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Low Cost Wearable AI Knee Rehabilitation System: Real-Time Motion Correction and Adaptive Training Based on Multimodal Sensing Fusion

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Abstract. The success of knee rehabilitation depends heavily on the correct execution of exercises. Currently, most treatments require supervision by physical therapists, which can be expensive. When exercises are performed without a therapist, incorrect movements are often used, increasing the risk of re-injury. To address this, a low-cost, wearable smart knee rehabilitation system is introduced in this study. A combination of multimodal sensors is employed to provide real-time motion correction and adaptive training. By integrating IMU data, visual pose estimation, and muscle signals (EMG), three-dimensional knee angles are accurately measured. Common mistakes such as knee collapse, twisting, or insufficient bending can be detected. Instant feedback is delivered through a display interface, guiding users to correct their posture and thereby improving exercise quality while reducing injury risk. Additionally, the system incorporates a smart training feature. Surface EMG (sEMG) is used to monitor muscle fatigue and movement accuracy. When fatigue is detected, the workout is automatically adjusted—by reducing speed or decreasing the number of repetitions. This approach reduces the dependence on expensive clinical equipment. The integration of multimodal sensor data with an adaptive system makes home rehabilitation more scientific, accurate, and user-friendly. Finally, this research provides a low-cost, high-precision real-time tracking prototype for smart home monitoring.

Keywords: Knee joint rehabilitation, IMU, Mediapipe, Posture estimation, Intelligent Rehabilitation Solution

1. Introduction

1.1. Background

Knee joint injuries – including ligament tears, meniscus injuries, and cartilage wear–affect tens of millions of patients worldwide. According to statistics from the World Health Organization (WHO) and relevant bone and joint research institutions, tens of millions of people globally require joint surgery or rehabilitation therapy for lower extremity injuries each year; among these cases, knee joint injuries and their subsequent rehabilitation account for the vast majority (approximately 60%–

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65%) [1]. The effectiveness of treating knee joint overuse or postoperative rehabilitation largely depends on the standardization of the training exercises. (as shown in Figure 1)

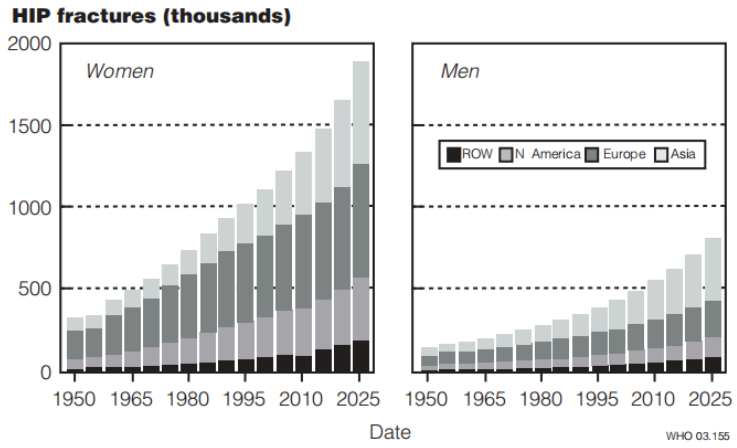

Figure 1. Estimates of the number of hip fractures between 1950 and 2025 by gender and region

Traditional rehab methods have some major problems. Usually, after surgery, patients have to go to a clinic where a physical therapist watches them exercise using specialized equipment. Relying on a person for observation and evaluation is expensive and time-consuming. Because of this, it is really hard to keep doing these exercises at home.There is a big risk of getting hurt again because patients don't get real-time feedback. When patients exercise at home alone, no professional guidance is available. Movements can easily be performed incorrectly—like letting their knee collapse inward or twist out of place. Patients may also overexert themselves, leading to excessive muscle fatigue. These issues can lead to poor recovery, the formation of incorrect habits, or even secondary injuries [2]. Finally, good physical therapy isn't available everywhere. In places with fewer hospitals or clinics, it is very hard for patients to get long-term, high-quality care.Recently, though, things like biomechanics, wearable sensors, and computer vision have improved a lot. Studies show that by combining cheap sensors (like IMUs) with camera-based posture tracking, accurate tracking can be achieved for how a person's joints move in real time [3].

1.2. Objectives and innovations

To solve these problems, a low-cost, wearable AI knee rehabilitation system was developed. By mixing AI algorithms with different types of sensors, the goal is to provide patients with accurate, real-time, and adjustable support while they exercise at home.

