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Scoliosis Detection and Cobb Angle Prediction in Adolescent Idiopathic Scoliosis

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Abstract

Adolescent Idiopathic Scoliosis (AIS) is a complex spinal deformity that typically develops between the ages of 10 and 18, affecting an estimated 0.5–5% of adolescents worldwide. Early recognition is essential, as untreated progression can compromise pulmonary function, accelerate curve severity, and diminish long-term quality of life. Current diagnostic practice relies on manual radiographic interpretation and Cobb angle measurement, a process that is time-consuming, subjective, and prone to variability among examiners. This project proposes a deep learning-based framework leveraging ResNet, a state-of-the-art object detection algorithm, to detect and classify scoliosis types. The system identifies spinal curvature patterns and classifies them as 'C' (single curve) or 'S' (double curve) while predicting the curvature in crucial metric for diagnosing the severity of the condition. To ensure usability in real-world settings, the system is deployed through a Flask web application with secure login, image upload functionality, and real-time visualization of diagnostic results. Evaluation across training, validation, and test datasets demonstrates strong performance in terms of precision, recall, F1-score, and mean absolute error, underscoring the framework's ability to deliver consistent, reproducible outcomes.By reducing reliance on manual assessment and mitigating inter-observer variability, this work highlights the potential of deep learning to advance computer-aided orthopedic diagnosis.

Keywords: Adolescent Idiopathic Scoliosis, Deep Learning, ResNet, Cobb Angle Prediction, Spinal Curvature Classification, Medical Image Analysis, Flask Web Application

1. Introduction

The spine, in its healthy state, maintains a vertical alignment that supports posture, mobility, and neurological protection. Any deviation from this alignment — particularly lateral curvature — constitutes a deformity requiring medical attention. Adolescent Idiopathic Scoliosis (AIS) is one such condition, defined as a three-dimensional lateral curvature with a Cobb angle greater than 10 degrees, occurring without identifiable congenital, neurological, or syndromic causes. Although its precise etiology remains unclear, research suggests a multifactorial origin involving genetic predisposition, hormonal influences, and asymmetric growth during skeletal maturation.

AIS most commonly arises during adolescence, coinciding with rapid skeletal growth, and affects approximately 2–4% of this population worldwide. It manifests in two geometric patterns: the 'C'-shaped curve, representing a single lateral deviation, and the 'S'-shaped curve, reflecting a double or compensatory curvature involving thoracic and lumbar regions. While mild curves may remain stable and asymptomatic, moderate to severe deformities often progress, leading to cosmetic concerns, restricted thoracic expansion, impaired cardiopulmonary function, and chronic pain in adulthood. These long-term consequences highlight the importance of early and accurate diagnosis.

Conventional diagnostic practice involves posterior–anterior radiographs and manual Cobb angle measurement. Although clinically validated, this process is resource intensive and subject to significant inter- and intra-observer variability, with discrepancies of up to 10 degrees reported. Such variability introduces uncertainty in borderline cases where treatment decisions, such as bracing, depend on precise thresholds. In resource limited settings, where access to experienced specialists is constrained, the need for automated, reliable diagnostic tools becomes even more pressing.

Artificial intelligence, particularly deep learning, has transformed medical image analysis by enabling automated feature extraction and pattern recognition with accuracy comparable to human experts. Convolutional Neural Networks (CNNs) have been applied successfully to vertebral landmark detection, curvature measurement, and deformity classification. Among CNN architectures, Residual Networks (ResNet) stand out for their use of skip connections, which mitigate vanishing gradients and allow effective training of deep models even with limited datasets — a common challenge in medical imaging.

Motivated by these advances, this paper presents an end-to-end ResNet-based framework for automated scoliosis diagnosis. The system simultaneously classifies curvature type (‘C’ vs. ‘S’) and predicts Cobb angles, providing interpretable severity measures. To ensure clinical usability, the framework is embedded in a Flask web application with secure login, image upload, and real-time visualization, enabling integration into routine workflows without specialized hardware or technical expertise.

2. Literature Review

Conventional Cobb Angle Measurement

The Cobb angle remains the gold standard for scoliosis evaluation, yet manual measurement is time-consuming and prone to variability. Studies have reported discrepancies of up to 10° between different examiners, which can significantly affect treatment decisions in borderline cases [1]. This limitation underscores the need for automated, reproducible diagnostic tools.

