Real-time Lateral Sitting Posture Monitoring using MediaPipe

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This paper presents a real-time sitting posture monitoring system using MediaPipe's BlazePose model, implemented on both edge computing hardware (Raspberry Pi 5) and a standard Windows 11 laptop. The system detects 33 body landmarks from live video input and estimates postural deviations by analyzing joint angles. We evaluate the model's performance under various lighting conditions and hardware constraints. Results show angle estimation within ±2° error on average, but limitations persist in poor lighting and for user-specific anatomical variations. A comparative analysis of CPU, RAM, and FPS performance across platforms is also included. This lightweight approach enables portable, low-cost ergonomic health monitoring.

CCS Concepts: • **Human-centered computing** → **Ubiquitous and mobile computing systems and tools**; • **Computing methodologies** → *Computer vision problems*; • **Applied computing** → Health care information systems.

Additional Key Words and Phrases: Posture monitoring, MediaPipe, Raspberry Pi, Edge computing, Computer vision, BlazePose, Ergonomics, Real-time systems

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1 INTRODUCTION

In today's increasingly digital and sedentary society, prolonged sitting has become the norm in work, learning and recreational environments. The average office worker spends upwards of 75% of their workday seated at a desk, often maintaining static postures for extended periods [3]. Unfortunately, such behavior frequently involves poor postural habits, including lateral spinal deviations, forward head posture and slouching, which are linked to the development of chronic musculoskeletal disorders (MSDs) such as lower back pain, neck strain, and shoulder discomfort [2, 10]. The World Health Organization reports that low back pain is the leading cause of disability globally, affecting more than 540 million people at any given time [18]. These health issues impact individual well-being and result in significant economic burdens due to decreased productivity, increased healthcare costs, and absenteeism [14].

Despite the recognized importance of maintaining proper posture, most individuals lack awareness and real-time feedback mechanisms to correct their sitting habits. Physiotherapy and ergonomic training can help, but their benefits diminish without continuous monitoring and intervention. Traditional solutions, such as smart chairs and wearable devices, have emerged to fill this gap, but their adoption is limited by cost, discomfort, and the need for specialized hardware [1, 9].

This paper presents a novel real-time lateral posture monitoring system that leverages the power of computer vision and lightweight edge computing. Implemented entirely on a Raspberry Pi 5 equipped with the Raspberry Pi Camera Module 2, the system uses Google's MediaPipe [11] pose estimation framework to track lateral posture non-intrusively and provide instant feedback. By removing the dependency on cloud computing or expensive GPUs, this solution offers an accessible and scalable alternative for widespread deployment in offices, educational institutions, and homes. Our approach aims to empower users to maintain healthier sitting postures proactively, thereby reducing the risk of MSDs and improving overall productivity and well-being.

2 MOTIVATION

The motivation for this work arises from the growing prevalence of sedentary lifestyles and the corresponding rise in posture-related health problems. Office environments, where employees often remain seated for prolonged periods, are particularly vulnerable to posture-induced musculoskeletal disorders, which are among the most common occupational health issues worldwide [12]. Poor sitting posture not only causes physical pain and discomfort but also leads to cognitive fatigue and decreased work efficiency, compounding the challenges faced by organizations striving to maintain employee health and productivity [15].

Although physiotherapists and ergonomics experts recommend maintaining optimal posture, adherence is challenging without continuous, objective monitoring. Current technologies aiming to provide posture feedback — such as smart chairs embedded with pressure sensors or wearable devices that monitor spinal alignment — have demonstrated effectiveness but suffer from practical limitations. These include high costs, intrusiveness, complex setup, and limited user comfort, restricting their suitability for everyday use in typical office or home settings [4, 13].

There is a clear and pressing need for a solution that is low-cost, non-intrusive, easy to deploy and capable of real-time posture monitoring and feedback. Advances in computer vision, particularly in pose estimation frameworks like MediaPipe [5], provide an opportunity to meet this need by enabling accurate, markerless tracking of human posture using only standard cameras. Coupled with affordable and powerful edge computing platforms such as the Raspberry Pi 5, this technology can democratize posture monitoring and encourage healthier habits on a large scale. Our project addresses these gaps by developing and validating a practical, real-time lateral sitting posture monitoring system that operates entirely on edge hardware without reliance on cloud resources, thus ensuring privacy, affordability, and accessibility.

