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Camera-Based Smart Mirror with Machine Learning for Postural Analysis: System Development and Reliability Evaluation

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Abstract. Early postural assessment using camera-based systems remains technically challenging due to variability in user positioning and limited evaluation of measurement repeatability. This study presents the development and repeatability evaluation of a smart mirror system for automated postural analysis using pretrained pose estimation and rule-based geometric classification. The system consists of a fixed camera mounted above a mirror and a connected computing device for real-time processing and visual feedback. Anatomical landmarks were detected from standardized anterior, posterior, and lateral views using an AI-based pose estimation model, and postural asymmetry was quantified using bilateral distance ratios and angular deviation thresholds derived from literature. Reliability was evaluated through repeated measurements to assess the consistency of landmark detection and postural classification outputs. Forty adolescents (age 12.8 ± 0.56 years; 28 males, 12 females) participated in present study. The system intra-rater reliability was evaluated by calculating Intraclass Correlation Coefficients (ICC) for the landmark data and Cohen's Kappa for posture classifications. The system demonstrated excellent reliability for key landmarks in scapula (ICC = 0.98, 95%CI 0.97-0.99) and hip-knee-ankle (ICC = 0.98, 95%CI 0.98-0.99). The classifications for scoliosis assessment also showed excellent agreement ($\kappa = 0.90$). These results indicate that the proposed system can produce repeatable posture measurements under controlled conditions; however, this study evaluates repeatability only and does not assess diagnostic accuracy or clinical validity. Further validation against clinical reference standards is required before broader application.

Keywords: computer vision system, digital health, camera-based sensing, machine learning

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1. Introduction

Postural problems, particularly scoliosis, remain a significant public health concern in children and adolescents [1,2]. Scoliosis is a complex three-dimensional (3D) spinal deformity, pathologically defined by a lateral deviation in the coronal plane, coupled with axial vertebral rotation [3], which together manifest as a structural curvature and a loss of normal sagittal alignment [4]. Scoliosis prevalence is significantly higher in females and peaks during adolescence, with an overall prevalence of 3.01% among adolescents aged 10–15 years, highlighting its link to rapid skeletal growth [5]. If left untreated, adolescent idiopathic scoliosis (AIS) can potentially progress leading to severe pain, cardiopulmonary complications, reduced social participation, and increased mortality [6]. Therefore, early identification with comprehensive and structured prevention strategy are crucial for implementing non-surgical interventions which can significantly reduce the likelihood of progression and prevent the necessity of invasive surgery [5][7].

Despite the importance of early screening, current scoliosis detection practices rely heavily on clinical examinations and radiographic confirmation [8][9]. For adolescents in several countries, school-based screening programs are hindered by high resource demands and a lack of trained personnel [10–12] The inaccessibility of radiographic assessment as the gold standard to detect scoliosis and the risk of exposure to harmful radiation further complicates early detection [13]. These challenges have emphasized the need for affordable, non-invasive, and accessible alternative screening methods. Although various digital tools and mobile applications have been introduced to assist with posture monitoring, most existing technologies remain limited in school-based or community setting [14–16]. Many systems rely on applications that are highly sensitive to user positioning, manual interpretation, and assessor-dependent, reducing their effectiveness for reliable posture screening [15] [17]. From an engineering perspective, these limitations are largely attributable to uncontrolled camera geometry, variable viewing angles, and the absence of standardized acquisition conditions across repeated measurements [18].

