

Sitting Posture Corrector App on Raspberry Pi Using Edge AI

A realtime posture correction system

Pranav, Shreyas, Ashwin, RONALDA, Veningston

ACM India Winter School on Edge AI (Hackathon) @ IISc, Bangalore

January 4, 2026

Problem

- Works **on-device**
- Single camera in a **side view**.
- **MoveNet (TFLite)** estimates 17 body keypoints in real time.
- A calibrated scoring module maps posture deviation to **Score** $\in [0, 100]$.
- Raises **warning** to indicate **Good** / **Bad** posture.
- Moreover, we also suggest the reason for the bad posture to help identify corrective measures.

Problem

- Posture refers to the natural way one holds their body.
- In this project, we are analyzing desk posture, specifically through 2 parameters,
 - ① Neck Slouch
 - ② Torso Slouchthrough a side view camera and a Raspberry Pi.
- Goal: Detect sitting posture in real time and provide **actionable feedback** using a **0–100 score** and **warning**.
- We also aim to track **Focus Time** and **Idle Time** and alert the user about the same.

System Overview

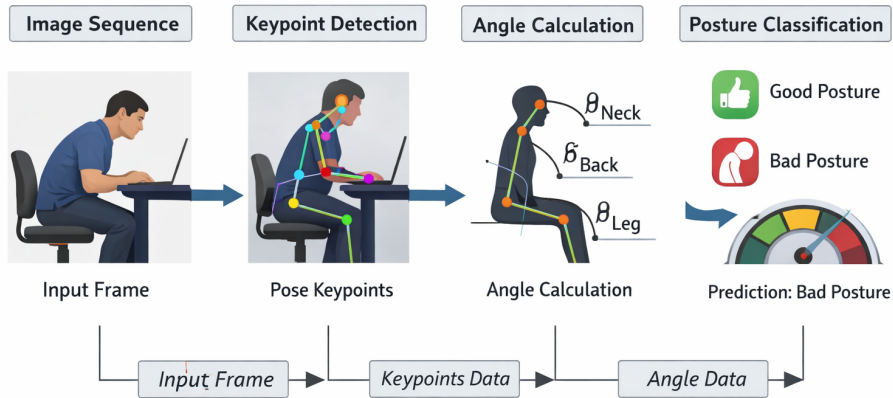


Figure 1: End-to-end pipeline for posture monitoring in side view: input video frames → MoveNet keypoint extraction → angle computation → posture prediction and score visualization.

- **Edge device:** Raspberry Pi (camera)
- **Compute:** On-device inference with `tflite_runtime`
- **Privacy:** Video stays local; only score/warning output leaves the pipeline

Pose Estimation with MoveNet

MoveNet outputs keypoints

$$\text{KP} = \{(x_i, y_i, c_i)\}_{i=1}^{17}$$

where, x_i, y_i, c_i are normalized coordinates and confidence. Interest points from head, shoulder, hip.

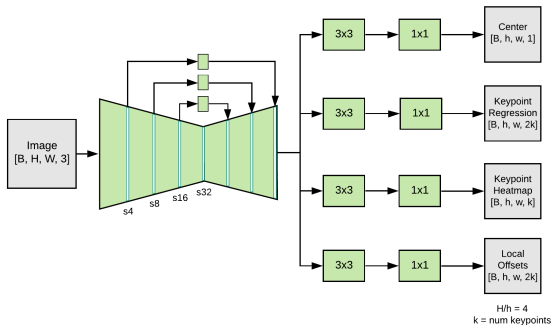


Figure 2: MoveNet Architecture

Calibration & Scoring Configuration [1/3]

Runtime & Keypoint Settings

- Frame resolution: **640×480**, frame rate: **30 FPS**
- Minimum keypoint confidence: $c_{\min} = 0.3$ (ignore low-confidence joints)
- Time scaling for testing: **TIME_RATE = 30.0** (accelerated evaluation)

Alert & Session Timing

- Bad posture alert after sustained deviation: **10 s**
- Idle alert after continuous sitting/standing: **30 min**
- Focus session minimum duration: **5 min**

Angle Calibration (Reference Ranges)

- **Neck angle** (ear–shoulder–hip):

$$\text{NECK_MIN} = 130^\circ, \text{NECK_OPT} = 180^\circ, \text{NECK_MAX} = 200^\circ$$

- **Torso angle** (shoulder–hip–knee):

$$\text{TORSO_MIN} = 45^\circ, \text{TORSO_OPT} = 90^\circ, \text{TORSO_MAX} = 135^\circ$$

Degrees change to count as head movement

- Movement-change thresholds (to detect activity):

$$\Delta\theta_{\text{head}} \geq 10^\circ, \quad \Delta\theta_{\text{leg}} \geq 10^\circ$$

