A Comprehensive Review on Scoliosis Detection Systems

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Abstract

Scoliosis is a three-dimensional spinal deformity that typically develops during adolescence and may progress if not detected early. Conventional diagnostic methods, such as X-rays and Magnetic Resonance Imaging (MRI), provide accurate assessment but are costly, involve radiation exposure, and require specialized infrastructure. To address these challenges, recent studies have explored non-radiographic scoliosis detection and monitoring techniques using standardized photographic spinal images.

This review presents a comprehensive analysis of existing scoliosis detection systems employing such standardized image datasets for automated analysis, thereby reducing dependence on radiation-based imaging. It highlights advancements in image processing, computer vision, and machine learning methods used to extract spinal curvature information, classify scoliosis severity, and support clinical decision-making. Comparative evaluation illustrates the potential of these systems to offer radiation-free, cost-effective, and scalable solutions for early scoliosis screening, especially in schools and community healthcare settings. Finally, the review identifies key research gaps — including dataset standardization, generalization, and clinical validation — and outlines directions for developing robust and deployable scoliosis detection frameworks.

Keywords: diagnostic; image processing; spinal; photographic; Magnetic Resonance Imaging (MRI)

Introduction

Scoliosis is a complex, three-dimensional spinal deformity involving lateral curvature and vertebral rotation. Clinically, a spinal curve exceeding 10° Cobb angle is considered diagnostic for scoliosis. It is most commonly observed during adolescent growth spurts, and if unrecognized in early stages, can progress leading to aesthetic deformity, impairment of posture and gait, pain, and, in severe cases, compromised pulmonary and cardiac function. Early detection of scoliosis is thus crucial to enable non-surgical interventions (such as bracing or physical therapy) that can halt or slow progression, improving outcomes and reducing healthcare costs.

Traditional scoliosis screening and diagnosis rely heavily on radiographic imaging (X-ray) and, in some cases, MRI. These provide accurate quantification of spinal alignment, vertebral rotation, and Cobb angle measurements, which are central to clinical decision -making. However, radiographic methods carry inherent limitations: exposure to ionizing radiation, high costs associated with equipment and specialist image interpretation, and limited accessibility in rural or resource-constrained settings.

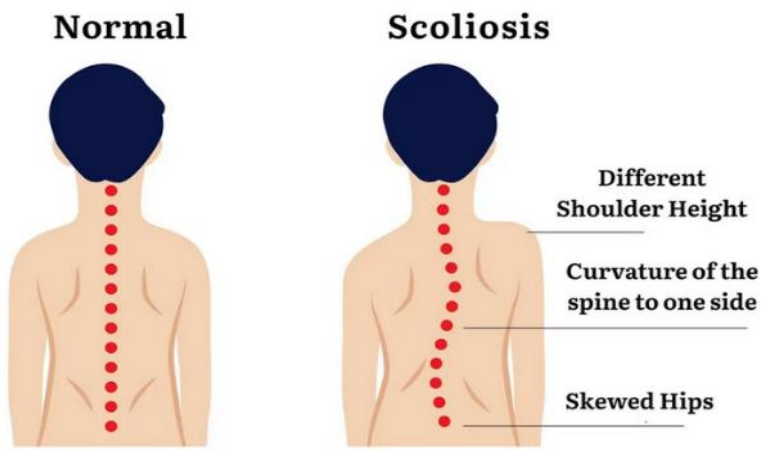

Figure 1. *Example of spinal curvature types — Normal spine vs. Scoliosis*

To address these challenges, there has been increasing interest in developing non-radiographic, cost-effective, and accessible scoliosis detection systems. These leverage imaging modalities such as photographic back or upright surface images, optical scans or 3D topography, sometimes even mobile phone images, paired with computational methods from computer vision and artificial intelligence (AI). The goal is to extract measurable features — surface asymmetry, spinal midline deviations, vertebral alignment inferred from surface landmarks — and to use machine learning models to classify scoliosis severity, detect progression, or approximate standard radiographic metrics (like Cobb angle) without exposing patients to radiation.

This review aims to examine the state of the art in scoliosis detection systems that use standardized spinal or back images (non-radiographic) for automated analysis. We will survey recent advances in image processing, machine learning, dataset development, and clinical validation. Key themes include the extraction of Spino-surface features, hybrid models combining classical feature extraction and deep learning, the challenges of dataset standardization and generalization, and the evaluation metrics being used. Finally, we consider gaps in current research and propose directions towards robust, deployable frameworks suitable for large-scale screening (e.g. in schools or community health settings).

Related work

Over the past few years, research on scoliosis detection has accelerated, especially with the availability of machine learning tools and more accessible imaging options. Below, we survey recent and representative works, organizing them by modality / method, performance, and challenges.