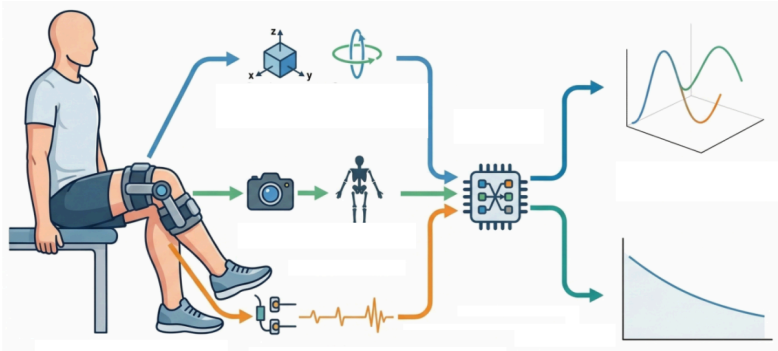

Figure 2. Multimodal data acquisition and system operation conceptual diagram

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The overall system architecture is illustrated in Figure 2. The system integrates unlabeled visual pose estimation based on MediaPipe, a lightweight IMU inertial sensor, and surface electromyography (sEMG) sensors. The IMU sensors are affixed to the patient's thigh and lower leg, respectively, to measure angular velocity, acceleration, and limb orientation [4]; an RGB camera simultaneously captures the positions of key points across the entire body and lower extremities (hip, knee, ankle, and foot). The complementary data from these two sensors enable the system to overcome the limitations associated with single-camera occlusion as well as eliminate the cumulative drift resulting from long use of the IMU sensor [5].

The system measures the 3D path of the knee in real time. It can clearly tell if a user is doing seven basic rehab exercises (like straight leg raises, wall squats, and hip abductions) the right way. It can also catch and correct common mistakes—like the knee collapsing inward, not bending enough, or twisting—in just milliseconds [6]. Using surface EMG sensors to track muscle activity and tiredness, the system creates a smart safety loop. If a patient gets too tired, it automatically lowers the workout intensity, like telling them to slow down or do fewer reps. This helps prevent muscle and bone injuries. Finally, an easy-to-use Unity interface was developed. The interface displays the user's skeleton posture, joint angles, and detected errors in real time. Correct positions light up green, while mistakes turn red to highlight the problem area. This makes home rehabilitation more engaging and encourages patients to adhere to their routine.

2. Literature review

To help people with knee or leg injuries get their movement back, researchers and companies have done a lot of work on motion tracking and smart rehab. Right now, most technologies fall into three main groups: camera-based (computer vision) systems, wearable sensor (IMU) systems, and physical signal monitors.Computer vision has become a popular tool for home rehab because reflective markers are not required on the patient's body. These visual systems mostly rely on depth cameras to track human joints [7]. Studies show that depth cameras work pretty well for medical checks. However, these cameras are usually bulky and expensive, and they only work well under good lighting conditions and when the user stands at the correct distance.

Another method uses wearable IMUs. Small IMUs are strapped to the thigh and calf, using accelerometers and gyroscopes to calculate the leg's speed and angle in real time [3]. IMUs are great for classifying leg exercises and analyzing how people walk because they collect data very quickly and are highly sensitive to movement. But there is a catch: cheap IMUs tend to "drift" over time. This makes it hard to keep track of the exact position of the legs compared to the room around them.Then there are surface EMG (sEMG) sensors, which track muscle condition. They use electrode pads stuck to the skin to detect electrical signals in the muscles. Research shows that when a muscle gets tired, the electrical wave gets bigger (higher RMS amplitude) and the frequency drops [8]. The problem is that most EMG systems today are just used as standalone lab tools and aren't connected to systems that correct your movement in real time.

The proposed system integrates these three approaches. It combines visual skeleton data from MediaPipe with IMU posture data from the thigh and calf. Camera data are used to correct the IMU drift error. At the same time, high-frequency IMU data are used to compensate for gaps when the camera loses sight of the leg. This collaborative fusion significantly improves the accuracy of knee angle estimates. Wireless EMG sensors were also integrated to measure muscle activity and track fatigue. When the fatigue level exceeds a certain threshold, the system automatically adjusts the number of repetitions, limits the range of motion, or prompts the user to rest. This creates a double safety net: it corrects movement patterns and protects fatigued muscles. The core hardware consists

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of an affordable IMU sensor module, a simple sEMG board, and a standard webcam or laptop camera, which keeps the overall setup cost low. Furthermore, a Python backend for computation was connected to a Unity frontend via UDP communication. This enables the calculated leg posture to be displayed instantly on screen. The use of red and green color coding, along with audio cues, provides clear indication of exercise correctness, which increases patient motivation for home rehabilitation.