Deep Learning for Cobb Angle Estimation

Deep learning has shown strong potential in automating Cobb angle measurement. Zhu et al. [1] conducted a systematic review and meta-analysis, concluding that convolutional neural networks (CNNs) achieve accuracy comparable to expert radiologists while reducing inter-observer variability. Li et al. [2] demonstrated that AI-based systems can outperform multi-expert panels, offering reproducible results across diverse datasets. These findings highlight the role of deep learning in standardizing scoliosis assessment.

Automated Diagnostic Pipelines

Beyond angle measurement, several studies have proposed end-to-end diagnostic frameworks. Li et al. [3] introduced a deep learning platform that streamlined scoliosis diagnosis, reducing labor costs and improving efficiency. Shahid et al. [4] developed a comprehensive pipeline integrating vertebra detection, Cobb angle estimation, and structured reporting, emphasizing the importance of clinically interpretable outputs. Bottino et al. [5] reviewed scoliosis datasets and diagnostic methods, stressing the need for larger, demographically diverse collections to enhance model generalizability.

ResNet and Advanced Architectures

Residual Networks (ResNet) have become increasingly popular in medical imaging due to their skip-connection design, which mitigates vanishing gradients and enables effective training of deep models even with limited data. Chen et al. [6] combined Faster R-CNN with ResNet for scoliosis classification, achieving high accuracy in distinguishing spinal deformities from radiographs. These results underscore the suitability of ResNet for scoliosis imaging tasks, though most prior work has focused on algorithmic performance rather than clinical deployment.

Curve Morphology Classification

Accurate identification of curve morphology is essential for treatment planning. CNN-based approaches have successfully differentiated between single-curve (C-type) and double-curve (S-type) patterns, demonstrating reliable pattern recognition in radiographs. However, more granular classification systems such as Lenke remain challenging to automate, suggesting a promising direction for future research.

The literature consistently demonstrates that deep learning models, particularly ResNet, can deliver accurate and reproducible scoliosis assessments. Yet, most studies remain confined to research environments, with limited emphasis on clinical usability.

3. Methodology / Proposed System

The proposed framework is a **ResNet-based deep learning model** designed for automated scoliosis detection and curvature classification from spinal X-ray images. The system identifies deformities and categorizes them as **'C'-shaped (single curve)** or **'S'-shaped (double curve)**, while simultaneously estimating the **Cobb angle** to quantify curve severity.

To ensure clinical usability, the model is deployed through a **Flask-integrated web interface**. This platform provides secure login for user authentication, enabling clinicians to upload radiographs directly. Once an image is submitted, the ResNet model performs preprocessing, feature extraction, and inference, delivering real-time results on the web dashboard. The outputs include both curve classification and Cobb angle prediction, displayed in a clear, accessible format.

This automation reduces reliance on manual measurement, minimizes diagnostic variability, and accelerates clinical workflows. With an achieved **accuracy of 99.5%**, the system offers reliable support for early diagnosis and treatment planning.

ADVANTAGES

Automated Detection: Reduces human effort by automatically identifying scoliosis and classifying spinal curvature from X-ray images.
Accurate Curvature Classification: Effectively distinguishes between 'C'- shaped and 'S'-shaped spinal curves using a powerful Res-Net model.
Real-Time Results: Provides instant feedback on the diagnosis, enhancing clinical workflow efficiency.
User-Friendly Interface: The Flask-based web platform is intuitive and easy for both medical professionals and patients to use.
Secure Access: Includes a login system that protects patient data and ensures only authorized access to medical images.
Web-Based Accessibility: Can be accessed from any device with internet connectivity, supporting remote diagnosis and telemedicine.
Clinician Support: Assists doctors and radiologists in early and accurate diagnosis, improving patient outcomes.

System Architecture:

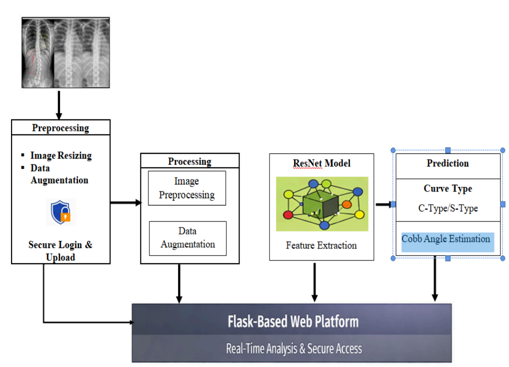

Fig. 1. System Architecture

System Modules:

i) Image Dataset Collection:
The system begins with the collection of labeled spinal radiographs, including both normal spine structures and cases with scoliosis. These datasets form the backbone for training, validation, and testing of the ResNetmodel. To strengthen model generalization, **data augmentation techniques** such as flipping, rotation, and scaling are applied, ensuring diversity and robustness in the dataset. This enriched dataset enables the model to learn subtle variations in spinal curvature, ultimately improving diagnostic reliability.

