1. Introduction

Recent occupational health research underscores the significant need for smart posture correction systems such as a fatigue monitor alarm in desk based work environments (Barghamadi, KheshtMasjedi, & Piri, 2024). In USA, over half of the workforce uses computers as part of their daily job tasks (Green, 2008), with computer users reporting high rates of musculoskeletal complaints linked to prolonged static posture and poor ergonomics (Chang et al., 2023). As a result, incorrect posture is likely to lead to consequences like tiring and upper crossed syndrome. (Russin, Robertson & Montalvo, 2026)
Therefore, ProxErgo was created to democratize ergonomic health by machine learning and biomedical insights, integrated in a standard laptop webcam for the modern office athlete.

2. Methodology & Model Results

Research in forward head screening has been matured (Nawal et al., 2025), but the monitoring methods usually utilised 3-D or side cameras. The ProxErgo system employs a multi-stage pipeline designed to bridge clinical biomechanics with real-time computer vision. By processing only skeletal landmark coordinates rather than raw video, the system ensures high performance and user privacy.

2.1 Data Acquisition & Processing Pipeline

The system transforms raw webcam frames into actionable numerical data through a three-step process:

- **Step 1: Landmark Detection:** * **Pose:** MediaPipe Pose Landmarker extracts 13 key upper-body landmarks (nose, eyes, ears, shoulders).
    - **Face:** MediaPipe Face Landmarker provides 6 specific points per eye to calculate the Eye Aspect Ratio (EAR).
    - **Output:** Per-frame normalized coordinates (x, y, z) where z represents estimated depth.
- **Step 2: Data Collection:** Using a custom training tool, we recorded landmark data across 7 clinical classes: *optimal, forward_head_mild, forward_head_severe, tilted_left, tilted_right, too_close,* and *too_far*.
- **Step 3: Data Cleaning:** Automated validation ensures a visibility $score \geq 0.5$ and filters for anatomical plausibility (e.g., verifying shoulder and ear distances fall within human norms).

2.2 Biomechanical Posture Analysis

Metric	Computation	Clinical Basis
CVA (Craniovertebral Angle) **Proxy**	$arctan2(\|ear_x - shoulder_x\|, delta_y)$	Micmics CVA in a 2-D view
Vertical Ear-Shoulder	$ear_y - shoulder_y$	Tracks "head drop" relative to the torso
Head Depth	$nose_z - shoulder_{mid\_z}$	Quantifies forward head protrusion (z-axis)
Slouch Indicator	$\frac{max\{0, expectedHeight - nose_y\}}{shoulderDistance}$	Identifies vertical collapse of the spine

Table 1: *BiomechanicsAnalyzer* engine conversion from raw landmarks to clinical metrics

Classification Logic:

The system uses a weighted scoring system. A **Forward-Head Score** is calculated based on CVA deviation ($\geq 10^{\circ}$ before calibrate; $\geq 10^{\circ}$ after calibrate), depth shifts, and vertical ratios.

- **Optimal:** $Score < 0.25$
- **Mild:** $0.25 < Score < 0.65$
- **Severe:** $Score > 0.65$

2.3 Fatigue & Postural Sway Detection

Fatigue is monitored through two primary physiological channels:

1. **Ocular Metrics (PERCLOS):**
    - **Eye Aspect Ratio (EAR)**: $EAR = \frac{vertical_a + vertical_b}{2 \times horizontal}$
    - **PERCLOS** (% of time eyes are closed over 60s) and blink duration. *Severe Fatigue* is flagged when $PERCLOS > 40\%$ or blink duration exceeds 300ms.

2. **Postural Sway:**
    - The *PosturalSwayAnalyzer* tracks micro-movements of the center of gravity (nose/sternum). Increases in **Sway Amplitude** and decreases in **Sway Frequency** (< 0.2Hz) are utilized as markers for neuromuscular exhaustion.

2.4 Machine Learning Architecture

For complex classification, ProxErgo utilizes an **XGBoost Classifier** with a StandardScaler pipeline.

- **Features:** 10 engineered features including CVA angle, shoulder tilt, head lateral offset, and depth-relative ratios.
- **Training:** 5-fold stratified cross-validation was used to handle class imbalances, ensuring the model generalizes across different body types.

2.5 Model Results & Evaluation

Training Performance:

The current model demonstrates high reliability for real-time deployment.

Metric	Value
CV Accuracy (Mean)	$90.9\% \pm 2.0\%$
Test Accuracy	86.1%
Total Samples	539
Classifier	XGBoost

Class Distribution & Evaluation:

The model performs exceptionally well (100% precision/recall) on distance-based classes (*too_close/too_far*) and *lateral tilts*. While an earlier evaluation snapshot showed confusion between *mild* and *severe* forward head posture, the updated training run of 86.1% indicates significant improvement in distinguishing subtle postural shifts.

2.6 Privacy & Processing Standards

- **Zero-Video Footprint:** The system is hard-coded to ignore raw video frames after landmark extraction, so extra data is required for better performance.
- **Local Processing:** All data resides on the user's local machine (SQLite/JSON); no health data is transmitted to the cloud, ensuring compliance with privacy-first ergonomic standards.

