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A Smart Motor Rehabilitation System Based on the Internet of Things and Humanoid Robotics

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Abstract: The Internet of Things (IoT) is gaining increasing attention in healthcare due to its potential to enable continuous monitoring of patients, both at home and in controlled medical environments. In this paper, we explore the integration of IoT with human-robotics in the context of motor rehabilitation for groups of patients performing moderate physical routines, focused on balance, stretching, and posture. Specifically, we propose the I-TROPHYTS framework, which introduces a step-change in motor rehabilitation by advancing towards more sustainable medical services and personalized diagnostics. Our framework leverages wearable sensors to monitor patients' vital signs and edge computing to detect and estimate motor routines. In addition, it incorporates a humanoid robot that mimics the actions of a physiotherapist, adapting motor routines in real-time based on the patient's condition. All data from physiotherapy sessions are modeled using an ontology, enabling automatic reasoning and planning of robot actions. In this paper, we present the architecture of the proposed framework, which spans four layers, and discuss its enabling components. Furthermore, we detail the current deployment of the IoT system for patient monitoring and automatic identification of motor routines via Machine Learning techniques. Our experimental results, collected from a group of volunteers performing balance and stretching exercises, demonstrate that we can achieve nearly 100% accuracy in distinguishing between shoulder abduction and shoulder flexion, using Inertial Measurement Unit data from wearable IoT devices placed on the wrist and elbow of the test subjects.

Keywords: motor rehabilitation; internet of things; humanoid robotics; ontology; human activity recognition; machine learning

Citation: Moghbelan, Y.; Esposito, A.; Zyrianoff, I.; Spaletta, G.; Borgo, S.; Masolo, C.; Ballarin, F.; Seidita, V.; Toni, R.; Barbaro, F.; et al. A Smart Motor Rehabilitation System Based on the Internet of Things and Humanoid Robotics. *Appl. Sci.* **2024**, *14*, 11489. https://doi.org/10.3390/app142411489

Academic Editors: Kai Guo and Hongbo Yang

Received: 25 October 2024
Revised: 18 November 2024
Accepted: 2 December 2024
Published: 10 December 2024

1. Introduction

Recent statistics on demographic trends in Europe show a clear increase in the median age, with a significant growth in the number and proportion of elderly people. Between 2019 and 2050, the EU population aged 75–84 is estimated to be 27%, reaching 129.8 million by 2050 [1]. This demographic shift is associated with a rise in high metabolic risk factors among Europeans, such as obesity, type-2 diabetes and cardiovascular diseases, all of which require healthcare support from public institutions. This support often includes moderate physical activities, focusing on balance, stretching, and posture, under the guidance of medical professionals [2,3]. In parallel, the COVID-19 pandemic has underlined the need to reduce pressure on healthcare workers and highlighted the importance of building sustainable healthcare systems that can leverage emerging information technologies (IT) [4].

Researchers have identified that monitoring vital signs, such as heart rate and oxygen saturation, is essential for timely intervention and prevention [5]. Through continuous monitoring, Internet of Things (IoT) systems can deliver real-time feedback to healthcare providers and reduce the need for frequent in-person visits [6–8]. Of the few works that simultaneously collect Inertial Measurement Unit (IMU) and physiological data [9–11], none are able to handle rehabilitation sessions composed of groups of patients. Furthermore, little effort has been devoted to automating such sessions, while ensuring high patient engagement.

This paper focuses on motor rehabilitation techniques for groups of patients performing moderate physical routines in controlled indoor environments, such as gyms or dedicated hospital rooms. Wearable IoT devices equipped with IMU sensors have been identified as portable and non-invasive solutions for patient monitoring, contributing to personalized healthcare management [6,7]. Similarly, camera-based solutions enhanced by Deep Learning (DL) techniques have been successfully applied to posture detection, gait analysis, and automatic error detection during exercises [12,13]. However, limited innovation has been brought about in the way physiotherapy sessions are delivered to patients. While telerehabilitation systems, now accessible via portable devices [14], enable home-based physiotherapy sessions and remote monitoring, they often lack the ability to personalize and adapt to the patient's individual condition.

In this paper, we propose a novel concept for a smart motor rehabilitation system that leverages the convergence of IoT, Artificial Intelligence (AI), and Robotics, to improve healthcare sustainability, enable fine-grained patient monitoring and provide personalized diagnoses. We call this system I-TROPHYTS (https://site.unibo.it/itrophyts/en accessed on 1 December 2024), an acronym for *IoT and humanoid RObotics for autonomic PHYsio-Therapeutic monitoring, coaching and supervision in smart Spaces*. In our proposed scenario, patients are continuously monitored during physiotherapy sessions using wearable IoT sensors that capture both movement and physiological responses, such as heart rate and oxygen saturation already mentioned. At the same time, a humanoid robot partially takes over the role of the physiotherapist by imitating certain human behaviors. Based on the collected IoT data and domain-specific information, the robot can decide to start the next exercise in the motor routine, suggest alternative exercises, assign cool-down periods, or alert medical personnel in case of detected anomalies. By introducing controlled automation in this domain, I-TROPHYTS aims to enhance the overall sustainability of healthcare systems, as a single physiotherapist could supervise multiple patient groups simultaneously. Furthermore, by employing non-invasive IoT monitoring techniques together with edge-based processing [15,16], we can continuously track individual patient performance over time and identify correlations that could lead to personalized therapies. The use of humanoid robotics may also increase patient engagement due to its morphological similarities to humans [17,18]. However, realizing this concept requires the development of an innovative hardware/software framework with contributions spanning multiple fields, including IoT, knowledge representation and robotics. The I-TROPHYTS framework ensures IoT data acquisition from two types of wearable devices (IMU-based and vital-sign sensors), and integrates ML algorithms for exercise recognition and motion tracking. Moreover, it enables the representation of physiotherapy session data—including both patient states and domain-specific rules—via a uniform and unambiguous knowledge representation in the form of an ontology. This ontology facilitates reasoning and decision-making by the humanoid robot. To summarize, the key contributions of this paper are as follows:

- We present the concept behind I-TROPHYTS for next-generation smart rehabilitation and the layered architecture that supports its implementation.

- We describe in detail the current development phase of the I-TROPHYTS framework, with a focus on the IoT data acquisition and processing pipeline, as well as the robotic architecture.
- We report experiments, involving multiple volunteers performing up to four motor routines, to assess the ability of the proposed IoT and ML-based techniques to automatically identify and distinguish between different exercises.

Our results demonstrate that a performed exercise can be accurately identified by leveraging IMU data from wearables. In particular, we achieve 100% accuracy in distinguishing a shoulder abduction from a shoulder flexion, using IMU data from IoT wearable devices placed on the wrist and elbow of our test subjects. We also show that the I-TROPHYTS framework can discern the exercise with high accuracy (>90%) employing just one signal (acceleration or gyroscope) from a single IoT sensor (placed on the wrist or elbow of an arm). This proves that the exercise being performed can be identified, even if the active arm is not equipped with a sensor.

The paper is organized as follows. Section 2 reviews the state of the art of IT solutions for rehabilitation systems, focusing on IoT and ML-based approaches. Section 3 introduces the I-TROPHYTS concept and components of the framework. Section 4 details the current design and development phase of the framework, focusing on the IoT sensing and edge processing layers. Section 5 describes experiments and performance results. Section 6 includes a discussion on ongoing work on data modeling and integration with robotic actuation. Section 7 concludes the paper.

