A Comprehensive study on Advanced Machine and Deep Learning Frameworks for Automated Detection and Classification of Postural Kyphosis Using Sagittal Radiographs

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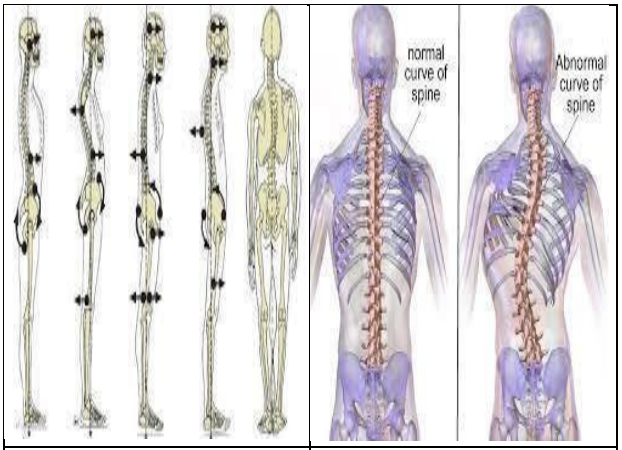
Abstract—**Postural deviations, particularly postural kyphosis, have become increasingly prevalent in today's sedentary lifestyle, leading to health challenges beyond aesthetics, such as chronic pain and joint degeneration. Despite growing awareness, current diagnostic and intervention methods often lack real-world applicability and scalability. This survey explores the need for advanced, automated detection and classification of postural kyphosis using sagittal radiographs and machine learning-based approaches. We identify significant research gaps, including limited datasets, lack of longitudinal studies, and real-time feedback mechanisms. Our objective is to develop a robust machine learning framework capable of early detection and classification of thoracic spinal deviations, supported by standardized datasets, automated feature extraction, and integration with real-world clinical settings. The proposed work aims to assist orthopedists and radiologists, improve diagnostic accuracy, and enhance intervention outcomes through scalable, AI-driven posture analysis.**

Index Terms—**Postural Deviations, Postural Kyphosis, Chronic Pain, Thoracic Spinal Deviations.**

I. INTRODUCTION

Among these, Postural Kyphosis has become the most prevalent form, especially among adolescents and adults in today's sedentary lifestyle. It is characterized by an excessive outward curvature of the thoracic spine, often exceeding 40– 45 degrees, leading to a visible forward bend known as a "hunchback" or "round-back." While mild kyphosis may not cause significant health problems, severe forms can result in discomfort, pain, or breathing

difficulties and may require interventions such as bracing or surgery.



Postural Deviations	Abnormal Curve of Spine

Fig. 1 Postural Deviations

The widespread incidence of postural kyphosis is

primarily attributed to prolonged screen time, slouched sitting postures, and reduced physical activity. Notably, postural kyphosis shown in figure 1 and 2, is a reversible condition if detected early and managed through posture correction exercises and lifestyle modifications. Deformities associated with poor posture include thoracic kyphosis, hyper-kyphosis, and forward head posture resulting from cervical kyphosis or loss of cervical lordosis.

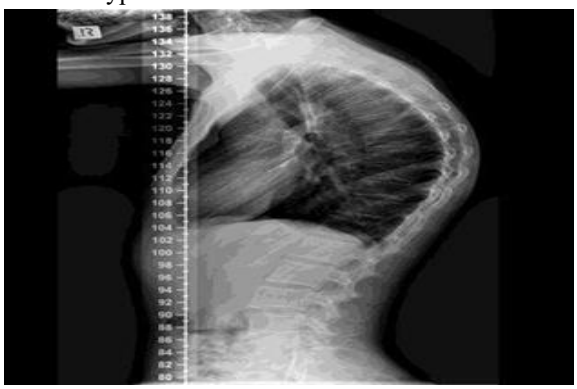


Fig. 2 Kyphotic thoracic spine (source: Internet)

The advancement of computer vision and machine/deep learning techniques offers innovative solutions to analyze posture and develop automated systems for posture detection and classification. However, current diagnostic, monitoring
and intervention methods often lack real-world applicability due to limitations such as small datasets, absence of longitudinal studies, inadequate real-time posture monitoring, and basic feature extraction approaches.