3 RELATED WORK

A wide range of technologies have been proposed for real-time posture monitoring, reflecting the growing recognition of sedentary

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behavior as a public health issue. Existing methods are broadly categorized into sensor-based, vision-based, and hybrid systems. Each of these approaches has been explored in both research and commercial contexts.

3.1 Sensor-Based Approaches

Sensor-based systems have traditionally dominated posture monitoring due to their high temporal resolution and ability to measure subtle body movements. These include inertial measurement units (IMUs), flex sensors, pressure mats, and force-sensitive resistors (FSRs) embedded into furniture or wearables.

Commercial devices like Lumo Lift and Upright GO use IMUs attached to the upper back to detect slouching and provide haptic feedback. These systems are lightweight and widely adopted but often limited to a single degree of freedom (e.g., forward flexion).

In academic research, Hu et al. [7] built a smart chair with flex sensors embedded in multiple zones (seat, backrest, armrests) and used an artificial neural network to classify up to seven different postures. Similarly, D. V. et al. [17] embedded flex sensors and vibrating motors into a cushion to detect spinal misalignment and actively guide posture correction. Pressure-based systems also remain popular, such as those used in wheelchair posture monitoring. For example, seating pressure mats integrated with capacitive sensors are used in rehabilitation settings to monitor and guide seating adjustments in real-time. While these systems offer high precision and are effective in controlled environments, they suffer from several practical limitations. First, they require specialized and often expensive hardware, making them less accessible to the average user. Second, they are inherently invasive, requiring either physical contact or fixed user positioning, which reduces flexibility and comfort. Moreover, wearable solutions demand consistent user compliance, which is difficult to maintain over time.

3.2 Vision-Based Approaches

Vision-based posture recognition systems are gaining popularity for their non-intrusive, scalable, and cost-effective nature. These systems use monocular RGB cameras, depth sensors, or RGB-D systems to extract features from the human body, applying either pose estimation or object detection techniques.

Earlier systems relied on handcrafted features such as Histogram of Oriented Gradients (HOG) combined with traditional classifiers like Support Vector Machines (SVMs) to detect postural deviations such as slouching or lateral leaning. While computationally efficient, these approaches often lacked generalization across different body types and environments.

With the advent of deep learning, CNN-based architectures such as VGG, ResNet, and YOLO became standard. Hoefflin et al. [6], for example, used YOLOv5s to classify lateral sitting postures from side-view RGB images. Their model achieved a mAP50 of 93.1%, highlighting the capability of object detection networks for real-time ergonomic monitoring. However, their system was trained and evaluated on a high-performance GPU setup, making real-world deployment on embedded hardware impractical.

Keypoint-based models have also been used for fine-grained posture detection. Ji-sheng et al. [8] leveraged AlphaPose, a model based on YOLOv3, to identify nine seated postures from skeleton landmarks with 98.55% accuracy. Yang et al. [19] introduced a hybrid CNN model fusing VGG and ResNet architectures to classify six postures from frontal camera views. Despite their accuracy, these approaches typically require high-resolution input, powerful inference engines, or GPU-accelerated environments to meet real-time constraints. Some systems go a step further by integrating depth sensing using Intel RealSense or Microsoft Kinect to capture 3D posture data. These allow for improved joint angle estimation and body tracking in 3D space. However, such setups tend to be expensive, computationally intensive, and sensitive to lighting and occlusion, which restricts their usability in cost-sensitive or mobile environments.

While vision-based systems show great promise for real-time posture monitoring, their hardware demands, energy consumption, and focus on frontal-view analysis limit their effectiveness in embedded and personalized health monitoring contexts. These limitations motivate the need for a lightweight, edge-deployable system that can accurately detect lateral postural deviations in real time.

3.3 Commercial Applications and Hybrid Systems

In recent years, a variety of commercial solutions have emerged that combine sensor-based and vision-based techniques for posture monitoring. These hybrid systems aim to enhance reliability by leveraging multiple input modalities and often feature sleek user interfaces to attract consumer adoption. However, despite their innovation, many such systems come with notable constraints that limit their scalability, generalizability, or practicality for everyday users.