2. Related Works

Many studies make use of wearables for early detection and diagnosis, to improve elderly care and reduce physiotherapy visits. In a recent work [6], researchers explored the value of wearable sensor data for timely prediction in stroke recovery patients, employing IMU sensors to collect movement and balance data. Participants were divided into ambulatory and non-ambulatory groups. By applying supervised ML classifiers, three models were trained to combine patient information with clinical and sensor data to predict outcomes. According to a review [7] of stroke rehabilitation research from 2009 to 2023, accelerometers (the most common) and gyroscopes paired with ML can improve stroke rehabilitation and remote monitoring. The study explores several ML techniques, including reinforcement learning, supervised, unsupervised, and semi-supervised learning. Tak et al. [9] presented a sensor-based 3D motion capture method that employs four IMU sensors placed on the trunk, pelvis, upper leg, and lower leg, to measure joint movement during a single-leg squat, demonstrating good to excellent concurrent validity with a conventional 3D motion capture system. Similarly, Bravi et al. [8] used two IMU sensors, placed on the wrist and upper arm, to measure the range of motion of the shoulder. Additionally, a Raspberry Pi served as a gateway, managing data collection, synchronization, and processing through dedicated software. Basmaji et al. [19] proposes a belt with IMU sensors and a High-Definition camera to highlight the need for posture monitoring to prevent spinal issues and musculoskeletal discomfort. Sensors are placed in the thoracic and thoracolumbar corners to monitor the flexion angle of the neck and upper back. The collected data are transmitted to a cloud server, and users can view and track their posture via a mobile application, enabling therapists to provide accurate follow-up and guidance. The solution described in [10] captures the therapist's movements, gathers data using RGB-Depth cameras, and allows therapists to record specific rehabilitation movements via a gesture-based Natural User Interface (NUI). These motions are then replicated by an exoskeleton robot on a patient. Future developments aim to integrate ML for automatic error detection during exercises and potentially provide feedback. Thakur et al. [20] propose a robot-assisted wrist physical rehabilitation system that uses accelerometer and magnetometer sensors embedded in a 3D-printed wearable band to monitor wrist movements such as flexion, extension, abduction, and adduction in stroke patients. By synchronizing the robot's actions with sensor feedback, it ensures precise execution of exercises, and can operate independently. Data are uploaded to a cloud server, enabling clinicians to track progress and adjust treatment plans based on feedback. The system supports both active rehabilitation and therapist-assisted use. The study presented in [11] aims to help paralyzed patients navigate smart cities with automatic limb control, suggesting a lightweight, intelligent exoskeleton system that employs data from multiple sensors and cameras to detect parameters like distance, obstacles, orientation, speed and acceleration. The system uses Artificial Neural Networks (ANNs) for data classification and AI-powered navigation for real-time motion control and prediction. While some data are processed locally to enable real-time corrective movements and prevent falls, cloud-based feedback is provided for remote monitoring and assistance.

In this context, the proposed work aims to develop an IoT system that facilitates synchronized motor rehabilitation. I-TROPHYTS jointly monitors patient movements and vital signs via non-invasive IoT devices to conduct physiotherapy sessions independently at home, while receiving real-time semi-autonomous supervision of their rehabilitation activities. Table 1 summarizes our literature review by comparing our solution with the state of the art. Among the reviewed works, I-TROPHYTS is the only solution that combines ML-based techniques and edge processing to support patient physiotherapy sessions conducted by a humanoid robot. Furthermore, it can handle the simultaneous monitoring of multiple users.

Table 1. Comparison of I-TROPHYTS with related work.

Paper	IMU Sensors	Vital Signs	ML Techniques	Edge Processing	Humanoid Robot
[6]	✓	✗	✓	✗	✗
[7]	✓	✗	✓	✓	✗
[9]	✓	✗	✗	✗	✗
[8]	✓	✗	✗	✗	✗
[19]	✓	✗	✗	✗	✗
[10]	✗	✗	✗	✗	✓
[20]	✓	✗	✗	✗	✓
[11]	✓	✗	✓	✓	✓
I-TROPHYS	✓	✓	✓	✓	✓

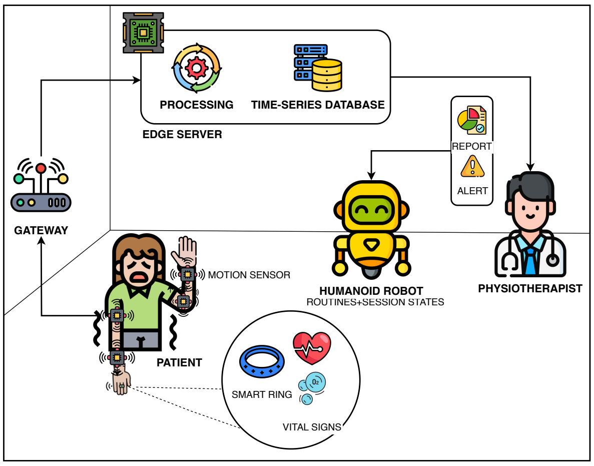
3. The I-TROPHYTS Framework

3.1. System Model

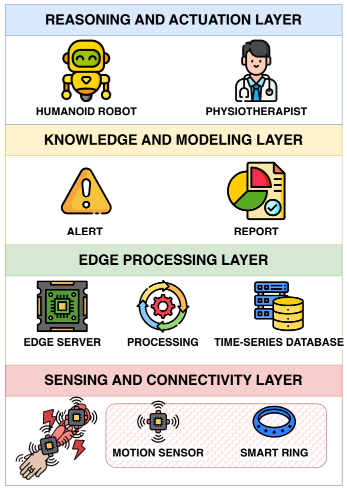
Here, we consider the system depicted in Figure 1a, which involves four primary actors: patients, a humanoid robot, a medical supervisor, and a pervasive IoT sensing and computing platform. Patients face high metabolic, cardio-respiratory and infectious risks, which makes them suitable for physical activities focused on balance, stretching, and posture. These activities are performed in dedicated indoor environments, such as gym spaces or rehabilitation rooms. In this paper, we will not delve further into the medical implications and motivations behind our work; interested readers can refer to [2,3] for examples of studies exploring the connection between reduced metabolic risk and the benefits of physical activity. Unlike traditional scenarios, where patients follow exercises guided by human physiotherapists, the role of the physiotherapist is taken by a humanoid robot that provides motor routines. The IoT sensing and computing platform enables monitoring of each patient's physiological and motor performance. Each patient is equipped with multiple wearable IoT devices, including IMU sensors that track the position of specific body parts. Additionally, patients wear at least one IoT device to monitor vital signs, such as heart rate and blood pressure. All collected data are transmitted from these devices to an Edge Server (ES), where sensor data from physiotherapy sessions is stored, aggregated and processed. Based on the current detected states of the patients, the robot can decide to continue the therapy plan by executing the next exercise in the sequence, assigning cool-down periods, or performing alternative exercises. It can also alert the human supervisor when necessary. The supervisor is responsible for programming the robot's motor routines, and can access all IoT data generated during the sessions for personalized diagnostics. We highlight some unique advantages of our approach compared to both traditional and smart rehabilitation solutions, as detailed in Section 2.

