Gait Patterns as Biomarkers: A Video-Based Approach for Classifying Scoliosis

Zirui Zhou[1†], Junhao Liang[1†], Zizhao Peng[1,2], Chao Fan[1], Fengwei An[1], and Shiqi Yu[1*]

[1] Southern University of Science and Technology, Shenzhen, China
[2] The Hong Kong Polytechnic University, Hong Kong, China

Abstract. Scoliosis poses significant diagnostic challenges, particularly in adolescents, where early detection is crucial for effective treatment. Traditional diagnostic and follow-up methods, which rely on physical examinations and radiography, face limitations due to the need for clinical expertise and the risk of radiation exposure, thus restricting their use for widespread early screening. In response, we introduce a novel, video-based, non-invasive method for scoliosis classification using gait analysis, which circumvents these limitations. This study presents Scoliosis1K, the first large-scale dataset tailored for video-based scoliosis classification, encompassing over one thousand adolescents. Leveraging this dataset, we developed ScoNet, an initial model that encountered challenges in dealing with the complexities of real-world data. This led to the creation of ScoNet-MT, an enhanced model incorporating multi-task learning, which exhibits promising diagnostic accuracy for application purposes. Our findings demonstrate that gait can be a non-invasive biomarker for scoliosis, revolutionizing screening practices with deep learning and setting a precedent for non-invasive diagnostic methodologies. The dataset and code are publicly available at `https://zhouzi180.github.io/Scoliosis1K/`.

Keywords: Scoliosis · Gait analysis · Non-invasive screening · Deep learning · Computer vision.

1 Introduction

Scoliosis, a complex spinal deformity characterized by a three-dimensional curvature, significantly impacts adolescents' physical well-being and quality of life worldwide. It is clinically assessed by measuring the Cobb angle, defined as the angle between the upper and lower end vertebrae on standing X-rays (Figure 1 (a)), with a threshold exceeding 10° indicating scoliosis [19, 16]. This early-stage

† Equal contribution.
* Corresponding author: yusq@sustech.edu.cn.

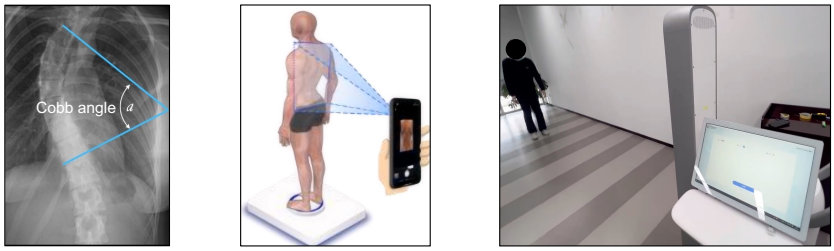

Fig. 1: Comparative overview of scoliosis diagnosis methods: (a) Traditional X-ray examination, the clinical gold standard [18]; (b) Non-invasive analysis of bare back photos [24]; (c) Our proposed gait analysis approach, which enables efficient, large-scale early adolescent screening to identify cases needing further radiographic investigation, highlighting its non-invasiveness and privacy-preserving nature.

condition is often asymptomatic, potentially leading to severe health issues if left undiagnosed [14]. In China, the prevalence of scoliosis among school-aged children is approximately 5.14% [6], underscoring the critical need for effective early screening methods.

Traditionally, scoliosis diagnosis and monitoring have relied on physical exams and radiography, necessitating significant clinical expertise and exposing patients to radiation, thus limiting early, widespread screening. Innovations in deep learning have led to the exploration of non-invasive scoliosis assessment methods, such as bare back photo analysis [21, 24]. Yet, these alternatives often raise concerns regarding privacy and efficiency. Addressing these challenges, we introduce a novel video-based method that uses gait as biomarkers for scoliosis, which obviates the need for direct bodily exposure (Figure 1 (b) v.s. (c)). Despite its potential, there are almost no related works benchmarking this promising direction in the literature, due to the lack of public datasets and baseline models.