This study introduces a camera-based smart mirror system for automated postural assessment based on pose estimation and rule-based geometric analysis. In contrast to handheld or mobile camera systems, the smart mirror provides a fixed camera–mirror configuration that establishes a consistent geometric relationship between the subject and imaging sensor, thereby reducing variability associated with camera distance, orientation, and operator handling [18]. The technical contribution of this study lies in the development of a fixed camera–mirror measurement configuration that integrates anatomical landmark detection [19] [20], angular and distance-based asymmetry metrics, and real-time visual feedback within an integrated measurement system. This architecture supports low-complexity operation and does not require specialized calibration procedures, which enhances its potential scalability and accessibility for repeated posture monitoring in school or community environments [21]. The proposed system is designed for automated posture screening and repeated posture monitoring through non-invasive image-based measurement and is not intended for clinical diagnosis, which requires radiographic confirmation. The novelty of this work resides in the unified system design and its reliability-focused evaluation, which together address a critical gap between laboratory-based pose estimation methods and practical posture screening platforms. The primary research question is whether the proposed system can provide reliable landmark measurements and consistent postural classifications across repeated trials in adolescents under standardized acquisition conditions.

2. Methods

2.1. Study Design

Participants were recruited from a junior high school and voluntarily participated in this study. Individuals with a history of spinal trauma, spinal surgery, severe orthopedic disorders, or musculoskeletal disorders within the previous six months were excluded to reduce potential confounding from pain-related postural adaptations. The smart mirror prototype and all assessments were conducted in accordance with the ethical guidelines of the Universitas Aisyiyah Yogyakarta Ethical Board (No. 4757/KEP-UNISA/VIII/2025). Written informed consent was obtained from parents or legal guardians prior to participation.

All images and extracted landmark data were anonymized using subject codes and stored on a secure institutional server (Universitas Aisyiyah Yogyakarta) with restricted access. Facial regions were excluded from analysis. Data were used solely for system evaluation and were not reused for model training. The primary endpoints of this study were the repeatability of anatomical landmark measurements and the consistency of rule-based postural classification outputs across repeated trials.

2.2. Instrumentation and System Architecture

The smart mirror prototype consisted of hardware and software components. The hardware comprised a semi-reflective mirror surface, an embedded high-resolution camera (UHD 4K camera resolution at 30fps, a 79.5° FOV, 4x digital zoom, AI tracking), and a compact processing unit that managed data acquisition and analysis. The mirror had dimensions of 1.2 cm (W) × 40 cm (L) × 150 cm (H), embedded with red-green-blue (RGB) camera. The camera was positioned above the mirror, mounted at a height of 150 cm from the floor (centered horizontally), strategically embedded within the mirror chassis to ensure an unobstructed, frontal-plane and sagittal – plane view of the user. In this system, the mirror functions as a visual medium that allows users to observe their posture during the measurement process, and it does not contain any embedded sensors. The primary sensing component was the camera, which automatically captured standardized images of the participant.

The camera was connected to a laptop computer via USB for data transmission and processing. Data acquisition was initiated when the participant was positioned approximately 3 m from the camera. The system captured images from standardized anterior, posterior, and lateral views. A consistent lighting environment and uncluttered background were used to minimize shadows and improve landmark visibility. Participants wore form-fitting clothing, removed bulky accessories, tied long hair to expose the scapulae and cervical region, and stood barefoot with arms relaxed at the sides and feet shoulder-width apart.

2.3. Algorithmic Workflow and Landmark Detection

Image processing and analysis were implemented using a Python-based pipeline executed through a Google Colab notebook environment utilizing OpenCV, TensorFlow, and MediaPipe Pose libraries. The computational workflow consisted of:

(1) Initialization of required libraries,
(2) Acquisition or upload of anterior, posterior, and lateral images,
(3) Human detection and anatomical landmark extraction using a pretrained pose estimation model (mediapipe pose), and
(4) Computation of geometric postural metrics, including inter-landmark distances and angular deviations.

MediaPipe Pose employs a pretrained deep learning model (CNN-based) for anatomical landmark detection only (figure 2). The system automatically detected anatomical landmarks across views, including pelvic landmarks and hip–knee–ankle (HKA) joints from the anterior view, scapular and pelvic landmarks from the posterior view, and head–shoulder alignment from the lateral view (Figure 1). Detected landmarks were overlaid on the image to allow visual verification and facilitate quantitative analysis. Geometric features were computed from two-dimensional landmark coordinates using Euclidean distance for bilateral height differences and vector-based angle calculations for joint and segment orientation.