3. Methodology

3.1. Multimodal data hardware acquisition

To accurately track knee angles and monitor the body's physical condition in real time, a low-cost, portable system was built to collect different types of data. The setup has three main parts: wearable IMU sensors to track the 3D movement and speed of the leg, surface EMG sensors to check for deep muscle fatigue, and an AI camera to map out the spatial positions of the body's skeleton joints. The hardware components are shown in Figure 3.

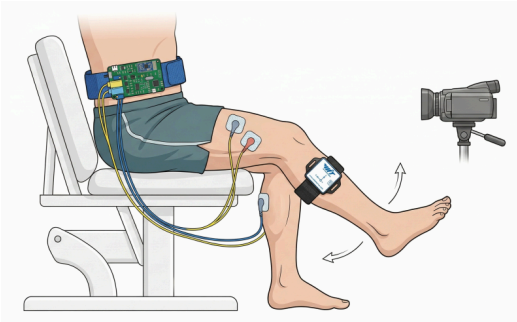

Figure 3. Multimodal system hardware wearable device diagram



Figure 4. IMU picture of real products

For motion tracking, the WT901PWIFI sensor was selected (shown in Figure 4). This is a high-performance 3-axis measurement module built on MEMS technology. It includes a 3-axis gyroscope, an accelerometer, and an electronic compass. Because of this, it can figure out its exact posture even during fast, dynamic movements. It boasts an accuracy of ±0.2° and is extremely stable

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—sometimes even beating out professional inclinometers. It also comes with a built-in Wi-Fi chip, making it easy to send data wirelessly over a local network [9].

During data collection, medical bandages are used to strap two IMU modules tightly to specific spots on the user's exercising leg. The first IMU is placed on the outside of the thigh (around the middle of the femur) to capture the thigh's posture in real time. The second IMU is placed on the front of the calf to track the lower leg. Both modules communicate over 2.4 GHz Wi-Fi. Custom TCP and UDP connections are established to stream these movement signals directly into the Python backend. By constantly comparing the angle difference between the thigh and the calf in 3D space, the system can calculate exactly how much the knee is bending, straightening, or twisting. The placement is illustrated in Figure 5.



Figure 5. Secure the IMU using the motion strap

To overcome the limitation of traditional motion capture systems in detecting physiological muscle activity, this project incorporates a portable six-channel surface electromyography (sEMG) sensor module. The six-channel EMG module consists of a front-end analog circuit for signal acquisition and a back-end digital signal filtering and processing unit. The front-end acquisition circuit captures electromyographic signals from the human arm or leg via channels 1–6, followed by a series of amplification and filtering operations on these signals; the middle section uses an SPDT switch to toggle between Envelope Mode and RAW Mode for signal output. In Envelope Mode, envelope detection is employed to generate dynamic EMG detection signals; in RAW Mode, raw EMG signals are outputted. The channel gain for both Envelope Mode and RAW Mode outputs can be adjusted using blue and white potentiometers. Additionally, an external single-channel Audio Output Interface is provided for transmitting raw signals; this audio interface allows users to select and output the raw waveform from any specific channel using jumper caps, facilitating real-time monitoring and analysis of the current EMG signals with external instrumentation. The back-end utilizes a STM32 development kit, designed for use with the six-channel EMG module, to acquire the signals output by the middle section and control LEDs to provide a rapid visual reference of the EMG signal intensity [10]. The EMG sensor module is shown in Figure 6.

