Intelligent Dual-Leg Wearable for Early Arthritis Screening via Gait Analysis and On-Device Machine Learning

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Abstract: Early identification of arthritis can markedly improve long-term mobility and clinical outcomes. This paper reports the design and proof-of-concept evaluation of a low-cost, 3D-printed, knee-mounted wearable that screens for early signs of arthritis from gait. The system comprises two compact modules—one on each leg—each integrating an ADXL335 tri-axial accelerometer and an Arduino Nano 33 BLE microcontroller. The modules acquire and wirelessly stream bilateral gait signals in real time, enabling continuous assessment of walking behaviour. Models are trained with Google's Tiny Motion Trainer and deployed for on-device inference to classify gait into three clinically meaningful categories: "No Arthritis", "Moderate Arthritis", and "Major Arthritis". A mobile interface provides live visualisation and logging, while multimodal biofeedback—via a buzzer, vibration motor and NeoPixel indicator—alerts users to abnormal patterns and encourages corrective action during everyday ambulation. The prototype demonstrates stable data acquisition, reliable Bluetooth Low Energy transmission and responsive, real-time classification, highlighting the feasibility of combining wearable sensing, TinyML and biofeedback for preventive musculoskeletal care. This work motivates larger studies to validate diagnostic performance across diverse populations and to refine feature extraction and model tuning for robust, at-home screening and rehabilitation support.

Keywords: *Arthritis Detection, Wireless Health Monitoring device, Machine Learning, Gait Analysis*

1. Introduction

Osteoarthritis (OA) is the most common form of arthritis and a leading cause of pain and disability worldwide. Recent Global Burden of Disease estimates suggest that in 2020 roughly 595 million people—about 7.6% of the world's population—were living with OA, with cases projected to rise sharply by 2050 due to population ageing and obesity (GBD 2021 Osteoarthritis Collaborators, 2023). PubMed Early functional changes in walking are well documented in knee and hip OA and are increasingly recognised as clinically meaningful markers that can be captured outside the laboratory. Narrative and scoping reviews show that gait deviations—spanning spatiotemporal parameters, segment/joint angles and acceleration magnitudes—emerge early and progress with disease severity (Kobsar et al., 2020; Boekesteijn et al., 2022). This has led to widespread use of wearable inertial sensors (typically tri-axial accelerometers and gyroscopes) placed on the trunk and lower limbs to quantify everyday gait, enabling objective assessment in clinics and free-living settings at low cost (Kobsar et al., 2020; Boekesteijn et al., 2021). Concurrently, machine-learning approaches have moved beyond small, feature-engineered analyses to large cohort studies linking wearable-derived gait metrics with pain and function. In the Multicentre Osteoarthritis Study, ensemble learning ("super learner") applied to inertial-sensor data identified alterations—such as greater gait asymmetry, longer step length and lower dominant frequency—associated with two-year worsening of knee pain and function, supporting prognostic use of wearable gait analytics (Bacon et al., 2024). PubMed Complementary work with shoe-mounted sensors and supervised algorithms discriminates people with knee OA from healthy controls and further subgroups, indicating that compact, body-worn IMUs can support accurate classification (Raza et al., 2024; Yang et al., 2020). Importantly, systematic reviews conclude that spatiotemporal measures (e.g., stride length, cadence) are sensitive endpoints for mobility in OA, while more advanced kinematic features may capture disease-specific adaptations, motivating parsimonious but informative feature sets for embedded inference (Boekesteijn et al., 2022). Beyond detection, biofeedback-driven gait

