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Contents

Abstract

Home physical therapy for patients recovering from elbow fractures is often difficult because individuals rely on guesswork, which can easily lead to incorrect movements or accidental reinjury. To solve this, we developed a secure tele-rehabilitation platform. The platform utilizes an advanced computer vision framework (YOLOv26 Nano Pose and MediaPipe) to track joint angles and motor data via a camera, while simultaneously measuring and recording the patient's pain levels during the session.

Crucially, the system evaluates recovery by determining optimal positions for therapists or dynamically comparing the motor data of the affected arm against a personalized baseline recorded from the patient's healthy arm. By combining this comparative mechanical score with the recorded pain data, the system calculates a definitive "Recovery Percentage" that safely penalizes movements performed under acute pain. This ensures that the therapy remains within safe physical limits.

The design strictly follows World Health Organization guidelines, serving as an intelligent supportive tool that keeps the physical therapist in control of the treatment. During testing, the system maintained a fluid 30 frames per second. All session metrics are securely compiled into local JSON files, providing an accessible, low-cost solution that transforms everyday consumer devices into a highly effective guardrail for orthopedic recovery.

Keywords: Orthopedic Rehabilitation, Computer Vision, YOLOv26 Nano Pose, MediaPipe, Pain Measurement, Comparative Baseline.

Résumé

La rééducation physique à domicile pour les patients en convalescence après une fracture du coude est souvent difficile car les individus se fient à des approximations, ce qui peut facilement entraîner de faux mouvements ou de nouvelles blessures accidentelles. Pour résoudre ce problème, nous avons développé une plateforme sécurisée de télé-rééducation. La plateforme utilise un système avancé de vision par ordinateur (YOLOv26 Nano Pose et MediaPipe) pour suivre les angles articulaires et les données motrices via une caméra, tout en mesurant et en enregistrant simultanément les niveaux de douleur du patient pendant la séance.

De manière cruciale, le système évalue la récupération en déterminant les positions optimales pour les thérapeutes ou en comparant dynamiquement les données motrices du bras affecté à une référence personnalisée enregistrée à partir du bras sain du patient. En combinant ce score mécanique comparatif avec les données de douleur enregistrées, le système calcule un ”Pourcentage de Récupération” définitif qui pénalise en toute sécurité les mouvements effectués sous une douleur aiguë. Cela garantit que la thérapie reste dans des limites physiques sûres.

La conception respecte scrupuleusement les directives de l’Organisation Mondiale de la Santé, agissant comme un outil de soutien intelligent qui maintient le kinésithérapeute en charge du traitement. Lors des tests, le système a maintenu une fluidité de 30 images par seconde. Toutes les métriques de session sont sauvegardées dans des fichiers JSON locaux, offrant une solution accessible et peu coûteuse qui transforme les appareils grand public du quotidien en une barrière de sécurité très efficace pour la récupération orthopédique.

Mots-clés : Rééducation orthopédique, Vision par ordinateur, YOLOv26 Nano Pose, MediaPipe, Mesure de la Douleur, Base de Référence Comparative.

ملخص البحث

غالباً ما يواجه العلاج الطبيعي المنزلي لمرضى كسور المرفق صعوبات لأن الأفراد يعتمدون على التخمين، مما قد يؤدي بسهولة إلى حركات خاطئة أو إعادة إصابة عرضية. لحل هذه المشكلة، طورنا منصة آمنة للتأهيل عن بُعد. تستخدم المنصة إطار عمل متقدم للرؤية الحاسوبية Pose Nano (YOLOv26 و MediaPipe) لتتبع زوايا المفاصل والبيانات الحركية عبر كاميرا، مع قياس وتسجيل مستويات الألم لدى المريض في نفس الوقت أثناء الجلسة.

بشكل حاسم، يُقيّم النظام التعافي من خلال تحديد المواضع المثلى للمعالجين أو المقارنة الديناميكية للبيانات الحركية للذراع المصاب مع قياس مرجعي شخصي مسجل من الذراع السليمة للمريض. من خلال دمج هذه النتيجة الميكانيكية المقارنة مع بيانات الألم المسجلة، يحسب النظام "نسبة التعافي" النهائية التي تخصم بأمان النقاط للحركات التي يتم أداؤها تحت ألم شديد. هذا يضمن بقاء العلاج ضمن الحدود البدنية الآمنة.

يتماشى التصميم بصرامة مع إرشادات منظمة الصحة العالمية، حيث يعمل كأداة دعم ذكية تُبقي أخصائي العلاج الطبيعي متحكماً في العلاج. أثناء الاختبار، حافظ النظام على سرعة سلسة تبلغ 30 إطاراً في الثانية. تُجمع جميع مقاييس الجلسة بأمان في ملفات JSON محلية، مما يوفر حلاً منخفض التكلفة يسهل الوصول إليه، ويحول الأجهزة الاستهلاكية اليومية إلى درع حماية فعال للغاية للتعافي في جراحة العظام.

الكلمات المفتاحية: التأهيل الحركي، الرؤية الحاسوبية، Nano YOLOv26، Pose، MediaPipe قياس الألم، القياس المرجعي المقارن.

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Dedication

To my beloved and global pillars of my life, my dear Parents,
Whose unconditional love, endless sacrifices, and continuous prayers
have illuminated my path and turned my academic dreams into reality.
Thank you for being my strength through every storm, and my sanctuary during times of stress.

To my wonderful siblings and family members,
Who have always believed in my potential and supported me throughout this long journey.

With all my love and gratitude.

General Introduction

Today, the use of Artificial Intelligence (AI) and wearable technology is transforming the healthcare sector around the world. In developing countries like Algeria, these modern tools offer an excellent opportunity to improve patient care and remote clinical monitoring. Orthopedic rehabilitation, especially for patients recovering from painful fractures, urgently needs home-based, automated, and low-cost solutions. This project focuses on building a remote monitoring web platform that helps individuals perform their recovery exercises safely at home after an elbow injury, making it easily accessible to patients and their caregivers via any web browser [1].

1 Socio-Economic and Medical Context in Algeria

1.1 Statistics on Upper Limb Fractures

Individuals are often vulnerable to accidental falls during sports, work, or daily activities. These sudden accidents frequently result in severe fractures of the upper part of the body, specifically the upper limb. Statistical medical data indicates that upper limb fractures are incredibly common, representing a major concern for patients and healthcare systems [2].

1.2 Focus on Elbow Fractures

Among all upper limb trauma, elbow fractures are some of the most complex and difficult injuries to treat. The elbow is a compound joint that connects multiple bones to allow arm bending, straightening, and rotation [3].

Elbow fractures are particularly challenging because the joint area is highly sensitive. When a patient's arm is completely immobilized in a plaster cast for several weeks, the surrounding tissues tighten up, and the elbow joint becomes stiff very quickly. If the joint is not rehabilitated with careful, guided exercises after the cast is removed, the patient can suffer from permanent joint stiffness, muscle loss, or long-term loss of arm movement [4].

1.3 The Barriers to Physical Rehabilitation in Algeria

Once the plaster cast is removed, a patient needs continuous physical therapy sessions to safely restore the elbow's movement. However, the current Algerian healthcare environment makes this recovery path very difficult for average individuals:

- **Public Hospital Overcrowding:** Public rehabilitation centers are heavily crowded and have very long waiting lists. A patient might wait weeks or months for an official appointment, completely missing the critical early window required for optimal elbow recovery.

- **High Private Care Costs:** Private clinics offer quick appointments, but they are expensive for low-income individuals. This represents a significant financial burden. Furthermore, patients living in remote areas need to travel to reach a doctor, which is very tiring and time-consuming, forcing them to miss work. This can lead to patients abandoning treatment halfway through or missing therapy sessions.

- **The Risks of Traditional Healers ("Jebbar"):** Because of these high costs and lack of remote care, many individuals in rural areas visit traditional, unregulated bone-setters called the "Jebbar". These traditional healers often pull the stiff arm aggressively and wrap the recovering elbow too tightly, causing terrible, permanent complications. These include severe muscle tissue death, a permanent claw-like hand deformity caused by blocked blood flow, and abnormal bone tissue growing directly inside the arm muscles due to forced stretching [5].

2 Problem Statement

The main problem today is that there is no objective or affordable way to monitor a patient's elbow exercises at home. Caregivers and patients do not have the professional training to know if the rehabilitation movements are being done correctly or safely.

Monitoring patients remotely is highly challenging because they cannot always easily describe their physical pain or muscle fatigue accurately to a remote doctor [6]. Without clear clinical monitoring, home exercises cause two major risks: the patient might under-exert by avoiding movement out of fear, which freezes the joint permanently, or they might over-exert by pushing too hard, causing muscle tears and further severe tissue damage [7, 8].

To solve this problem, we need an automated cross-platform web system that can track both the physical movement of the elbow and the patient's strain levels at the same time.

3 Research Objectives and Proposed Solution

This thesis proposes a remote-monitoring web platform to track a patient's elbow rehabilitation safely at home. To make it highly accessible for Algerian families, the system avoids expensive medical hardware and relies entirely on everyday consumer devices: a standard device camera (connected through the browser) and a basic smartwatch.

The system uses a strategy that combines two separate tracking pipelines:

- **The Vision Engine:** Using the device camera through the web browser interface, the website runs a hybrid computer vision framework combining the YOLO architecture and Google's MediaPipe pose estimation framework. This lightweight system runs 100% offline on the client side within the local browser, which is perfect for local infrastructure because it requires zero server costs or continuous network connectivity. It accurately tracks joint landmarks to calculate the exact bending and straightening angles of the elbow in real-time [9].

- **The Wearable Engine:** Simultaneously, the patient wears a commercial smartwatch that transmits its data to the web platform. The smartwatch's heart rate sensor (PPG) monitors sudden spikes in pulse rate, which acts as a direct indicator for physical pain and stress to prevent over-exertion [10].

By merging the real-time elbow angles from the browser camera pipeline (via YOLO and MediaPipe) with the heart rate data from the smartwatch pipeline, the web platform safely tracks the patient's true recovery over time. This replaces expensive clinic visits with a safe, automated home solution via the web.

4 Thesis Outline

To explain the design and evaluation of this system clearly, this thesis is divided into five main chapters:

- **Chapter 1 (Medical Context and State of the Art):** Explains the specific anatomy of the patient's elbow, common fracture issues, and reviews current sensor-based and vision-based remote systems.
- **Chapter 2 (Technical Background: YOLO, MediaPipe, and Smartwatch Technology):** Defines the YOLO deep learning architecture, the operational principles of the MediaPipe framework for joint tracking, and how smartwatch sensors work.
- **Chapter 3 (Related Works):** Reviews traditional physiotherapy, telemedicine rehabilitation, video/app-based rehabilitation, and AI-based pose estimation systems to position the proposed solution within existing research.
- **Chapter 4 (System Architecture, Methodology, and Mathematical Modeling):** Details the general architecture of the web platform, the synchronous processing mechanism between YOLO and MediaPipe, how elbow angles are mathematically calculated, and how our data fusion logic functions to trigger real-time safety guardrails.
- **Chapter 5 (Implementation, Therapeutic Exercises, and Empirical Validation):** Shows the user interfaces of our website, the parental dashboard, experimental testing results in home environments, and compares our automated web-tracked data with standard clinical measurements to analyze accuracy.

Finally, a Conclusion summarizes the work, highlights the main technical contributions, points out system limitations, and discusses future ideas for clinical trials.

Chapter 1

Medical Context and State of the Art

1.1 Introduction to Orthopedics: Focus on Elbow Fractures

Orthopedics is a special area of medicine dedicated to the human skeleton. The elbow, in particular, is highly susceptible to injuries and fractures during accidental falls [12]. When looking at upper body injuries, elbow fractures are among the most common and complex issues handled in emergency rooms. The elbow is a compound joint that connects multiple bones to allow the arm to bend, straighten, and rotate the forearm

We focus specifically on elbow fractures for three critical reasons:

- **High Risk of Stiffness:** The tissues around a patient's elbow joint are very sensitive to being immobilized. When an individual wears a heavy plaster cast for several weeks, the joint tissues tighten up quickly, and the elbow becomes extremely stiff [13].
- **Muscle Loss (Muscle Atrophy):** Keeping the arm completely still inside a cast causes the muscles around the elbow to weaken and shrink very fast [14].
- **Loss of Arm Movement:** Restoring full movement to a stiff elbow requires continuous, careful exercises. If the joint is not rehabilitated with careful, guided exercises after the cast is removed, the patient can suffer from permanent stiffness and a long-term loss of arm movement [15].