To tackle the identified gaps, Table 1 presents the first set of research questions. The survey investigates a new
machine and deep learning system that automatically spots and sorts postural kyphosis in lateral-view X-rays. By drawing on large datasets and combining modern feature- extraction and classifier techniques, the work seeks to boost accuracy, widen scalability, and improve everyday use in clinics.

Table 1 Research questions on automatic detection and classification of postural kyphosis

RESEARCH QUESTIONS

Based on the research gaps identified, the scope of postural kyphosis, and the proposed development of a machine or deep learning framework for automated detection and classification, this survey sets out to answer the questions listed below

1. How machine learning and deep learning methods can be applied to automatically detect and classify different grades of the postural kyphosis using lateral-view spine radiographs?
2. What are the critical visual features and biomechanical markers in sagittal spinal images that indicate the presence and severity of postural kyphosis?
3. How can noise reduction, normalization, and segmentation techniques be optimized for enhancing sagittal X-ray images to improve feature extraction for kyphosis detection?
4. What machine or deep learning and ensemble models provide the most accurate and scalable performance for the classification of spinal alignment deviations (normal, Postural kyphosis, Hyper-kyphosis)?
5. How can the developed models be validated using real-world clinical datasets, and how does their performance compare with traditional diagnostic methods?
6. What strategies can be developed to integrate automated kyphosis detection models with real-time feedback mechanisms for posture correction applications?

II. RELATED WORKS

Coskun et al. [1] classified sitting postures using skeletal data from Kinect v2, capturing 25 joint positions from 30 subjects sitting in five postures for 30 seconds each, resulting in 49,580 labeled samples. Machine learning models like K- Nearest Neighbors (KNN) and Neural Networks (NN) achieved high classification accuracy. However, the study was limited to only five posture types, lacked real-world implementation strategies, and was based on short-term observations without longitudinal studies. It did not explore real-time user feedback mechanisms, and comparative analysis with newer technologies like wearables or advanced ML models was absent, suggesting future work to broaden posture types, assess long-term effects, and integrate real- time applications.

Klishkovskaia et al. [2] proposed posture detection

algorithms using non-marker-based motion capture, tested on a small group of 10 subjects. While achieving accuracy comparable to machine learning and neural network methods, the study lacked detailed comparative analysis and was confined to controlled settings, limiting real-world applicability. It also did not evaluate long-term algorithm performance through longitudinal studies. Additionally, integration with wearable technologies, user experience feedback, and scalability to larger datasets or complex movements were not addressed, highlighting key areas for future improvement to enhance generalizability and practical use.

Kim et al. [3] evaluated a posture analysis system based on the computer vision that showed a high 94% conformity rate but was limited to lumbar, thoracolumbar, and mild thoracic curves, excluding moderate and major double curves. The system assessed only coronal plane images without considering sagittal plane deformities like thoracic kyphosis. Analytical accuracy across different clinical settings and populations was not fully validated, and system performance was highly dependent on hardware specifications. Furthermore, the dataset consisted mostly of minor deformities, suggesting the need for expanded datasets and lateral imaging to improve AI training and clinical reliability. Nguyen et al. [4] highlights key limitations in spinal alignment evaluation. Current research mostly focuses on localized regions, neglecting global spinal alignment, which is crucial for overall spinal health. The study also identifies limitations in X-ray image quality, suggesting the use of image-to-image deep learning techniques for clearer images. Manual measurement methods are time-consuming and dependent on radiologists, with potential for AI-based automation to improve efficiency and reduce errors. The method, validated with a small dataset, requires testing with larger and diverse datasets for better generalizability. Additionally, the study could benefit from addressing interobserver variability and integrating more spinal parameters. Real-world clinical testing is also needed to assess its practical application.

Sagar Suresh Kumar et al. [5] evaluates several classifiers, including Support Vector Classifier (SVC), Naive Bayes, Logistic Regression, K-Nearest Neighbors (KNN), Random Forests, Multi-Layer Perceptron (MLP), Convolutional Neural Networks (CNN), and Long Short-term Memory Networks (LSTM). However, the study focuses on only three postures: sitting, standing, and lying down, limiting its real- world applicability. The classifiers were tested using data from Microsoft Kinect cameras, but performance may vary with different datasets or sensor technologies. Future work could explore real-time processing, user variability, and multimodal data integration, as well as the need for longitudinal studies to assess classifier adaptability over time. These areas could enhance the robustness and relevance of posture detection in diverse applications.