Our response to these obstacles is the development of Scoliosis1K—a groundbreaking dataset featuring over 1k adolescents and 400k frames, setting new standards for video-based adolescent scoliosis screening. Opting for silhouette data to respect privacy and enhance usability, we draw upon existing gait recognition techniques [1, 3, 4, 9, 2] to create ScoNet, demonstrating gait's viability as a scoliosis biomarker. Furthermore, ScoNet's initial vulnerability to sample imbalance prompted the development of ScoNet-MT, an enhanced, multi-task learning model.

This work contributes significantly to the field by: (1) creating the first large-scale dataset Scoliosis1K for video-based scoliosis classification, establishing a new benchmark for the research community; (2) introducing ScoNet, the first baseline model for scoliosis classification through gait analysis, and evolving it into the novel ScoNet-MT to better handle real-world data complexities; and (3) demonstrating that ScoNet-MT exhibits promising diagnostic accuracy for application purpose, underscoring the potential of gait as non-invasive biomarker for

scoliosis and showcasing the transformative impact of deep learning in healthcare diagnostics.

2 Dataset

2.1 Overview of Scoliosis1K

To the best of our knowledge, Scoliosis1K represents the first large-scale dataset tailored for video-based scoliosis classification. The samples therein fall into three diagnostic categories: positive (Cobb angle $> 10°$), neutral (Cobb angle $\approx 10°$), and negative (Cobb angle $< 10°$). The data was from 1,050 adolescent participants from a middle school in China. The dataset includes 447,900 silhouette images from 1,493 video sequences. Three sequences of different categories are shown in Figure 2. The study was approved by the relevant ethics committee, and informed consent was obtained from all participants and their guardians.

2.2 Data Collection and Preprocessing

The videos were captured at the 720p resolution by a camera. The participants were suggested to walk along a corridor. The camera was set at a distance range of 1.4 to 4.2 meters from the participants. The data collection was designed to simulate a controlled yet natural walking environment conducive to accurate biomechanical analysis. Each sequence, containing about 300 frames at 15 frames per second, was annotated by scoliosis experts. The experts used well established scoliosis screening methods, visual assessments and the Adams Forward Bend Test, to estimate the categories that the participants belonged to. The experts did not estimate the categories by watching videos. They estimate the categories by checking the participants' body. Then all videos from that participant would be labeled as the category of that participant.

Fig. 2: Some silhouettes in the Scoliosis1K dataset. (a) positive, (b) neutral, and (c) negative samples.

Table 1: The statistics of the Scoliosis1K dataset. The dataset contains diversity on diagnostic categories and participant demographics.

	Attributes	All	Positive	Neutral	Negative
Scoliosis1K	Number of Participants	1050	176	82	792
	Number of Sequences	1493	493	200	800
	Sex(F/M)	641/409	113/63	49/33	479/313
	Age(years, mean ± std)	15.2 ± 1.5	14.3 ± 1.0	14.0 ± 0.6	15.5 ± 1.5
	Height(cm, mean ± std)	163.2 ± 8.8	161.6 ± 7.1	161.4 ± 6.7	163.7 ± 9.3
	Weight(kg, mean ± std)	51.9 ± 10.7	48.3 ± 8.4	46.7 ± 7.8	53.3 ± 11.1

Due to the relatively fewer positive scoliosis cases, individuals diagnosed with the condition were encouraged to contribute multiple sequences. It helped mitigate the dataset's potential class imbalance, enhancing its analytical reliability and robustness.

In the preprocessing phase, the raw video footage underwent a rigorous conversion process to binary silhouette sequences. Choosing silhouettes serves two primary purposes: firstly, to anonymize participant data, safeguarding their privacy; and secondly, to make the deep learning mehtod focus on the body region nor the background. These silhouettes, which form a fundamental component of our dataset, retain critical gait features while discarding irrelevant background information. The detailed description of silhouette extraction is presented in Section 3.1.