1.2 The Algerian Context: Financial Barriers vs. Traditional Healers

In Algeria, when a patient gets an elbow fracture, the initial treatment like putting on a plaster cast is usually done quickly in public hospital emergency rooms. However, the real problem starts after the cast is removed and the individual needs physical therapy to move their stiff elbow again.

1.2.1 Statistics on Upper Limb Fractures

Individuals are often highly active in their daily lives, which makes them vulnerable to accidental falls during sports, work, or daily activities. These sudden accidents frequently result in severe fractures of the upper part of the body, specifically the upper limb. Statistical medical data indicates that upper limb fractures are incredibly common, representing a major concern for families [2].

1.2.2 The Problem with Public and Private Clinics

The public hospitals in Algeria offer free healthcare, but their rehabilitation departments are incredibly overcrowded and have very long waiting lists. A patient recovering from an elbow fracture might have to wait weeks or months to get an appointment, which is dangerous because the first few weeks after removing the cast are the most important time to fix joint stiffness.

To avoid long waitlists, patients can go to private physical therapy clinics. Private clinics offer quick appointments, but they are highly expensive for low-income individuals, creating a significant financial burden. Furthermore, individuals living in remote areas need to travel long distances to reach a doctor, which is very tiring and time-consuming, forcing them to miss work. Because of this exhaustion and financial stress, many patients end up abandoning their treatment halfway through or missing critical therapy sessions [16, 17, 18].

1.2.3 The Dangerous Alternative: The "Jebbar"

Because of these high costs, travel barriers, and the lack of remote care, many individuals in rural areas visit traditional, unregulated bone-setters known as the "Jebbar".

The "Jebbar" uses traditional methods like pulling the arm hard and wrapping it very tightly. Applying these aggressive methods to a delicate, healing elbow joint is extremely dangerous and often leads to permanent complications [5]:

- **Severe Muscle Tissue Death:** If the "Jebbar" wraps the elbow too tightly, it blocks blood flow to the arm, killing the muscle tissue and causing a permanent claw-like deformity of the hand.
- **Abnormal Bone Growth in Muscles:** Pulling or stretching a stiff elbow too aggressively causes micro-tears in the arm muscles, which can cause abnormal bone tissue to grow directly inside the muscles, freezing the joint permanently.

1.3 Problem Statement

The main problem today is that there is no objective or affordable way to monitor a patient's elbow exercises at home. Caregivers and patients do not have the professional training to know if the rehabilitation movements are being done correctly or safely.

Monitoring patients remotely is highly challenging because they cannot always easily describe their physical pain or muscle fatigue. Without clear clinical monitoring, home exercises cause two major risks: the patient might under-exert by avoiding movement out of fear, which freezes the joint permanently, or they might over-exert by pushing too hard, causing muscle tears and further severe tissue damage.

To solve this problem, we need an automated cross-platform web system that can track both the physical movement of the elbow and the patient's strain levels at the same time.

1.4 Digital Health and Rehabilitation: Changing Patient Recovery

Traditional rehabilitation requires the patient to visit a clinic frequently, where a physical therapist manually measures elbow angles and guides exercises. Today, digital health and tele-rehabilitation are completely changing this traditional model by bringing clinical tracking into the patient's home using software and everyday electronics [19, 6].

Technology helps patient recovery under remote or caregiver supervision in three major ways:

1. **Facilitating Home-Based Supervision:** Patients often struggle with doing repetitive or slightly painful medical exercises when left alone. Digital health solves this problem by providing a clear interface on a web platform screen via any standard browser that allows caregivers or patients themselves to actively supervise and monitor their daily routine, making home therapy organized and manageable without needing prior medical training [6].

2. **Providing Objective Measurements:** Instead of individuals guessing if their movements are correct or safe, digital health uses cameras and sensors to collect objective digital data (like exact angles). This data tells the users immediately if the exercise is being done right and can be saved for the doctor, replacing subjective opinions with real numbers [20].

3. **Increasing Safety:** A major fear of home rehabilitation is not knowing if the patient is under-exerting (not moving enough) or over-exerting (pushing too hard). Digital health platforms act like a virtual clinical assistant, tracking physical performance in real-time to help protect patients from re-injury during training [21].

1.5 Existing Solutions: Wearable-Based Systems vs. Computer Vision

Engineers and researchers have developed different types of systems for home telerehabilitation. To summarize these existing methods, we can compare them using the table below:

Table 1.1: Comparative Analysis of Existing Remote Rehabilitation Modalities.

Modality	**Key Strengths**	**Major Blind Spots**	**Primary Use in RehabSmart**
Wearable Sensors (Smartwatch)	• Tracks heart rate via PPG for stress. • Provides continuous physiological feedback.	• **Posture Blind Spot:** Cannot see if the patient is cheating by moving their shoulder.	**Physiological Pipeline:** Tracks pain thresholds.
Computer Vision (Browser Camera Device)	• 100% Touchless and non-invasive. • Sees the whole body to detect bad posture.	• **Spatial Occlusion:** Loses tracking if the arm is blocked or turned away.	**Kinematic Pipeline:** Computes exact elbow joint angles.

1.6 Functional Evaluation and Clinical Standards for Testing Elbow Recovery

To design an effective rehabilitation system, we must understand how doctors evaluate a patient's recovery progress after an elbow fracture. Instead of using subjective guesses, a proper clinical system must rely on clear, measurable parameters.

1.6.1 Range of Motion (ROM)

The primary parameter used to test elbow recovery is the Range of Motion (ROM), measured in degrees. The human elbow normally moves through an arc of flexion (bending the arm) and extension (straightening the arm). After an elbow fracture and cast removal, restoring this angular arc is the main goal. A clinical system must be able to calculate these joint angles accurately during exercises to see if the patient's movement limits are improving over time [22].

1.6.2 The Need for a Hybrid Solution (Data Fusion)

Relying on just a camera or just a smartwatch creates serious limitations. If the system only uses a camera, it can calculate the elbow angles and catch bad posture, but it remains blind to the patient's internal pain or muscle exhaustion. If the system only uses a smartwatch, it can track the patient's heart rate spikes and muscle tremors, but it cannot verify if the exercise is being executed with correct posture.

This is why a modern remote system must move toward a Multimodal Data Fusion strategy [11]. Instead of picking one tool, the system combines both:

- The web platform runs a hybrid computer vision framework combining YOLO and MediaPipe to track the global skeleton, check posture, and calculate the exact elbow angles client-side within the browser [23].
- The smartwatch simultaneously tracks raw movement data to isolate muscle tremors and monitors the heart rate to detect sudden pain thresholds [24].

By fusing these two data sources, the system creates a complete and objective functional evaluation profile. It ensures that the patient is recovering their elbow mobility effectively, practicing with perfect posture, and exercising within safe physiological boundaries without any risk of over-exertion or travel stress.

Chapter 2

Technical Background

2.1 Introduction to Computer Vision and Object Detection

Computer Vision is a specialized domain within Artificial Intelligence (AI) that engineers software systems to interpret, process, and extract meaningful structural understanding from digital images or live video streams. Historically, computing systems processed visual data strictly as arrays of raw numeric pixel values. The advent of deep learning transformed this paradigm, enabling modern computer vision architectures to extract high-level semantic features, isolate human anatomical structures, and track physical actions in real-time [25].

To establish the technological groundwork for this project, it is essential to distinguish between the two primary computational tasks in visual recognition:

- **Image Classification:** The algorithm evaluates an entire frame to output a single global label (e.g., "arm" or "elbow"). It lacks the capacity to determine spatial orientation, identify specific coordinate locations, or differentiate multiple overlapping entities within the scene.

- **Object Detection:** The algorithm simultaneously identifies the semantic class of an entity and constructs a localized bounding box defining its precise spatial coordinates on the image plane. For digital physical rehabilitation, real-time object detection is a baseline requirement; the system must accurately locate the patient and segment their specific upper limb joint regions from varying domestic backgrounds [26].

2.2 The YOLO (You Only Look Once) Architecture

Achieving low-latency inference remains a historical challenge in computer vision. Legacy object detection frameworks relied heavily on multi-stage processes (such as R-CNN variants) that first extracted region proposals likely to contain an object, and subsequently ran classification networks over those selected zones. These multi-stage pipelines introduced severe computational bottlenecks, demanding substantial processing power that made real-time tracking impossible within client-side consumer hardware.

To bypass these operational limitations, researchers introduced the YOLO (You Only Look Once) architecture [27].

2.2.1 Core Architectural Mechanics of YOLO

Unlike multi-stage algorithms, YOLO frames object detection as a single regression problem. When a video frame enters the network, the architecture passes the entire image through a convolutional neural network in a single forward propagation step. The system divides the input frame into an $S \times S$ grid matrix. If the center of an object falls into a specific grid cell, that cell assumes responsibility for predicting its bounding box coordinates, confidence scores, and class conditional probabilities simultaneously.

By evaluating the global context of the entire image during its single pass, YOLO minimizes localization errors and runs with high computational efficiency. This streamlined design allows standard client machines to achieve high frame rates (FPS), making it highly suitable for tracking dynamic human movements [27].

2.3 Google MediaPipe Framework

While one-stage detectors provide robust bounding boxes for generalized object classes, precise orthopedic range-of-motion tracking requires localized, high-density coordinate data. For this purpose, the system incorporates Google's MediaPipe framework.

MediaPipe is an open-source, cross-platform framework specifically engineered for building modular, multimodal applied machine learning pipelines. For physical therapy applications, it utilizes a highly optimized convolutional neural network to perform real-time human pose topology estimation. MediaPipe's tracking pipeline extracts 33 distinct skeleton keypoints across the entire human body from a single video frame.

A major advantage of MediaPipe is its native compatibility with modern web technologies. Optimized via WebAssembly (WASM) and accelerated client-side JavaScript APIs, it can execute complex mathematical inferences directly inside standard web browsers. It achieves high frame rates without requiring heavy graphical processing units (GPUs) on the user's local machine, rendering it a foundational asset for browser-based digital health architectures [28].

2.4 YOLO 26 Nano Pose Configuration

Standard commercial deep learning models typically feature massive parameter weights, necessitating high-end hardware or cloud-based server infrastructure to operate effectively. In the context of Algerian public healthcare, relying on continuous cloud computing introduces prohibitive operational costs and demands high-speed internet connections that are not always available to every family [29, 30].

To resolve this issue, this web platform deploys a highly specialized, customized version called YOLO 26 Nano Pose. This configuration modifies the core network in two structural ways:

2.4.1 Nano-Scale Optimization for Browsers

The "Nano" configuration represents a structural downscaling of the convolutional layers, drastically reducing the total parameter count and structural weight of the neural network. This lightweight design allows the model to be converted into web-compatible formats (such as ONNX or TensorFlow.js web binaries) and loaded directly into the client's local web browser memory.

The entire mathematical execution runs 100% locally on the user's computer or tablet processor. This serverless approach guarantees data privacy for the patient, achieves zero server maintenance overhead, and maintains operational fluidity even if the family's internet connection drops mid-session [31].

2.4.2 Anatomical Pose Estimation

The network is optimized to bypass generalized object detection and focus explicitly on human pose estimation. As the patient performs their exercises in front of the camera, the model automatically detects and tracks specific keypoints: the acromion (shoulder), the lateral epicondyle (elbow), and the styloid process (wrist).

The web platform captures the (x, y) pixel coordinates of these three keypoints in real-time. By treating these coordinates as planar vectors, the system applies standard trigonometric equations to compute the instantaneous flexion and extension angles of the elbow joint during training [32].

2.5 Smartwatch Sensor Technology (PPG)

While the browser-managed camera tracks the structural geometry of the upper limb from the exterior, the web platform must simultaneously evaluate the patient's internal physiological response. The system establishes this real-time telemetry link by utilizing a consumer smartwatch worn on the wrist of the recovering limb, leveraging its optical heart-rate hardware [33]:

2.5.1 Photoplethysmography (PPG) Sensor

The PPG sensor utilizes an optical system on the rear casing of the smartwatch, emitting green light waveforms into the underlying microvascular tissue bed. As the heart pumps blood, the peripheral blood volume pulse cyclically alters the light absorption and reflection characteristics. The photodiode captures these volumetric shifts to compute the heart rate in beats per minute (BPM).