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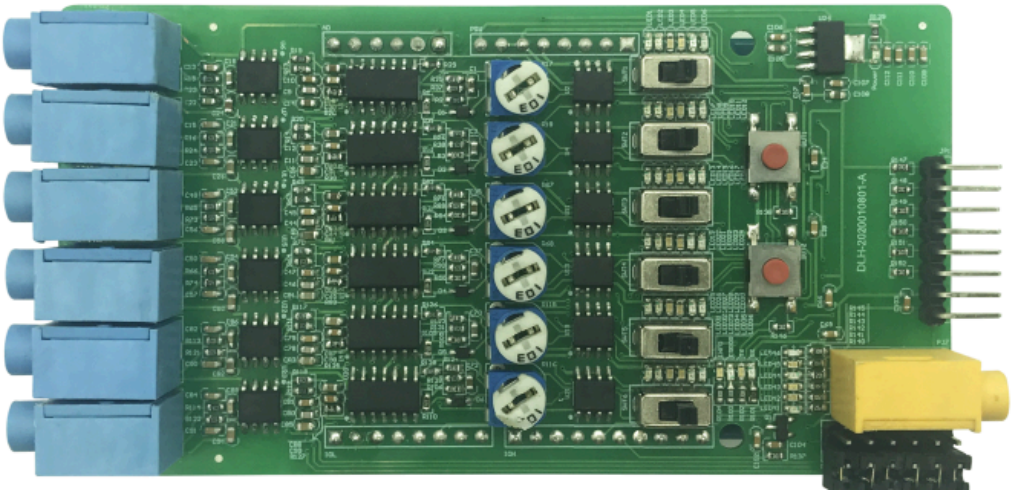

Figure 6. Electromyographic sensor physical diagram

The system features a built-in Bluetooth module that pairs with a compatible Bluetooth receiver. When the Bluetooth receiver is connected to the host device, it enables communication with the sensor over a serial port. This allows for Serial port data processing implemented using Python, enabling real-time acquisition of data from all channels of the electromyography (EMG) sensor for analysis.The muscle electrical sensor is secured around the waist with a strap and attached to the target muscle using a sensor patch to capture muscle activity data. The wearing method is depicted in Figure 7.



Figure 7. The electromyographic sensor is worn around the waist and detects muscle electrical activity via a patch

3.2. Mediapipe model detect

For the computer vision part, Google's MediaPipe Engine is used to extract the leg skeleton. It is an open-source, lightweight framework that runs great on standard computers. Its built-in MediaPipe Pose 3D model, which is perfect for building custom projects or running on cheap, everyday devices at home. The MediaPipe key-point detection model is shown in Figure 8.

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Figure 8. Mediapipe limb key joint detection schematic diagram

When a standard RGB webcam records the user, the MediaPipe model first finds the person in the frame. Then, it uses a neural network to output the 3D coordinates of 33 standard body joints in real time. Since the project focuses on knee rehabilitation, the code filters the data to just track specific joints: the hips, knees, ankles, and feet. For every frame of the video, these joints get standardized (x, y) coordinates representing their pixel positions on the screen.

θ_{knee} Once those coordinates are obtained, the Python backend uses basic vector geometry to calculate the knee bending angle. Taking one leg as an example, vector u (from the hip to the knee) and vector v (from the ankle to the knee) are defined. The current knee angle can be found by calculating the angle between these two vectors:

$$u = P_{hip} - P_{knee}, \quad v = P_{knee} - P_{ankle} \tag{1}$$

$$\theta_{knee} = arccos(\frac{u \cdot v}{||u||\,||v||}) \tag{2}$$

θ_{knee} Using this math, the system doesn't just measure normal bending and straightening. It can also precisely catch the most dangerous mistakes people make during home rehab, like the knee caving inward or twisting out of place. It does this by checking if the hip, knee, and ankle fall out of alignment from a side view. If the knee angle drifts past the safe limits set for that specific exercise, the system instantly logs the bad movement. It then uses this data to trigger the interactive error-correction on the screen.

3.3. Multimodal data fusion and action error correction

The system utilizes Python to fuse multimodal data; the IMU transmits its data to the Python terminal via Wi-Fi, while surface electromyography (EMG) data is sent to the Python terminal via Serial. Finally, the Mediapipe model is invoked on the Python side to perform real-time motion detection and assess the accuracy of the movements. The system is preconfigured with seven sets of geometric and kinematic thresholds for common knee rehabilitation movements; for each frame, the system evaluates whether the performed movement meets the required standard. During the subject's movement, EMG sensors capture raw bioelectrical signals from the leg muscles at a high sampling rate.

When muscle fatigue occurs, the neuromuscular system recruits more motor units to maintain the same force output level, resulting in a significant increase in the amplitude of the electromyogram

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(EMG) curve. This system determines the degree of muscle fatigue by comparing the initial baseline EMG data with the average EMG values obtained after sustained muscle activity. Based on the real-time fatigue level, the system employs a dynamic adaptive regulation logic to prevent secondary injury caused by excessive fatigue [11].