1. *Scalability*. Our system can serve multiple patients simultaneously and can be easily replicated across different environments or rooms.
2. *Privacy*. Our system was intentionally designed to avoid the use of camera-based solutions for monitoring patients during sessions, focusing instead on wearable IMU-based sensors. Although numerous studies have demonstrated the accuracy of computer vision technologies for posture tracking [21,22], significant challenges remain, especially regarding the privacy of the recorded individuals, an issue that cannot be overlooked in medical environments.
3. *High Patient Engagement*. The presence of a humanoid robot increases patient engagement, thanks to the empathy induced by somatic similarity recognition, as discussed in [17,18,23].
4. *Fine-Grained Personalization*. Our approach enables continuous monitoring of each patient's motor and vital states, allowing long-term data collection to generate personalized clinical reports.

At the same time, we recognize that our solution is not targeted at a fully automated, AI-driven medical scenario, which could raise concerns about fully delegating decision-making responsibility to AI systems [24,25]. Instead, the human supervisor retains the ability to intervene in cases of alarms from the IoT system, or any malfunctions, ensuring a balance between automation and human supervision.



(**a**) I-TROPHYTS framework



(**b**) Architecture layers

Figure 1. Framework and architecture of I-TROPHYTS.

3.2. Technological Components

The I-TROPHYTS framework provides the technologies needed to enable the IoT robotic environment depicted in Figure 1a. Its components, which span across the IoT, knowledge modeling, and robotics domains, are organized into four distinct layers, as shown in Figure 1b.

The layers are detailed as follows:

- *Sensing and Connectivity Layer*. This layer is responsible for collecting IoT data from patients, via sensors embedded in wearable devices, and transmitting the data towards the ES, via wireless Machine to Machine (M2M) links.
- *Edge Processing Layer*. This layer temporarily stores and aggregates, on the ES, raw time-series data from each patient, including IMU data and vital signs. It extracts second-layer information relevant to the physiotherapy session, such as automatic

identification of exercises within the motor routine, 3D tracking of each sensor position, and statistical features derived from vital signs. As future work, we plan to offload some of these tasks to the extreme edge, specifically to IoT wearable devices, to reduce the amount of raw data transferred from them, thus improving both privacy and energy efficiency, in line with the edge computing approach.

- *Knowledge Modeling Layer*. This layer is responsible for modeling and organizing information related to the physiotherapy domain, enabling better data management and supporting semi-automatic decision-making by the robot. The knowledge includes: (*i*) second-level information generated by the Edge Processing Layer, which provides quantitative data on the current states of the session and individual patients; and (*ii*) domain-specific rules and constraints, such as how a physiotherapist would assess the correct execution of an exercise or respond to partial failures. We plan to develop semantic ontologies, specific to the physiotherapy domain [26], to model these rules, as discussed further in Section 6.
- *Reasoning and Actuation Layer*. This layer uses the dynamic state of the session (provided by second-layer IoT information from the knowledge modeling layer) and the static set of domain rules and constraints to plan the next actions of the I-TROPHYTS framework. We distinguish between two types of outputs: (*i*) robotic actuation, which controls the physical mobility of the humanoid robot, including decisions about the next exercise in the sequence and precise control of the robotic joints; and (*ii*) interaction with the human supervisor, which involves recording the session data to a remote storage, detecting alert conditions and notifying medical supervisors, if necessary.

4. Framework Development

Here, we discuss the deployment and enabling technologies of the I-TROPHYTS framework. More precisely, we detail the implementation of the first two layers: Section 4.1 describes the Sensing and Connectivity Layer, while Section 4.2 shows the development of the Edge Processing Layer. The upper two layers are still under development, and the ongoing activities are described later in the paper, in Section 6.

4.1. Sensing and Connectivity Layer

Figure 2 depicts the implemented IoT monitoring system used in motor rehabilitation sessions. Two classes of wearable IoT devices are deployed to monitor patients: (*i*) smart rings, worn by each individual to track vital signs, such as heart rate and oxygen saturation; and (*ii*) IMU-based devices, used to surveil body movement, with each patient potentially wearing multiple devices at various locations.

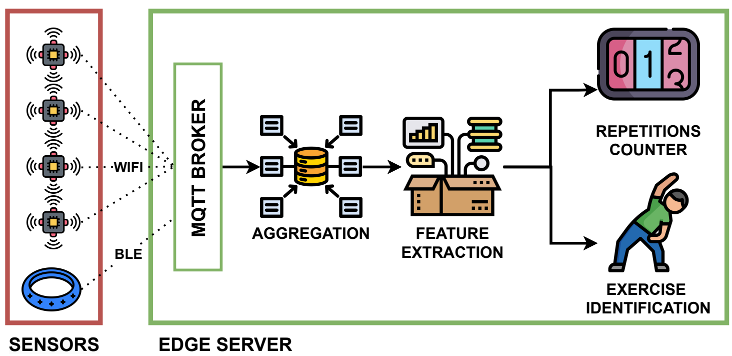


Figure 2. Implementation of the first two layers of I-TROPHYTS.

The complete list of features collected by IoT devices for patient monitoring is presented in Table 2.

Table 2. Features collected from IoT devices for patient monitoring in I-TROPHYTS.

Feature	Device
Heart Rate	Smart Ring
Oxygen Saturation	Smart Ring
Acceleration Data (x, y and z)	IMU Device
Gyroscope Data (x, y and z)	IMU Device

At regular intervals, raw data from both smart rings and IMU devices are transmitted to the ES via wireless links. Smart rings utilize Bluetooth Low Energy (BLE) [27] technology for communication, while we use WiFi for IMU-based devices due to the bandwidth required to transfer the complete IMU time-series. Additionally, the Message Queuing Telemetry Transport (MQTT) protocol is employed, which enables IMU-based devices to publish data to the broker and subscribe to configuration updates, such as changes in acquisition frequency.

4.2. Edge Processing Layer

As shown in Figure 2, the ES server includes the MQTT broker and a custom software stack, which performs the following tasks:

- Receiving the vital sign data transmitted from the smart ring via BLE connection.
- Receiving the time-series transmitted from each IMU-based device via MQTT subscription.
- Aggregating the time-series from different IMU-based devices into time windows of size T_f second.
- Extracting statistical features, namely **mean**, **maximum**, **minimum**, and **standard deviation**, from each time window of the IMU data, and storing them in a database, which, in our implementation, is InfluxDB (https://www.influxdata.com/ accessed on 1 December of 2024).
- Computing second-level information from the statistical features.

We focus on two types of information automatically extracted from IMU data: (*i*) identification of the type of exercise routine currently performed by each patient; and (*ii*) a repetitions count for that routine.

Exercise identification is performed using an independent and modular application. We have implemented several traditional and deep ML algorithms, which serve as a library of options for the system administrator to choose the most suitable one for their specific context. Section 5 provides a quantitative comparison of the classification performance of the implemented algorithms.