2.3 Demographics and Dataset Characteristics

Table 1 provides a demographic and clinical overview of Scoliosis1K. It illustrates its comprehensiveness for adolescent scoliosis screening. The dataset's design reflects a commitment to scale and diversity, encompassing a wide array of participant attributes and gait patterns. This variety underpins the dataset's potential to train deep models for scoliosis classification based on gait.

2.4 Implications for Scoliosis Research

Scoliosis1K can improve the research in scoliosis diagnosis on the following aspects:

- **Scale and Scope:** To the best of our knowledge, it constitutes the first large-scale dataset for automatic scoliosis diagnosis. It can make scoliosis diagnosis by computer vision feasible.
- **Innovation in Non-Invasive Screening:** By providing high-quality, annotated silhouettes data, Scoliosis1K addresses the critical need for non-invasive diagnostic tools in scoliosis screening. This fosters innovation by enabling the exploration of new methods that prioritize patient safety and privacy.

Furthermore, Scoliosis1K bridges a vital gap in the availability of high-quality, annotated images for non-invasive scoliosis screening. This contribution not only catalyzes innovation in healthcare technology but also sets the stage for expansive future research in automated scoliosis diagnosis. The dataset paves the way to improve the public health, especially in regions where medical services are limited.

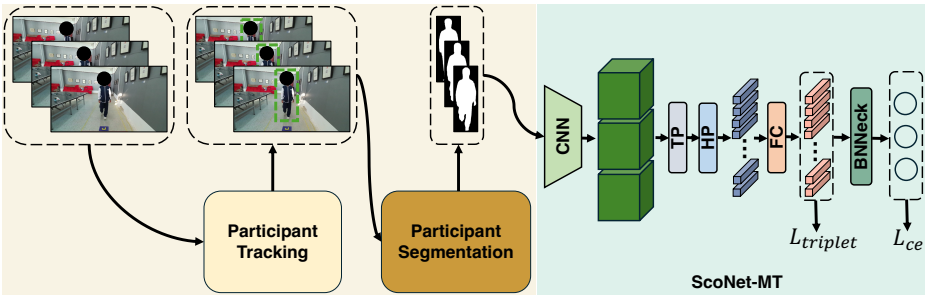

Fig. 3: The Proposed Pipeline: Initially, the participant is tracked throughout the video, with non-participant entities, such as clinicians, being excluded. Subsequently, the participant's silhouette is segmented. Finally, ScoNet-MT classifies the scoliosis based on gait analysis.

3 Methodology

This section introduces our innovative approach for scoliosis classification through analyzing gait patterns in videos. Our method consists of three main stages: participants tracking, participants segmentation, and gait-based scoliosis classification. Figure 3 illustrates the entire pipeline.

3.1 Participants Tracking and Segmentation

We employed BYTETracker [25] for precise person tracking in videos. BYTETracker can enhance the tracking accuracy by valuing each detection box, facilitating the recovery of objects hidden by occlusion and the removal of non-relevant false detection. It utilizes a tracklet similarity for effective differentiation between the participant and the background, and ensures the accurate and consistent tracking.

Following tracking, participant segmentation is achieved by inputting cropped person image region into PP-HumanSeg [22, 10], which is a robust deep model designed for precise human segmentation. Utilizing a deep neural network architecture, PP-HumanSeg combines an encoder, Spatial Pyramid Pooling Module (SPPM), and Flexible and Lightweight Decoder (FLD) to produce binary masks—referred to as silhouettes. Subsequently, we normalized the silhouettes to a fixed size with a similar manner of gait recognition methods [7].

3.2 Scoliosis Classification based on Gait

We recognize gait can be a non-invasive biomarker for scoliosis. To this end, we introduce ScoNet and its enhanced model, ScoNet-MT, both aimed at automating the classification process with high efficiency.