Tavana et al. [6] highlights several limitations as the study uses a small dataset of 1000 radiographic images, which affects the generalizability and robustness of the model, as deep learning typically requires larger datasets. While data augmentation and transfer learning are employed, more advanced augmentation techniques could further improve model performance. The study mainly focuses on low-level image representations, and future research could explore additional feature extraction methods for better classification accuracy. The paper suggests integrating advanced techniques like vertebrae segmentation and Cobb angle measurement to enhance diagnostic accuracy. Furthermore, the study acknowledges the lack of research on automated evaluation versus human expert evaluation, and future work could explore other machine learning algorithms to improve classification outcomes.

Hida M et al. [7] highlights several areas for improvement. It lacks comprehensive validation against established methods, such as those using physical markers or clinical assessments. Future research could compare the accuracy and reliability of this new method with traditional techniques. Longitudinal studies are needed to assess the long-term effectiveness of marker less measurements, especially in tracking posture changes in at-risk populations. The study may also suffer from a limited sample diversity in terms of age, gender, and body types, affecting the generalizability of the findings. Additionally, environmental factors like lighting and background could influence measurement accuracy, necessitating

further exploration. Research is also needed on user training and practical implementation in clinical settings, as well as integrating posture measurements with other health metrics for a comprehensive understanding of overall health.

Batistão et al. [8] identifies age, gender, BMI, and physical activity as factors influencing postural deviations but highlights a lack of understanding of how these intrinsic and extrinsic factors interact. Future research could explore this interplay over time. The study's cross-sectional design offers a snapshot of postural deviations, but longitudinal studies are needed to track how factors like physical activity and BMI impact posture as children grow. Additionally, while the study highlights a high prevalence of postural deviations, it does not explore intervention strategies. Research focusing on preventive and rehabilitation programs for children and adolescents is needed. The study also lacks diversity in its sample and could benefit from including different socioeconomic and ethnic groups. Advanced assessment tools, like 3D motion analysis, could provide a more detailed understanding of postural deviations.

Chauhan et al. [9] identifies several research gaps. It uses a small dataset of 81 samples from Kaggle, limiting the robustness and generalizability of the models. Future research could employ larger, more diverse datasets to improve model performance and evaluate how well these models perform across various datasets or real-world clinical environments. The study focuses on hyper parameter tuning but could benefit from advanced feature engineering or the inclusion of additional features, such as imaging data, to improve accuracy. The paper also does not explore hybrid models that combine multiple algorithms. Future work could address model explainability, fairness, and bias, particularly with small, potentially unbalanced datasets. Additionally, real-time clinical applications of the models need to be explored, focusing on practical challenges like computational costs and system integration.

The paper "Prediction Formulae of Sagittal Alignment in Thoracolumbar Kyphosis Secondary to Ankylosing Spondylitis After Osteotomy" by Luo J et al. [10] used Cobb angles measured on lateral radiographs to assess spinal parameters, with a focus on thoracic kyphosis (TK) as the Cobb angle between the T4 upper endplate and T12 lower endplate.

Moon Y J et al. [11] employs the Forward Neck Tilt Angle (FNTA) as a key non-invasive measurement, alongside various radiographic sagittal alignment parameters like Cervical Sagittal Alignment (CSA), Craniometrical Angle
(CCA), T1 Slope (T1S), Cervical Lordosis (CL), Cranial Tilt (CranT), Cervical Tilt (CervT), C7 Slope (C7S), and Thoracic Kyphosis (TK), all derived from whole-spine standing lateral radiographs. Both studies contribute valuable metrics for assessing postural deviations and spinal alignment in specific conditions.

- Thoracic kyphosis (TK; T4–T12 Cobb angle) the curvature between T4 and T12

Nguyen T.P et al. [12] discusses on Convolutional Neural Networks (CNNs) for feature extraction from radiographic images, identifying anatomical landmarks like femoral heads, sacrum, and vertebrae (L1, T1, C2). The model uses a multi- order decentralized CNN approach to detect broader regions and then specific vertebrae, enhancing accuracy. Geometric equations integrate with CNNs to compute angular spinal parameters such as thoracic kyphosis and lumbar lordosis, using incidence angles of inflection points (Iaips). Despite using high-quality whole-spine radiographs, the study is limited by a single-institution dataset, a lack of analysis in severe deformities, and challenges in detecting thoracic and pelvic landmarks. Further research is needed for broader generalization, more accurate landmark detection, and evaluation of distance parameters.