The Zami Smart Chair integrates pressure sensors into the seat and backrest and pairs them with a smartphone app that utilizes the device's camera to capture posture data. While the combination of pressure distribution and camera input allows for richer posture analysis, the system is inherently tied to the specific chair model. Users are required to place and orient their phone cameras correctly to achieve reliable tracking. This dependency on physical configuration introduces variability and limits the system's use outside its prescribed environment.

Similarly, the ErgoChair by Autonomous features built-in sensors to track recline and seating position. It connects to desktop software that provides real-time feedback, suggesting posture adjustments and reminding users to take breaks. While ergonomically beneficial, the solution is hardware-locked, expensive, and not portable. It also fails to offer detailed biomechanical insights such as spinal alignment or lateral deviations—critical for detecting asymmetric postures that lead to musculoskeletal disorders [16].

Fidgetware-based systems that use capacitive fabrics, force-sensitive textiles, or stretch sensors in chair covers offer an elegant passive monitoring alternative. These are unobtrusive and do not rely on user compliance.

However, such systems suffer from sensor drift, calibration issues, and difficulty in distinguishing subtle posture variations, especially lateral deviations. Furthermore, they often lack real-time visual context and require custom hardware fabrication, limiting their commercial scale and accuracy across user demographics.

Recent innovations have also seen posture analysis integrated into video conferencing platforms, especially in the era of remote work. These AI-enhanced systems analyze webcam footage to detect head tilt, forward lean, or shoulder imbalance. While they are easy to deploy, their reliance on frontal-view geometry, variable lighting conditions, and cloud-based inference raises privacy concerns, data latency, and limited field of view issues. Most importantly, they cannot effectively detect lateral leaning, which is a strong indicator of spinal asymmetry and poor ergonomic behavior.

While hybrid commercial systems represent progress in accessible posture correction, they are often cost-prohibitive, tied to proprietary hardware or insufficiently equipped to detect lateral asymmetries. These shortcomings highlight the urgent need for a low-cost, flexible, and real-time solution that is platform-independent and privacy-preserving.

3.4 Embedded and Lightweight Approaches

In recent years, the proliferation of edge-computing platforms such as the Raspberry Pi, NVIDIA Jetson Nano, and Google Coral has opened up new possibilities for low-power, real-time posture monitoring systems. These platforms offer sufficient processing power to run lightweight machine learning models locally, without reliance on cloud infrastructure. This shift toward edge computing is especially critical for privacy-sensitive applications like human pose tracking, where local inference eliminates the need to transmit personal data externally.

Among the most significant advancements in this space is MediaPipe [11], an open-source framework developed by Google for real-time perception pipelines. Its BlazePose module can detect 33 keypoints on the human body from a single RGB camera stream, allowing for detailed posture analysis including joint angles, body orientation, and limb alignment—all processed efficiently on CPU-only devices. Unlike traditional object detection models that rely on bounding boxes and high-resolution imagery, MediaPipe provides direct skeletal landmark extraction, making it ideal for deployment on embedded systems. This efficiency has enabled a range of real-world applications. For example, MediaPipe has been successfully implemented on Raspberry Pi 4 to develop yoga posture correction tools and slouch-detection systems for seated users [5]. These implementations deliver live feedback on posture quality, encouraging real-time self-correction without the need for expensive sensors or complex setups. Such systems demonstrate the viability and responsiveness of MediaPipe-based pose estimation in resource-constrained environments.

However, despite these successes, most existing edge-based posture applications focus predominantly on frontal-view analysis, such as detecting forward slouching or shoulder hunching. Lateral deviations such as leaning excessively to one side while seated—remain underexplored, even though they are known to cause spinal asymmetry, discomfort, and long-term musculoskeletal issues. Additionally, current solutions often lack portability, suffer from occlusion (in top-down or front-facing views) or are tailored to very specific postures like yoga asanas.

Recognizing these gaps, our project draws direct inspiration from the proven accuracy, efficiency, and portability of MediaPipe-based implementations, while pushing the boundaries further by focusing on lateral sitting posture detection from a side-view perspective. By deploying this system, we introduce a solution that remains entirely on-device, respects user privacy, and detects asymmetric postural behaviors in real time—bridging a key gap in existing embedded posture monitoring research. This approach not only extends the capabilities of lightweight vision systems but also lays the foundation for scalable and affordable ergonomic interventions across classrooms, offices and personal workspaces.