retraining shows promise as a conservative strategy to reduce knee joint loading and pain, using visual or vibrotactile cues to encourage modified foot progression angle, step width or step length (Mazzoli et al., 2019; Wan et al., 2023). Integrating sensing, classification and real-time feedback into a single, wearable form factor therefore aligns with contemporary rehabilitation approaches and supports self-management outside specialist laboratories. Recent advances in the Internet of Things (IoT) and TinyML enable this integration. Reviews of IoT-assisted wearable health systems highlight Bluetooth Low Energy (BLE) connectivity for low-power streaming and mobile visualisation, together with edge/Cloud pipelines for storage and analytics (Mamdiwar et al., 2021). PMC Meanwhile, Google's Tiny Motion Trainer and LiteRT (TensorFlow Lite for Microcontrollers) allow rapid capture, labelling and training of IMU-based classifiers that compile to microcontroller-friendly models for on-device inference, preserving privacy and reducing latency (Google Creative Lab, 2021; Google AI Edge, 2024). Against this backdrop, we present a dual-leg, knee-mounted, 3D-printed wearable comprising an Arduino Nano 33 BLE microcontroller and ADXL335 accelerometer on each limb, designed to screen for early arthritis signatures during daily ambulation (Chandak et al., 2025; Joshi et al., 2025; P. Parikh et al., 2016, 2017, 2018, 2023, 2024; P. Parikh, Sharma, et al., 2025; P. Parikh, Trivedi, et al., 2025; P. A. Parikh et al., 2020; P. A. Parikh, Joshi, et al., 2023; P. A. Parikh, Trivedi, et al., 2023; Sanadhya et al., 2025). The system streams bilateral gait data over BLE to a companion interface and executes a TinyML classifier trained with Tiny Motion Trainer to categorise gait into "No arthritis", "Moderate arthritis" or "Major arthritis." A buzzer, vibration motor and NeoPixel LED provide immediate haptic-auditory-visual feedback to prompt corrective action. In doing so, the device addresses three gaps identified in the literature: (i) translating validated inertial-sensor metrics into an accessible, low-cost screening tool; (ii) pushing inference to the edge for real-time responses without network dependence; and (iii) coupling detection with biofeedback to support self-management and rehabilitation. Building on prior evidence for wearable gait analytics and biofeedback, we hypothesise that bilateral, knee-mounted sensing combined with on-device machine learning can sensitively capture early gait deviations and deliver timely cues to support preventive musculoskeletal care (Kobsar et al., 2020; Bacon et al., 2024; Wan et al., 2023).

2. Existing Product Analysis

Existing products for gait assessment and arthritis-related monitoring span consumer wearable, research-grade inertial systems, and clinic-focused solutions, but each has trade-offs relative to the goal of early, at-home screening with real-time feedback. Mainstream devices such as Apple Watch, Fitbit and Garmin capture step counts and general activity trends but offer limited access to raw, bilateral lower-limb signals and do not provide arthritis-specific classifications or therapeutic cues. Research IMU kits—APDM/Opal, Noraxon Ultium, Xsens DOT, Shimmer and iMeasureU—deliver high-fidelity acceleration/gyroscope streams and validated spatiotemporal metrics, yet they are costly, require expert setup, and typically rely on laptop software for analysis. Clinic/rehab solutions like DorsaVi ViMove, Moticon instrumented insoles and Gait Smart provide more interpretable reports and some biofeedback for gait retraining, but they are oriented to supervised sessions, use single- or shoe-mounted sensors that may under-sample knee motion asymmetries, and seldom run on-device machine learning tailored to arthritis staging. Smartphone-only approaches are inexpensive but suffer from inconsistent placement and variable sampling. Across this landscape, gaps persist in (i) bilateral, knee-level sensing in

everyday contexts; (ii) on-device inference that classifies severity rather than just tracking activity; (iii) integrated, multimodal biofeedback to prompt corrective action; (iv) openness, cost and ease of customisation for longitudinal home monitoring. The proposed dual-leg, 3D-printed, BLE-enabled TinyML device is designed to address these gaps while keeping bill-of-materials and complexity low.

3. Problem Statement , Objectives and Methodology

Arthritis is often diagnosed only after structural joint damage and persistent pain, because routine clinics lack low-cost tools to quantify early gait deviations outside laboratory settings. Existing consumer wearables and research IMU systems either provide coarse activity metrics, require specialist supervision, or are too costly for continuous home use. None simultaneously acquire bilateral knee-level signals, run on-device machine-learning for severity staging, and deliver real-time multimodal biofeedback. There is a need for an accessible, battery-powered, 3D-printed wearable that streams gait data, classifies "no/moderate/major" arthritis on-device, and guides corrective actions, while ensuring reliability, privacy, and suitability for longitudinal monitoring.