To count repetitions, we developed a simple algorithm to estimate the number of repetitions by identifying peaks in accelerometer signals inspired by the work in [28], assuming that each peak corresponds to a moment of maximum effort during the exercise. This approach treats the problem of exercise repetition detection as a task of finding local maxima in the signal shape. To focus on the signal features that are most relevant for predicting motion, we used accelerometer data from a single device. Now, the accelerometer measures acceleration along three axes (X, Y, Z). To obtain a unified signal that captures the overall motion intensity, we computed the acceleration magnitude, which can be defined as follows, for a device d, at time t and without loss of generality:

$$a_d(t) = \sqrt{\text{accelerometerX}_d(t)^2 + \text{accelerometerY}_d(t)^2 + \text{accelerometerZ}_d(t)^2}\,. \quad (1)$$

To reduce noise in the acceleration magnitude and make peak detection reliable, we applied a moving average smoothing technique with window size w. Let W be the total number of windows over which smoothing can be applied, in the dataset. We define the smoothed acceleration magnitude $\tilde{a}_d(t)$ as the collection of points $\alpha(w)$ at a specific time t,

$$\alpha(w) = \frac{1}{w}\sum_{j=0}^{w} a_d(j) \ , \tag{2}$$

$$\tilde{a}_d(t) = \{ \ \alpha(w_i) \qquad \forall\, i \in [1, W] \ \} \ . \tag{3}$$

Finally, we detect peaks in the smoothed acceleration magnitude $\tilde{a}_d(t)$, using a threshold value $\tilde{\beta}$ and a minimum peak distance criterion σ. Let λ be the total number of points in the dataset; we defined $\tilde{\beta}$ as the mean of the smoothed signal over all time points,

$$\tilde{\beta} = \frac{1}{\lambda}\sum_{t=1}^{\lambda} \tilde{a}_d(t) \ . \tag{4}$$

Let t_p be the time index corresponding to a peak signal, and let σ be the distance between two peaks signals defined as $|\tilde{a}_d(t_{p_i}) - \tilde{a}_d(t_{p_{i-1}})|$. We define a peak as the maximum local point $p(t)$ if all the following four conditions are satisfied:

$$p(t) = \begin{cases} \tilde{a}_d(t_p) & > & \tilde{a}_d(t_{p-1}) \\ \tilde{a}_d(t_p) & > & \tilde{a}_d(t_{p+1}) \\ \tilde{a}_d(t_p) & > & \tilde{\beta} \\ |\tilde{a}_d(t_p) - \tilde{a}_d(t_{p-1})| & \geq & \sigma \end{cases} \ . \tag{5}$$

5. Performance Evaluation

In this section, we present the performance evaluation of the system. First, the methodology used for data collections is described in detail, including the procedures and techniques employed. Next, the results section presents the evidence derived from the data, along with the analysis of performance metrics.

5.1. Data Collection Methodology

The goal of this section is to describe the experimental setup and procedures used, detailing the exercises performed, and the technical aspects of data acquisition, as well as the type of the hardware and the data recorded. Starting from the experimental design, two different exercises were designed to represent the movements:

- **A**: shoulder flexion; participants are expected to move their arm reaching 180 degrees, as illustrated in Figure 3a.
- **B**: shoulder abduction; participants are expected to move their arm reaching 90 degrees, as shown in Figure 3b.

Then, given the need to perform the exercises with both arms, they were further divided into two subcategories:

- **L**: left arm.
- **R**: right arm.

From this, we derived four specific-side exercises: **AR**, **AL**, **BL**, **BR**.

To collect data and ensure that the results could be generalized across individuals, the study involved six volunteers, called "subjects 1 to 6" to protect their privacy: two women and four men, aged 25 to 35 and healthy. No particular characteristics of any of them are noteworthy; all subjects were in a comparable physical condition for the purposes of the study. Each participant was instructed by watching an explanatory video with all the methods of performing the exercises, to allow everyone to execute the exercises in the same way and as similarly as possible. Each volunteer spent approximately 10 min on each exercise, for a total of 40 min, to ensure balanced and comparable data collection across individuals.

(**a**) Movement A (**b**) Movement B

Figure 3. Illustration of two exercises performed during the experiments.

Data were collected using four ESP32 devices, two on each arm (one above and one below the elbow). In particular, the microcontroller, formally designated as ESP32-S3-Touch-LCD-1.28 and visible in Figure 3a, is a high-performance MCU board developed by Waveshare. It features an onboard 1.28-inch capacitive touch display, a Li-ion battery, and a six-axis sensor, comprising a three-axis accelerometer and a three-axis gyroscope. The device is equipped with a 32-bit Xtensa LX7 dual-core processor, with a maximum main frequency of 240 MHz, and supports both 2.4 GHz Wi-Fi (802.11 b/g/n) and Bluetooth 5 (LE). We collected accelerometer and gyroscope data, representing the movements made by an user during the exercises, with a fixed frequency of 50 Hz. To provide a visual representation of the motion patterns captured by the sensors, Figures 4 and 5 show the raw signals recorded by the ESP32 units, for exercise **A** performed with the right arm and exercise **B** performed with the left arm, respectively. A frequency image of the accelerometer and gyroscope data gives some key insights into the patterns and characteristics of the motion, or vibrations, captured by the sensor. Transforming time-domain signals into a frequency-domain representation helps identify dominant frequencies which, in turn, provide guidance to distinguish between different types of movement or detect specific vibration patterns. Indeed, since motion is three-dimensional in space and distributed across all axes, from the figures provided, it seem evident that some axes are more influenced than others. Figure 4 shows how, for the accelerometer sensor, the X and Z axes are most affected, which reflects motion along the corresponding body axes. Similarly, in Figure 5, the most affected axes are Y and Z, which reflects motion along the corresponding body axes, confirming the direction of the movement.

During the exercise, participants were asked to wear a smart ring, the COLMI R02, visible in Figure 3a, which allowed us to monitor their biometric data, including blood oxygen (SpO2) and heart rate (HR). The ring build by COLMI is equipped with heart rate and blood oxygen sensors, capable of transmitting data every 30 s.

After data collection, the raw values were processed and resampled to create six separate datasets, one for each subject. Since we collect data from four devices, recording two types of signals, and each signal is recorded along three axes (X, Y, Z), we collected 24 features per device. This results in a total of 96 device-specific features, with the data resampled at 100 ms intervals to ensure consistency.

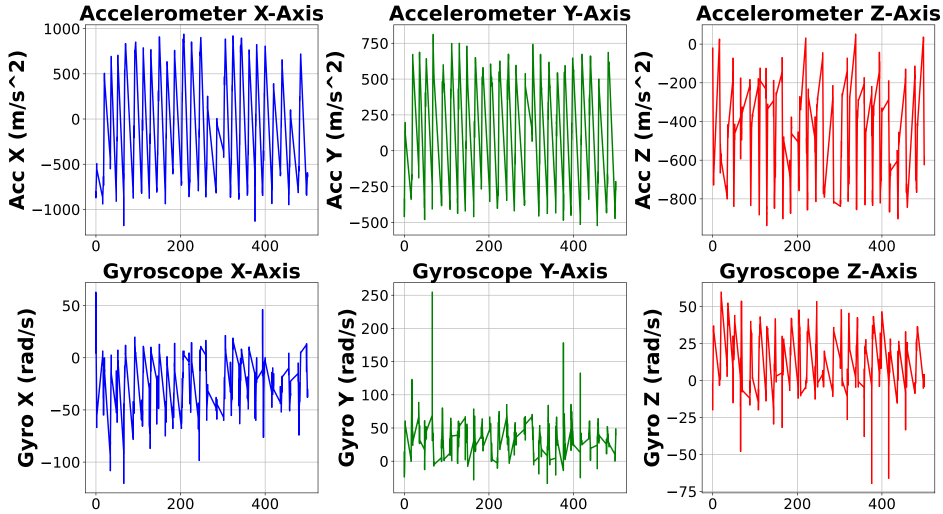


Figure 4. Accelerometer and gyroscope raw data—AR exercise.