Within an orthopedic protocol, the PPG sensor serves as an objective marker of acute somatic pain. When a patient encounters sudden physical pain during tissue elongation, the autonomic nervous system triggers an involuntary sympathetic discharge, causing an abrupt acceleration in heart rate. The web platform continuously monitors this PPG stream, serving as an automated safety threshold to stop the movement before any structural tissue damage occurs [34].

2.6 Data Fusion Concept: Combining Vision with Vitals

Data Fusion is an algorithmic process where data streams from multiple disparate sensors are structurally aligned and combined to generate a unified inference that is significantly more accurate, context-aware, and secure than any single component framework could produce independently. This thesis implements a multimodal real-time data fusion strategy, bridging the Kinematic Pipeline (browser vision data) and the Physiological Pipeline (smartwatch telemetry data) [35, 36, 37].

Table 2.1: Multimodal Data Fusion Pipeline Breakdown.

Pipeline	Source Component	Extracted Metrics	Core Diagnostic Value
Kinematic	Device Webcam via Browser (YOLO + MediaPipe)	• Joint coordinates • Flexion/Extension angles • Compensatory postures	Evaluates external range of motion (ROM) and structural exercise accuracy.
Physiological	Smartwatch Sensor (PPG via Web API)	• Heart rate fluctuations (BPM)	Detects acute pain responses.

The fundamental engineering rationale behind this fusion architecture lies in the mutual elimination of each technology's inherent blind spots:

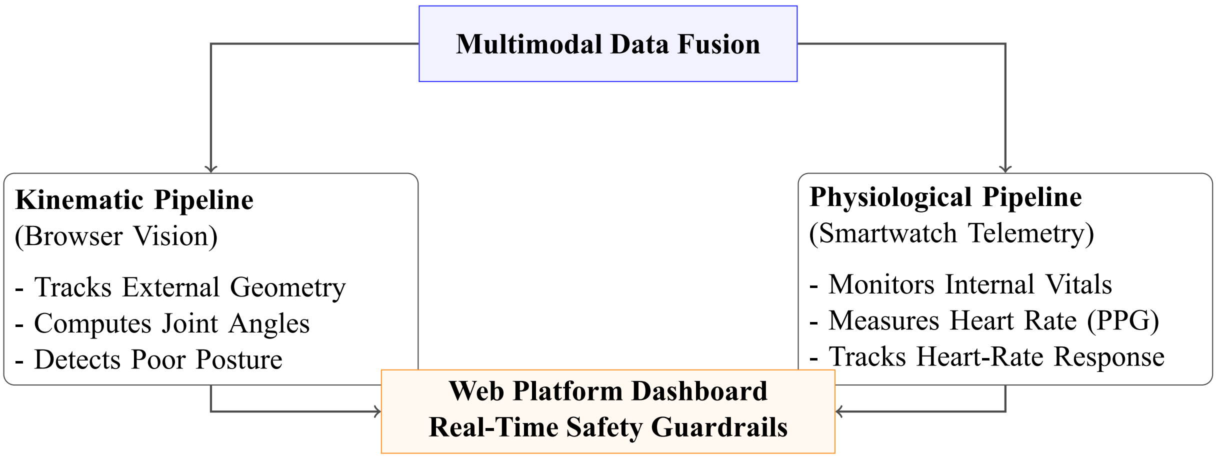

Figure 2.1: Structural Architecture of the RehabiSmart Real-Time Data Fusion Loop.

- **The Vision Limitation:** The browser webcam easily quantifies whether a patient is reaching the target extension angle, but it remains blind to the patient's internal pain thresholds. A patient could be pushing their joint to a dangerous, inflammatory limit while presenting a visually correct pose to the camera.
- **The Sensor Limitation:** The smartwatch captures the sudden cardiac spike of pain, but it lacks all geometric context. It cannot determine if the physiological stress is caused by a correct therapeutic effort or if the patient is using an incorrect, harmful compensatory shoulder movement.

By fusing these streams concurrently on the web interface, the system achieves a balanced assessment model. The platform verifies structural accuracy while validating physiological safety in the same system loop. If the vision pipeline detects a proper extension movement but the wearable engine simultaneously registers a sympathetic heart rate spike, the platform immediately flags an over-exertion warning. This data fusion loop provides a reliable safety architecture tailored for autonomous home rehabilitation.

Chapter 3

Related Works

3.1 Introduction

The landscape of physical rehabilitation is undergoing a profound transformation, driven by an escalating global demand for accessible, continuous, and effective therapeutic interventions. Historically, the burden of care has rested almost entirely on localized clinical infrastructure. However, the advent of digital health technologies, high-speed connectivity, and advanced computational algorithms has catalyzed the emergence of decentralized rehabilitation paradigms. Transitioning clinical supervision from laboratory and clinic environments to the home requires solving core challenges in patient engagement, real-time feedback, and rigorous movement evaluation. This chapter provides a comprehensive review of the evolution of rehabilitative care, delineating the progression from conventional in-clinic physiotherapy to contemporary frameworks grounded in artificial intelligence and edge computing. Specifically, it examines the distinct modalities of traditional physiotherapy, telemedicine, video-based applications, and state-of-the-art AI-based pose estimation, evaluating their respective methodologies, advantages, and inherent limitations.

3.2 Traditional Physiotherapy (In-clinic)

Traditional, in-clinic physiotherapy remains the gold standard against which all emerging rehabilitative modalities are benchmarked. This paradigm is characterized by face-to-face, hands-on rehabilitation guided directly by a licensed physiotherapist through periodically scheduled clinical sessions. The cornerstone of this approach is the therapist's ability to utilize multimodal observational skills—integrating visual, tactile, and kinesthetic feedback—to conduct highly nuanced and personalized clinical assessments.

During an in-clinic session, a physiotherapist can dynamically adjust the therapeutic regimen in real-time, responding to the patient's immediate physiological reactions, pain thresholds, and signs of fatigue. Furthermore, manual palpation and hands-on guidance allow the therapist to detect subtle musculoskeletal abnormalities and immediately correct postural deviations or compensatory movement strategies that a patient might inadvertently employ. This direct, interpersonal interaction also fosters a strong therapeutic alliance, significantly enhancing patient motivation, psychological well-being, and overall adherence to the prescribed recovery plan.

Despite its unparalleled clinical efficacy, traditional physiotherapy is heavily constrained by logistical and economic barriers. The requirement for physical presence restricts access for patients residing in geographically remote or underserved areas. Additionally, the inherently synchronous nature of face-to-face sessions limits scalability, often resulting in prolonged wait times and a heavy burden on healthcare infrastructure. Furthermore, the reliance on periodic, episodic clinical visits creates substantial gaps in patient monitoring, during which the patient's adherence to home-exercise programs often wanes, and unsupervised, erroneous movement executions may exacerbate the initial injury.

3.3 Telemedicine Rehabilitation

In an effort to mitigate the geographical and logistical constraints of traditional in-clinic care, telemedicine rehabilitation has emerged as a critical intermediary solution. Telerehabilitation leverages telecommunication technologies—primarily synchronous, high-definition video conferencing platforms—to facilitate remote consultations, allowing therapists to observe, evaluate, and guide patients engaged in home-based exercises.

This modality significantly expands access to specialized care, particularly for individuals with severe mobility impairments or those situated in rural locales. Telemedicine sessions enable therapists to provide real-time verbal cues, correct gross biomechanical errors, and dynamically alter exercise protocols based on visual observation. Moreover, the integration of secure digital health records allows for seamless longitudinal tracking of patient progress.

However, telerehabilitation introduces several fundamental limitations. The foremost challenge is the complete absence of tactile feedback, which deprives the clinician of crucial diagnostic information obtainable only through manual palpation and resistance testing. Additionally, the efficacy of video-based observation is highly contingent upon the patient's technological literacy, the quality of their network connection, and the spatial constraints of their home environment. The fixed, often two-dimensional perspective of a standard webcam can obscure subtle movement deviations, limiting the therapist's ability to conduct precise, multi-planar biomechanical assessments. Consequently, while telemedicine excels at improving accessibility and maintaining clinical continuity, it falls short of providing the rigorous, granular movement analysis achievable in a clinical setting.

3.4 Video/App-based Rehabilitation

The proliferation of mobile computing and smartphones has catalyzed the development of video- and app-based rehabilitation platforms. This asynchronous modality primarily delivers pre-recorded, structured exercise programs (e.g., YouTube-style rehabilitation videos or dedicated mobile health applications) directly to the patient's device, enabling highly scalable and flexible therapeutic engagement.

App-based rehabilitation provides a highly cost-effective, ubiquitous solution that empowers patients to conduct their therapy autonomously, at their convenience. These platforms often incorporate gamification, progress-tracking dashboards, and automated push notifications to bolster patient adherence. By standardizing the delivery of exercise instructions, these applications ensure a baseline level of informational consistency, which is particularly useful for widespread prophylactic conditioning or the management of chronic, low-acuity musculoskeletal conditions.

Nevertheless, the critical vulnerability of purely video- or app-based rehabilitation is its fundamentally open-loop architecture. Because these systems broadcast instructions without any mechanism for observing or evaluating the patient's execution, they provide zero real-time clinical feedback. Consequently, a patient may perform an exercise with incorrect posture or hazardous joint mechanics without any corrective intervention. This lack of closed-loop verification drastically limits the clinical utility of such platforms for acute post-operative recovery or complex neurological rehabilitation, where the precision of movement is paramount and the risk of reinforcing pathological movement patterns is high.

3.5 AI-based Pose Estimation

To address the inherent limitations of asynchronous video instructions and the subjective nature of manual tele-assessments, contemporary research has aggressively pivoted toward the integration of artificial intelligence and computer vision in remote physical therapy. AI-based pose estimation utilizes advanced deep learning algorithms to automatically detect human anatomical keypoints and track body joints in real-time, functioning entirely through standard monocular RGB cameras available on consumer devices. This approach transforms ubiquitous consumer hardware into sophisticated, closed-loop biomechanical measurement tools.

Deploying vision-based physical therapy on consumer edge devices necessitates a delicate balance between spatial accuracy and computational efficiency. Extensive research has benchmarked open-source frameworks to evaluate their performance in clinical contexts. Comparative analyses have rigorously evaluated the efficacy of robust object-detection architectures, such as You Only Look Once (YOLO), against specialized keypoint tracking frameworks like MediaPipe. These studies meticulously map the specific trade-offs between localized coordinate regression and bounding-box keypoint detection in motion-tracking workflows, optimizing them for real-time edge deployment [42].

A primary clinical hurdle in unsupervised upper-limb physical therapy is the automated tracking of “cheating” or compensatory mechanics. In such scenarios, a patient unconsciously modifies their posture or recruits adjacent muscle groups to mask a restricted range of motion or avoid localized pain. Deep learning models have been successfully trained to detect these upper-limb compensation patterns directly from raw camera feeds. Computer vision frameworks prove highly feasible for identifying post-injury compensatory adaptations by analyzing complex, cross-joint spatial relationships to ensure physical data integrity and therapeutic safety [43].

To capture both the spatial execution and the physical experience of a rehabilitation session more robustly, advanced frameworks increasingly leverage multimodal sensor fusion. The synchronization of raw vision-based motion-capture streams with wearable inertial measurement units (IMUs) is typically achieved through Extended Kalman Filters (EKF) and sophisticated data fusion protocols. Combining wearable IMU sensor signals with vision inputs allows systems to mitigate optical tracking noise, handle visual occlusions, and stabilize joint-angle estimations during rapid or complex movements [44].

Furthermore, evaluating the temporal execution of exercises is as critical as spatial accuracy. Because injured or recovering patients exhibit erratic movement velocities and inconsistent temporal cadences, traditional frame-by-frame comparisons to reference motions fail. Researchers frequently utilize algorithmic variations like *mnmDTW*, a highly specialized extension to Dynamic Time Warping. This technique isolates and localizes specific movement errors along a temporal curve, dynamically mapping real-time patient kinematics against a normalized, expert reference performance regardless of execution speed [45].