ScoNet utilizes a ResNet-inspired $\mathcal{E}$ architecture to transform participant silhouettes $\mathbf{s}$ into 3D feature maps $\mathbf{f}$:

$$\mathbf{f} = \mathcal{E}(\mathbf{s}) \in R^{n \times c \times h \times w},$$

where n, c, h, and w denote the gait frames, channel, height, and width dimensions, respectively. Temporal Pooling (TP) [1] condenses these into essential features z:

$$z = TP(\mathbf{f}) \in R^{c \times h \times w}.$$

Horizontal Pooling (HP) [5] segments these maps, pooling them into vectors z_s, with global pooling on 16 horizontal segments for comprehensive feature extraction:

$$\mathbf{f}' = \text{maxpool}(z_s) + \text{avgpool}(z_s).$$

A dedicated fully connected layer then maps these vectors into the metric space, with BNNeck [11] refining the feature space ahead of the final classification stage, utilizing cross-entropy loss to gauge the fidelity between predicted and actual labels:

$$L_{ce} = -\sum_{i=1}^{n} y_i \log(\widehat{y}_i).$$

ScoNet-MT extends ScoNet by integrating multi-task learning with a Gait Recognition (GR) task that emphasizes distinctive human motion patterns, reducing bias from non-gait related factors. This model applies triplet loss to distinguish subtle gait variations crucial for scoliosis classification. For each training batch, N triplets are formed, each consisting of an anchor sequence $\mathbf{s}_i^a$, a positive sequence $\mathbf{s}_i^p$ sharing the same identity, and a negative sequence $\mathbf{s}_i^n$ with a different identity:

$$L_{triplet} = \sum_{i=1}^{N} \max\left(0, \|f(\mathbf{s}_i^a) - f(\mathbf{s}_i^p)\|_2^2 - \|f(\mathbf{s}_i^a) - f(\mathbf{s}_i^n)\|_2^2 + \alpha\right),$$

where $f(\cdot)$ is the embedding function transforming each sequence into an embedding space, $\|\cdot\|_2$ is the Euclidean norm, and α is a margin enforcing separation between the positive and negative matches. This configuration enhances the model's ability to effectively discriminate between classes. The total loss function, combining both cross-entropy and triplet losses, optimizes ScoNet-MT for precise scoliosis classification:

$$L_{total} = L_{ce} + L_{triplet}.$$

4 Experiments

4.1 Setup

Evaluation Protocol. We divided the dataset into a training set and a test set with 745 and 748 sequences respectively, maintaining a realistic ratio of positive:neutral:negative samples at 1:1:8 in the training set. Specifically, the sequence numbers for the three classes are 74, 74 and 596. The performance of the models was evaluated using three metrics, accuracy, sensitivity, and specificity. The metrics are defined as follows:

- Accuracy: The proportion of samples that are correctly classified out of the total number of samples.
- Sensitivity: The proportion of true positives (actual scoliosis, correctly classified) out of all positives (actual scoliosis).
- Specificity: The proportion of true negatives (actual normal, correctly classified) out of all negatives (actual normal).

Implementation Details. Our models, ScoNet and ScoNet-MT, are based on PyTorch [13] and OpenGait [3], and their input image sizes are all 64×44. The triplet loss with a margin of 0.2 is employed for training. The positive sequence within each triplet is selected from the same gait sequence as the anchor sequence, yet comprises distinct frames. We adopted 30 frames from each gait sequence as input in the experiments. All the models have been trained by using an SGD optimizer [17] with an initial learning rate of 0.1 and a weight decay of 0.0005. The learning rate can be reduced by a factor of 10 at 10000, 14000, and 18000 iterations respectively. All models were trained for 20000 iterations.

4.2 Results

ScoNet-MT exhibits significant improvements in accuracy and specificity over the initial ScoNet model, as detailed in Table 2. The model's accuracy has been increased by 30.7% and specificity increased by 43.3%. The improvements demonstrate the effectiveness of multi-task learning. While ScoNet-MT's sensitivity outperforms traditional methods such as the *Adams forward bend test* and the *scoliometer*, its specificity, though slightly lower, indicates the potential for

Table 2: Comparison of our method with conventional scoliosis screening techniques. * refers to results directly cited from [8]. Best results are in bold.