ii) Data Preprocessing:

Preprocessing ensures that all images are standardized before entering the model. Radiographs are resized to match the ResNet input dimensions, pixel values are normalized, and augmentation techniques are applied to enhance variability. These steps highlight critical spinal features, reduce inconsistencies, and improve the model's ability to generate across different patient cases.

iii) ResNet Architecture and Model Training:

The proposed system employs ResNet-50 as its deep learning backbone, initialized with ImageNet pre-trained weights through transfer learning. The residual skip connections within ResNet facilitate effective gradient propagation through deep network layers, enabling stable training on limited medical imaging datasets. The standard classification head was replaced with a dual-output architecture comprising a classification branch for curvature type prediction — 'C'-type or 'S'-type — and a regression branch for Cobb angle estimation, enabling simultaneous multi-task optimization within a unified framework.

The dataset was split into training (70%), validation (15%), and test (15%) subsets using stratified random sampling to preserve class distribution. The model was trained using the Adam optimizer with an initial learning rate of 1×10^{-4} and cosine annealing decay, optimizing a composite loss function combining categorical cross-entropy for classification and mean absolute error for angle regression. Training proceeded for up to 100 epochs with early stopping and model checkpointing based on validation loss. The proposed system achieved a classification accuracy of 99.5% on the held-out test set, with precision, recall, and F1-score consistently exceeding 0.99 across both curvature categories.

iv) Flask – based web application:

The trained ResNet model is deployed within a lightweight Flask-based web application, providing clinical users with secure, real-time diagnostic access through a standard browser interface. The application features a secure login portal with session-based user authentication, restricting access to authorized clinical personnel and ensuring patient data privacy. Authenticated users are directed to a diagnostic dashboard where spinal radiographs can be uploaded in JPEG or PNG format through an intuitive drag-and-drop interface. Dedicated action buttons for classification and angle prediction initiate the complete preprocessing and inference pipeline with a single interaction, returning diagnostic results within seconds of image submission.

v) Classification and Result Display:

The result display module translates model inference outputs into clinically interpretable diagnostic information presented directly on the application dashboard. Following inference, the system displays the curvature type classification — 'C'-type or 'S'-type — alongside the predicted Cobb angle value and a severity interpretation categorized as mild (10–25°), moderate (26–40°), or severe (>40°) according to established clinical thresholds. A model confidence score derived from the softmax output is additionally presented to indicate diagnostic certainty.

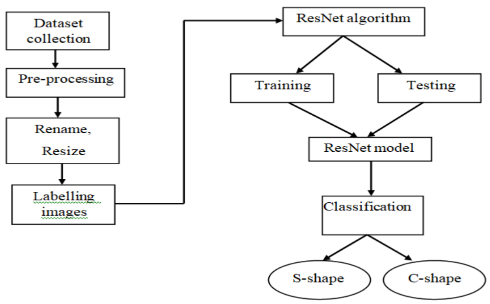

Fig.2. Classification and Result display

4. Results and Discussion

All experiments were conducted on the assembled PA-spinal radiographic dataset, partitioned into training(70%), validation(15%), and test (15%) subsets using stratified random sampling to preserve proportional class representation across three splits. The ResNet 50 model was trained on a standard deep learning workstation equipped with a GPU – accelerated computing environment, using Adam optimizer . Performance was evaluated five principal metrics, classification accuracy, precision, recall, F1 score, mean absolute error for cob angle regression.