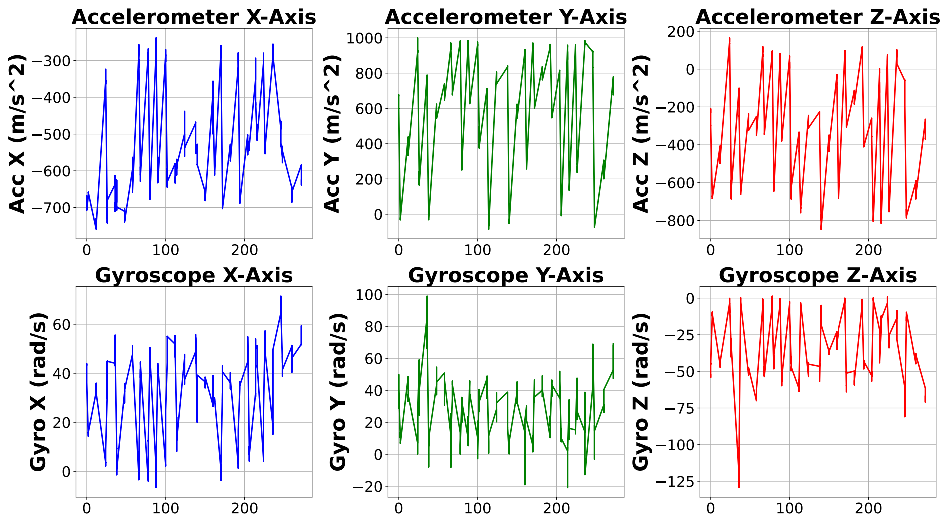


Figure 5. Accelerometer and gyroscope raw data—BL exercise.

5.2. Results

To evaluate their performance in recognizing the activities performed by the participants, specifically the exercises they executed, a comparative analysis between various algorithms was conducted. After an extensive literature review, it was analyzed that tree-based algorithms supporting vector machine and neural networks are the most commonly used classifiers for Human Activity Recognition (HAR) tasks [29,30]. Therefore, in this work, we propose the evaluation of several algorithms, including a Feed Forward Neural Network (FFNN) [31] as a DL approach, and traditional ML methods, such as Decision Tree (DT) [32], Random Forest (RF) [33], Gradient Boosting (GB) [34], and Support Vector Machine (SVM) [35]. Given the nature of the data collected and the objectives of this study, the analysis focused not only on the accurate classification of exercises, but also on assessing the adaptability of the models to new data. With multiple study participants, three key aspects were explored, which we, respectively, called Personalized, Traditional, and Inboard Learning, as listed below.

- **Personalized Learning**: evaluates how well the models were able to recognize activities when analyzing each participant individually.
- **Traditional Learning**: evaluates the performance when combining data from all participants.

- **Inboard Learning**: tests the generalization of models by training on data from some participants and scoring on data from others, measuring how well the models can adapt to unseen data.

Before analyzing the performance, it is worth mentioning that, for both Personalized and Traditional Learning approaches, the experiments were conducted by averaging the results over multiple runs, and the calculated confidence interval was 95%. In each run, different hyperparameter configurations were used to optimize the performance of the models. The hyperparameters included variations in learning rate, batch size, and network architecture, to identify the optimal settings for each learning strategy. Table 3 presents the hyperparameter configurations for each model implemented in this study.

Table 3. Set of Hyperparameters.

Model	Hyperparameter Set	
Support Vector Machine	C:	[0.1, 1, 10, 100, 1000],
	gamma:	[1, 0.1, 0.01, 0.001, 0.0001],
	kernel:	[‘rbf’, ‘poly’, ‘sigmoid’]
Decision Tree	criterion:	[‘gini’, ‘entropy’, ‘log_loss’],
	splitter:	[‘best’, ‘random’]
Random Forest	n_estimators:	range(50, 250, 50),
	criterion:	[‘gini’, ‘entropy’, ‘log_loss’]
Gradient Boosting	n_estimators:	range(50, 250, 50),
	criterion:	[‘squared_error’, ‘friedman_mse’]
Feed Forward Neural Network	Batch Size:	[8, 16, 32, 64, 128 256, 512],
	Hidden Sizes:	[8, 16, 32, 64, 128, 256, 512]’,
	Learning Rate:	[0.01, 0.001, 0.0001],
	Depths *:	[1, 2, 3, 4],
	Dropout Probability:	[0.1, 0.2, 0.3, 0.4, 0.5]

* Depths is the number of times a network hidden layer will be used.

This process ensured a robust evaluation, by accounting for variability in model performance due to different training conditions. In the case of Inboard Learning, we evaluated the generalization capabilities of the models using a leave-one-out approach. Specifically, with six subjects, we iteratively selected each participant as a test subject, ensuring that each individual was used, as a test case, exactly once. During each iteration, the model was trained on data from the remaining five participants. After completing all six combinations, we calculated the average performance across all iterations, to provide a comprehensive assessment of the model's ability to generalize to unseen subjects. To facilitate a more complete understanding of the following results, we provide an explanation of the performance metrics employed. The evaluation was conducted using the Accuracy metric, which serves to quantify the proportion of accurate predictions (True positive, TP) made by the models in all runs. Additionally, the F1-Score was used, as it combines the Precision and Recall metrics into a single unit, thus ensuring that both false positives (FP) and false negatives (FN) are minimized.

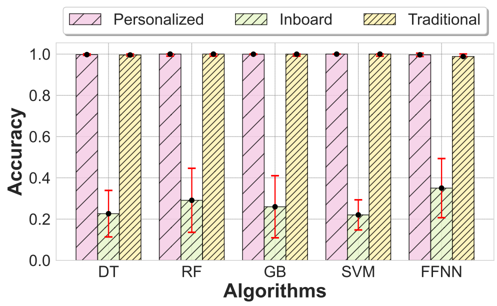
$$Accuracy = \frac{TP}{TP + TN + FP + FN}, \tag{6}$$

$$F1_{score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}, \tag{7}$$

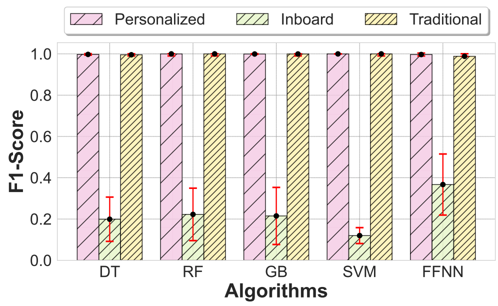
$$Precision = \frac{TP}{TP + FP}, \tag{8}$$

$$Recall = \frac{TP}{TP + FN}. \tag{9}$$

As shown in Figure 6a,b, there is a similar pattern in all evaluations. If we compare the algorithms based on their ability to detect activities when analyzing each participant individually or together, the performance is equivalent and all the algorithms achieve optimal results, reaching 100% accuracy. In terms of generalization, a similar pattern can also be observed, but with a completely different trend: all the algorithms seem to be unable to generalize across different subjects (Inboard Learning); only the FFNN was able to achieve the best accuracy, with a value of 35%. The best-performing algorithm was selected for further investigation, focusing on the importance of each signal (accelerometer and gyroscope) and their individual impact on model performance. We also assessed the minimum number of devices required for accurate activity classification, by progressively training the model with data from one device up to all available devices. Both personalized and traditional aspects were taken into account, to better understand individual variations across different users and scenarios. Specifically, this approach was adopted to gain insights at the individual level, and also to understand how the usage of different devices, including those not directly involved in the movement, affects the model's ability to accurately classify the activity. The analysis was conducted as follows: given the availability of four different devices, we tried to generalize the results as much as possible by testing all possible combinations for every possible number of devices used in the data collection. For each combination, we evaluated performance using accelerometer data, gyroscope data, and a blending of both.