Under normal conditions, the system executes movements according to a preset rehabilitation exercise plan (e.g., 20 repetitions per set). During moderate-to-high fatigue levels, the system automatically activates an adaptive reduction mechanism, decreasing the number of training repetitions and the performance criteria, as well as shortening the duration required to complete each set. When excessive fatigue is detected, the interface immediately displays an alert, advising the participant to stop training immediately and transition into a relaxation and rest phase – thereby establishing a safe "perception–decision–regulation" closed-loop system.

3.4. Cross-platform communication and implementation of a unity virtual interactive interface

To make the rehabilitation exercises easy to follow and perform, the software was built using Python for the backend data processing and Unity 3D for the frontend graphics.

Rehab needs to happen in real time with no lag, so the Python code was connected to Unity using a fast UDP socket. Once Python finishes processing the sensor data and recognizing the pose for a frame, it packs all the important info—like the X, Y, and Z coordinates of the joints, the joint angles, a true/false flag showing if the move is correct, and the fatigue level—into a small JSON string. It shoots this string over the local network to Unity, which keeps the on-screen movement smooth and glitch-free.

The Unity frontend has a few main parts. First, there's a menu where users can just click to pick their daily workout. Seven core rehabilitation exercises were programmed (like straight leg raises, wall pushes, clamshells, and single-leg balances). Users can do these in stages based on how hard they want to work: easy, medium, or hard.The Unity frontend interface is shown in Figure 9.

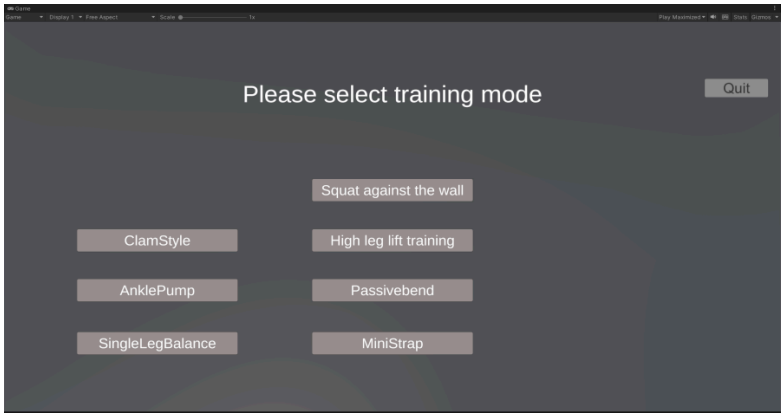

Figure 9. User selection interface

A real-time 3D virtual skeleton was also built (as shown in Figure 10). As soon as Unity gets the UDP data, it updates the positions of the leg joints on the screen. This means the 3D model moves exactly when the user moves.

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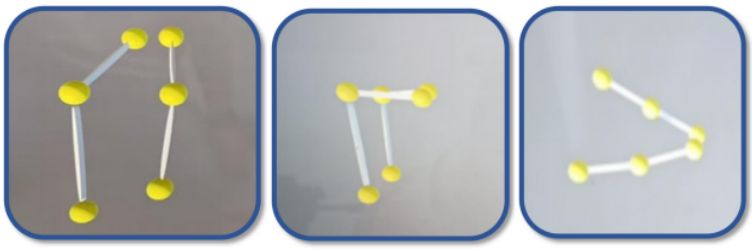

Figure 10. Virtual human lower-limb skeletal node visualization diagram

The system gives visual feedback to correct mistakes as they happen. If the user is doing the exercise right, the skeleton's bones and a status box glow green, and a "Pass" badge pops up. But if the system catches a mistake—like the foot turning inward or the knee not bending enough—the screen flashes red so the user knows right away that their form is off. Examples are provided in Figure 11.

