showed a standard error of the estimate of 8.6° for the thoracic kyphosis and 11.5° for the lumbar lordosis. Similarly, for the manual measurement of the spinopelvic parameters on digital radiographs with basic software tools, values of the interrater standard error of measurement between 2.5° and 6.2° were reported [26], whereas our automated method resulted in standard errors of the estimate between 2.7° and 9.5°. It should be noted that, although the accuracy of the predictions shows room for improvement, the non-stochastic nature of the method allows for a perfect reproducibility, i.e., an intra-class correlation coefficient of 1, whereas it varies between 0.8 and 0.99 for manual and computer-aided methods [24, 26].

The reason for the perfectible accuracy of the method can be mostly attributed to the limited size of the training dataset. Indeed, the size used in the current study (443 couples of images) should be regarded as very low in the context of machine learning research, in particular for training deep neural networks. However, in the medical imaging field, collecting a large number of images and generating the corresponding ground truth, in our case by performing the 3D reconstruction by means of sterEOS software, although being performed with increasing effort in our institutes, is challenging and very time-consuming. Furthermore, the applicability of data augmentation, an effective strategy to increase the size of the training data by random rotations, cropping, flipping, etc., is inherently more restricted in medical imaging compared to other fields of research, for example handwriting recognition or face detection, in which there is no need to follow strict protocols for the acquisition of the image. As a matter of fact, in studies similar to the current one (e.g., [8]) the number of images is most commonly in the range of hundreds. Another limitation is the use of a distinct localizer for each landmark; a more refined architecture outputting all landmarks together may take advantage of the correlation between the landmarks and may therefore provide more accurate results. Furthermore, the ground truth data extracted from the sterEOS reconstructions, although well investigated and validated [27, 28], may likely be affected by non-negligible measurement errors, which can act as confounding factors in the statistical analysis. As a matter of fact, previous studies showed intra-class correlation coefficients between 0.738 and 0.988 in the measurement of sagittal parameters by means of sterEOS software [27], which can be deemed as good-to-excellent but prove that this method is not free from inaccuracies.

Interestingly, the parameter which had the best accuracy, PT, was the only one which was not dependent on the polynomial interpolation between the predicted points. Indeed, PT was calculated based only on the location of the hip centers and the center of the S1 end plate and had thus no link with the polynomial. Therefore, the interpolation, which was aimed to improve the accuracy of the predicted vertebral orientations by acting as a smoothing filter, should be considered as a limitation of the work and should be optimized in future research.

In conclusion, the deep learning method here presented was able to automatically determine the shape of the spine in biplanar radiographs and to calculate the value of anatomical and posture parameters in a wide scenario of clinical conditions with a very good visual performance, despite limitations highlighted by the statistical analysis of the results. We believe that this method has the potential to be the starting point for an accurate fully automated radiological analysis of spinal deformities, the main limiting factor being the availability of a sufficiently large training dataset.

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Compliance with ethical standards

Conflict of interest The authors declare that there is no conflict of interest regarding the publication of this article.

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