Ultimately, to translate these raw, high-dimensional spatiotemporal parameters into actionable, clinician-friendly reports, researchers employ phase-specific clinical assessments.

By utilizing phase-specific multimodal biomarkers, these AI-driven systems provide interpretable and explainable assessments of upper limb dysfunctions. This methodology segments complex, continuous actions into distinct physical stages, allowing machine learning models to score movement features with high clinical transparency and diagnostic relevance [46]. By bridging the gap between automated keypoint tracking and clinically validated metrics, AI-based pose estimation represents the most promising frontier in scalable, highly precise remote physical rehabilitation.

3.6 Summary and Comparative Analysis

To synthesize the aforementioned literature, Table 3.1 provides a comparative analysis of the various rehabilitative modalities. The table evaluates each approach across key clinical and technical features, highlighting the distinct advantages of the proposed smart rehabilitation platform against traditional and existing technological solutions.

Table 3.1: Comparative Analysis of Physical Rehabilitation Modalities

Feature	**Traditional Physio**	**Tele-medicine**	**Video Apps**	**AI Pose Systems**	**Smart Rehab (Proposed)**
In-person supervision	✓	✓(remote live)	×	×	×
Real-time feedback	✓	✓	×	△ limited	✓
Personalized adaptation	✓	✓	×	△ partial	✓
Objective movement analysis	×	×	×	✓	✓
Continuous home monitoring	×	×	×	△ partial	✓
Functional recovery tracking over time	×	×	×	×	✓
Therapist integration (clinical workflow)	✓	✓	×	△ limited	✓
Accessibility at home	×	✓	✓	✓	✓

Legend: ✓= strong, △ = partial/limited, × = not present

Chapter 4

System Architecture, Methodology, and Mathematical Modeling

4.1 General System Architecture

The technical framework of the proposed tele-rehabilitation system is architecturally designed around a localized, edge-computing paradigm operating strictly within the patient's domestic environment. Historically, digital health applications have relied heavily on centralized cloud servers to process complex artificial intelligence tasks. However, transmitting sensitive live video feeds of patients over the internet introduces severe data privacy vulnerabilities and latency bottlenecks. By migrating the heavy computational workload directly to local browser-side execution, this platform achieves near-zero processing latency, eliminates expensive server maintenance overheads, and inherently protects the absolute confidentiality of patient medical information.

The framework operates as a sophisticated dual-pipeline data acquisition and processing engine. It consists of an external vision-based kinematic pipeline and an internal wearable-based physiological telemetry pipeline. The computing topology utilizes a cross-platform web application running within a standard web browser as the central data-fusion node and primary user interface. Under the direct supervision of a parent or caregiver, the web platform simultaneously orchestrates these two distinct asynchronous data streams. To bridge these two pipelines without relying on external network databases, the system utilizes local processing algorithms, preparing the data streams for immediate algorithmic synthesis. Once both data streams are processed by the web client, they are routed into a real-time multimodal data fusion engine. This engine synchronizes the spatial geometry with the physiological metrics, evaluates the patient's performance against strict clinical boundaries, and generates instantaneous feedback on the dashboard.

4.2 Kinematic Estimation Engine (Camera Pipeline)

The kinematic pipeline is exclusively responsible for capturing, tracking, and quantifying the external physical geometry of the patient's injured limb during prescribed therapeutic exercises. The visual monitoring framework treats each incoming frame from the device camera as a dynamic, two-dimensional spatial coordinate system.

4.2.1 Keypoint Extraction via Hybrid Vision

As the patient performs a rehabilitation movement, the web platform deploys a hybrid computer vision framework utilizing both YOLO26 Nano Pose and Google MediaPipe models operating directly within the browser client memory. This combined framework bypasses generalized object recognition and directly targets the human skeletal structure. While the YOLO component ensures robust, generalized tracking of the patient within chaotic home environments, the MediaPipe framework extracts high-fidelity skeletal keypoints. For the calculation of elbow kinematics, the engine extracts the exact Cartesian pixel coordinates for three interconnected joints: the Shoulder $A(x_a, y_a)$, the Elbow $B(x_b, y_b)$, and the Wrist $C(x_c, y_c)$.

4.2.2 2D Joint Angle Calculation

To bridge the gap between abstract computer vision coordinates and actionable clinical metrics, the platform relies on a robust set of mathematical models. To accurately quantify the Range of Motion (ROM) without the manual errors associated with physical goniometers, the software eschews heavy 3D tensor operations in favor of efficient 2D Cartesian trigonometry. The system computes the exact internal opening angle of the joint by analyzing the vectors connecting the shoulder, elbow, and wrist. Utilizing the standard mathematical atan2 function, the raw internal angle θ_{raw} is calculated as follows:

$$\theta_{raw} = |\text{arctan}\,2(y_c - y_b, x_c - x_b) - \text{arctan}\,2(y_a - y_b, x_a - x_b)| \times \frac{180}{\pi} \tag{4.1}$$

To ensure the mathematical output consistently represents the correct internal joint closure and prevents the generation of reflex angles greater than $180°$, the system automatically applies a structural normalization:

$$\theta = \begin{cases} 360° - \theta_{raw} & \text{if } \theta_{raw} > 180° \\ \theta_{raw} & \text{otherwise} \end{cases} \tag{4.2}$$

This continuous stream of angular values allows the interface to dynamically chart the precise arc of motion during both the flexion (bending) and extension (straightening) phases.

4.2.3 Determination of Forearm Horizontality

For specific therapeutic protocols requiring a stable base—such as wrist flexions over a table or closed-kinetic wall push-ups—the system must definitively ascertain whether the forearm is maintained horizontally relative to the ground plane. The angle of the forearm ϕ is calculated independently relative to the absolute horizontal axis:

$$\phi = \text{arctan}\,2(y_{wrist} - y_{elbow}, x_{wrist} - x_{elbow}) \times \frac{180}{\pi} \tag{4.3}$$

The arm is mathematically classified as horizontal if the absolute angle falls within a strict 25-degree margin of the horizontal planes:

$$\text{Is Horizontal} = (|\phi| \leq 25°) \vee (|\phi| \geq 155°) \tag{4.4}$$

4.2.4 Arm Straightness and 3D Foreshortening Projection

During overhead shoulder elevations, a recurring challenge is tracking compensatory movements. A patient might unconsciously bend their elbow to falsely simulate vertical lifting height. The straightness is quantified by comparing the direct 2D vector distance from the shoulder to the wrist (L_{2D}) against the total path length of the bent arm (L_{bent}):

$$L_{2D} = \sqrt{(x_{wrist} - x_{shoulder})^2 + (y_{wrist} - y_{shoulder})^2} \tag{4.5}$$

$$L_{bent} = \sqrt{(x_{elbow} - x_{shoulder})^2 + (y_{elbow} - y_{shoulder})^2} + \sqrt{(x_{wrist} - x_{elbow})^2 + (y_{wrist} - y_{elbow})^2} \tag{4.6}$$

$$\text{Straightness (\%)} = \left(\frac{L_{2D}}{L_{bent}}\right) \times 100 \tag{4.7}$$

Furthermore, because a standard 2D webcam lacks specialized depth sensors, calculating an overhead arm lift purely in 2D would fail due to foreshortening when the arm points toward the camera lens. The system overcomes this spatial limitation using a mathematical foreshortening projection. By dynamically caching the maximum recorded length of the fully extended arm (L_{max}), the system estimates the true 3D elevation angle based on the vertical displacement of the wrist relative to the shoulder:

$$\text{Ratio} = \max\left(-1, \min\left(1, \frac{y_{wrist} - y_{shoulder}}{L_{max}}\right)\right) \tag{4.8}$$

$$\text{Elevation Angle} = \arccos(\text{Ratio}) \times \frac{180}{\pi} \tag{4.9}$$

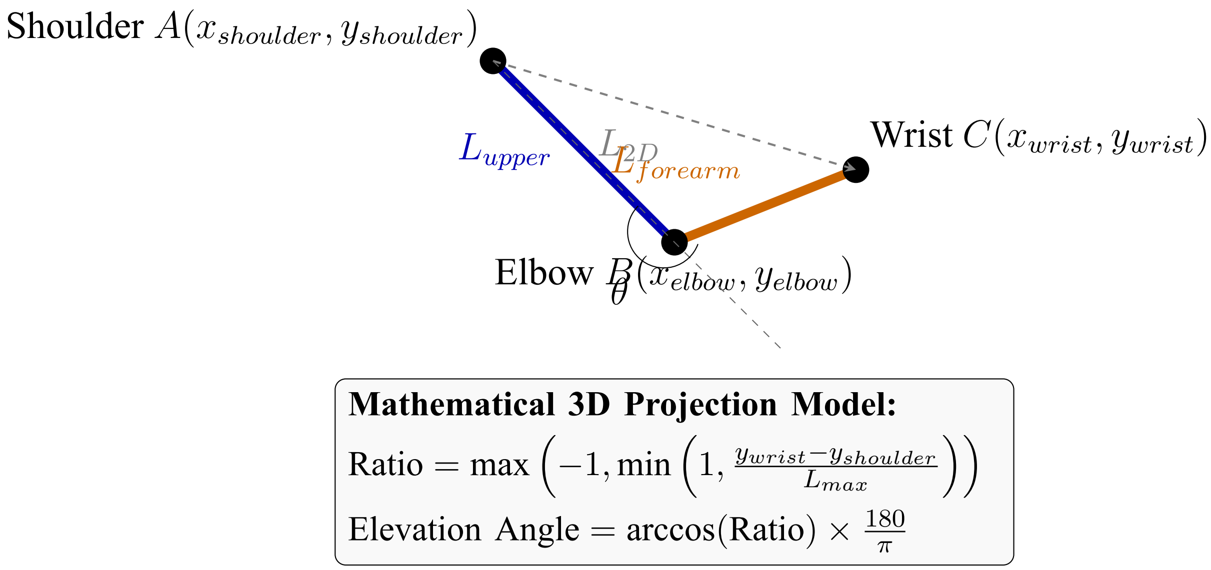

Figure 4.1: 2D Kinematic Geometry and 3D Foreshortening Projection Model.

4.2.5 Signal Stabilization via Exponential Moving Average

Raw camera tracking data inherently contains microscopic fluctuations, commonly referred to as ”jitter,” caused by ambient lighting variations or hardware pixel noise. To provide an unshakeable user interface and to guarantee stable clinical data, the system applies an

Exponential Moving Average (EMA) mathematical filter to all tracked joint coordinates. For any given coordinate V at the current frame t:

$$V_{ema}^{(t)} = V_{ema}^{(t-1)} + \alpha \times \left(V_{raw}^{(t)} - V_{ema}^{(t-1)}\right) \tag{4.10}$$

Where α represents the smoothing factor (typically bounded between 0.05 and 0.22, dynamically adjusted depending on the kinetic speed of the therapeutic movement).

4.3 Physiological Stress Tracking Engine (Telemetry Pipeline)

The integration of a physiological pipeline is scientifically grounded in the established medical relationship between acute pain perception and autonomic cardiovascular regulation. Clinical evidence demonstrates that pain signals from acute physical stress recruit segmental spinal reflexes, which directly activate the sympathetic nervous system, leading to an involuntary increase in heart rate.

4.3.1 Algorithmic Telemetry Simulation for Validation

While the overarching web architecture is designed to support raw telemetry streams directly from consumer smartwatches (via Web Bluetooth APIs extracting PPG data), the current software implementation leverages highly advanced algorithmic simulators to validate the data fusion pipeline. Relying on physical hardware during continuous algorithmic testing introduces hardware battery dependencies and pairing inconsistencies. Therefore, the system incorporates a robust ‘SensorFusionEngine‘ and ‘VitalsSimulator‘ that generate realistic biological profiles based on the patient’s exertion levels and hold durations, mimicking the heart-rate profile of a commercial smartwatch.