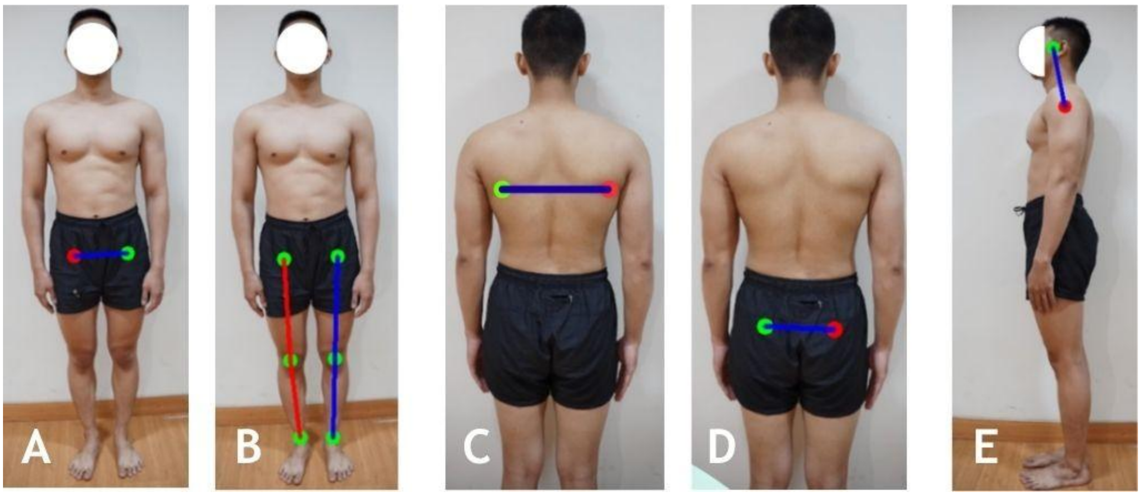

Figure 1. Anatomical landmarks localization for postural analyzation (A) Anterior pelvic, (B) Anterior Hip-Knee-Ankle, (C) Posterior scapula, (D) Posterior pelvic, (E) Lateral head

2.4. Rule-based Classification Framework

A pretrained pose estimation model (MediaPipe Pose) was used solely for anatomical landmark detection. Classification was implemented using deterministic rule-based geometric criteria in which extracted landmark features were compared against predefined threshold values derived from biomechanical and clinical posture literature.

Postural categories were determined algorithmically using predefined geometric thresholds of asymmetry (e.g., scapular angle, pelvic height difference, craniovertebral angle, trunk tilt) (table 1). Screening outcomes were defined relative to literature-based geometric thresholds rather than radiographic Cobb angle. For each metric, computed values were compared with fixed threshold values to generate binary or categorical screening outputs (normal vs asymmetrical), ensuring transparent and reproducible classification logic.

Table 1. Literature-derived thresholds used for rule-based classification

Landmark	Parameter	Treshold	Reference
Anterior			
Pelvic	ASIS height difference	> 5 mm	[22][23][24]
HKA	HKA angle	<178° valgus; >182° varus	[25]
Posterior			
Scapula	Scapular angle	> 9°	[26]
Pelvic	Iliac crest height difference	≥ 10 mm	[27]
Scoliosis	Plumb line deviation	>1.5 cm	[28]
Lateral			
Head-shoulder	Craniovertebral angle	<50° (FHP)	[29]