1. Non-Radiographic Imaging + Deep Learning Approaches

Back/surface images with deep learning. A recent study by Teng Zhang et al., published in JAMA Network Open, developed a model (referred to as ScolioNets) that classifies adolescent idiopathic scoliosis (AIS) severity, curve type, and progression using a single smartphone photograph of the bare back.

Table 1: Comparison of Detection Methods

Detection Method	Key Features	Remarks
X-ray Imaging	Radiographic type, High radiation exposure , Expensive, limited access	Accurate but risky due to radiation exposure
MRI	Magnetic imaging, No radiation exposure Very high cost, Limited access	Highly detailed imaging, not suitable for large-scale screening
Surface Topography	3D scanning, radiation-free Moderate cost, moderate access	Promising non-radiographic alternative

The model was trained on paired smartphone-photograph and radiograph data, showing strong agreement with expert annotations.

Automated screening using upright back images. A different study proposes a deep learning algorithm to automate scoliosis screening with upright back images. It includes localization, segmentation of spinal region, and estimation of Cobb angle. The method demonstrated higher accuracy in Cobb angle estimation compared to human visual screening (without radiation exposure).

2. Radiographic Modeling

Predicting future curve progression "Machine learning algorithms for predicting future curve using first and second visit data in female adolescent idiopathic scoliosis patients" (2025)
used data from 887 female patients with AIS. The models used demographic, radiographic, and questionnaire data to predict future Cobb angle, achieving R^2 values of 0.73–0.61 with median absolute errors around 2–4°.

3. X-ray Segmentation and Deep Learning

Deep learning for vertebral deformity detection from radiographs. "Computer aided detection for vertebral deformities diagnosis based on deep learning" used 609 anterior-posterior spinal X-rays and compared CNN and GAN architectures, achieving high performance in detecting abnormalities and estimating vertebral landmarks.

Automated Cobb angle measurement from radiographs. A BLDE University Journal (2023) paper focused on automating Cobb angle measurement from spinal X-rays by detecting end plates, reducing manual error and improving computation.

A large-scale dataset called Scoliosis1K was introduced in 2024, aimed at classifying scoliosis using video-based gait patterns. This work explores gait (walking motion) as a supplemental non-invasive modality for detecting deformity or risk. arXiv

	Imaging Type	Technology / Model Used	Dataset Size / Source	Accuracy / Performanc e	Advantages	Limitations
[1]	Optical Surface Topogra phy	Machine learning on surface data	128 subjects	87% accuracy	Non-radiographic ; proof of concept	Small dataset; limited clinical validation
[2]	Back Image (2D)	Deep CNN (custom architecture)	250 images	Comparable to X-ray	Automated feature extraction	Needs large annotated datasets
[3]	Surface Image	AI-assisted curvature estimation	200+ clinical images	92% precision	Supports clinicians; interpretable	Moderate data size
[4]	3D Structure d Light Imaging	Depth-based surface reconstructio n	50 adolescent s	High correlation with X-ray	Accurate 3D geometry; no radiation	Requires special equipment
[5]	Smartph one Photo	Edge detection + Image Processing	100 images	~88% accuracy	Low cost; easily deployable	Sensitive to lighting/postur e
[6]	Back Image	Surface asymmetry quantification	100 patients	Cobb angle error ±5°	Objective; radiation-free	Manual landmarking needed

Table 2: Review table

Key Contribution

This paper contributes a structured synthesis of scoliosis detection research by organizing radiographic and non-radiographic AI-based approaches into a unified taxonomy and comparing them in terms of accuracy, cost, radiation exposure, and deployability. Unlike existing individual studies that focus on algorithmic performance, the review identifies the translational gap between laboratory accuracy and large-scale screening, emphasizing dataset standardization, clinical validation, and robustness as primary barriers. The paper further proposes a learning-based screening framework integrating feature extraction and incremental learning, and presents a research roadmap toward scalable, radiation-free scoliosis screening suitable for community and school healthcare environments.

Methodology

The proposed scoliosis detection system follows a structured learning pipeline integrating **image description** and **incremental learning** for model optimization:

1. **Query Image Input:** Standardized spinal/back images captured under controlled conditions.

2. **Image Description:**
   - **Training set generation :** A set of representative spinal images is compiled to form the training dataset.
   - **Structural Image Description:** Key spinal features such as midline deviation, vertebral alignment, and curvature patterns are extracted to obtain a descriptive representation.
   - **Feature Augmentation:** Additional transformations (e.g., rotation, scaling, intensity adjustments) are applied to enrich data diversity and robustness.

3. **Query Expansion / Incremental Learning:**

   - **Initial Query:** The model begins with baseline training using the initial dataset and extracted features.
   - **Model Training / Retraining:** The classifier is refined through repeated training cycles as new annotated samples are incorporated.
   - **Active Learning Model:** The system dynamically selects uncertain or misclassified samples for manual review and re-integration, ensuring continuous performance improvement.