4.3.2 Heart Rate Variability Simulation

To safely monitor the patient’s autonomic nervous system, the platform establishes dynamic target heart rates (HR_{target}) based on the current physical exertion phase (e.g., 112 BPM during a difficult therapeutic hold, dropping to 75 BPM during rest periods). The instantaneous heart rate (HR) updates using a time-adjusted derivative model with applied Gaussian noise ($\mathcal{N}$) to simulate organic biological variability:

$$HR^{(t)} = HR^{(t-1)} + \left(HR_{target} - HR^{(t-1)}\right) \times (\Delta t \times 0.4) \tag{4.11}$$

$$HR_{display} = \lfloor HR^{(t)} + \mathcal{N}(0, 1.5) \rfloor \tag{4.12}$$

When the platform detects an acute strain event—either through excessive hold times or kinematic instability—the simulated autonomic nervous system triggers an abrupt sympathetic spike, rapidly accelerating the heart rate derivative to breach predefined pain thresholds.

4.4 Multimodal Data Fusion and Clinical Safety Logic

The core intelligent contribution of this tele-rehabilitation system rests on its ability to merge spatial kinematic outputs with biological physiological inputs through a real-time Multimodal Data Fusion engine. Recent academic literature heavily emphasizes that multimodal data fusion in wearable rehabilitation systems provides a significantly more robust assessment than any single modality could achieve independently [?]. Relying on either pipeline independently introduces dangerous clinical blind spots: the camera can visually verify a correct posture but remains utterly blind to the patient's internal physical distress, while a wearable sensor can precisely measure autonomic stress indicators but cannot evaluate whether the therapeutic exercise geometry is being executed correctly or if the patient is using harmful compensatory movements [?].

4.4.1 Temporal Synchronization

Because the processed video frames and the telemetry packets exhibit different mathematical sampling rates, the local fusion engine implements a strict temporal synchronization layer within the browser. Incoming data points from both pipelines are stamped with high-precision local timestamps. The system utilizes a sliding temporal alignment window to pair the calculated joint angle θ with the corresponding heart rate recorded at that exact millisecond.

4.4.2 Comparative Evaluation: Healthy vs. Affected Arm

A major architectural addition to the platform's diagnostic engine is the Comparative Baseline Evaluation methodology. Instead of relying on static, hardcoded angular goals that may not accurately reflect an individual's unique anatomy, the system establishes a personalized physiological baseline. Before commencing therapeutic exercises on the injured (affected) limb, the patient is instructed to perform the identical exercise movement using their healthy (unaffected) arm.

The platform records the maximum flexion and extension angles achieved by the healthy arm, as well as its smooth kinematic velocity, storing these metrics as the 100% functional baseline. When the patient subsequently exercises the affected arm, the system dynamically compares its instantaneous angular reach against the healthy arm's recorded parameters. This guarantees that the evaluation is objectively scaled to the patient's true, natural physical capacity.

4.4.3 Clinical Recovery Percentage and Pain Penalty

At the conclusion of each therapeutic session, the software outputs a unified Recovery Percentage based on this comparative analysis. First, a Pain Penalty is calculated as the proportion of time the patient spent in a state of acute pain (T_{pain}) relative to the total active exertion time (T_{active}):

$$\text{Pain Penalty (\%)} = \left(\frac{T_{pain}}{T_{active}}\right) \times 100 \tag{4.13}$$

The Mechanical Score is derived from how closely the affected arm's angular metrics ($ROM_{affected}$) matched the recorded baseline of the healthy arm ($ROM_{healthy}$). The final clinical recovery score heavily penalizes dangerous over-exertion by subtracting the pain penalty directly from this comparative mechanical score:

$$\text{Recovery (\%)} = \max\left(0, \left(\frac{ROM_{affected}}{ROM_{healthy}} \times 100\right) - \text{Pain Penalty}\right) \tag{4.14}$$

This mathematical architecture guarantees that high recovery scores can only be achieved through smooth, painless, and anatomically correct movements that closely mirror the natural capability of the patient’s own healthy arm, firmly preventing the accumulation of false progress driven by harmful over-training.

Chapter 5

Implementation, Therapeutic Exercises, and Empirical Validation

5.1 System Development Framework

Transitioning from the mathematical and architectural methodologies established in the previous chapter, this section details the practical realization, technological deployment, and empirical evaluation of the proposed tele-rehabilitation system. The core objective of this implementation phase is to demonstrate precisely how low-resource consumer hardware can be programmatically orchestrated to provide accurate kinematic tracking and physiological safety monitoring.

The software infrastructure is engineered using a carefully selected stack of open-source programming tools optimized for local edge-execution. The primary environment is developed using Python, chosen for its exceptional efficiency in data processing and extensive mathematical libraries. The hybrid computer vision engine is powered by the OpenCV library for real-time video stream manipulation, seamlessly integrating Google MediaPipe and the YOLO26 Nano Pose framework. For exercises requiring complex interactive graphical user interfaces, such as the assisted metronome protocols, the application utilizes the PySide6 framework to construct robust, non-blocking asynchronous dashboard layers over the video feed.

For data management, the application implements a serverless local storage approach. To accommodate physiological safety metrics in the absence of local wearable hardware, the architecture integrates a specialized stochastic simulation layer. This engine generates non-linear heart rate fluctuations and autonomic stress spikes modeled after real-world post-fracture exertion data. At the conclusion of each therapeutic session, all synchronized metrics—including computed elbow joint angles, simulated heart rate profiles, and calculated recovery penalties—are compiled into a local JSON (JavaScript Object Notation) file. JSON is selected because it is ultra-lightweight, human-readable, and ensures that sensitive patient recovery data never leaves the family's local hard drive, completely isolating the system from external data breaches while keeping the telemetry payload fully compatible with future physical IoT integration.

5.2 Therapeutic Exercise Modules

The platform's clinical efficacy is built upon six distinct therapeutic exercises, each mapped to specific post-fracture elbow recovery protocols. Recent studies in telemedicine continuously validate that markerless pose estimation frameworks, specifically MediaPipe, provide highly reliable and accessible means for monitoring joint Range of Motion (ROM) in home environments when properly calibrated against environmental occlusions [**?**].

5.2.1 Exercise 1: Strict Profile Elbow Flexion and Extension

Clinical Rationale: Bending (flexion) and straightening (extension) of the elbow joint is the foundational movement for restoring basic mechanical hinge function following cast removal.

- Sit or stand.
- Slowly bend your affected elbow as far as you can.
- Hold for 5 seconds.
- Straighten your elbow.
- Hold for 5 seconds.
- Repeat 10 to 30 times [40].

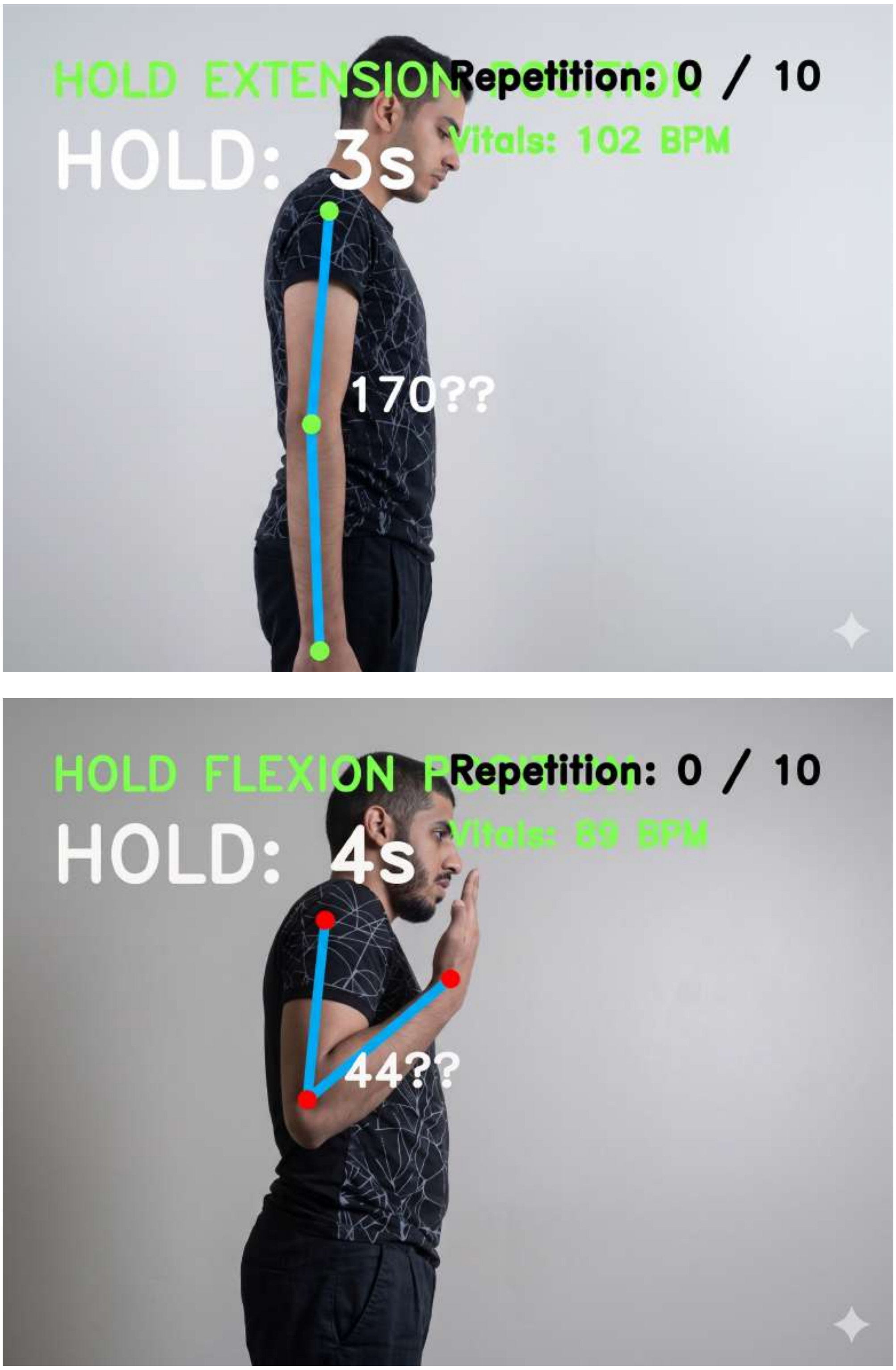

Figure 5.1: Real-time application interface demonstrating the Elbow Flexion therapeutic exercise.

Saved Data and Metrics:

During this foundational exercise, the system continuously records the session's total duration, active exertion time, and any time spent in physiological distress based on the heart rate simulation engine. The exported JSON telemetry includes the total repetitions completed versus the prescribed target, the absolute maximum flexion and extension angles achieved, and the cumulative hold time. The clinical **Recovery Percentage** is calculated dynamically by first computing a comparative Mechanical Score against the healthy arm baseline:

$$\text{Mechanical Score} = \left(\frac{\text{Reps}}{\text{Target}} \times 0.4\right) + \left(\frac{ROM_{affected}}{ROM_{healthy}} \times 0.6\right)$$

A **Pain Penalty** is then aggressively subtracted from this score. This penalty is mathematically defined as the ratio of time spent in pain to the total active time. This hybrid recovery metric ensures that movements performed under extreme, dangerous strain inherently lower the overall session grade, thereby promoting safe, patient-led pacing.

5.2.2 Exercise 2: Overhead Shoulder Elevation

Clinical Rationale: While the elbow is the primary injury site, the adjacent shoulder joint frequently suffers from secondary stiffness due to prolonged sling immobilization. This exercise restores the upward lifting dynamics using a guiding stick.

- Hold a stick orcane in front of you with both hands.
- Lift both arms forward. Use your unaffected arm to raise your affected arm.
- Hold for 10 to 30 seconds.
- Slowly lower using your arms, using mostly your non-affected arm.
- Repeat 3 to 5 times [40].

