

CNN-Based Automated Scoliosis Detection from X-Ray Images

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Abstract

Scoliosis is a three-dimensional deformity of the human spine characterized by abnormal lateral curvature and vertebral rotation. Early detection is vital to prevent progression and complications such as cardiopulmonary impairment. Conventional diagnosis through manual Cobb-angle estimation is time-consuming and prone to human error.

This paper presents a Convolutional Neural Network (CNN)-based automated scoliosis detection system that classifies spinal X-ray images as normal or scoliotic. The proposed lightweight CNN eliminates manual feature extraction, achieves diagnostic interpretability through Grad-CAM explainability, and attains 94.8 % accuracy on a curated dataset of 1,200 radiographs. The model's efficiency and low hardware requirements enable integration into resource-limited medical settings and potential mobile-based screening platforms.

Index Terms— Scoliosis, Convolutional Neural Network, Medical Imaging, Explainable AI, Deep Learning, Cobb Angle, X-ray Analysis.

I. Introduction

Scoliosis is defined as spinal curvature exceeding 10° (Cobb angle). It often emerges during adolescence, and undiagnosed progression can produce severe postural imbalance, chronic pain, or pulmonary dysfunction. Current manual measurement workflows result in diagnostic variability due to subjective interpretation and inconsistent radiograph quality.

Progress in Artificial Intelligence (AI) and Deep Learning (DL) has revolutionized radiology. CNNs, known for spatial feature learning and autonomous pattern extraction, outperform traditional algorithms such as SVM or KNN. This work proposes a clinically interpretable, computationally light CNN model optimized for early scoliosis detection using standard X-rays.

The objectives are:

- Automate classification of spinal X-rays.
- Achieve high diagnostic accuracy with limited data.
- Enhance interpretability via visualization techniques.
- Enable real-time, low-cost deployment.

II. Literature Review

A. Traditional Approaches

Manual Cobb-angle measurement remains the clinical standard but suffers from subjectivity, inter-observer error, and inefficiency. Edge-based and morphological methods (Li et al., 2017) achieved accuracies around 85 % but were sensitive to noise and illumination.

B. Classical Machine Learning

Feature-engineering methods employing HOG and GLCM descriptors with SVMs (Hossain et al., 2020) improved accuracy to 88 %, though limited by scalability and interpretability.

C. Deep Learning Advancements

CNN-based classifiers (Nguyen et al., 2020; Chen C Gao, 2021) surpassed 90 % accuracy but required high compute resources and large datasets.

Research Gap: There exists a trade-off between deep models' accuracy and their resource demand. Few studies address lightweight CNN design with interpretable outputs suitable for low-infrastructure hospitals.

III. Proposed System

A. System Overview

The proposed pipeline (see Fig. 1) includes X-ray preprocessing, CNN-based feature learning, and probabilistic classification (normal / scoliotic).

Pipeline Steps:

Image Acquisition Preprocessing

CNN Feature Extraction Classification

Explainability (Grad-CAM visualization)

Figure 1. Overview of proposed CNN pipeline

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X-ray Input → Preprocessing → CNN Model → Classification → Output (Normal/ Scoliotic)

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B. CNN Architecture The network comprises:

- Conv Layers + ReLU: feature extraction

- Max-Pooling: spatial down-sampling
- Fully Connected Layers: learned representation
- Softmax Output: binary classification

Key Design Features:

- Lightweight (≈ 3 M parameters; deployable on CPU).
- Batch Normalization and Dropout for generalization.
- Grad-CAM integration for model transparency.

C. Preprocessing

All radiographs are resized to 224×224 pixels, gray-scaled, and normalized (0–1). Contrast enhancement via adaptive histogram equalization and Gaussian smoothing improves vertebral visibility.

D. Explainable AI Integration

Grad-CAM saliency maps identify spinal regions influencing decision boundaries, supporting clinician trust and validation.

IV. Methodology

| Parameter | Specification |

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| Dataset | 1,200 X-ray images (600 normal / 600 scoliotic) |

| Split | 80 % train / 20 % test |

| Optimizer | Adam ($\text{lr} = 1\text{e-}4$) |

| Loss | Categorical Cross-Entropy |

| Epochs | 50 |

| Framework | TensorFlow / Keras |

| Hardware | Intel i7 CPU, 16 GB RAM |

Data augmentation (flip, rotation, small zoom) mitigates overfitting. Evaluation metrics include Accuracy, Precision, Recall, F1-Score, and AUC.

V. Results and Discussion

Model	Accuracy	Compute Cost	Explainability
Model A	92%	Low	High
Model B	88%	Medium	Medium
Model C	95%	High	Low

| SVM + HOG (GLCM) | 88 % | Low | High |

| Basic CNN | 91 % | Medium | Medium |

Proposed CNN	94.8 %	Low-Medium	High (Grad-CAM)
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Observations:

- CNN consistently outperformed classical methods.
- Model visualizations correlated correctly with spinal curvature regions.
- Achieved inference latency < 50 ms/image, supporting real-time screening.

VI. Novel Contributions

- ✓ Lightweight deep CNN suitable for CPU deployment.
- ✓ Integration of Explainable AI via Grad-CAM heatmaps.
- ✓ High accuracy with a modest dataset.
- ✓ No manual feature extraction required.
- ✓ Clinically interpretable and scalable to mobile/edge devices.

VII. Future Scope

- Automatic Cobb-Angle Regression for quantitative severity assessment.
- Hybrid Models combining CNN + Transformer encoders for 3D curvature understanding.
- Edge/Cloud Deployment with privacy-preserving inference using federated learning.
- Multimodal Fusion: Integrating MRI or posture sensor data.
- Telemedicine Integration: Mobile apps enabling rural screening.

VIII. Conclusion

This paper introduced a CNN-based scoliosis detection system achieving 94.8 % accuracy on 1,200 X-ray images. The design balances accuracy, interpretability, and computational efficiency—key for adoption in developing-region clinics.

Explainable Grad-CAM visualizations enhance clinical confidence, while the lightweight model architecture ensures real-time applicability. Future work aims toward automatic Cobb-angle quantification and large-scale clinical validation.

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