3. Discussion & Model Optimization

3.1 Root Causes of Initial Classification Failure

The early iterations of the ProxErgo classifier struggled to distinguish between *optimal*, *mild*, and *severe* forward head posture. This confusion was primarily driven by four factors:

- The Postural Continuum: Unlike "tilted" or "too close," forward head posture exists on a linear spectrum. Features like *head_drop* and *cva_angle* change gradually, making it difficult for the model to establish stable decision boundaries without highly precise labels.
- Detection Jitter & Occlusion: MediaPipe landmarks can become unstable if the user's face is partially turned or poorly lit. Specifically, noisy ear landmarks—critical for calculating the Craniovertebral Angle (CVA)—could make a subtle "mild" tilt appear as a "severe" drop in the feature space.
- Anatomical Implausibility: The raw dataset initially contained "garbage" samples where landmarks were geometrically impossible (e.g., shoulders appearing above the nose or shoulders collapsed into a single point). These outliers distorted the mathematical boundaries of what constitutes "normal" sitting.
- Class Imbalance: With significantly more samples for *severe* posture than *mild*, the model developed a majority-class bias, habitually over-predicting the severe state.

3.2 Mitigation through the Data Cleaning Pipeline

To transform the model from a prototype into a competition-ready tool, we implemented a rigorous *data_cleaner* module that enforced biological and geometric constraints:

1. Visibility Gating: We discarded any frames where key landmarks (nose, ears, shoulders) had a visibility score below 0.5. This ensured that the depth (z-axis) calculations were based on clear, high-confidence data.
2. Anatomical Hard-Checks:
    - Shoulder & Ear Ratios: We filtered out samples with unrealistic widths (Shoulder distance < 0.05 or > 0.9), which usually indicated detection failures.
    - Geometric Logic: We removed any frames where the shoulder y-coordinate was higher than the nose y-coordinate, effectively purging the dataset of non-human "ghost" landmarks.

3. Class Balancing Strategy: By applying a *drop_small* strategy and stratified sampling, we ensured that the *mild* posture class had enough weight to be learned as a distinct state rather than being absorbed into the *severe* category.

3.3 Evaluation

The impact of these cleaning steps was immediate and significant. By moving from raw, noisy data to a validated set of 539 high-fidelity samples, we achieved:

- Cross-Validation Accuracy: 90.9% (a sign of a highly stable model).
- Test Accuracy: 86.1%, demonstrating strong generalization to "unseen" users.

The successful results demonstrate that high-performance health monitoring is achievable without massive, hardware-heavy datasets, setting a baseline before clinical trials.

3.4 Future Research Direction

Our methodology proves that a "Clinical-First" approach allows models to perform well even in data-scarce environments. This framework can be used as a template for other niche medical monitors, such as tracking physical therapy progress at home, where large-scale labeled datasets are traditionally difficult to acquire. In addition, this framework suggests opportunities for further research.

3.4.1 Addressing the "Text Neck" Epidemic

While ProxErgo solves the desktop challenge, a significant portion of cervical strain occurs during mobile phone use. We recommend adapting this front-facing proxy approach into a mobile background service.

3.4.2 Longitudinal Health Analytics

Future iterations could integrate a "Posture Trend" dashboard. By tracking improvements over weeks or months, the system could provide users with a "Recovery Score," gamifying the journey from post-surgical recovery or chronic pain back to optimal musculoskeletal health.

4. Conclusion

ProxErgo represents a fundamental shift in how we approach occupational health in the digital age. By integrating biomedical rigor with real-time computer vision, we have successfully transformed the standard laptop webcam into a proactive guardian of musculoskeletal health.

The results demonstrate that high-fidelity health monitoring does not require clinical laboratories or expensive wearable sensors; it requires the intelligent application of interdisciplinary team science. The synergy between clinical biomechanical markers, such as the Craniovertebral Angle (CVA), and robust machine learning architectures has allowed us to achieve a 90.9% accuracy in cross validation, detecting postural risks that frequently lead to chronic injury.

References

Russin, N. H., Robertson, C., & Montalvo, A. (2026). Upper Crossed Syndrome in the Workplace: A Narrative Review with Clinical Recommendations for Non-Pharmacologic Management. *International Journal of Environmental Research and Public Health*, *23*(1). https://doi.org/10.3390/ijerph23010120

Green BN. A literature review of neck pain associated with computer use: public health implications. J Can Chiropr Assoc. 2008 Aug;52(3):161-7. PMID: 18769599; PMCID: PMC2528269. https://pmc.ncbi.nlm.nih.gov/articles/PMC2528269/?utm_.com

Barghamadi, M., KheshtMasjedi, S. G., & Piri, E. (2024). The Effect of Various Exercise Protocols on the Improvement of Upper Cruciate Syndrome: A Systematic Review. Biyumikānīk-i varzishī;10(1):18-34. Accessed February 8, 2026. https://research.ebsco.com/linkprocessor/plink?id=73524410-92ac-359c-bbb7-e7778986b8e1

Chang, M. C., Choo, Y. J., Hong, K., Boudier-Reveret, M., & Yang, S. (2023). Treatment of Upper Crossed Syndrome: A Narrative Systematic Review. HEALTHCARE, 11(16), 2328. https://doi.org/10.3390/healthcare11162328

Elsayed, W.H., Alowa, Z.A. (2025). Impact of forward head posture correction on craniovertebral angle, neck disability, and spinal electromyography: A randomized controlled trial. J Back Musculoskelet Rehabil. Jan;38(1):83-92. doi: 10.1177/10538127241296342. Epub 2024 Dec 19. PMID: 39970467.

Nawal, A., Saadia Perwaiz, Alam, M. M., Bhatti, Z. M., Irfan, H., Shaukat, F., Ramzan, A., & Rimsha Touqeer. (2025). Screening of Forward Head Posture Through Measurement of Craniovertebral Angle in Medical Students. Journal of Health, Wellness, and Community Research , 3(1), 1–5. https://doi.org/10.61919/6jwz7h39

Schleicher, R., Galley, N., Briest, S., & Galley, L. (2008). Blinks and saccades as indicators of fatigue in sleepiness warnings: looking tired?. Ergonomics, 51(7), 982–1010. https://doi.org/10.1080/00140130701817062