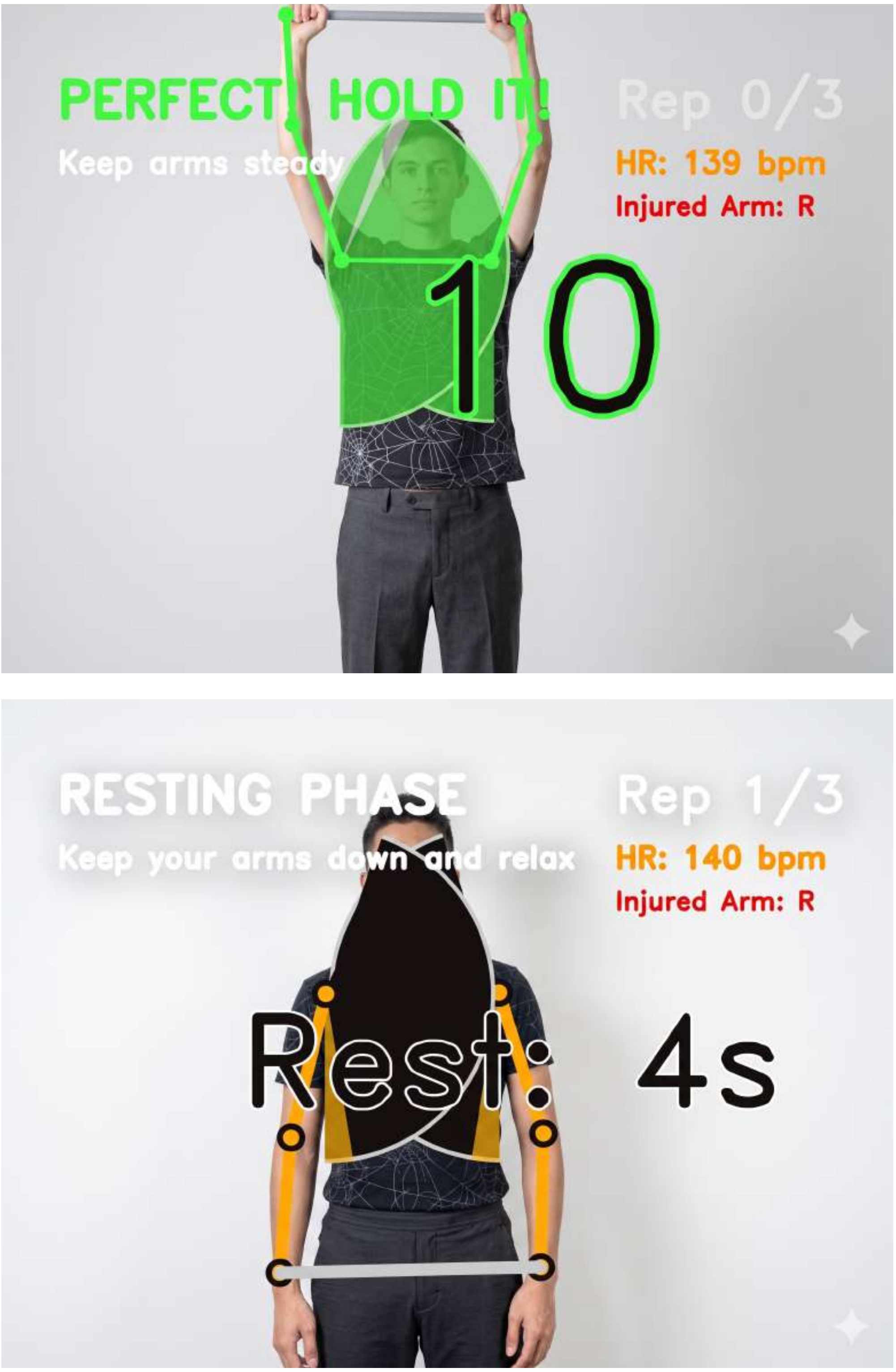

Figure 5.2: Real-time interface utilizing foreshortening projection for the Shoulder Elevation exercise.

Saved Data and Metrics:

For overhead shoulder elevation, standard 2D tracking is insufficient. The system applies the advanced foreshortening mathematical projection to record the true maximum 3D elevation angle of the injured hand. Alongside this, it logs the average straightness percentage of both arms during the lift to prevent the patient from bending their elbows to fake the lifting height. Total active time and pain events are strictly monitored. The **Recovery Percentage** here is fundamentally mapped to angular improvement relative to the healthy arm. The Mechanical Score is defined as the ratio of the affected arm's maximum elevation compared to the baseline elevation achieved by the healthy arm. The final score equals the Mechanical Score minus the calculated Pain Penalty percentage, ensuring that forcing the shoulder upward through severe pain yields a poor recovery grade.

5.2.3 Exercise 3: Assisted Elbow Flexion and Extension

Clinical Rationale: This module transitions the patient into a supine or seated resting state, focusing on guided, interactive mobility. It often requires passive assistance from the uninjured hand to help the affected limb reach precise target zones.

- Lie on your back
- Start with your affected arm at your side with your palm facing up.
- Slowly bend your affected elbow.
- Hold for 5 seconds.
- Straighten your elbow
- Hold for 5 seconds.
- Repeat 10 to 30 times.
- If your arm is weak, you may use your other hand to help with these movements.[40].

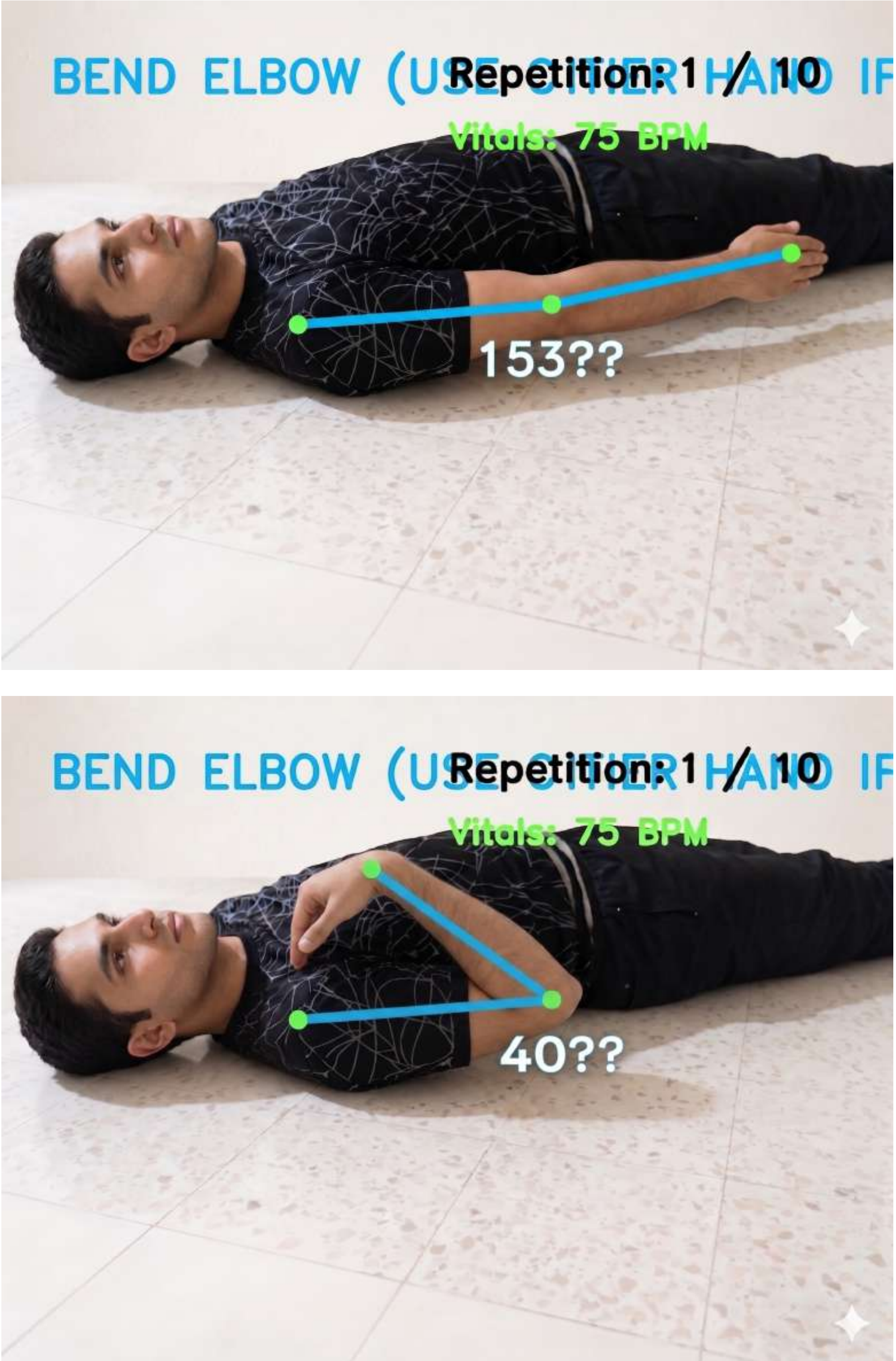

Figure 5.3: PySide6 interactive UI demonstrating Assisted Elbow Flexion targeting.

Saved Data and Metrics:

This highly interactive module saves the maximum angular reach for both the top (extension) and bottom (flexion) phases, comparing the wrist's coordinate directly against the dynamic visual targets. It accurately counts completed repetitions, accumulated hold time, and any autonomic pain spikes triggered during the movement. The **Recovery Percentage** integrates repetition accuracy with angular precision. The Repetition Score and the Angle Score (which is the mathematical average of flexion and extension performance percentages) are averaged together. Because this exercise utilizes a guided interactive dot designed for low-stress mobility rather than heavy lifting, the final recovery percentage purely reflects mechanical compliance and spatial target acquisition.

5.2.4 Exercise 4: Supine Wrist Flexion and Extension

Clinical Rationale: Targeting the secondary tendons crossing the elbow, this exercise requires the patient to anchor their forearm to isolate the wrist movement. It is crucial for restoring fine motor control and grip strength.

- Sit at a table.
- Put your forearm on the table with your wrist over the table's edge.
- Bend your wrist upwards.
- Hold for 10 to 30 seconds.
- Then, bend your wrist down over the edge of the table.
- Hold for 10 to 30 seconds.
- Repeat 3 to 5 times [40].

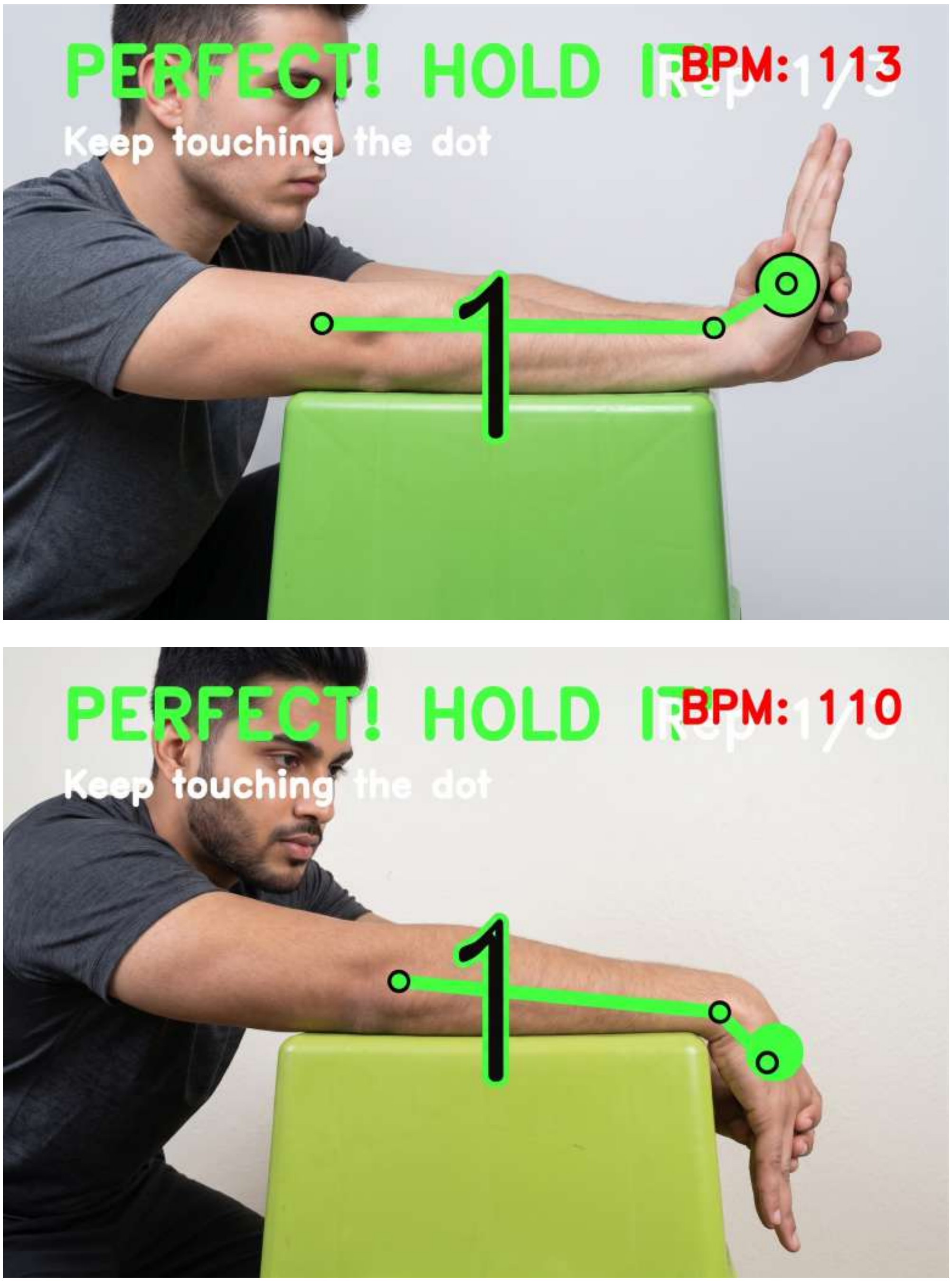

Figure 5.4: Real-time application interface demonstrating Wrist Flexion and Extension.