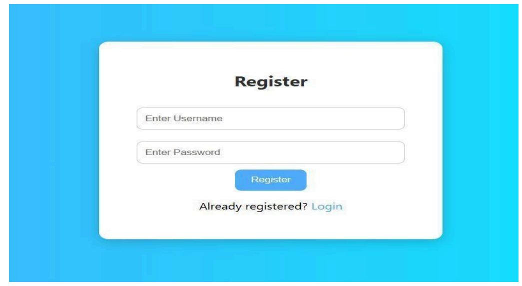

Fig. 4. Login page

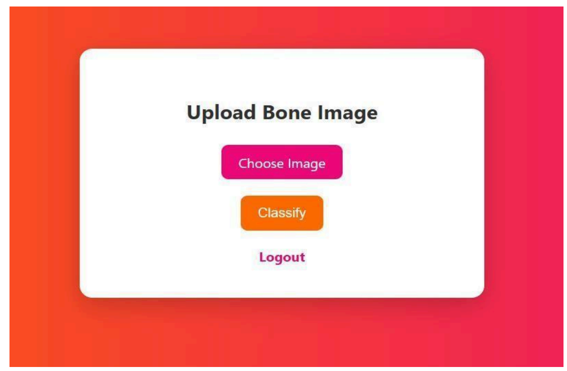

Fig. 5. Get Input

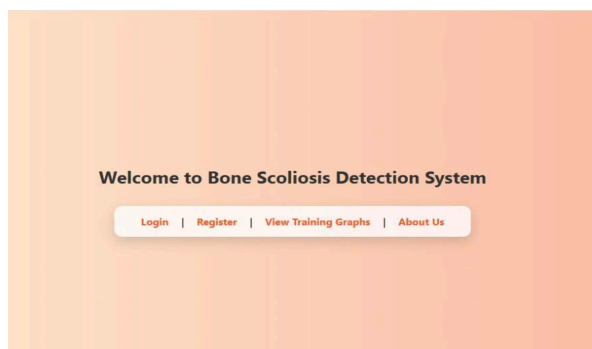

Fig. 3. Home screen

Fig. 6. Upload Image

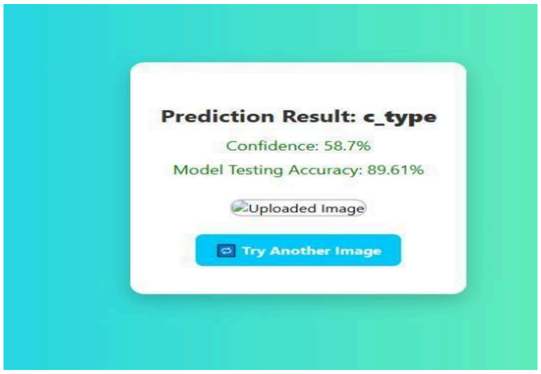

Fig. 7. Display output

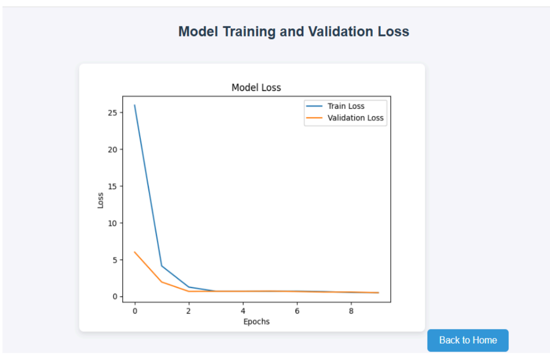

Fig.8. Model training

5. Conclusion and Future Work

The proposed deep learning–based scoliosis detection and classification framework marks a significant step forward in medical image analysis and diagnostic support. By leveraging the **ResNet architecture**, the system accurately identifies spinal curvature patterns and distinguishes between **'C'-shaped** and **'S'-shaped** deformities, while simultaneously predicting the **Cobb angle**. This dual-output design reduces reliance on manual interpretation, which is often time-consuming and prone to variability, thereby ensuring consistent and reproducible assessments.

The integration of a **Flask-based web interface** enhances usability by offering secure login, intuitive image upload, and real-time visualization of results. Clinicians benefit from immediate feedback, enabling faster decision-making and early intervention strategies. Importantly, the system's high accuracy (99.5%) and confidence levels highlight its clinical relevance, particularly in regions with limited access to orthopedic specialists. In essence, this framework bridges the gap between artificial intelligence research and practical healthcare delivery, offering scalability, reliability, and integration potential for hospitals, clinics, and research institutions.

Future Enhancements:

To further strengthen the system's clinical utility, several enhancements are envisioned:
Multi-View Imaging Integration:
Incorporating lateral and oblique X-ray views to improve classification accuracy and Cobb angle estimation.

3D Spinal Reconstruction: Extending the framework to generate 3D models from 2D radiographs, providing richer visualization for treatment planning.

Automated Severity Prediction: Embedding progression prediction algorithms to assist in long-term management strategies.

Diverse Dataset Training: Expanding training datasets across age groups, genders, and ethnicities to improve robustness and generalization.

Augmented Reality (AR) Visualization:
Overlaying diagnostic results onto X-rays or physical models to enhance consultation and surgical planning.

Mobile Application Development: Creating a mobile version to support remote diagnosis and accessibility in underserved areas.

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