Method	Accuracy	Sensitivity	Specificity
Adams Test* [8]	-	84.4%	**95.2%**
Scoliometer* [8]	-	90.6%	79.8%
ScoNet (Ours)	51.3%	**100.0%**	33.2%
ScoNet-MT (Ours)	**82.0%**	99.0%	76.5%

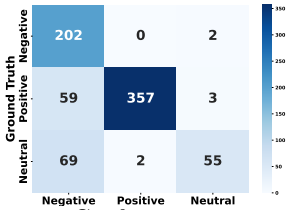

Fig. 4: Confusion matrix of ScoNet-MT.

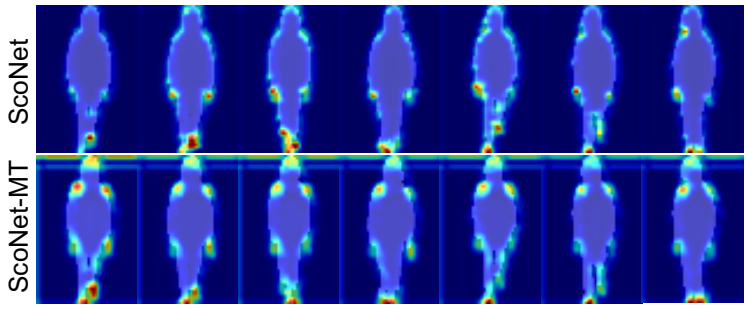

Fig. 5: Visualization results of our method.

Table 3: Performance comparisons of ScoNet-MT against some baseline models and ScoNet. Best results are in bold.

Method	Accuracy	Sensitivity	Specificity
1) Baseline CNN	45.5%	99.0%	27.0%
2) Baseline CNN-Triplet	56.3%	77.0%	85.0%
3) Baseline CNN-MT	57.8%	96.1%	44.4%
4) ScoNet	51.3%	100.0%	33.2%
5) ScoNet-Triplet	61.2%	100.0%	46.6%
ScoNet-MT (Ours)	82.0%	99.0%	76.5%

Table 4: Test set accuracy of ScoNet and ScoNet-MT, influenced by various class distributions (positive, neutral, negative) in the training phase.

Pos:Neu:Neg	ScoNet	ScoNet-MT
1:1:2	91.4%	95.2%
1:1:4	88.6%	90.5%
1:1:8	51.3%	82.0%
1:1:16	23.7%	49.5%

further improvement. These findings underscore the potential of our approach to exceed the capabilities of human experts in adolescent scoliosis screening. The confusion matrix (Figure 4) provides detailed insights into the model's precision, especially in differentiating between negative and other cases, albeit with some overlap between positive and neutral classifications.

The heatmaps in Figure 5 illustrate our model's focus using the technique [23] to highlight the regions of interest within the gait. Although ScoNet focuses predominantly on the extremities, ScoNet-MT, through multi-task learning, extends its analysis to critical areas such as the head and shoulders, aligning with key indicators of motion patterns related to scoliosis identified in the literature [12, 15, 26, 20].

4.3 Ablation Studies

Baseline Comparisons. Since the proposed solution should be the first video-based one using a large-scale image dataset and a deep model, we could not find some other similar methods in the literature to compare. To show the feasibility and effectiveness, we compared ScoNet-MT with various baseline models in the ablation experiments. The baseline models include: 1) *Baseline CNN:* A foundational model trained using cross-entropy loss without horizontal pooling or BNNeck. 2) *Baseline CNN-Triplet:* An enhancement of the Baseline CNN, incorporating triplet loss to refine category differentiation. 3) *Baseline CNN-MT:*

An extension of the Baseline CNN that includes multi-task learning with identity information to promote better generalization. 4) *ScoNet:* Our initial model. 5) *ScoNet-Triplet:* A variation of ScoNet that integrates triplet loss to enhance feature discrimination. Table 3 details the performance comparison, demonstrating that ScoNet-MT significantly surpasses all baseline models, particularly highlighting the efficacy of multi-task learning in improving diagnostic precision.