Incidence Angle Of Inflection Points (Iaips).
Specifically, thoracic kyphosis is calculated as:
Thoracic kyphosis = T1 incidence − L1 incidence

The study "Automatic Recognition of Whole-Spine Sagittal Alignment and Curvature Analysis through a Deep Learning Technique" by Weng C.H et al. [13] used 2361 whole-spine lateral radiographs from multiple institutes, with 1800 images annotated after excluding unsuitable ones. The images were divided into training (1500 images) and testing (300 images).

Deep learning models used include a landmark localizer to predict 25 vertebral landmarks (C2-C7, T1-T12, L1-L5, and S1) and a numerical algorithm for calculating spinal curvature angles like thoracic kyphosis (TK) and lumbar lordosis (LL) based on inflection points (IPs) and apices (APs). The model showed good reliability with an Intraclass Correlation Coefficient (ICC) > 0.85, and the median localization error ranged from 1.7 mm for cervical landmarks to 4.1 mm for thoracic landmarks.

Rao Farhat Masood et al. [14] leverages publicly released composite datasets and existing MRI datasets to develop a more automated and objective method for assessing lumbar spine disorders. The team built a hybrid network that fuses ResNet features with a U-Net decoder to segment vertebral bodies, reaching a Dice coefficient score of 0.97 and IoU of
0.86. Images were divided into 360 training and 154 testing samples in a 70-to-30 ratio. The model is fine-tuned using transfer learning, with the Ada delta optimizer and cross- entropy loss function. The study addresses gaps in subjective assessments, inadequate quantitative analysis, and a lack of automated classification for disorders like spondylolisthesis, showcasing deep learning's superiority over traditional methods for spinal measurements and disorder classification.

Yeh YC et al. [15] employs a two-stage deep learning model that automatically measures sagittal Spino-pelvic parameters. The primary dataset consists of 2900 whole- spine lateral radiographs, which were de-identified for patient confidentiality. The model integrates Retina Net in the first stage for detecting areas of interest like C7, S1, and femoral heads, addressing class imbalance in object detection tasks. The second stage utilizes a U-Net architecture for precise landmark detection and segmentation. Key spinal parameters analyzed include:

- T1 Slope (T1S): The angle of the T1 vertebra relative to the horizontal.
- Global Thoracic Kyphosis (GTK): The curvature of the entire thoracic spine.
- Proximal Thoracic Kyphosis (PTK): The curvature between T1 and T5.
- Main Thoracic Kyphosis (MTK): The curvature between T5 and T12.

Mamata S koban et al. [16] focuses on applying deep learning to detect and analyze spinal deformities. It uses a dataset of 1,765 lateral vertebrae images and 12,600 simulated projections to improve model accuracy. The study employs a deep feed-forward neural network for vertebrae localization, achieving 96% accuracy with a runtime under 3 seconds, suitable for clinical use. A dual-network approach is used, combining a localization and segmentation network for large CT scans. Additionally, a mechanistic machine learning algorithm is utilized to track curve by integrating clinical data and physical growth equations.

Table 2 Summary of a significant literature survey finding

Sl no.	Title of the paper	Key Findings	Research Gaps/Future work
1.	Conformity assessment of Computer Vision-Based Posture analysis System	Limited curve types, 94% conformity rate using coronal imaging	Need to include sagittal imaging, optimize for hardware differences, expansion of dataset to more complex deformities
2.	Intelligent evaluation of global spinal alignment by a Decentralized CNN	Measures 12 parameters, limited focus on global spinal alignment	Use larger datasets, address interobserver variability, automate measurement processes
3.	Comparison of Classifiers for Posture Detection	Limited postures, Uses ML and DL models (SVC, CNN, LSTM)	Test for complex postures, improve real-time processing, integrate multimodal data sources
4.	sification of Spinal Curvature types using Radiography images	Small dataset (1000 images), need for data augmentation.	Use advanced feature extraction, integrate vertebrae segmentation, can explore other machine