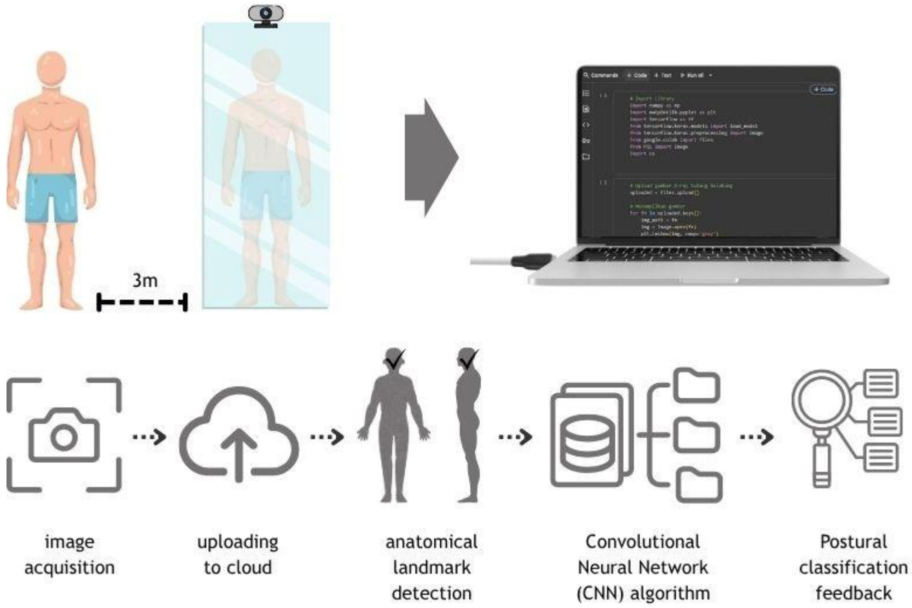

Figure 2. Smart mirror system design workflow

2.5. Reliability Assesment Protocol

Each participant underwent three repeated measurements under identical acquisition conditions. A 10-minute interval was provided between trials, and participants stepped away and repositioned before each measurement to simulate repeated screening. The same operator conducted all measurements. Output classifications were blinded during repeated trials to minimize observer bias. This protocol was designed to assess within-session repeatability rather than diagnostic accuracy or inter-operator agreement.

2.6. Statistical Analysis

To assess reliability, the intraclass correlation coefficient (ICC) was used to evaluate intra-rater agreement (repeatability). The ICC values were interpreted based on the classification system proposed by Wahlund (1998) as follows: values below 0.70 were considered non-acceptable, 0.71 to 0.79 acceptable, 0.80 to 0.89 was very good, and 0.90 to 1.00 means excellent [30][31]. The significance level was set at *p-value* <0.05. All statistical analyses were performed using IBM SPSS Statistics for Windows, Version 27. Cohen's Kappa was used to assess agreement of categorical postural classifications across repeated trials. Reliability thresholds were selected to reflect suitability for screening consistency rather than clinical diagnostic validity.