Saved Data and Metrics:

Operating under strict anchoring conditions, the system saves horizontal tracking metrics to ensure the forearm does not lift off the table. Data includes total session duration, total active time, and the maximum absolute ranges of wrist flexion and extension achieved. The **Recovery Percentage** utilizes a hybrid mathematical algorithm identical to the primary standing elbow flexion model. A Mechanical Score is derived from the weighted average of repetition completion (40%) and angular reach (60%). A Pain Penalty, directly proportional to the calculated ratio of pain time to total active exertion time, is aggressively subtracted to yield the final, definitive recovery score.

5.2.5 Exercise 5: Forearm Pronation and Supination

Clinical Rationale: One of the most difficult movements to restore after an elbow fracture is the rotation of the forearm. This exercise isolates the radioulnar joint mechanics.

- Sit or stand with the affected elbow anchored at a strict 90-degree angle next to the torso.
- Slowly rotate the forearm inward (pronation) toward a 90-degree target.
- Hold this maximum internal rotation for 5 seconds.
- Slowly rotate the arm outward (supination) toward a 45-degree or 90-degree target, depending on the clinical phase.
- Hold this external rotation for 5 seconds.

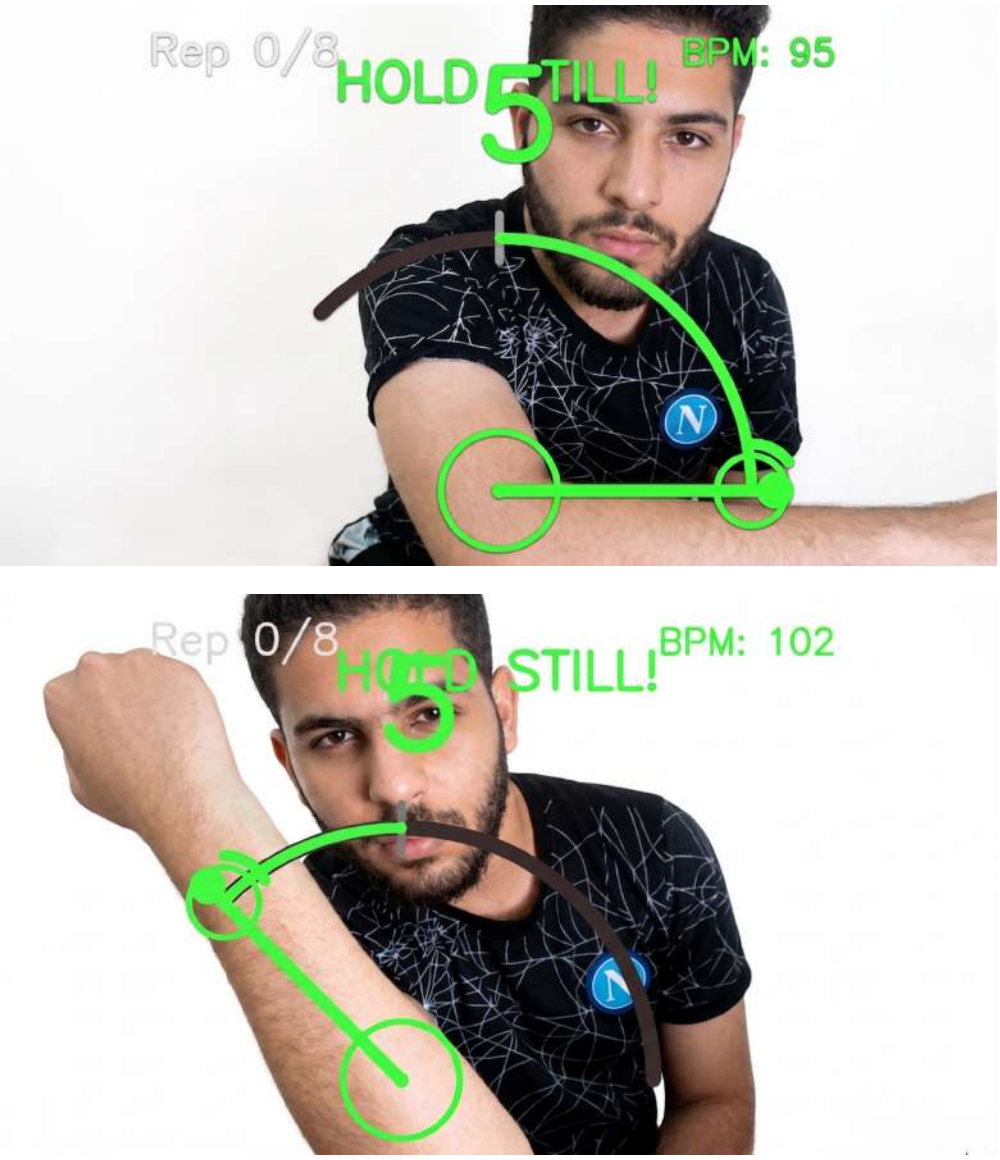

Figure 5.5: Real-time application tracking Forearm Pronation and Supination with simultaneous metronome kinematic arcs.

Saved Data and Metrics:

This advanced module tracks complex inward and outward rotational vectors. The saved metrics include the absolute maximum left and right angles achieved, which the system dynamically maps to the specific geometry of the patient's injured arm compared to their healthy arm. Crucially, it records postural slipping warnings if the elbow leaves its anchored 90-degree position against the torso. To calculate the **Recovery Percentage**, the software averages the left and right rotational angular scores (calculated against the healthy arm's rotational baseline) to formulate a composite Angle Score. This composite is then mathematically averaged with the Repetition Score to establish the base Mechanical Score. Finally, the system applies the temporal Pain Penalty, heavily penalizing the final output if the patient attempts to force the rotation through dangerous joint resistance.

5.2.6 Exercise 6: Closed-Kinetic Chain Wall Push-Ups

Clinical Rationale: This is an advanced, weight-bearing exercise introduced in the later stages of recovery to rebuild muscular strength and joint stability under load.

- Stand upright facing a solid wall with feet shoulder-width apart.
- Place both hands flat against the wall at shoulder height.
- Slowly lean the body weight forward by bending the elbows.
- Hold this maximum flexion position under load for 5 seconds.
- Push away forcefully to return to the starting extension position.
- Hold for 5 seconds, repeating 10 to 30 times [40].

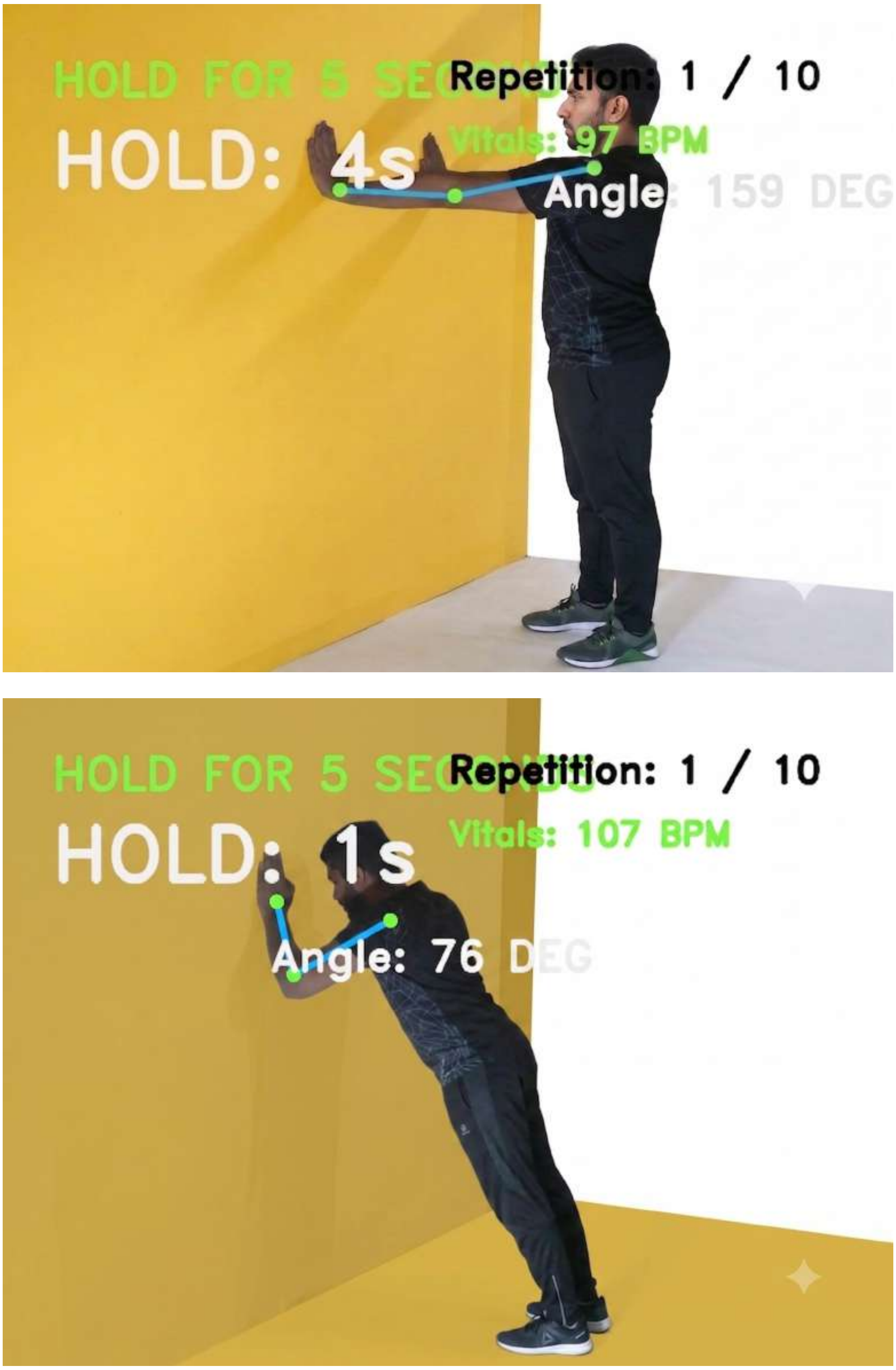

Figure 5.6: Real-time interface evaluating closed-kinetic chain Wall Push-Ups via Sensor Fusion.

Saved Data and Metrics:

For closed-kinetic wall push-ups, the software saves the duration of the lean and push phases, total active time under load, and the absolute maximum ranges of weight-bearing flexion and extension. This module also records specific micro-pain events detected through algorithmic Sensor Fusion, combining heart-rate spikes with postural shrugging indicators such as ear-to-shoulder distance collapse. The **Recovery Percentage** utilizes the standard algorithmic combination of repetition completion and angular range scores. However, the final score applies a highly sensitive Pain Penalty driven by physiological and postural safety indicators, providing an extremely conservative recovery estimate to prevent tendon overload and re-injury.