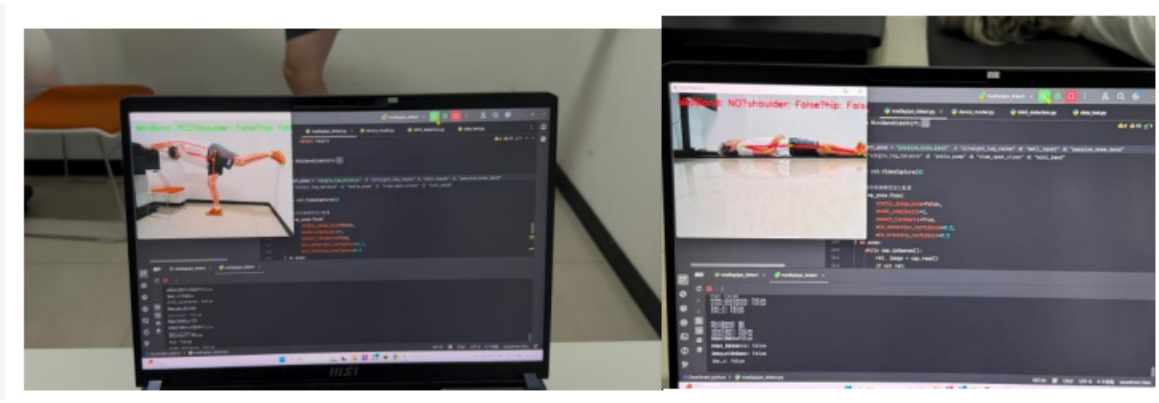

Figure 11. Correct action prompts vs. incorrect action prompts

4. Experimental design and result analysis

To validate the system's effectiveness, accuracy in error detection, and suitability for home rehabilitation, experiments were conducted. Following standard medical guidelines for knee surgeries and overuse injuries, the seven core knee exercises were loaded into the system. Since patients have different abilities depending on their recovery stage, these seven exercises were grouped into three difficulty levels based on required strength and balance.

Easy：

• Straight leg raise： Elevate the affected limb to approximately 30–45° in the supine position; this primarily exercises the quadriceps muscle strength.

• Passive knee flexion / Passive knee bending： Slowly flex the knee joint with assistance to restore initial range of motion.

• Ankle pump： Promotes lower limb blood circulation through ankle flexion and extension, helping to reduce postoperative swelling.

• Clam exercise / Buckling： In the side-lying position, place both feet together with the knees bent outward to exercise the gluteus medius muscle for pelvic stabilization.

Medium：

• Wall squats： Squat with your back against a wall, maintaining a bent knee position statically to enhance quadriceps endurance.

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• Mini lateral shift/Mini strap lateral step: Perform small-amplitude lateral movements using an elastic band; primarily designed to target the outer thigh muscles.

Hard：

• One-legged balance： Standing on one foot to maintain body center of gravity; high-intensity training enhances deep proprioception and stability in the knee joint.

The subject wears an IMU sensor and faces an AI camera while sequentially performing the seven aforementioned movements. During this process, the subject deliberately performs non-standard movements (e.g., knee valgus during a static squat or insufficient leg lift height) to verify whether the Python algorithm can generate real-time red-cross error alerts via the Unity interface and display a green checkmark upon the movement meeting the standard criteria; this serves as the functional validation of the action-handling functionality for the prototype system. The exercise set is shown in Figure 12.



Figure 12. From left to right, top to bottom is mini side shift, wall squats, ankle pump, straight leg raise, passive knee flexion, buckling

The test results demonstrate that the system is highly accurate at recognizing all seven core exercises. When a user does a move right, the Unity screen shows a green light and counts the rep perfectly. But if it spots a mistake—like the knee caving inward or not bending enough—the screen flashes a red warning in just 30 milliseconds and highlights the specific joint. This provides the precise real-time guidance that was intended. Compared to using cameras or IMUs alone, the fusion of both data types significantly reduces noise and dropped frames. The joint angles it calculates are accurate enough to meet the standards for clinical rehab.

The electromyographic channel data effectively validate the system's closed-loop safety protection logic.

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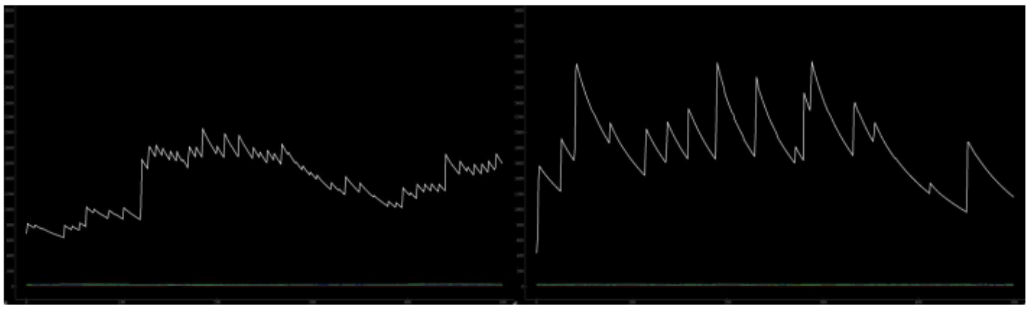

Figure 13. EMG recording at the onset of exercise versus EMG recording 10 minutes after continuous high-intensity training

EMG waveforms were also recorded, as presented in Figure 13. Recordings were taken at the start of the workout and again after 10 minutes of continuous high-intensity training. By the 10-minute mark, the target muscles exhibited clear signs of fatigue from sustained effort. Consequently, the EMG wave amplitude approximately doubled compared to baseline (increasing from baseline to a peak of over 3000). When the Python code detects this substantial amplitude increase and the fatigue index reaches 75%, the smart adjustment feature is activated. The target repetition count in Unity is automatically reduced from 20 to 15, prompting the user to slow down or rest. This mechanism prevents users from making compensatory movements (using other body parts to cheat the exercise) when fatigued, thereby reducing the risk of secondary injury.