4 PROJECT AIM

This project aims to develop a real-time system for monitoring lateral sitting posture using the MediaPipe BlazePose model deployed on a Raspberry Pi 5 with the Logitech camera. The system extracts key upper-body landmarks to assess postural deviations such as shoulder misalignment, neck inclination, and torso tilt. By implementing the pipeline on a low-power edge device, the work demonstrates the feasibility of accurate, real-time posture assessment without reliance on high-end hardware. This approach aims to enable an affordable, portable and low-power solution for continuous posture monitoring in everyday environments, thereby contributing to the prevention and management of musculoskeletal disorders associated with poor sitting posture.

5 METHODOLOGY

This section outlines the design and logic behind the proposed posture monitoring system, which classifies seated postures as either good or bad based on body landmark analysis. The system is built on MediaPipe's Pose estimation framework and leverages real-time video input from a camera or pre-recorded video source.

5.1 System Objectives

The primary objective of the system is to provide real-time feedback on lateral sitting posture by analyzing alignment and inclination of specific upper body landmarks. The system detects and classifies posture status using geometric calculations and time-based thresholds to determine whether a user maintains ergonomic sitting behavior.

5.2 Hardware and Platform

The system was initially developed and tested on a Windows 11 laptop using the integrated webcam. It was further designed for deployment on edge-computing platforms, specifically a Raspberry Pi 5 paired with the Logitech camera, enabling low-power, real-time inference at the edge.

5.3 Software Stack

The system is implemented in Python 3.10, utilizing the following libraries:

- MediaPipe (v0.10.8) for pose detection and landmark tracking.
- OpenCV (v4.8.1) for video frame capture, image processing, and visualization.
- NumPy, math, and sounddevice for numerical operations and audio feedback.

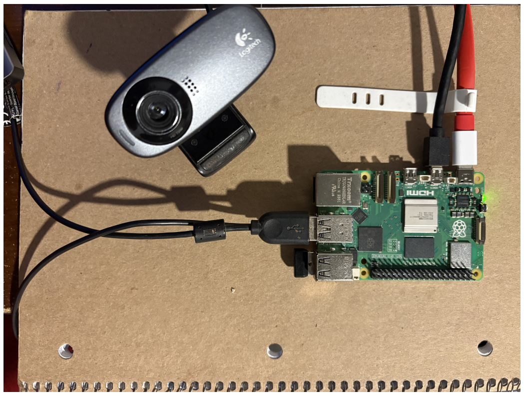

Fig. 1. Hardware Setup

MediaPipe provides a CPU-efficient pipeline, making it suitable for embedded platforms like the Raspberry Pi.

5.4 Landmark Detection and Measurement

The system extracts 33 upper-body landmarks per frame using MediaPipe's Pose solution. For posture assessment, keypoints from the left and right shoulders, ears and hips are utilized. From these, the system computes:

- Shoulder Offset: the Euclidean distance between the left and right shoulders, used to assess lateral symmetry.
- Neck Inclination Angle: the angle between the shoulder and ear landmarks relative to the vertical axis.
- Torso Inclination Angle: the angle formed between the hip and shoulder, also relative to the vertical.

5.5 Posture Classification

The classification into "good" or "bad" posture is based on geometric thresholds. The system uses default thresholds if not specified by the user. If the neck inclination angle exceeds 25 degrees or the torso inclination angle exceeds 10 degrees, the system labels the posture as bad. Otherwise, the posture is classified as good.

These threshold values are adjustable parameters and the default values were empirically derived based on preliminary testing [15].

5.6 Temporal Analysis and Alerting

To monitor prolonged posture patterns, the system tracks the duration of consecutive bad posture frames. If a user maintains bad posture for a cumulative duration exceeding a predefined time threshold (default: 180 seconds), a warning is issued. Conversely, when posture is corrected, the timer resets.

5.7 Performance Monitoring

For platform comparison, the system implements real-time performance monitoring using the following metrics:

- `FPS (Frames Per Second)`: Calculated as:

$$\text{FPS} = \frac{1}{t_{\text{frame}}}$$

where $t_{\text{frame}} = t_{\text{process}} + t_{\text{render}}$ is measured using OpenCV's high-resolution timestamps:

$$t_{\text{start}} = \texttt{cv2.getTickCount()}$$
$$t_{\text{frame}} = \frac{\texttt{cv2.getTickCount()} - t_{\text{start}}}{\texttt{cv2.getTickFrequency()}}$$

Processing time (t_{process}) includes landmark detection and posture classification, while rendering time (t_{render}) covers visualization operations. A 10-frame moving average smooths transient fluctuations.