			learning algorithms
5.	Comparative analysis of supervised machine and deep learning algorithms for kyphosis detection	Models: LR, NB, SVM, KNN; small dataset (81 samples)	Use diverse datasets, explore hybrid models(ensemble techniques), focus on real-time clinical application
6.	Prediction formulae of sagittal alignment in thoracolumbar kyphosis	Parameters: Cobb angles, thoracic kyphosis (T4-T12)	Need to Expand to other spinal parameters, validate across clinical settings
7.	Spinal Measurement via Incidence Angle of Inflection using regional and global spinal parameters	Hierarchical CNNs for detecting landmarks, parameters: Incidence angles.	Improve detection for complex deformities, test in broader clinical settings
8.	Automatic recognition of whole-spine sagittal alignment and curvature analysis	Used 2361 radiographs; landmark localizer with B- spline functions, parameters :ICC, inflection points, cobb angles, curvature angles	Address anatomical variance, use more diverse datasets, improve landmark detection
9.	Investigation on Efficient Deep Learning Framework for Spinal Deformities A Review	used 1,765 lateral vertebrae images and 12,600 simulated projections to improve model accuracy of 96%.	Insufficient generalization of models, Underexplored multimodal data fusion, Inadequate integration with clinical workflow.

Table 3 Research Objectives

[1] To develop a robust data Pre-processing and segmentation pipeline for sagittal radiographs.

[2] To extract and quantify relevant spinal features from medical imaging data.

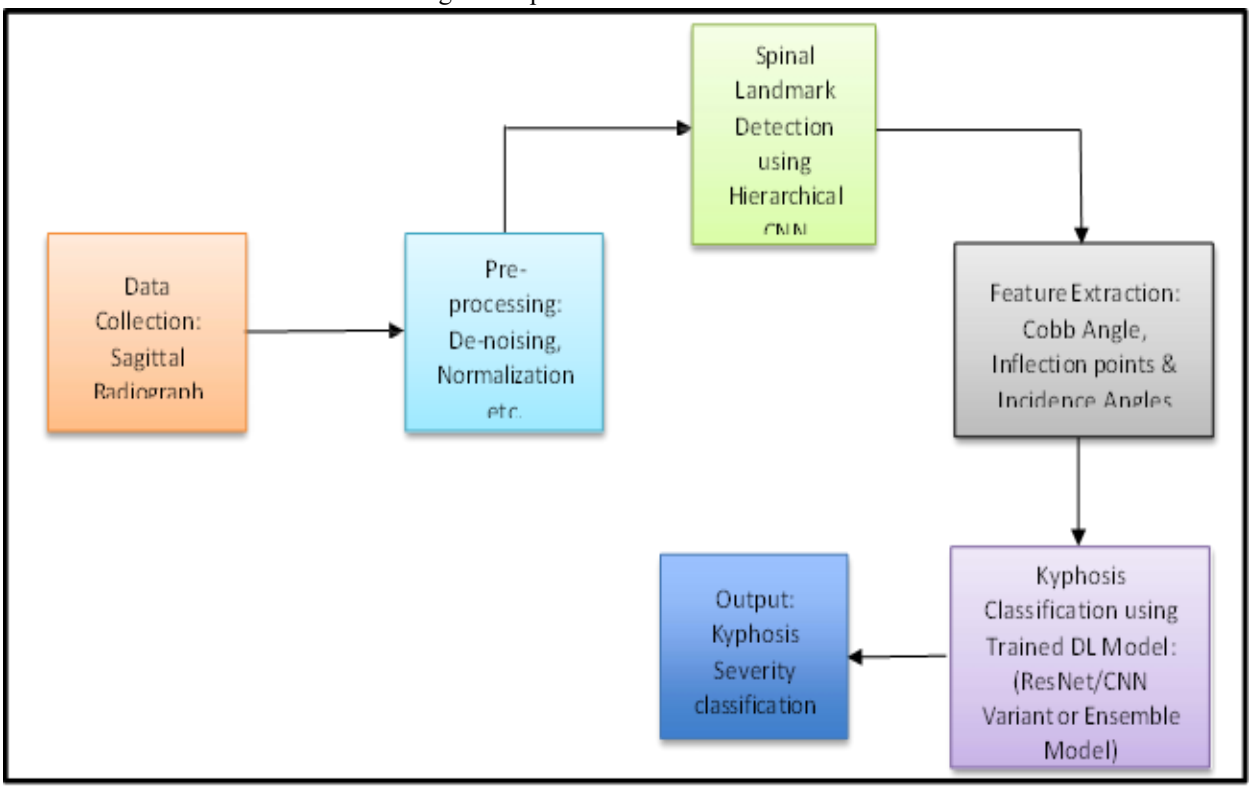
[3] To design and validate advanced machine learning models for posture detection and classification, with a focus on optimizing performance.