During the testing conducted at the rehabilitation center, a preliminary seven-day system usability assessment was carried out. This multi-sensor framework was used to continuously record the subjects' joint kinematic data for evaluating system stability and system usability. The test scenario is depicted in Figure 14.

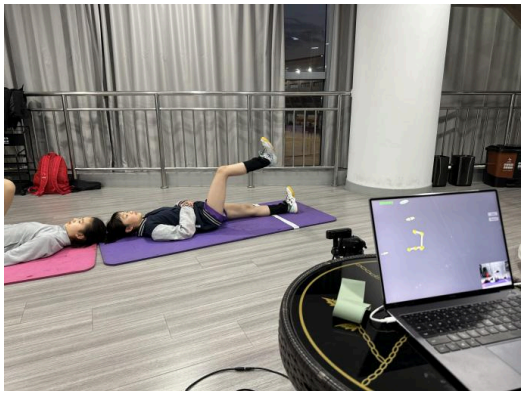

Figure 14. Test experiments conducted at the rehabilitation center

The Passive Knee Bending test measures the flexion angle error at full knee flexion – that is, the discrepancy between the actual angle and the healthy reference angle; a smaller angle indicates better knee flexion capability and more optimal recovery.

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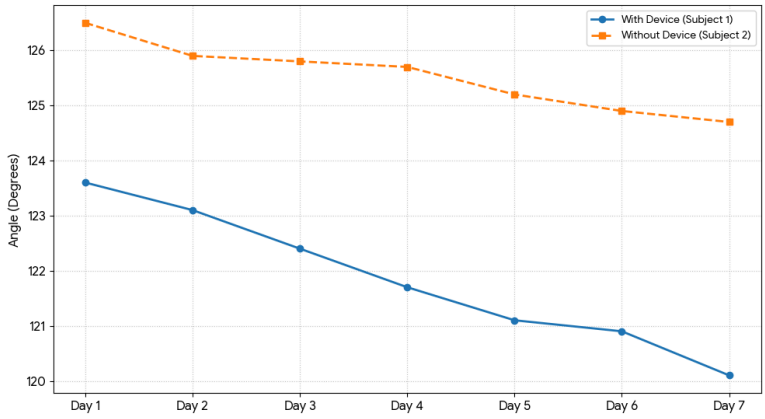

Figure 15. Passive knee flexion test result graph

The experimental line graph shows that, among patients using this device, the knee flexion deviation angle decreased from 123.6° on Day 1 to 120.1° on Day 7, indicating effective restoration of the joint range of motion and continuous improvement in flexion function; among patients not using this device, this angle decreased from 126.5° on Day 1 to 124.7° on Day 7. During the experiment, it was observed that the system could accurately recognize movements and determine their correctness, demonstrating the system's usability. The test results are shown in Figure 15.

The Buckling test measures the maximum standard abduction angle achieved when the patient lies on their side with the thigh abducted horizontally; a larger angle indicates better gluteal muscle strength and greater restoration of joint abduction range of motion.