- `CPU%`: Sampled at 1Hz using:

$$\text{CPU\%} = \frac{\Delta t_{\text{CPU}}}{\Delta t_{\text{wall}}} \times \frac{100}{N_{\text{cores}}}$$

Implemented via `psutil.cpu_percent(interval=1.0)`. For Raspberry Pi's ARMv8 architecture, this reports single-process utilization due to architectural constraints, while on x86 systems it measures system-wide utilization.

- `RAM (MB)`: Working set memory calculated as:

$$\text{RAM (MB)} = \frac{\texttt{psutil.Process().memory\_info().rss}}{1048576}$$

where RSS (Resident Set Size) represents non-swapped physical memory. This excludes shared libraries to isolate application-specific consumption.

This instrumentation enables quantitative comparison of computational efficiency between edge (Raspberry Pi - ARM) and desktop (x86) platforms, particularly regarding MediaPipe's pose estimation overhead under different hardware constraints.

6 IMPLEMENTATION

This section details the operational characteristics and deployment modes of the posture monitoring system.

6.1 Input Modes

The system supports two modes of operation:

- Real-time Monitoring: Captures frames from a webcam or an external camera for immediate posture analysis.
- Offline Evaluation: Processes pre-recorded video files, useful for retrospective ergonomic studies.

Frame capture is handled using OpenCV's cv2.VideoCapture() API, with configurable input sources.

6.2 User Configurable Parameters

To ensure adaptability across different user profiles and environmental setups, the system provides configurable parameters that can be set via command-line arguments in the Python script. These thresholds influence how posture is interpreted and allow users to calibrate the system based on camera perspective, user body dimensions, or specific ergonomic guidelines. The customizable parameters are:

- Video Source (–video): This parameter specifies the input stream for posture monitoring. A value of 0 initializes the system with a live webcam or the external USB camera feed. Alternatively, the user can provide a file path to a pre-recorded video (e.g., –video sample.mp4) for offline analysis.

- Offset Threshold (–offset-threshold): This value sets the maximum acceptable vertical offset between the left and right shoulder landmarks, used to infer lateral misalignment. A higher value makes the system more tolerant to minor asymmetries, while a lower value enforces stricter posture evaluation. Typical values range from 50 to 150 pixels depending on the camera resolution and distance.
- Neck Angle Threshold (–neck-angle-threshold): This angle (in degrees) sets the upper limit for acceptable neck inclination relative to the vertical axis. Values exceeding this threshold are considered indicative of forward head posture or slouching. The default value is 25°, but this can be adjusted based on ergonomic standards or user comfort.
- Torso Angle Threshold (–torso-angle-threshold): Similar to neck inclination, this parameter defines the acceptable range for torso tilt relative to the vertical. Deviations beyond this threshold typically suggest slumping or leaning. The default is set to 10°, but it may be relaxed in cases of more dynamic or non-rigid sitting environments (e.g., soft chairs).
- Time Threshold (–time-threshold): This parameter determines the time duration (in seconds) after which a sustained bad posture triggers an alert. It defines how tolerant the system is to transient slouching. For example, a –time-threshold 180 means the posture must be continuously bad for 3 minutes before raising a warning. This helps prevent false positives caused by temporary movements or shifts.

These adjustable parameters provide flexibility and control, allowing the system to be tailored to a variety of physical setups and user ergonomics. The use of command-line arguments enables rapid experimentation and deployment without the need to modify source code, supporting both usability and extensibility.

6.3 Visualization and Feedback

For each frame processed by the system, a comprehensive visual overlay is rendered on the video output to provide intuitive and actionable feedback to the user. This includes the following elements:

- **Pose Landmarks and Skeletal Connections:** Using MediaPipe's pose estimation module, the system tracks 33 anatomical keypoints. On-screen visualizations display specific landmarks (for example, shoulders, ears, hips) along with connecting lines that represent anatomical segments such as the neck and torso. This skeletal visualization assists the user in understanding posture alignment in real-time.
- **Inclination Angle Annotations:** The system computes the neck and torso inclination angles based on geometric relationships between relevant keypoints. These angles are superimposed numerically on the live video feed near the corresponding joints. They serve as quantitative indicators of posture deviation.
- **Posture Classification with Color Coding:** Each frame is classified into one of two posture categories: good or bad. This classification is determined by evaluating whether the measured inclination angles exceed predefined thresholds. The classification is reflected using color-coded annotations: green indicates good posture and red indicates bad posture. These visual cues allow for immediate posture assessment without requiring textual interpretation.
- **Cumulative Posture Duration:** The system tracks the duration for which the user remains in either posture category. The current duration (in seconds) is displayed prominently on the frame, enabling users to observe trends and identify prolonged poor posture episodes. This temporal feedback is essential in raising awareness of habitual slouching.
- **Performance Metrics Display**: System vitals are shown in the top-right corner with dynamic color coding
- **Data Logging Implementation:** Performance metrics and posture classification results are recorded to CSV files for offline analysis.

Collectively, these visual elements promote user engagement and encourage self-correction. The system thus functions not only as a diagnostic tool but also as a real-time biofeedback mechanism for posture rehabilitation.

6.4 Embedded Development

To demonstrate the system's portability and viability in edge computing environments, the posture monitoring pipeline was deployed on a Raspberry Pi 5 equipped with an external USB Logitech camera. This configuration supports a compact, cost-effective, and power-efficient implementation suitable for continuous monitoring in resource-constrained settings such as study desks, classrooms, or rehabilitation centers.

The deployment leverages the optimized, CPU-only pipeline provided by MediaPipe, which eliminates the need for external GPU or TPU acceleration. MediaPipe's BlazePose model is lightweight enough to run on the Raspberry Pi's ARM Cortex-A76 processor cores in real-time, enabling live inference at acceptable frame rates. This efficiency allows for real-time landmark detection, posture classification, and visual feedback without compromising responsiveness.

Moreover, the use of Raspberry Pi OS (64-bit) and Python 3 ensured seamless integration with the existing OpenCV and MediaPipe libraries. The same posture analysis script used on the Windows desktop platform was reused with minimal modification, highlighting the cross-platform compatibility of the system architecture.

This embedded setup validates the feasibility of deploying posture correction systems on affordable consumer-grade hardware, opening up possibilities for scalable, decentralized health and ergonomic monitoring solutions.

7 RESULTS AND DISCUSSION

The proposed posture monitoring system was evaluated based on its accuracy in detecting inclination angles, robustness under varying conditions, and performance across two different hardware platforms: a Windows 11 laptop and a Raspberry Pi 5.

7.1 Angle Estimation Accuracy

The system achieves a neck and torso inclination angle measurement precision of approximately ±2°, which is sufficient for distinguishing between upright and slouched postures in most users. The

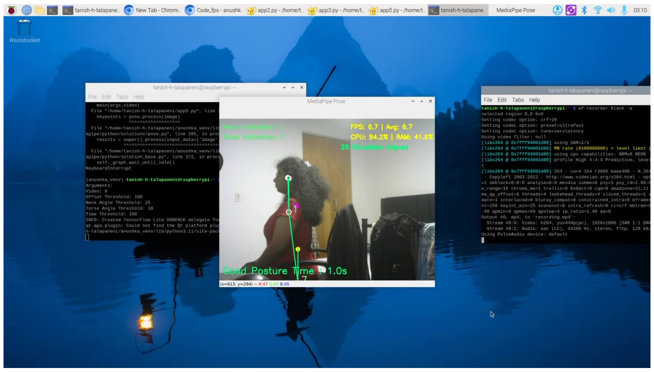

Fig. 2. Validated "good posture" classification in Raspberry Pi 5 hardware setup. Keypoints (spine curvature, shoulder alignment, ear-over-shoulder) correctly identified and validated against ergonomic standards.