Class-imbalanced Distribution. Given the inherent imbalance in scoliosis case distribution, we analyzed the performance of ScoNet and ScoNet-MT across various class ratio settings in the training set. The sequence numbers for these settings were 186:186:373 for roughly 1:1:2, 124:124:497 for 1:1:4, and 41:41:663 for 1:1:16, reflecting real-world scenarios where negative cases are predominant. Table 4 outlines our findings, which indicate that ScoNet-MT consistently outperforms ScoNet across all ratios. This robust performance even in highly imbalanced conditions highlights ScoNet-MT's adaptability and its ability to mitigate overfitting, underscoring its superior diagnostic accuracy in realistic settings.

5 Conclusion

Our study has demonstrated the effectiveness of utilizing gait as non-invasive biomarkers for scoliosis. The introduction of the Scoliosis1K dataset, alongside the development of the ScoNet and ScoNet-MT models, represents a substantial advancement in this domain, enabling early and precise scoliosis classification.

The implications of our work are extensive, offering a scalable and privacy-preserving diagnostic tool with the potential to revolutionize adolescent scoliosis screening, particularly in resource-limited regions. Future work will focus on enhancing the diversity of our dataset, identifying additional biomarkers, and exploring effective methods. If a mature large-scale scoliosis screening solution can be built using vision based gait analysis, it will benefit a huge number of children, especially those in developing countries.

Acknowledgments. This work was supported in part by the Shenzhen International Research Cooperation Project (Grant No. GJHZ20220913142611021) and ACCESS (AI Chip Center for Emerging Smart Systems), which is sponsored by InnoHK funding, Hong Kong.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

References

1. Chao, H., Wang, K., He, Y., Zhang, J., Feng, J.: Gaitset: Cross-view gait recognition through utilizing gait as a deep set. IEEE Transactions on Pattern Analysis and Machine Intelligence **44**(7), 3467–3478 (2021)
2. Fan, C., Hou, S., Wang, J., Huang, Y., Yu, S.: Learning gait representation from massive unlabelled walking videos: A benchmark. IEEE Transactions on Pattern Analysis and Machine Intelligence (2023)