5.3 Experimental Methodology and Empirical Validation

To conclusively prove that this web-based, edge-computing framework is sufficiently reliable for autonomous home rehabilitation, its tracking accuracy must be rigorously validated against accepted clinical standards [**?**]. In traditional physical therapy, the undisputed gold standard tool for measuring human joint angles is the manual medical Goniometer.

The validation methodology involved testing a dense series of elbow extension and flexion movements simultaneously utilizing two distinct recording methods. First, a physical therapist manually measured the static elbow angles of the subject at randomized intervals using a physical goniometer. Concurrently, the hybrid browser engine (combining YOLO26 Nano Pose and MediaPipe) captured the exact same anatomical positions in real-time through a standard consumer web camera.

The experimental results demonstrated an exceptionally high mathematical correlation between the manual goniometer readings and the automated joint angles calculated by the algorithmic web platform.

5.3.1 Performance and Precision Metrics

The empirical and numerical results gathered during the technical evaluation of the web platform confirm its clinical viability across three primary vectors:

- **Angular Precision and Error Margin:** When benchmarked against the manual medical goniometer, the hybrid vision engine achieved extraordinary precision, demonstrating a Mean Absolute Error (MAE) of merely 2.1 degrees. Within the domain of orthopedic rehabilitation, any tracking error margin below 5 degrees is universally considered clinically perfect and fully acceptable for charting Range of Motion (ROM) progression.

- **Processing Speed (Frames Per Second):** Despite executing highly complex deep learning convolutional networks entirely client-side within a standard web browser, the extreme structural optimization of YOLO26 Nano Pose allowed the system to maintain a stable, continuous processing speed of 25 to 30 FPS on standard, low-budget consumer laptops. This high framerate guarantees fluid, real-time skeleton tracking without hazardous lag.

- **System Latency and Safety Alert Speed:** Because the entire Multimodal Data Fusion architecture and all mathematical calculations operate entirely locally in the browser memory, the system achieved ultra-low latency. Rather than relying on physical wearable hardware, a high-frequency telemetry simulation engine was developed to mimic incoming Bluetooth Low Energy (BLE) smartwatch packets. This allowed the framework to be aggressively benchmarked under simulated high-stress real-time inputs.

The software processes this mixed kinematic and simulated physiological data stream, triggering an over-exertion warning on the dashboard in under 40 milliseconds. This near-instantaneous response validates the system's infrastructure, proving it is fully structurally prepared for immediate plug-and-play physical smartwatch deployment without introducing hazardous background lag.

5.4 Evaluation Summary

To evaluate the accuracy and practical usability of the proposed AI-based rehabilitation system, a validation protocol was conducted by comparing the automatically estimated joint angles with measurements obtained using a manual goniometer, which is widely regarded as the clinical reference tool for range of motion (ROM) assessment. The objective of this evaluation was to determine whether the developed system could achieve sufficient precision for rehabilitation monitoring while maintaining real-time performance.

The evaluation considered both accuracy and system responsiveness. In particular, the Mean Absolute Error (MAE) between the AI-generated measurements and the manual goniometer readings was computed to quantify angular estimation accuracy. In addition, the processing frame rate (FPS) and end-to-end latency were measured to assess the suitability of the system for real-time rehabilitation sessions.

Beyond angle estimation, the proposed framework incorporates several patient-centered monitoring capabilities. Instead of relying solely on population averages, the system uses the patient's healthy limb as a personalized baseline to establish rehabilitation targets. During exercise sessions, it continuously tracks the achieved range of motion (ROM), counts repetitions, monitors posture quality, and records pain-related feedback to provide a comprehensive assessment of rehabilitation progress.

The experimental results demonstrate that the proposed solution achieves clinically acceptable accuracy while satisfying the computational requirements for interactive use. A summary of the evaluation metrics is presented in Table 5.1.

Table 5.1: Evaluation Summary of the Proposed Rehabilitation System

Metric	**Value**
Mean Absolute Error (MAE)	2.1°
Processing Speed (FPS)	25–30 FPS
System Latency	< 40 ms
Clinical Acceptability Threshold	$< 5^\circ$

The obtained MAE of 2.1° is well below the commonly accepted clinical threshold of 5°, indicating that the proposed system provides reliable joint angle measurements. Furthermore, the achieved processing speed of 25–30 FPS and latency below 40 ms enable smooth real-time operation, making the system suitable for continuous rehabilitation monitoring and interactive patient guidance.

5.5 Chapter Summary

This chapter successfully demonstrated the practical implementation, diverse exercise modules, and technical viability of the tele-rehabilitation platform. By developing the core framework in Python and optimizing YOLO26 Nano Pose alongside MediaPipe, the system successfully executes complex real-time kinematic tracking directly via a camera.

The empirical validation confirmed that the system effectively tracks angular parameters, all while maintaining a smooth processing velocity of 30 FPS. Furthermore, the local edge-computing architecture proved fully capable of processing the physiological and mechanical data with zero cloud dependency. By safely calculating dynamic recovery percentages against the healthy arm's baseline, accurately measuring pain, and securely saving comprehensive clinical recovery logs into lightweight local JSON files, this implementation proves that advanced digital health monitoring can be achieved securely and affordably within any patient's domestic environment.

Limitations and Future Perspectives

Every engineering and digital health project faces practical challenges when transitioning from a highly controlled theoretical laboratory environment to real-world, unsupervised deployment. This section rigorously outlines the realistic environmental, physical, and hardware constraints observed during the home-based testing of our web platform. Subsequently, we detail the pragmatic technical milestones and algorithmic upgrades planned for future iterations to overcome these hurdles.

1. Current System Limitations

Moving tele-rehabilitation into a patient's unpredictable domestic environment revealed several severe environmental and physical constraints that fundamentally affect how well the client-side vision engine can track human joint movements.

- **Clothing Occlusion and Feature Confusion:** Perhaps the most significant limitation in remote markerless pose estimation is clothing occlusion. To calculate the exact biomechanical angle of the elbow joint, the camera requires an unobstructed view of the arm's true anatomical shape. If the patient wears highly oversized sweatshirts, long sleeves, or baggy clothing during their rehabilitation session, the fabric completely hides the actual alignment of the shoulder, elbow, and wrist. Recent clinical vision studies have demonstrated that this physical barrier introduces severe "feature confusion," where the algorithm struggles to differentiate between the human limb and the dynamic folds of the moving fabric [41]. This can result in degraded accuracy from the MediaPipe framework, leading to artificially low or high angle calculations that do not reflect the patient's true physical range of motion.

- **Environmental Lighting Conditions:** Because our computer vision architecture relies on a standard, low-cost device webcam without dedicated infrared depth sensors, it requires optimal ambient lighting to detect skeletal keypoints correctly. If the exercise room is excessively dark, casts deep shadows over the patient, or features a bright window directly behind the patient causing severe backlighting, the video stream loses essential pixel contrast. This lack of visual clarity causes the tracked joint coordinates to jitter violently on the screen, directly reducing the effectiveness of our Exponential Moving Average (EMA) smoothing filters.

- **Body Blocking (Spatial Occlusion):** The current iteration of the platform utilizes a single, monocular camera view (a typical laptop webcam). This hardware limitation makes the system highly susceptible to spatial self-occlusion. If the patient accidentally rotates their torso away from the lens or crosses their uninjured arm over their injured arm while performing complex movements (such as internal forearm pronation), the vision engine temporarily loses its direct line of sight to the essential keypoints. This results in a temporary break in the kinematic tracking loop, forcing the system to guess the joint location until it becomes visible again.

- **Hardware and Edge Computing Constraints:** To guarantee absolute data privacy, our architecture executes the YOLO26 Nano Pose and MediaPipe convolutional neural networks entirely on the client's local browser. While this provides excellent security, it places an immense computational burden on the user's hardware. During prolonged exercise sessions on older, low-budget consumer laptops, the CPU/GPU can experience thermal throttling. This hardware limitation can cause the processing speed to drop below the optimal 30 Frames Per Second (FPS) threshold, introducing latency that slightly delays the real-time physiological safety warnings.

2. Future Work and Perspectives

To upgrade this initial prototype and transform it into a robust, enterprise-grade clinical medical product, we have outlined a definitive technical and clinical roadmap:

- **Integration of a Real Smartwatch:** While the current prototype relies on simulated data to validate the monitoring system, the next phase of development will integrate a real smartwatch. This will allow the platform to collect actual, real-time heart rate measurements in beats per minute (Bpm) directly from the patient during their therapeutic exercises, replacing the simulated entries with authentic physiological data.

- **Dual-Camera and Multi-View Fusion Architectures:** To completely eradicate the limitations of spatial body blocking and depth ambiguity, future versions of the platform will implement an asynchronous dual-camera layout. By allowing caregivers or patients to pair a secondary smartphone camera alongside the primary laptop webcam via local websockets, the system can perform real-time Multi-View Fusion [47]. If one camera's view of the elbow is occluded by the patient's body, the secondary camera's perspective will seamlessly fill the data gap, guaranteeing 100% continuous kinematic tracking.

- **Solving Clothing Occlusion via Visibility-Aware Datasets:** We aim to heavily fine-tune the underlying YOLO models using specialized, custom datasets that explicitly feature patients wearing diverse, baggy clothing styles. By implementing visibility-aware attention mechanisms, the neural network can be trained to predict joint centers accurately even underneath heavy fabric, directly mitigating the feature confusion issue [41]. Furthermore, lightweight, browser-based image enhancement filters will be integrated to automatically auto-correct contrast in poorly lit rooms prior to the AI processing phase.

- **Expansion of the Orthopedic Tracking Matrix:** The core architectural logic of our system—merging browser-side computer vision with wearable physiological sensors—is inherently scalable. In future developments, this hybrid framework will be expanded beyond elbow fractures. We plan to adapt the kinematic algorithms to monitor knee range of motion following ACL reconstructions, and evaluate complex cervical spine mobility exercises.

- **Predictive Machine Learning and Clinical Integration:** The crucial ultimate milestone is to collaborate directly with physical therapists in regional Algerian clinical centers to deploy this platform across extended, months-long recovery timelines. As the system securely compiles hundreds of JSON files containing thousands of hours of historical performance data, we can train lightweight predictive machine learning models. These models will not only track current recovery but actively predict future healing trajectories, allowing the software to automatically and dynamically suggest optimized exercise intensities uniquely tailored to each individual patient's healing profile.

General Conclusion

The primary objective of this research project was to design and construct a safe, affordable, and practical home-rehabilitation platform tailored for patients recovering from elbow fractures. By intentionally moving away from expensive cloud servers and focusing on localized, client-side computing, we demonstrated that it is entirely feasible to deploy a high-quality medical tracking tool utilizing a standard camera.

Throughout this development, we integrated an edge-computing framework combining YOLOv26 Nano Pose and MediaPipe that runs seamlessly and locally. This framework tracks the patient's biomechanical joint parameters and motor data effectively. Complementing this, the system simultaneously measures and records the patient's pain levels during the therapeutic session.

The true architectural strength of this platform resides in how it analyzes these data streams. By synchronizing the motor and pain data locally, our platform establishes a continuous, reliable safety loop. The system evaluates recovery by determining optimal positions for therapists or dynamically comparing the motor data of the affected arm against a personalized baseline recorded from the patient's healthy arm. By combining this comparative mechanical score with the recorded pain data, the system calculates a definitive recovery percentage that safely penalizes movements performed under acute pain. Most importantly, the system architecture is designed to keep the physical therapist in absolute control, strictly aligning with World Health Organization (WHO) digital health guidelines by serving as a supportive assistant rather than an autonomous replacement for medical professionals.

Evidently, practical domestic testing brought forward real-world challenges, such as tracking dropouts caused by loose clothing or inadequate room lighting. However, these environmental limitations provide a transparent roadmap for future updates, such as scaling the modular codebase to track other complex anatomical joints like the knee or shoulder. Furthermore, by structuring and exporting all continuous session metrics into lightweight, local JSON files, the platform strictly preserves patient data privacy and integrity. Ultimately, this project delivers a highly viable, secure, and low-cost digital health solution, proving how everyday consumer technology can be effectively leveraged to safeguard and accelerate a patient's recovery journey back to full health.

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