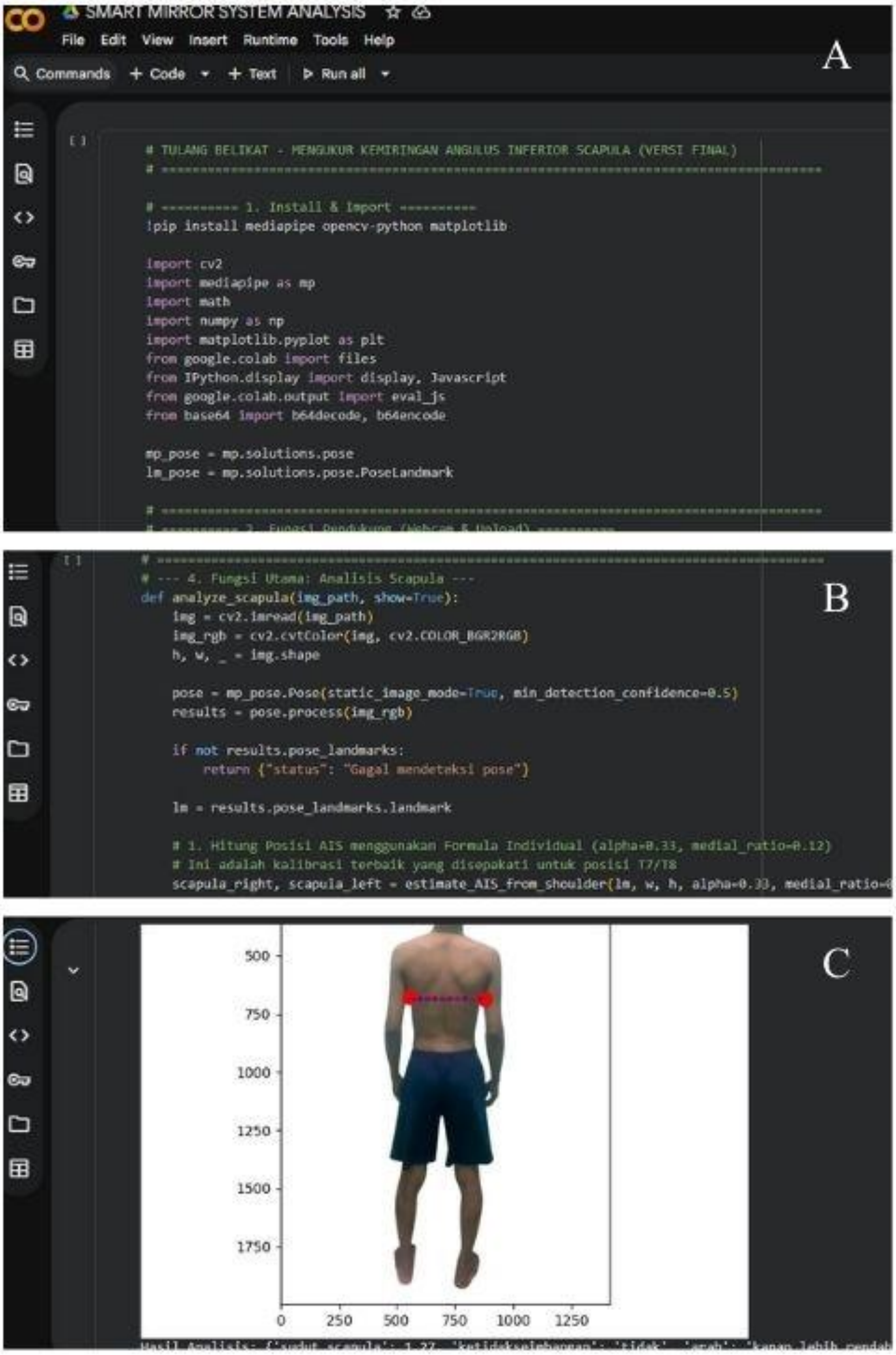

Figure 3. Google Colab interface posture-analysis workflow: (A) library initialization, (B) landmark-detection function for scapular assessment, and (C) visualization of detected landmarks used for postural evaluation

3. Results and Discussion

3.1. *Systematics Overview*

Fourty participants (age 12.8 ± 0.56, 28 males, 12 females) were included in initial feasibility testing of smart mirror between July 2025 and September 2025. Parameters assessed included system functionality, accuracy of posture recognition, and user experience in following instructions. The prototype successfully integrated hardware and software components, as evidenced by all participants being able to follow the pictorial instructions without difficulty. The smart mirror generated quantitative feedback on head–neck angle, shoulder tilt, pelvic asymmetry, hip–knee–ankle (HKA) alignment, bilateral scapular position, and scoliosis screening outcomes.

The proposed algorithm required the user's reflection to be positioned within a predefined capture region, with anatomical landmarks aligned to balance reference points. Users initiated the self-screening procedure by positioning themselves in front of the mirror and completing an image acquisition sequence consisting of three standardized views. The camera captured images automatically once a stable posture was detected, and the system processed the images in real time.

Prior to the preliminary study, it was anticipated that the smart mirror might reduce the time required for postural assessment by healthcare providers, although device operation and camera alignment were expected to pose challenges. In practice, the total workflow from image capture to result generation typically ranged from 30 to 60 s per session, with a maximum duration of approximately 4 min in cases requiring image recapture. Participants reported no major difficulties in understanding or following system guidance, and the system detected improper positioning or occlusion and prompted recapture when necessary. This outcome may be attributed to the provision of standardized instructions and participant familiarization before assessment. These findings suggest that structured user guidance is essential for achieving efficient and repeatable acquisition conditions.