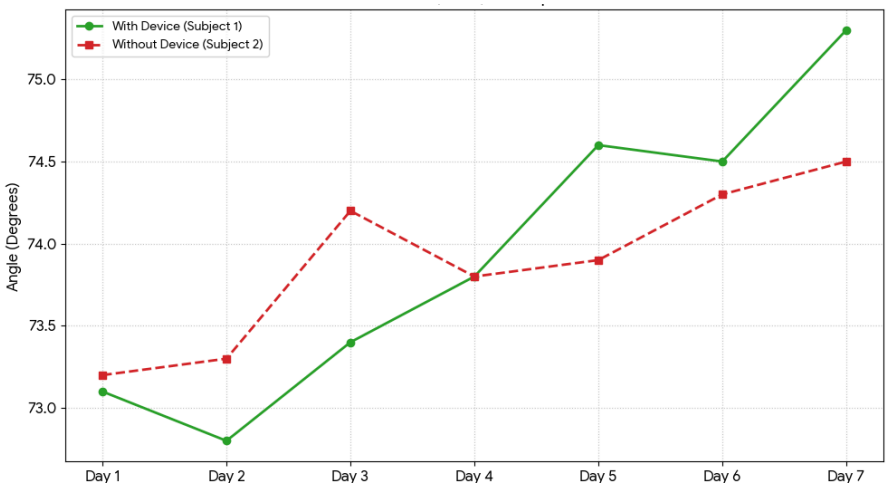

Figure 16. Buckling experiment result diagram

In the buckling test (Figure 16), the initial joint abduction angle for patients who used the device on day 1 was 73.1°; by day 7, this angle had increased to 75.3° – a value indicating that, through systematic error-correction training, the subjects regained 2.2° of range of motion; in contrast, for patients who did not use the device, the abduction angle by day 7 was only 74.5°. In conclusion, the proposed low-cost wearable AI knee rehabilitation system can collect three-dimensional knee joint motion data in real time; it enables the construction of personalized rehabilitation models and the correction of incorrect movement patterns, thereby reducing the risk of secondary injury.

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5. Conclusion

Overall, this project successfully developed a low-cost, wearable AI knee rehabilitation system that accurately tracks exercises and corrects mistakes at home. By integrating MediaPipe computer vision, lightweight IMU sensors, and EMG pads on standard equipment, the hardware cost is kept low while maintaining clinically relevant knee angle measurement precision.

Data from multi-day testing demonstrate that the system contributes meaningfully to rehabilitation by providing quantitative movement analysis. Incorrect postures are detected rapidly and the data are logged for review. In effect, the system functions as a digital physical therapist, offering patients a more affordable training approach while ensuring that exercises are performed safely. Furthermore, tracking EMG amplitude to assess muscle fatigue demonstrates that the system can detect when a user becomes exhausted and adjust the workout accordingly. This creates a dual-layer safety mechanism: it corrects improper movement patterns and protects fatigued muscles. Ultimately, this approach addresses the primary challenges of home-based physical therapy—lack of real-time feedback, reduced patient motivation, and the risk of re-injury. It offers a practical, innovative solution for smart and accessible home healthcare.

References

[1] WHO Scientific Group on the Prevention and Management of Osteoporosis (2000 : Geneva, Switzerland). (2003). *Prevention and management of osteoporosis : report of a WHO scientific group*. World Health Organization. https://iris.who.int/handle/10665/42841

[2] Hellstén, T., et al. (2025). Reliability of computer vision-based pose estimation for measuring hip and knee motion. *Healthcare Tech Lett.*

[3] Tannous, H., et al. (2016). Multi-sensor fusion scheme to improve knee flexion kinematics. *Sensors*.

[4] Al Borno, M., et al. (2022). OpenSense: An open-source toolbox for IMU-based kinematics. *J. NeuroEng. Rehab.*

[5] Wang, L., et al. (2023). Effectiveness of a digital rehabilitation program based on computer vision and AR. *J. Orthop. Surg. Res.*

[6] Hu, R., et al. (2024). Markerless 3D pose estimation of musculoskeletal patients based on smartphone video. *Front. Bioeng. Biotech.*

[7] Wochatz, M., Tilgner, N., Mueller, S., Rabe, S., Eichler, S., John, M., Völler, H., & Mayer, F. (2019). Reliability and validity of the Kinect V2 for the assessment of lower extremity rehabilitation exercises. *Gait Posture, 70*, 330–335. https://doi.org/10.1016/j.gaitpost.2019.03.020

[8] Cifrek, M., Medved, V., Tonković, S., & Ostojić, S. (2009). Surface EMG based muscle fatigue evaluation in biomechanics. *Clin Biomech (Bristol), 24*(4), 327–340. https://doi.org/10.1016/j.clinbiomech.2009.01.010

[9] Lee, T.-Y., Chen, Y.-L., & Fan, Y.-C. (2021). Next-generation electronics and sensing technology. *Sensors, 21*, 7958. https://doi.org/10.3390/s21237958

[10] Massó, N., Rey, F., Romero, D., Gual, G., Costa, L., & Germán, A. (2010). Surface electromyography applications in the sport.

[11] Seel, T., et al. (2014). Joint angle estimation using inertial motion capture: A comparison of filtering methods. *IEEE Trans. Biomed. Eng.*