(**a**) Accuracy



(**b**) F1-Score

Figure 6. Comparison of accuracy and F1-Score metrics in evaluating different learning algorithms.

In Figures 7 and 8, we reported the mean and confidence interval of the analyzed metrics, varying the number of devices for both personalized and traditional scenarios. Each column represents the combined results, accounting for all possible device permutations. For instance, focusing on the personalized scenario, the column for a single device reflects the combined results of analyzing the individual data from each sensor (i.e., left wrist, right wrist, left elbow, right elbow). The analysis reveals that, in a personalized scenario, using only one device with accelerometer data, good performance in activity classification is already achieved, measured in terms of accuracy with a score of 93%. As more devices are added, performance improves even when using only one signal type. In particular, when comparing both scenarios (personalized and traditional), we can observe a similar trend where using only two devices with all signal types comes close to the best performance of the algorithm, reaching a total score of 98%, which would otherwise require all devices and signals. Furthermore, the narrow confidence intervals for accelerometers indicate consistent results across different combinations, while the wider confidence intervals for gyroscopes for a small number of devices indicate greater variability in the classification task.

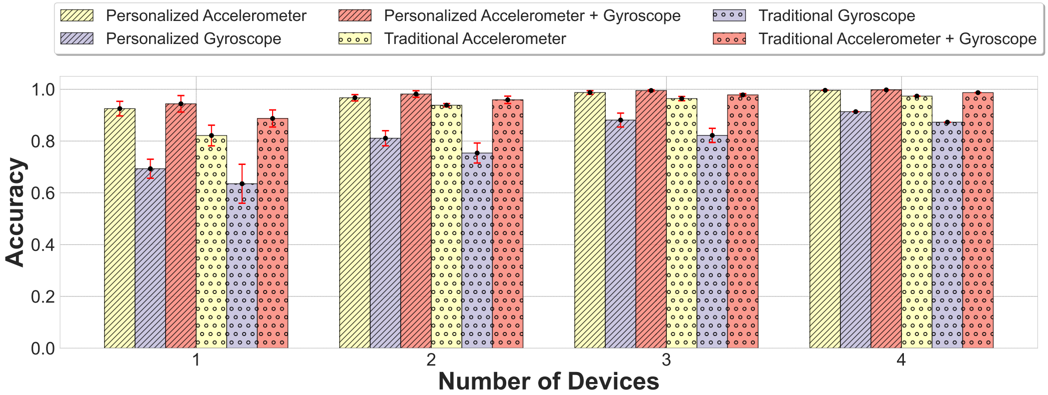


Figure 7. Comparison of Accuracy for evaluating FFNN performance using different signals on a variable number of devices.

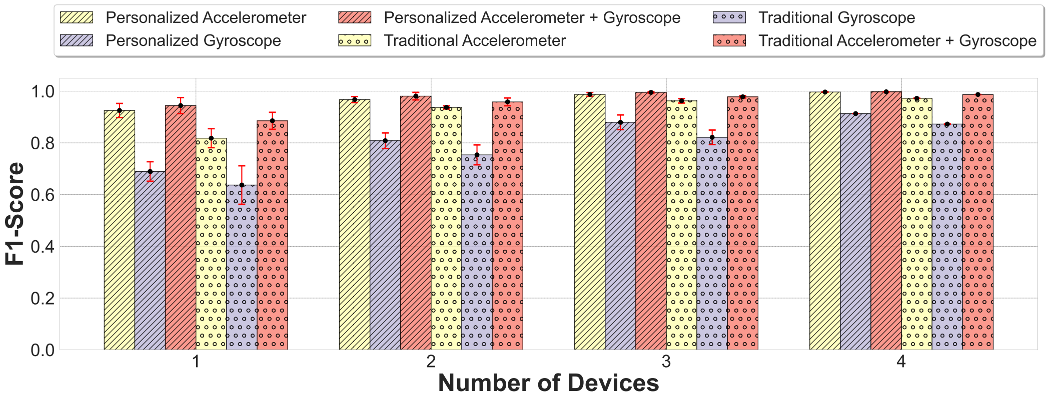
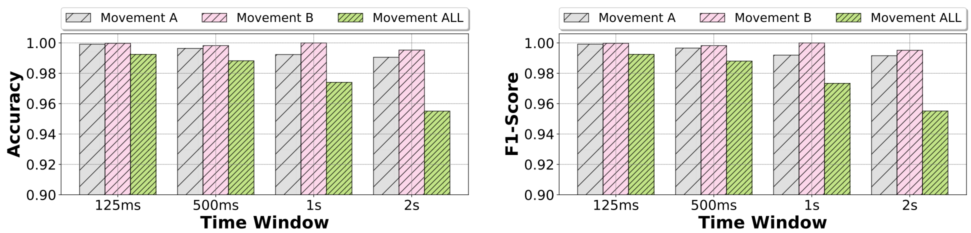


Figure 8. Comparison of F1-Score for evaluating FFNN performance using different signals on a variable number of devices.

In Figure 9a,b, we investigated the ability to predict motions using the best-performing algorithm, namely the FFNN algorithm. Specifically, we analyzed the prediction accuracy and F1-score for movement **A**, movement **B**, and the combination of both motions across different time windows, from 125 milliseconds (ms) to 2 s. In the smallest time window of 125 ms, accuracy is close to 100%, while there is a performance loss for a time window of 2 s. The results indicate a clear correlation between increased time windows and lower accuracy rates for motion classification.

Table 4 presents the average inference time for each tested algorithm. All techniques showed inference times under 1 s. Furthermore, excluding SVM (which is the slowest), all models achieved inference times under 100 ms, demonstrating that the tested set of techniques is suitable for real-time scenarios.



(**a**) Accuracy (**b**) F1-Score

Figure 9. Accuracy and F1-Score for predicting motion using FFNN across different time windows.

Table 4. Inference Time (in seconds) of each algorithm.

Model	Mean	Std
Support Vector Machine	0.6887	0.0063
Decision Tree	0.0010	0.0001
Random Forest	0.0170	0.0050
Gradient Boosting	0.0549	0.0006
Feed Forward Neural Network	0.0152	0.0159

As previously mentioned, during the activity, participants were asked to wear a smart ring to monitor their heart rate and oxygen saturation levels. Figure 10 illustrates the patient's heart rate fluctuations over a predetermined period of time while performing the AL exercise. It is evident that exercise may cause an increase in heart rate variability, highlighting the physiological differences between a male and female subject during a 24 min exercise session, with the female subject's heart rate peaking at **120–130 bpm**, while the male subject's heart rate remains just below **90 bpm**. The oxygen saturation levels collected during the experiments remained stable, showing no notable patterns or significant variations.