3.2. *Intra–rater Reliability*

Manuscripts The reliability analysis demonstrated varying levels of agreement across anatomical landmarks (Table 2). Excellent reliability was observed for the HKA point (ICC = 0.98, 95%CI 0.98-0.99) and Scapula (ICC = 0.98, 95%CI 0.97-0.99) measurements, indicating high consistency between repeated assessments. While the pelvic landmark showed the lowest, yet still acceptable for anterior pelvic (ICC = 0.72, 95%CI 0.57-0.86) but non-acceptable for posterior pelvic (ICC = 0.50) measurements. The reliability for the posterior pelvic landmark was unacceptable and exhibited considerable uncertainty, as indicated by a wide confidence interval (95%CI 0.18-0.71). In the evaluation of postural asymmetry and scoliosis detection (Table 3), the system showed strong agreement between repeated assessments, with Kappa values ranging from 0.68 to 0.90. The highest reliability was observed in scoliosis screening ($\kappa = 0.90$, 95%CI 0.84-0.96). These findings confirm the system's ability to generate repeatable data necessary for clinical analysis in posture analysis.

Table 2. Reliability smart mirror assessments in detecting posture landmarks

Landmark	ICC	95% CI	p-value	Classification
Anterior				
Pelvic	0.72*	0.57 - 0.86	p <0.001	Acceptable
HKA	0.98*	0.98 - 0.99	p <0.001	Excellent
Posterior				
Scapula	0.98*	0.97 - 0.99	p <0.001	Excellent
Pelvic	0.50	0.18 - 0.71	p <0.002	Non-acceptable
Lateral				
Head-shoulder	0.84*	0.81 - 0.94	p <0.001	Very good

Notes: HKA (Hip-Knee-Ankle), p <0.005, *Acceptable variables

Table 3. Reliability smart mirror assessments in detecting posture asymmetry and scoliosis

Posture assessment	Kappa (κ)	95% CI	p-value
Anterior Pelvic Asymmetry	0.81	0.73 - 0.89	0.001
Hip-Knee-Ankle Alignment	0.77	0.69 - 0.85	0.001
Posterior Scapula Asymmetry	0.85	0.78 - 0.91	0.001
Posterior Pelvic Asymmetry	0.79	0.70 - 0.87	0.001
Lateral Head-Shoulder Alignment	0.68	0.58 - 0.78	0.001
Scoliosis Screening	0.90	0.84 - 0.96	0.001
Notes: p <0.005			

3.3. Result Analysis

Smart mirrors represent a promising tool for posture screening and monitoring in adolescents. The present findings indicate that the system demonstrates high feasibility for posture monitoring, supporting the need for safe, repeatable, and cost-effective screening approaches in community settings. The excellent reliability observed for scapular and HKA landmarks provides evidence that the algorithm can consistently quantify postural features that are visually prominent and geometrically well defined. This high repeatability is likely attributable to the algorithm's ability to identify bony prominences and joint centers that exhibit clear visual contrast and reduced soft tissue interference. These findings are consistent with previous studies validating the use of pose estimation libraries such as MediaPipe for extracting kinematic information from 2D images in controlled environments [15] [32]. Convolutional neural networks (CNNs) provide a robust framework for automated landmark detection through hierarchical extraction of visual features [33]. Pose estimation models (PEMs) built on this framework can automatically locate key anatomical points, enabling the subsequent calculation of joint angles and alignment parameters for static postural assessment. Performance variability across repeated measurements was quantified using ICC confidence intervals and session-level timing dispersion, indicating that landmarks with high visual contrast exhibited narrower confidence bounds and lower temporal variance compared with proximal pelvic landmarks [32][34].