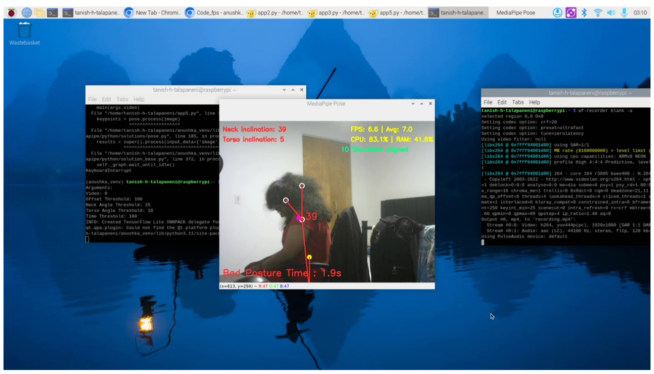

Fig. 3. Validated "bad posture" classification using Raspberry Pi 5 hardware. Keypoints accurately detected but reveal ergonomic deviations

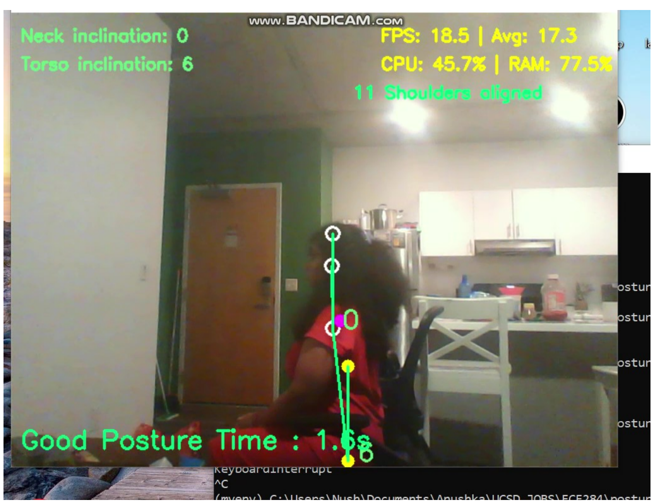

Fig. 4. Validated "good posture" classification during code execution on laptop hardware. Keypoints confirm ergonomic alignment

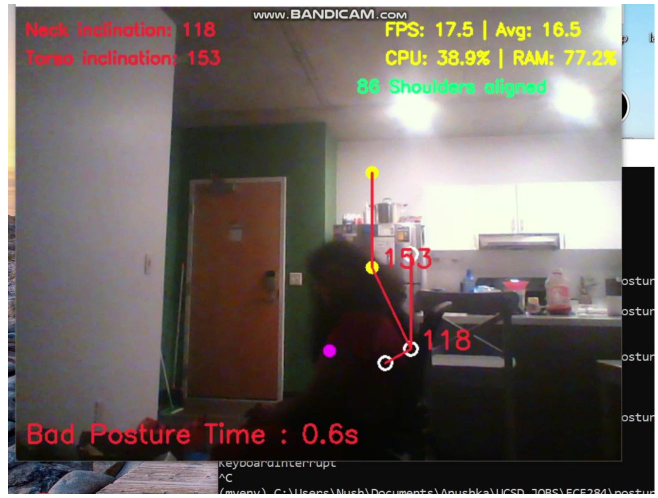

Fig. 5. Lateral sitting posture under suboptimal illumination. Keypoint detection failure due to low contrast, demonstrating lighting dependency in monocular pose estimation [8]

angles are calculated using Euclidean vectors between key body landmarks detected by MediaPipe.

7.2 Robustness and Limitations

- **Lighting Sensitivity:** Under low illumination, the system often fails to detect the required keypoints, leading to misclassifications or dropped frames [8]. This limits deployment in poorly lit environments.
- **User-Specific Thresholds:** The system's angle-based thresholds are static and not personalized. User needs to select the thresholds wisely for accurate posture classification. Due to variations in torso length and shoulder-to-neck proportions [16], what may be good posture for one user may be misclassified as bad for another.
- **Orientation Limitation:** The posture monitoring algorithm is designed for lateral (side-facing) postures. Front-facing postures are frequently misclassified due to reduced depth cues and symmetry in shoulder landmarks [17].

7.3 Hardware Deployment Comparison

The posture monitoring system was tested on both a Raspberry Pi 5 (equipped with a Logitech camera module) and a Windows 11 laptop with an Intel i5 processor. The table below summarizes key performance metrics:

Metric	Raspberry Pi 5	Windows 11 Laptop
Average FPS	7	18
CPU Usage	80% (dedicated to script)	42% (system-wide)
RAM Usage	42%	78%

Table 1. Performance Comparison between Embedded and Desktop Deployment

Note: On the Raspberry Pi, CPU usage reflects the portion of the total processing capacity utilized solely by the posture monitoring script, as it is the only major active process on the board. In contrast, on the Windows laptop, CPU usage is system-wide and includes background processes like the operating system, services, and unrelated applications. Hence, laptop CPU metrics can underrepresent the script's actual computational demand.