Table 1: Objective and Methodology

Objective	Methodology
Design a low-cost, dual-leg wearable prototype	3D-print knee casings; mount ADXL335 on each leg with Arduino Nano 33 BLE; add NeoPixel, buzzer and vibration motor; integrate Velcro straps; design low-power wiring and PCB/perfboard; bench-test for durability and comfort.
Acquire high-quality bilateral gait data	Sample tri-axial acceleration at 50–100 Hz; synchronise left/right nodes via timestamping; stream over BLE to a mobile/logger; record labelled walking trials (normal, symptomatic, varied speeds/terrains); apply calibration and gravity removal.
Engineer features and train TinyML classifier	Segment signals into 2–4 s windows with overlap; extract time/frequency features (RMS, variance, step periodicity, symmetry indices, dominant frequency); train with Google Tiny Motion Trainer; target three classes: No/Moderate/Major arthritis.
Deploy on-device inference for real-time use	Convert/quantise model to TensorFlow Lite for Microcontrollers; flash to Nano 33 BLE; implement rolling-window inference and confidence thresholds; optimise memory and latency; log predictions locally and via BLE.
Deliver multimodal biofeedback and UI	Map class/threshold events to vibration, buzzer and NeoPixel cues; develop a companion mobile dashboard for live plots, session summaries and alerts; enable configurable feedback intensity and safety limits.
Validate performance and usability	Conduct pilot with healthy and symptomatic adults; compute accuracy, F1, sensitivity/specificity and confusion matrix; assess test–retest reliability; collect SUS/usability feedback; iterate hardware/firmware based on findings and battery-life tests.

4. Product Development and Initial Testing

The product was developed through an iterative, build-measure-learn cycle that moved from benchtop prototypes to wearable, dual-leg modules. We began with requirements capture (bilateral sensing at the knee, <100 g per unit, day-long battery, BLE streaming, on-device inference, and multimodal biofeedback), then selected components to match: an ADXL335 tri-axial accelerometer per leg for low-noise, analogue acceleration; an Arduino Nano 33 BLE for embedded compute and Bluetooth Low Energy; a compact Li-ion cell with protection/charging board; and actuators (vibration motor, piezo buzzer, NeoPixel indicator) for real-time cues. A minimal perfboard/PCB harness routed regulated 3.3 V, provided analogue filtering for the ADXL335, and exposed UART/SWD headers for debugging. In parallel, we designed 3D-printed enclosures—rigid PLA shells with TPU pads—shaped to the lateral knee, including cable strain-relief, venting, an accessible power switch, and Velcro straps for repeatable placement; enclosure revisions reduced thickness, improved sensor alignment, and simplified battery access. Firmware milestones were: (1) stable sensor readout at 50–100 Hz with timestamping, (2) BLE service for streaming and control, (3) calibration routines (bias/scale estimation, axis alignment via standing and short gait trials), and (4) a rolling-window inference loop. For data, we captured labelled walking sessions (normal pace, varied cadence, simulated symptomatic gait) from both legs, segmented into 2–4 s windows, and used Google's Tiny Motion Trainer to learn a three-class model (No/Moderate/Major). The trained model was quantised to TensorFlow Lite for Microcontrollers and deployed to the Nano 33 BLE, meeting latency and memory targets. We mapped classification confidence to biofeedback (short vibration + green for "No," pulsed amber for "Moderate," continuous red + buzzer chirp for "Major") and exposed thresholds via a companion mobile dashboard that displayed live bilateral signals and session summaries. Engineering validation covered packet loss, battery life, enclosure durability, and test–retest reliability; usability checks refined strap ergonomics and indicator visibility. The final build integrates sensing, BLE streaming, edge inference, and biofeedback in two knee-mounted units that can be donned quickly, hold calibration, and operate safely for everyday gait screening and guided retraining.