3. Fan, C., Liang, J., Shen, C., Hou, S., Huang, Y., Yu, S.: Opengait: Revisiting gait recognition towards better practicality. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 9707–9716 (2023)
4. Fan, C., Peng, Y., Cao, C., Liu, X., Hou, S., Chi, J., Huang, Y., Li, Q., He, Z.: Gaitpart: Temporal part-based model for gait recognition. In: Proceedings of the IEEE/CVF conference on Computer Vision and Pattern Recognition. pp. 14225–14233 (2020)
5. Fu, Y., Wei, Y., Zhou, Y., Shi, H., Huang, G., Wang, X., Yao, Z., Huang, T.: Horizontal pyramid matching for person re-identification. In: Proceedings of the AAAI conference on artificial intelligence. vol. 33, pp. 8295–8302 (2019)
6. Hengwei, F., Zifang, H., Qifei, W., Weiqing, T., Nali, D., Ping, Y., Junlin, Y.: Prevalence of idiopathic scoliosis in chinese schoolchildren: a large, population-based study. Spine **41**(3), 259–264 (2016)
7. Iwama, H., Okumura, M., Makihara, Y., Yagi, Y.: The ou-isir gait database comprising the large population dataset and performance evaluation of gait recognition. IEEE Transactions on Information Forensics and Security **7**(5), 1511–1521 (2012)
8. Karachalios, T., Sofianos, J., Roidis, N., Sapkas, G., Korres, D., Nikolopoulos, K.: Ten-year follow-up evaluation of a school screening program for scoliosis: Is the forward-bending test an accurate diagnostic criterion for the screening of scoliosis? Spine **24**(22), 2318 (1999)
9. Liang, J., Fan, C., Hou, S., Shen, C., Huang, Y., Yu, S.: Gaitedge: Beyond plain end-to-end gait recognition for better practicality. In: European Conference on Computer Vision. pp. 375–390. Springer (2022)
10. Liu, Y., Chu, L., Chen, G., Wu, Z., Chen, Z., Lai, B., Hao, Y.: Paddleseg: A high-efficient development toolkit for image segmentation. arXiv preprint arXiv:2101.06175 (2021)
11. Luo, H., Gu, Y., Liao, X., Lai, S., Jiang, W.: Bag of tricks and a strong baseline for deep person re-identification. In: Proceedings of the IEEE/CVF conference on Computer Vision and Pattern Recognition workshops. pp. 0–0 (2019)
12. Mahaudens, P., Detrembleur, C., Mousny, M., Banse, X.: Gait in adolescent idiopathic scoliosis: energy cost analysis. European Spine Journal **18**, 1160–1168 (2009)
13. Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., et al.: Pytorch: An imperative style, high-performance deep learning library. Advances in neural information processing systems **32** (2019)
14. Payne III, W.K., Ogilvie, J.W., Resnick, M.D., Kane, R.L., Transfeldt, E.E., Blum, R.W.: Does scoliosis have a psychological impact and does gender make a difference? Spine **22**(12), 1380–1384 (1997)
15. Kramers-de Quervain, I.A., Müller, R., Stacoff, A., Grob, D., Stüssi, E.: Gait analysis in patients with idiopathic scoliosis. European Spine Journal **13**, 449–456 (2004)
16. Reamy, B.V., Slakey, J.B.: Adolescent idiopathic scoliosis: review and current concepts. American family physician **64**(1), 111–117 (2001)
17. Ruder, S.: An overview of gradient descent optimization algorithms. arXiv preprint arXiv:1609.04747 (2016)
18. Thuaimer, A., Knipe, H., M, E.: Cobb angle: Radiology reference article (2024), `https://radiopaedia.org/articles/cobb-angle?lang=us`, accessed: 27 June 2024
19. Weinstein, S.L., Dolan, L.A., Cheng, J.C., Danielsson, A., Morcuende, J.A.: Adolescent idiopathic scoliosis. The lancet **371**(9623), 1527–1537 (2008)

20. Wen, J.X., Yang, H.H., Han, S.M., Cao, L., Wu, H.Z., Yang, C., Li, H., Chen, L.L., Li, N.N., Yu, B.H., et al.: Trunk balance, head posture and plantar pressure in adolescent idiopathic scoliosis. Frontiers in Pediatrics **10**, 979816 (2022)
21. Yang, J., Zhang, K., Fan, H., Huang, Z., Xiang, Y., Yang, J., He, L., Zhang, L., Yang, Y., Li, R., et al.: Development and validation of deep learning algorithms for scoliosis screening using back images. Communications biology **2**(1), 390 (2019)
22. Yuan, Y., Chen, X., Wang, J.: Object-contextual representations for semantic segmentation. In: European Conference on Computer Vision. pp. 173–190. Springer (2020)
23. Zagoruyko, S., Komodakis, N.: Paying more attention to attention: Improving the performance of convolutional neural networks via attention transfer. arXiv preprint arXiv:1612.03928 (2016)
24. Zhang, T., Zhu, C., Zhao, Y., Zhao, M., Wang, Z., Song, R., Meng, N., Sial, A., Diwan, A., Liu, J., et al.: Deep learning model to classify and monitor idiopathic scoliosis in adolescents using a single smartphone photograph. JAMA Network Open **6**(8), e2330617–e2330617 (2023)
25. Zhang, Y., Sun, P., Jiang, Y., Yu, D., Weng, F., Yuan, Z., Luo, P., Liu, W., Wang, X.: Bytetrack: Multi-object tracking by associating every detection box. In: European Conference on Computer Vision. pp. 1–21. Springer (2022)
26. Zhu, F., Hong, Q., Guo, X., Wang, D., Chen, J., Zhu, Q., Zhang, C., Chen, W., Zhang, M.: A comparison of foot posture and walking performance in patients with mild, moderate, and severe adolescent idiopathic scoliosis. PLoS One **16**(5), e0251592 (2021)