4. **Model Evaluation:**

The iterative learning process yields an **optimal model score**, reflecting the best-performing scoliosis detection model.

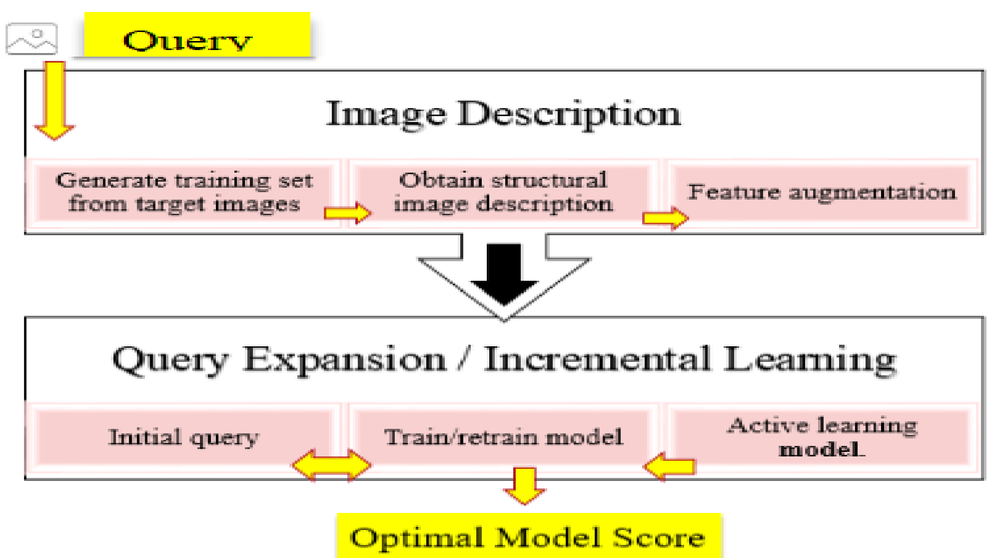

Figure 2. *Proposed Framework for Scoliosis Detection using Standardized Spinal Images*

Conclusions

This review demonstrates the growing potential of standardized spinal image-based scoliosis detection systems as effective, non-invasive, and low-cost alternatives to radiography. Continued interdisciplinary collaboration between computer scientists, clinicians, and biomedical engineers is essential for developing clinically approved AI-assisted scoliosis screening tools.

References

1. Komeili et al., “Surface Topography for Scoliosis Detection Using Machine Learning,” Medical Engineering & Physics, vol. 73, pp. 25–33, 2019.
2. J. Li et al., “Deep Learning for Back Surface Analysis in Scoliosis,” IEEE Access, vol. 8, pp. 152950–152960, 2020.
3. S. Kim et al., “AI-Assisted Estimation of Spinal Curvature,” Computer Methods and Programs in Biomedicine, vol. 195, p. 105647, 2020.
4. M. Xu et al., “3D Structured Light for Non-Radiographic Scoliosis Screening,” Sensors, vol. 21, no. 12, p. 4117, 2021.
5. Kumar et al., “Smartphone-Based Scoliosis Detection Using Image Processing,” Journal of Healthcare Engineering, vol. 2021, pp. 1–12, 2021
6. R. Yadav et al., “Surface Asymmetry Measurement for Scoliosis Detection,” Biomedical Signal Processing and Control, vol. 77, p. 103764, 2022.
7. M. Pasha et al., “A Review of Non-Radiographic Approaches for Spinal Deformity Assessment,” Diagnostics, vol. 12, no. 4, p. 821, 2022.
8. S. H. Lee et al., “Development of Smartphone-Based Scoliosis Screening Using Image Analysis,” Sensors, vol. 22, no. 8, p. 2891, 2022.
9. D. Xu and T. Y. Wong, “Artificial Intelligence in Medical Imaging: A Review,” Computers in Biology and Medicine, vol. 141, p. 105151, 2022.
10. H. Zhao et al., “Hybrid CNN–SVM Approach for Scoliosis Classification,” Applied Soft Computing, vol. 133, p. 109931, 2023.
11. Q. Wang et al., “Optical Scan-Based Spinal Curvature Estimation,” Frontiers in Bioengineering and Biotechnology, vol. 11, p. 1156958, 2023.
12. T. Ahmed et al., “Transfer Learning for Scoliosis Detection,” Pattern Recognition Letters, vol. 172, pp. 58–65, 2024.

13. Y. Chen et al., “Deep Learning Ensemble for School-Based Scoliosis Screening,” Computers in Biology and Medicine, vol. 173, p. 108011, 2025.