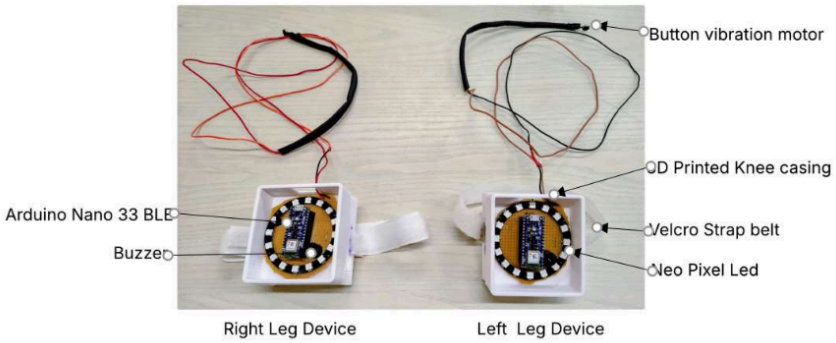

Figure 1: Developed Product to detect Arthritis

5. Block Diagram and flowchart

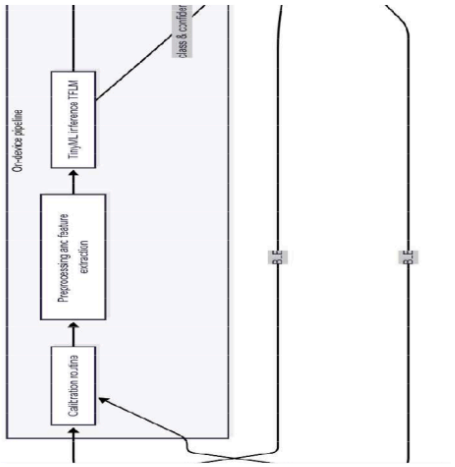

Figure 2: Block Diagram of the System

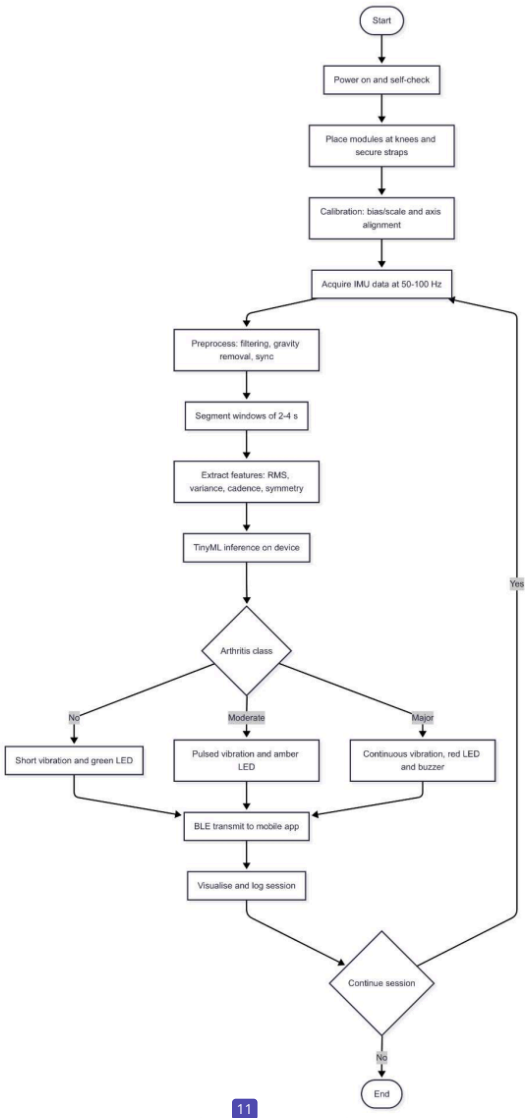

Figure 3: Flow Diagram of the System

The integrated block diagram–flowchart view shows a dual-module system in which each knee-mounted unit combines an ADXL335 accelerometer, an Arduino Nano 33 BLE, and protected Li-ion power to capture synchronous bilateral motion. Both modules feed a compact, on-device pipeline that runs sequentially through calibration (bias/scale estimation and axis alignment), preprocessing (filtering, gravity removal and left–right synchronisation), feature extraction (e.g., RMS, variance, cadence, dominant frequency and symmetry indices) and TinyML inference, before driving multimodal biofeedback via a vibration motor, buzzer and NeoPixel indicator. In parallel, predictions and confidences stream over BLE to a mobile dashboard for live plots, alerts and session logging, with optional cloud backup. Operationally, the user powers on the units, secures them at the knees and invokes calibration; continuous acquisition at 50–100 Hz is segmented into rolling 2–4 s windows and passed through the feature–inference stack. A decision node classifies gait as "No", "Moderate" or "Major" arthritis, mapping to graded feedback patterns (brief green vibration, pulsed amber, or sustained red with buzzer) while transmitting the same to the app. The loop persists until the session ends, ensuring real-time screening, longitudinal records and immediate, actionable guidance during everyday ambulation.