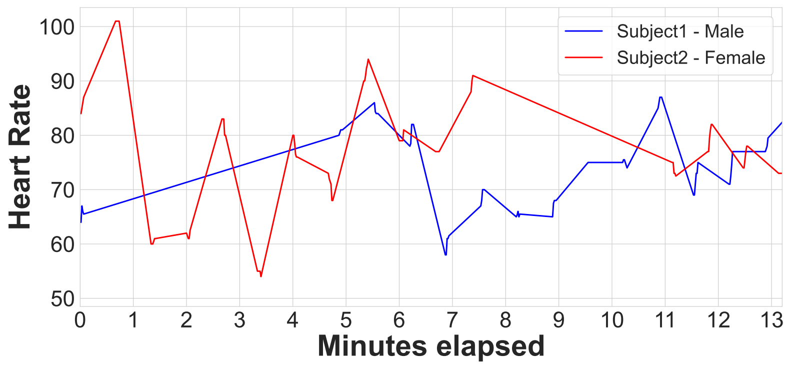


Figure 10. Heart rate comparison of two subjects—AL exercise.

The final analysis aimed to predict the number of repetitions a patient would perform for a given exercise, based on the algorithm described in Section 4.2. Figure 11 illustrates the peak identification performed by the repetition counter algorithm on the data collected during the execution of the AR exercise.

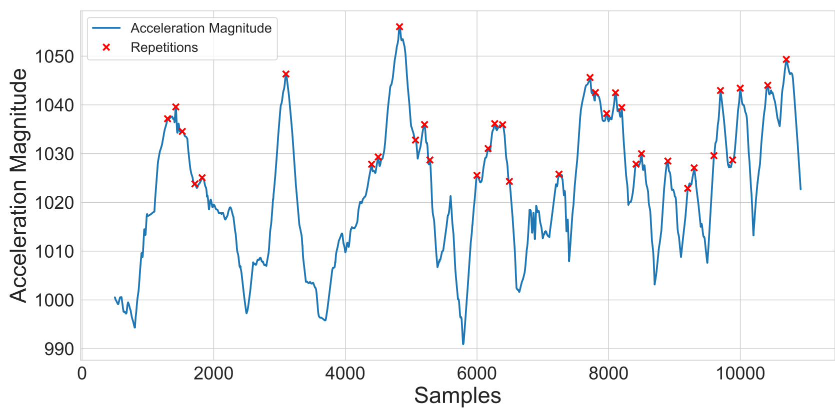


Figure 11. Peak detection—AR exercise.

To analyze performance across four different exercises and four different devices, we calculated the peaks for each exercise separately, and then averaged the results for each device. This approach allowed us to derive predicted peaks, which are the average of the peaks detected across all devices. We collected four separate data sets, one for each exercise, to accurately count the number of repetitions performed by the subject. Since the algorithm uses threshold and distance parameters to identify peaks, varying these values can significantly affect the number of peaks detected. Therefore, we explored different parameter values to understand their influence on the results, which are presented as confidence intervals. Figure 12 shows the results of the repetition counter algorithm. While the predicted repetitions are close to the actual counts, there are still some fluctuations due to the different parameters used in the algorithm, which significantly influence the number of peaks detected in the signal.

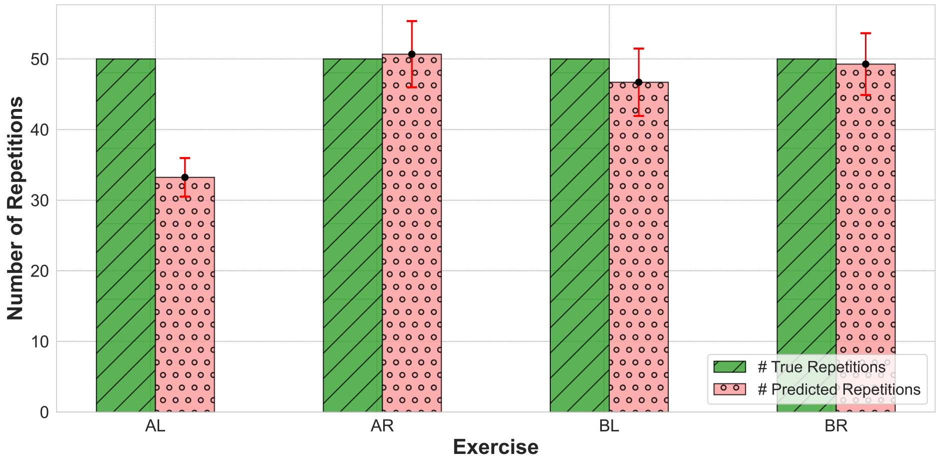


Figure 12. Predicted versus actual repetitions of exercises.

6. Ongoing Activities

6.1. Knowledge Modeling Layer

The concept behind I-TROPHYTS for next-generation smart rehabilitation relies on the integrated use of several types of information (physiological/clinical/training data, exercise targets, actual and expected performance, and so on). To ensure that all this information is treated in a coherent and consistent way, a symbolic layer is forecast, with the purpose of providing the necessary structure for information integration. More specifically, it allows to integrate and present the available information about patients, the patient's history and the ongoing session in a unified way, which is then used to organize and cluster into readable data by the people in charge of the session, namely the physiotherapist. Once this knowledge systems is in place, it becomes possible to apply formal reasoning to anticipate the development of dangerous patient states, and to inform the physiotherapist of the actual status and quality of the patient's performance. In particular, the I-TROPHYTS system must keep track of patients, each with their own specific clinical history, whose data may need to be treated in a personalized way, a situation that usually goes beyond the scope of ML methodologies. On the other hand, there are physiotherapists who are used to having a visual and holistic view of the patient, and are not trained to interpret the variety and complexity of sensory data. Furthermore, the knowledge layer would make the data easily accessible and comprehensible, ensuring that the system is accountable [36]; it also ensures that the system is extensible (e.g., towards the inclusion of new sensors, data types, and medical guidelines, to stay up to date with the evolution of technology and medical practice) and flexible (e.g., adaptable to new types of patients or changes in session scenarios and activities). To guarantee these properties, the knowledge layer will be based on an applied ontology, that incorporates rigorous modeling criteria (OntoClean [37]) and methodologies (Dogma [38]). The layer will be aligned with a solid foundational ontology (DOLCE [39]).

The ontology can classify the physiological qualities of a person, the relevant features of their movements, as well as the abilities they possess. Likewise, it organizes the sequence of planned (physical) movements, the ideal exercise execution, the joint and muscles activated during the exercise, and assembles the constraints (gathered from physiotherapists) that exist between the state of the individual and the planned exercise. All this information will be treated in relation to the current context [40], to provide time-sensitive information management and, perhaps, compare it with data from previous sessions. The effort to encode the physiotherapist's knowledge, which will cover his/her concerns in terms of remote control of the patient, is a complex task that raises new research questions and is still ongoing.