In contrast, the poor reliability observed for posterior pelvic landmarks highlights an important methodological limitation. The wide confidence interval suggests substantial variability in landmark detection. Posterior pelvic landmarks are inherently difficult to visualize due to their dependence on body composition, pelvic tilt, and axial rotation [35][36]. This limitation was likely exacerbated by participant attire, particularly loose-fitting trousers, which obscured the contours of the pelvic girdle and hindered consistent landmark localization [34]. This observation underscores a known challenge in image-based posture analysis, where proximal landmarks with low visual contrast are more difficult to detect reliably than distal and more exposed joints [37][38]. Failure modes were primarily associated with (i) partial occlusion of pelvic landmarks, (ii) low ambient lighting reducing edge contrast, and (iii) unstable subject posture during acquisition. These failure conditions resulted in increased recapture frequency and contributed disproportionately to variability in posterior pelvic measurements [39] [40].

Complementing the landmark-level analysis, categorical classification of postural asymmetry demonstrated substantial to almost perfect agreement, particularly for scoliosis screening and posterior scapular asymmetry. The high reliability observed for scapular assessment may be explained by the superficial anatomical location of the scapula and its clear visual asymmetry when mal-aligned, making it amenable to detection by computer vision algorithms. This pattern is consistent with prior reports indicating higher accuracy of pose estimation systems for landmarks with minimal occlusion and strong visual contrast [37][38]. Furthermore, the strong agreement observed for overall screening outcomes suggests that the system's rule-based decision logic effectively integrates multiple reliable geometric features into a stable composite output [38]. This indicates that deterministic geometric thresholds can partially compensate for variability in individual landmark localization by aggregating multiple spatial features into robust classification decisions [40].

Several limitations were identified. First, some users experienced difficulty with camera detection or connection, commonly due to insufficient device permissions or improper hardware configuration. Second, landmark detection occasionally failed when room lighting conditions were suboptimal, requiring repeated image capture. Third, system performance was occasionally reduced by delayed processing linked to limited internet bandwidth. These findings indicate that environmental robustness and computational efficiency remain key engineering challenges. Future system development should prioritize improvements in hardware connectivity, lighting tolerance of pose detection algorithms, and local (offline) processing capability [41]. Additional enhancements in user interface (UI) and user experience (UX) design may improve usability and reduce acquisition errors across broader age groups [42]. Such refinements would support the implementation of smart mirror systems as accessible tools for posture screening and longitudinal monitoring.

Importantly, the proposed system is intended for posture screening and monitoring rather than clinical diagnosis. Classification outcomes are based on literature-derived geometric thresholds and were not validated against radiographic reference standards. Therefore, the present results should be interpreted as indicators of measurement repeatability rather than diagnostic accuracy.

4. **Conclusion**

This study presents a prototype smart mirror system for non-invasive posture and scoliosis screening based on image-based landmark detection and rule-based classification. The system was technically validated in terms of intra-rater repeatability of landmark measurements and stability of rule-based screening outputs under standardized acquisition conditions, indicating technical feasibility for posture monitoring applications. However, the current findings are limited to measurement repeatability under standardized conditions and have not yet been validated against external clinical reference standards. The sample size and controlled acquisition environment also limit generalizability. Accordingly, the system should be regarded as an early-stage screening and monitoring prototype rather than a deployable clinical or community tool.

The next technical validation step will involve comparison of system outputs with established clinical reference measures and evaluation under variable lighting, clothing, and positioning conditions. Future work will focus on transforming the mirror into an integrated digital panel capable of displaying analysis results directly and providing user controls through an interactive mirror-based interface, as well as improving landmark robustness through additional sensing modalities and extended longitudinal testing.

Declaration of AI and AI assisted technologies in the writing process

During the preparation of this work, the author(s) used Google Gemini to assist with language editing, manuscript organization, and improving the clarity of scientific writing. The AI tool was not used to generate, analyze, or interpret research data. All scientific decisions, analyses, interpretations, and conclusions were performed and verified by the authors. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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