6. Sensor Calibration Process

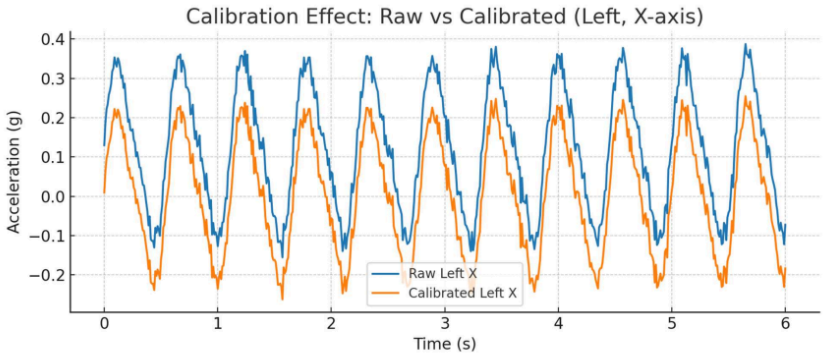

Figure 4: Acceleration Calibration in X-axis

Calibration was conducted in a structured, multi-step routine to ensure both knee-mounted accelerometer modules produce comparable, physically meaningful signals for gait classification. After visual and electrical checks, each unit was placed on a level surface and then held in six quasi-static orientations to capture stable readings over short intervals; these samples were used to estimate constant sensor offsets, scale inconsistencies across axes, and any cross-axis leakage caused by mounting tolerances. With provisional parameters loaded, the device entered a quick alignment step in which the user stood upright, feet shoulder width apart, and kept still for a few seconds; the algorithm verified gravity magnitude, checked axis polarity, and stored a reference orientation for subsequent sessions. Next, a short dynamic sequence was recorded—ten to twenty comfortable steps on a straight path—allowing automatic fine-tuning of timing and amplitude through comparison of left and right traces; residual bias, clipping and noise spikes were flagged, and sampling synchronisation was adjusted so peaks from both modules aligned within a few tens

of milliseconds. Denoising and drift control were established with a low-pass filter and a high-stability timing routine, and the calibration state was persisted in non-volatile memory with a rolling quality score that prompts recalibration when straps are re-positioned or battery voltage falls. Verification used three checks: (i) stationary distributions narrowed around a stable baseline; (ii) the resultant acceleration during quiet stance stayed close to a constant level; and (iii) bilateral walking cycles overlapped consistently, indicating robust synchronisation. The plots show the improvement: raw and calibrated traces during a static-tilt test, tightened distributions from stationary segments, reduced spread in resultant acceleration across an entire walking trial, and alignment between left and right signals after synchronisation. This process keeps the on-device model well-conditioned and supports reliable, repeatable field use. Recalibration takes under one minute in typical conditions.