Final Posture Score (0–100)

$$\text{Score} = W_{\text{neck}} \cdot S_{\text{neck}} + W_{\text{torso}} \cdot S_{\text{torso}}, \quad W_{\text{neck}} = 0.5, \quad W_{\text{torso}} = 0.5$$

Good posture if Score \geq **75**

Algorithm Outline

- 1 Capture frame, preprocess to MoveNet input size.
- 2 Run MoveNet inference \rightarrow keypoints $\{(x_i, y_i, c_i)\}$.
- 3 Apply confidence gating; compute head/shoulder/hip and other midpoints.
- 4 Extract angle features: neck flexion, torso slouch.
- 5 Drive ALERT based on Score and hold time.

Resource Footprint (CPU & RAM)

- Measure CPU utilization and RAM usage.
- Report peak RAM and average CPU load.

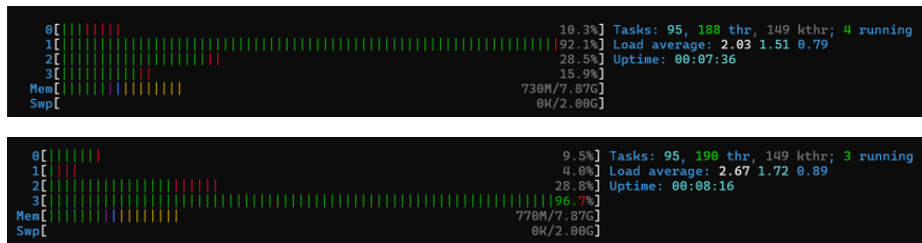


Figure 3: Memory Footprint (No Inference vs. With Inference)

End-to-End Dataflow of the Mobile App

- ❶ **Periodic Activity Logging on RPi** - The posture monitoring pipeline runs continuously to record **activity log every 10 seconds** and **append locally to CSV files** to enable lightweight storage and offline availability.
- ❷ Flask server running on Rpi serves this data as JSON responses using a custom API.
- ❸ The **Flutter-based Mobile App** periodically requests the JSON data over the local network (Wi-Fi/hotspot), parses the response, and visualizes user activity in a dashboard.
 - Posture score trends over time,
 - Good vs. bad posture duration summaries,
- ❹ **End-to-End Data Flow**

Pose & Scoring (RPi) → CSV Logs (every 10s) → Flask API (JSON) → Mobile App → Dashboard

- EdgeAI posture corrector runs locally on Raspberry Pi with real-time feedback.
- Calibration enables robust scoring under a single camera view.

- Multi-view posture estimation (for true 3D triangulation).
- Upgrade from single-person MoveNet to a multi-person pose pipeline (detect persons → run pose per ROI)
- Expand classes (e.g., asymmetric sitting, phone neck).



BBC News.

"Sitting straight 'bad for backs" (BBC News, 2006).

<http://news.bbc.co.uk/2/hi/6187080.stm>.



Yi-Lang Chen et. al.,

"Postural Variabilities Associated with the Most Comfortable Sitting Postures: A Preliminary Study".

Healthcare (Basel), 6;9(12):1685, 2021.

<https://doi.org/10.3390/healthcare9121685>.



Yuri Kwon et. al.,

"The effect of sitting posture on the loads at cervico-thoracic and lumbosacral joints".

Technol Health Care. 26(Suppl 1):409–418., 2018.

<https://doi.org/10.3233/THC-174717>.



Donald D et. al.,

"Sitting biomechanics Part I: Review of the Literature".

Journal of Manipulative and Physiological Therapeutics, Vol 22(9), 594-609, 1999.

[https://doi.org/10.1016/S0161-4754\(99\)70020-5](https://doi.org/10.1016/S0161-4754(99)70020-5).



Oana-Ruxandra Stincel et. al.,

"Assessment of Forward Head Posture and Ergonomics in Young IT Professionals – Reasons to Worry?" .

Med Lav. 114(1), 2023.

<https://doi.org/10.23749/mdl.v114i1.13600>.



David A Titcomb et. al.,

"Evaluation of the Craniovertebral Angle in Standing versus Sitting Positions in Young Adults with and without Severe Forward Head Posture".

Int J Exerc Sci. 17(1):73–85., 2024.

<https://doi.org/10.70252/GDNN4363>.



Dae-Hyun Kim et. al.,

"Neck Pain in Adults with Forward Head Posture: Effects of Craniovertebral Angle and Cervical Range of Motion".

Osong Public Health Res Perspect. 9(6):309–313, 2024.

<https://doi.org/10.24171/j.phrp.2018.9.6.04>.



Physio-Pedia.

"Craniovertebral angle".

https://www.physio-pedia.com/Craniovertebral_angle.

Thank you!

Questions?