The results presented in Table1 highlight the performance tradeoffs between embedded and desktop deployments of the real-time posture monitoring system.

As expected, the Windows 11 laptop outperformed the Raspberry Pi 5 in terms of average frame rate (FPS), achieving 18 FPS compared to 7 FPS on the Raspberry Pi5. This is primarily due to the laptop's more powerful processor, higher clock speeds, and better memory bandwidth, allowing for smoother and faster video processing and inference using MediaPipe.

However, the Raspberry Pi's CPU usage was significantly higher at 80%, which reflects that the script is utilizing a substantial portion of the available processing power. Since the script is the only active high-compute task running on the Pi, this metric represents its dedicated usage. In contrast, the laptop reported lower CPU usage at 42%, but this is a system-wide measure that includes all active processes. Therefore, it likely underestimates the true share of resources consumed by the posture script alone.

Interestingly, RAM usage on the Raspberry Pi was also lower at 42% compared to 78% on the laptop. This aligns with our expectations: the Raspberry Pi runs a minimal operating system with fewer background services and GUI processes, allowing more efficient use of memory. On the laptop, background services from Windows, in addition to the GUI overhead and other applications, contribute to a higher baseline memory usage.

Overall, the results validate the feasibility of deploying the system on a resource-constrained embedded platform like the Raspberry Pi 5, with acceptable performance under real-time constraints. The lower FPS on the Raspberry Pi is still sufficient for posture analysis, given that posture changes occur relatively slowly. This makes the embedded setup a compelling option for low-cost, continuous posture monitoring in home or office environments, while the desktop deployment remains suitable for higher-resolution, faster-feedback applications.

8 CONCLUSION

This paper presented a lightweight, real-time posture monitoring system designed for prolonged sedentary environments, leveraging computer vision and edge computing. By using MediaPipe's pose estimation framework [5], the system effectively identifies key skeletal landmarks and computes critical angles—such as neck and torso inclination and shoulder alignment—to classify posture into two intuitive categories: good and bad.

Implemented on both a Windows 11 laptop and an embedded Raspberry Pi 5 system, the solution offers cross-platform flexibility. The laptop deployment achieves higher frame rates and smoother video feedback, while the Raspberry Pi version demonstrates sufficient real-time performance for low-power, always-on posture monitoring, making it ideal for continuous health tracking in homes and workplaces. The system's configurable thresholds allow adaptation to various body types and seating arrangements, and the visual feedback interface encourages user-driven correction without external prompts.

Quantitative results showed that the system maintains an angular error margin within ±2°, proving adequate for practical applications. Nevertheless, limitations such as misclassification under poor lighting and inability to reliably detect posture in front-facing views highlight areas for refinement. Overall, the proposed system demonstrates a scalable and affordable alternative to expensive ergonomic solutions, fostering greater accessibility to posture correction tools.

9 FUTURE WORK

While the current system successfully supports lateral posture monitoring in seated positions, several enhancements can broaden its applicability and robustness:

- **Support for Standing Postures:** Future iterations will incorporate detection of poor posture while standing, including slouching, uneven shoulder alignment, and forward head posture. This will enable comprehensive posture tracking throughout various daily activities.
- **Multi-View Support:** Current limitations in front-facing posture classification will be addressed by leveraging 3D pose estimation [19] to improve robustness across different viewing perspectives.
- **User Calibration Module:** Since optimal posture thresholds can vary based on individual anthropometry, a one-time calibration step could allow the system to adapt dynamically to each user's body proportions. This would reduce misclassifications and improve accuracy.
- **Application-Specific Posture Templates:** Tailoring posture evaluation for specific use-cases—such as students in classrooms, professionals at workstations, or gamers—can allow context-aware monitoring. For example, a template for a typing position may prioritize wrist and neck alignment, while a gaming posture template may include head tilt and screen distance.
- **Longitudinal Health Tracking:** Beyond real-time alerts, extending the system to track long-term posture trends and generate personalized reports could offer valuable insights for users and physiotherapists alike.

These future directions aim to make the system more adaptive, accurate, and applicable to diverse scenarios, ultimately contributing to better musculoskeletal health through accessible technology.

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