Table 4 Analysis on existing Methodologies

Sl.no	Methodology	Authors	Data Type	Strengths	Limitations	Suitability for Kyphosis Detection
1.	Hierarchical CNNs, Radiographs	Nguyen, T.P, Kim, J.-H, Kim, S.-H, Yoon, J, Choi, S.-H. et al [12]	Sagittal Radiographs	Accurate landmark detection, supports curvature and angle analysis	Needs broader clinical validation	Very High
2.	CNN, Landmark Localization, B-spline	Weng, C.H., Huang, Y.J., Fu, C.J. et al [13]	Sagittal Radiographs	Large dataset (2361 samples); precise curvature modeling	Sensitive to anatomical variance	Very High

3.	Deep feed- forward neural network	Mamata S koban, Vijay P Singh, Rajesh Bodade et al [16]	Sagittal Radiographs	Large dataset (1765 samples), localization and segmentation network	Inadequate integration with clinical workflow	Very High
4.	Decentralized CNN for Spinal Alignment	Nguyen, T.P, Jung, J.W, Yoo, Y.J. et al [4]	Spinal Imaging	Measures multiple alignment parameters; interpretable	Smaller dataset; interobserver variability	High
5.	Traditional ML (SVM, LR, NB, KNN)	Chauhan, A.S. Lilhore, U.K. Gupta, A.K. Manoharan, P. Garg, R.R. Hajjej, F. Keshta, I. Raahemifar, K. et al [9]	Small Radiograph Dataset	Easy to implement; lightweight models	Poor generalization on small datasets; lacks curvature sensitivity	derate to Low

Fig. 3 Prospective Solution Architecture



III. PROPOSED SOLUTION

Based on the analysis of related works, prospective solution architecture is framed. The architecture is given in Figure 3.

Postural Kyphosis classification begins with data collection, where sagittal X-ray images of the spine are acquired. These images undergo various image processing techniques such as de-noising and normalization etc. to enhance quality and consistency. Then, inputs are further processed to detect spinal landmarks using a hierarchical convolutional neural network (CNN), which provides the foundation for precise anatomical analysis. From these landmarks, key features such as Cobb angle,

inflection points, and incidence angles are extracted to quantify spinal curvature. These features are then input into a trained deep learning model—such as Res Net, a CNN variant, or an ensemble model—for the classification of kyphosis severity. The final output of the pipeline is a classification that reflects the degree or the severity of kyphosis present shown in Table 5, enabling automated assessment and potential clinical decision support.

Table 5 Expected Outcome

Severity Class	Description
Normal : Thoracic angle < 40°	No abnormal curvature
Moderate Postural Kyphosis - 41°–55°	More visible curve, still correctable
Severe / Hyper Postural Kyphosis - > 55°	Pronounced curve, urgent posture correction needed

IV. CONCLUSION

The comprehensive study on existing literature on automated posture detection and classification, with a specific focus on postural kyphosis, highlights the transformative potential of computer vision, machine and deep learning methods in addressing spinal alignment disorders. The surveyed studies demonstrate significant advancements in leveraging sagittal radiographs and other imaging modalities to detect and classify postural deviations, particularly postural kyphosis, which is increasingly prevalent due to sedentary lifestyles and prolonged screen time. Techniques such as convolutional neural networks (CNNs), U-Net, and ensemble classifiers have shown promising results in achieving high accuracy in spinal parameter measurement and posture classification. However, several critical research gaps persist, including limited dataset diversity, lack of longitudinal studies, challenges in real-world applicability, and insufficient integration of real-time
feedback mechanisms.

The proposed solution framework aims to address these gaps by developing an advanced DL based system for automatically detecting and classifying the postural kyphosis using lateral view spine X-rays. By establishing a standardized dataset, implementing robust pre- processing and segmentation pipelines, and utilizing state- of-the-art feature extraction and classification models, this work seeks to enhance diagnostic accuracy, scalability, and clinical applicability. Furthermore, exploring real- time feedback systems and integrating findings with wearable technologies could empower both clinicians and patients to manage postural deviations effectively. The ultimate goal of this research is to help orthopedists and radiologists create a clinically feasible support system that will enable early detection, prompt intervention, and better results when treating postural kyphosis and associated spinal deformities.

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