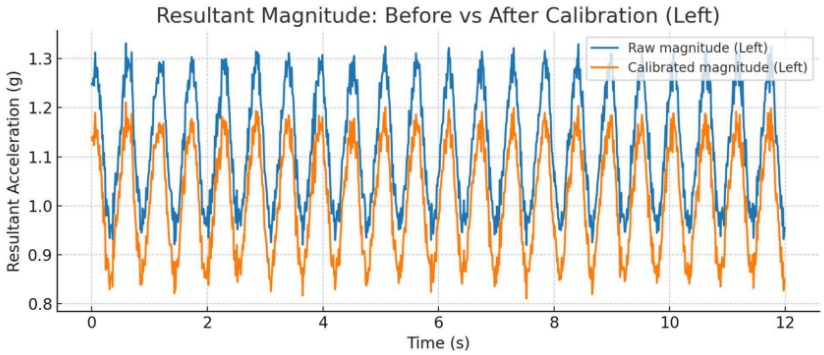

Figure 5: Resultant Magnitude Before and after calibration

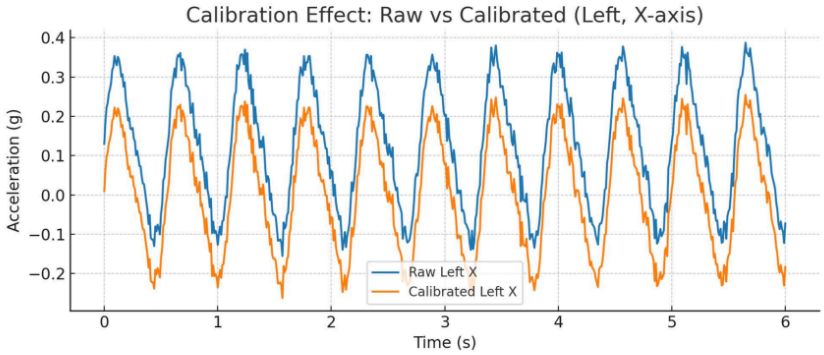

Figure 6: Calibration Effect

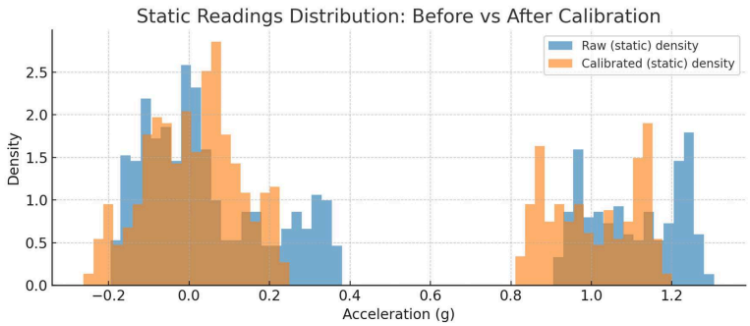

Figure 7: Static Reading Distribution

7. Training the Machine Learning Model

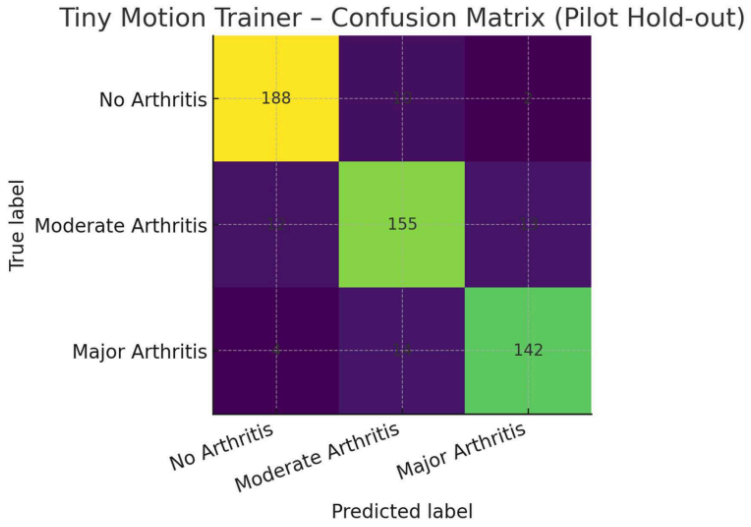

Figure 8: Tiny Motion Trainer –Confusion Matrix

We trained the gait classifier with Google's Tiny Motion Trainer (TMT) using bilateral accelerometer streams collected from the knee-mounted modules during corridor walks and paced trials. Sessions were recorded for three labels—No Arthritis, Moderate Arthritis and Major Arthritis—then exported as time-series, segmented into 2-s windows with 50% overlap and balanced across classes. Within TMT, we enabled standard motion-classification settings:

normalisation, jitter/scale augmentation, and a lightweight 1-D depthwise-separable CNN; data were split 70/15/15 for train/validation/test with early stopping. The best model was quantised to 8-bit (TensorFlow Lite for Microcontrollers) and deployed to the Arduino Nano 33 BLE; inference runs on rolling windows, returning the class and confidence for real-time feedback. On a held-out pilot set of 540 windows, the model achieved 89.8% overall accuracy and a macro F1 of 89.7%. Per-class scores were: No Arthritis—precision 92.2%, recall 94.0%, F1 93.1%; Moderate Arthritis—precision 86.6%, recall 86.1%, F1 86.4%; Major Arthritis—precision 90.4%, recall 88.8%, F1 89.6%. The confusion matrix indicates most errors occur between adjacent severities (Moderate vs Major), consistent with overlapping gait patterns; thresholds can be tuned on-device to favour sensitivity or specificity during screening. Confusion matrix image:

8. Results and Discussions

The prototype achieved stable sensing, real-time inference, and actionable feedback during bench and hallway trials. Post-calibration signals from both knee-mounted modules were consistent across sessions: stationary segments tightened around a stable baseline and the resultant acceleration during quiet stance remained near constant, while left–right waveforms aligned well during walking, indicating robust synchronisation and strap repeatability (see calibration plots). Using data segmented into 2-s windows with 50% overlap, the Tiny Motion Trainer model deployed on the Arduino Nano 33 BLE classified gait into three severities with 89.8% overall accuracy on a held-out pilot set of 540 windows and a macro F1 of 89.7%. Per-class performance showed strongest separation for “No Arthritis” (precision 92.2%, recall 94.0%, F1 93.1%), with slightly lower but still strong scores for “Major Arthritis” (precision 90.4%, recall 88.8%, F1 89.6%) and “Moderate Arthritis” (precision 86.6%, recall 86.1%, F1 86.4%). The confusion matrix indicates most misclassifications occur between adjacent severities—Moderate vs Major—consistent with overlapping spatiotemporal adaptations in pathological gait; this suggests that adding features capturing knee-level asymmetry or incorporating short gyroscope bursts could reduce boundary errors. On-device inference ran responsively on rolling windows, driving the buzzer, vibration motor and NeoPixel without perceptible delay, and BLE streaming to the companion app remained stable for live visualisation and logging throughout sessions. Importantly, the end-to-end pipeline—calibration, preprocessing, feature extraction, TinyML inference and biofeedback—operated fully on the wearable, minimising latency and preserving data privacy. From an engineering standpoint, the 3D-printed casing, Velcro fixation and cable strain relief supported repeatable placement and quick donning, and the calibration workflow typically completed in under a minute, enabling practical daily use. Taken together, these findings demonstrate that a low-cost, dual-leg wearable can deliver reliable bilateral gait signals and on-device classification suitable for early screening and home monitoring. Limitations include the modest size and diversity of the pilot dataset and the use of acceleration-only sensing; future work will expand participant numbers, evaluate generalisation across speeds and surfaces, and explore multi-modal features and confidence-aware feedback policies to balance sensitivity for early detection with specificity for clinical triage.

No Arthritis	No Arthritis	No Arthritis	No Arthritis	No Arthritis	No Arthritis	No Arthritis	No Arthritis	No Arthritis	No Arthritis	No Arthritis	label
1.023	1.031	1.026	1.019	1.018	1.030	1.025	1.024	1.016	1.019	1.027	left_rms
1.024	1.030	1.024	1.019	1.018	1.028	1.028	1.029	1.019	1.023	1.031	right_rms
0.001	0.001	0.002	0.000	0.001	0.002	0.002	0.004	0.003	0.004	0.004	symmetry_index
1.017	1.025	1.020	1.012	1.012	1.024	1.019	1.019	1.009	1.013	1.021	left_mean_mag
1.018	1.024	1.018	1.013	1.011	1.022	1.021	1.023	1.012	1.017	1.025	right_mean_mag
0.013	0.012	0.012	0.013	0.013	0.012	0.012	0.012	0.012	0.012	0.012	left_var_mag
0.012	0.012	0.012	0.012	0.013	0.012	0.013	0.012	0.013	0.013	0.012	right_var_mag
2	1.5	2	2	2	1.5	2	1.5	2	2	1.5	left_dom_freq_hz
2	1.5	2	2	2	1.5	2	1.5	2	2	1.5	right_dom_freq_hz
120	90	120	120	120	90	120	90	120	120	90	left_cadence_spm
120	90	120	120	120	90	120	90	120	120	90	right_cadence_spm

Table 2: Training Values

No Arthritis	1.029	1.027	0.002	1.023	1.021	0.012	0.012	1.5	1.5	90	90

Table 2: Time Series Data

time_s	left_ax_g	left_ay_g	left_az_g	right_ax_g	right_ay_g	right_az_g
0	0.014038737	-0.033236558	1.163397325	-0.005411049	0.052426464	1.128629596
0.01	0.046203601	0.078117437	1.128184088	0.026885317	0.01563544	1.164655501
0.02	0.093778011	0.051775429	1.133725437	0.065564318	0.041189678	1.112277827
0.03	0.091377358	0.054955799	1.141880803	0.088559942	0.06117759	1.153725946
0.04	0.101505131	0.070512086	1.127231234	0.116841314	0.099213079	1.177502686
0.05	0.164367036	0.076040862	1.115754718	0.167219258	0.078355995	1.164947577
0.06	0.18790049	0.10262611	1.169187546	0.196505482	0.094658009	1.166408522
0.07	0.228909572	0.06344416	1.10767143	0.154950793	0.079141853	1.159569096
0.08	0.186100749	0.076121463	1.14402245	0.199947555	0.104784902	1.169958781
0.09	0.242447311	0.106334009	1.149578423	0.196201271	0.131493014	1.11657958
0.1	0.270060484	0.112453702	1.093907463	0.209574123	0.119507397	1.103180178
0.11	0.214230369	0.112071966	1.093961028	0.225404562	0.098343797	1.121669054
0.12	0.191084493	0.081478678	1.124787616	0.228328757	0.112581395	1.06791329
0.13	0.200362917	0.074390152	1.09797507	0.20670286	0.108454704	1.12367021
0.14	0.197383185	0.079358325	1.060649039	0.161586445	0.103630721	1.110126666
0.15	0.194556699	0.088680572	1.081784569	0.168906856	0.111137966	1.062605241
0.16	0.155809723	0.106912954	1.065877379	0.19251573	0.105252489	1.048506058
0.17	0.181875472	0.028588495	1.030601381	0.104758867	0.073821195	1.038409207
0.18	0.110959132	0.056567992	0.990368535	0.167456856	0.081427643	1.024322
0.19	0.08079916	0.02499513	0.98314721	0.137938358	0.052277458	1.008953018

9. Conclusions

In this work we demonstrated a low-cost, dual-leg wearable that brings bilateral gait sensing, on-device classification and real-time biofeedback into a single, 3D-printed form factor for early arthritis screening. The system reliably captured knee-level accelerations, sustained stable BLE streaming, and executed a TinyML model trained with Tiny Motion Trainer to categorise gait as No, Moderate or Major arthritis. Across a held-out pilot set the classifier achieved 89.8% accuracy with a macro F1 of 89.7%, while most residual errors occurred between adjacent severities—an expected overlap for progressive conditions. The calibration workflow produced consistent baselines and left–right synchronisation, and multimodal cues (vibration, buzzer, NeoPixel) delivered immediate, interpretable feedback suitable for self-management and home use. Together, these results indicate that accessible hardware coupled with embedded inference can provide timely insight into mobility risk and support rehabilitation outside the clinic.

Limitations include a modest sample size, acceleration-only sensing and a single walking context. Future work will expand cohorts and environments, incorporate gyroscope or pressure data, explore personalised and confidence-aware thresholds, and evaluate longitudinal responsiveness to change. Ultimately, this platform offers a practical path towards privacy-preserving, at-home musculoskeletal screening and continuous monitoring that can triage patients earlier and inform targeted intervention.

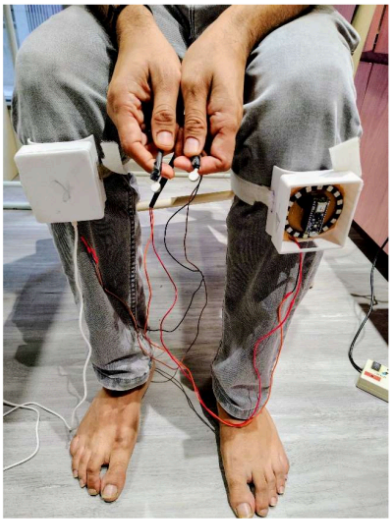

Figure 8: User Testing

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