6.2. Reasoning and Actuation Layer

The next step is to give the robot the ability to control the interaction with the patient, the doctor and its environment. The robot must be able to decide which action to perform by exploiting the knowledge base at its disposal and the information collected by the sensors. To this end, we are investigating the development of a multi-agent system behind a specific cognitive architecture. The agent paradigm that best fits the requirements of the project is the Belief-Desire-Intention (BDI) paradigm [41,42], which mainly refers to the logic of practical reasoning, i.e., the type of reasoning that leads to the deliberation of a decision in order to achieve a goal. To ensure the use of the agent paradigm in robotics, it was necessary to study how to reconcile the typical abstractions of agent design (agent, role, task, action, message, communication, capability, and so on) with those of the programming frameworks most widely used in robotics in recent years.

The Robot Operating System (ROS) [43,44], together with a robot simulator like Gazebo (https://gazebosim.org/home accessed on 1 December 2024), offers a powerful tool for programming robots through the possibility of using building blocks, such as nodes, topics, and plugins. To develop a cognitive architecture for the implementation of the complex robotic system under discussion, we first aimed to integrate the agent paradigm into ROS and Gazebo [45,46] to have a set of design abstractions useful to formalize the activities of a reliable robotic system design process. The result of this study led to the identification of mapping paths between the elements of the agent paradigm, namely agents, tasks, actions, goals, and those of the framework components entailed in the development of the robotic system with ROS, mainly nodes and topics.

This preliminary phase was necessary to think about a possible agent-based cognitive architecture. Moreover, it led to the possibility of managing the complexity of the healthcare scenario through the agent paradigm and defining, at the implementation level, the nodes and topics needed for the chosen healthcare scenarios; details on the implementation of the healthcare scenario can be found in [47,48].

In the I-TROPHYTS project, we chose to use the NAO robot, which has twenty-five degrees of freedom and is equipped with seven touch sensors placed on the head, hands and feet [49]. Readers interested in the mechatronic design of the NAO humanoid robot may refer to the work of D. Gouaillier et al. [49].

We have created a robotic system with nodes and topics that allows the NAO robot to receive some input from the sensors, on the patient's condition, and to formulate a suggestion that takes into account the health conditions and the way in which the physiotherapy exercises are performed. This is still a first prototype from which we can deduce a possible cognitive architecture through a bottom-up approach. We have set up an initial model of a hybrid architecture, centralized at the top level of the knowledge management module and distributed in the individual modules as shown in Figure 13.

The advantage of this construction is that it is designed to be highly modular, with minimal coupling based on a three-tier structural pattern. Each module can be implemented in a multi-perspective approach: this means that for the sensing module, for example, a peer agent architecture, or another type of simple and efficient processing of input information, even without agents, could be sufficient. Instead, the reasoning module needs a BDI agent implementation, since it mainly contains the reasoning module, which allows to reason about the action to be taken, and the anticipation module, which allows the robot to "imagine" the outcome of its actions, compare it with the post-condition associated with the chosen action, and then decide whether to actually execute it or change strategy. In the future, we will further refine the architecture by detailing the architectural pattern of the agents in each sub-component, while also gathering feedback from the implementation of the I-TROPHYTS scenarios.

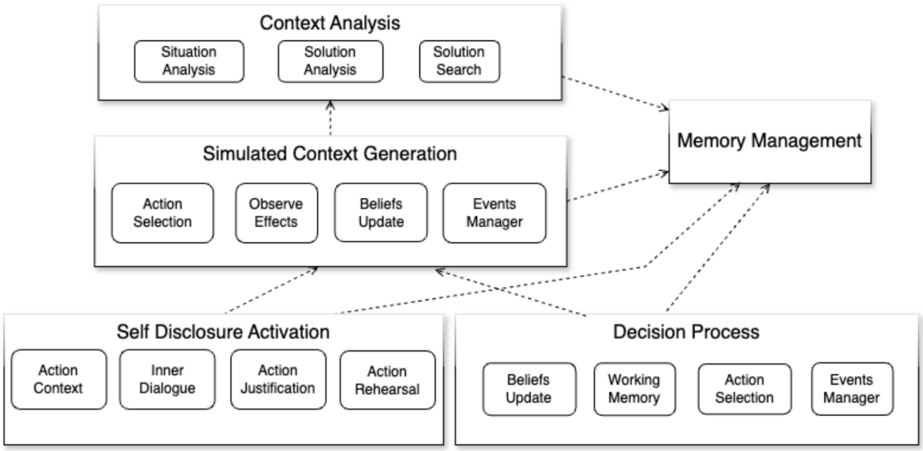


Figure 13. Agent-based cognitive architecture for structuring robotic systems that can monitor, suggest, explain in complex scenarios.

7. Conclusions

This paper introduces the I-TROPHYTS framework for smart motor rehabilitation in controlled environments. Our work advances the current state of the art by making three contributions. First, the I-TROPHYS framework integrates four layers, incorporating contributions from IoT, edge computing, knowledge modeling and robotics. Second, we present the design and implementation of the data collection and edge processing layers. We describe in detail the IoT system used to monitor patients' motor activities and vital signs during rehabilitation sessions. Additionally, we illustrate edge processing techniques to identify the type of exercise (via ML approaches) and count the number of repetitions performed by the patient. Third, we test our algorithms through small-scale experiments involving six participants performing four stretching exercises. Our experimental results indicate that, by using ML techniques with accelerometer sensors, we can achieve close to 100% accuracy in identifying exercises. Moreover, the results highlight the importance of proper tuning of the time window for feature extraction and the significance of personalized training, as different patient data show different patterns of sensor data when performing the same exercise. Similarly, our proposed automatic repetition counting technique demonstrated satisfactory performance, closely matching the number of repetitions.

We plan several future actions to fully realize and validate the I-TROPHYTS framework. First, we plan to increase the number of subjects involved in our data collection to improve our current dataset and provide a more comprehensive analysis. In the sensing layer, we aim to explore BLE Mesh technology [50,51] to develop multi-hop sensor networks in indoor environments to improve energy efficiency in data collection. However, we face challenges such as transmitting IMU time-series over BLE, which currently suffers from limited throughput and scalability. In the data processing layer, we plan to include additional algorithms to track sensor trajectories, allowing us to quantify the accuracy and effectiveness of each patient's movements. These data will be represented in the knowledge modeling layer via a unified ontology, which will model all relevant data and relations in the physiotherapy session, applying formal reasoning to anticipate potentially harmful states for patients. Such anticipation may support the realization of a Digital Twin (DT) of the physiotherapy session, which is the main goal of the SORTT project [52]. At the actuation layer, we plan to integrate real-time IoT data into our proposed agent-based cognitive architecture for robot control. From a business perspective, we aim to investigate the economic attractiveness and cost-effectiveness of commercializing and implementing the framework in the healthcare industry. Finally, we plan to collaborate with physiotherapy professionals and researchers to (1) gather expert feedback on the system features required for live physiotherapy sessions (e.g., specific movement angles, user interface display preferences), and (2) use the I-TROPHYTS framework in real, professionally supervised physiotherapy sessions. In such sessions, we will assess the patient acceptance and collect metrics related to user experience, engagement, and physiotherapist feedback.

Author Contributions: Conceptualization, Y.M., I.Z., C.M., V.S., R.T., F.B. (Fulvio Barbaro), G.D.C., F.P.Q. and M.D.F.; Methodology, Y.M. and A.E.; Software, Y.M. and A.E.; Validation, A.E.; Investigation, Y.M., A.E., I.Z., G.S., S.B., C.M., F.B. (Fabiana Ballarin), V.S., R.T., F.B. (Fulvio Barbaro) and M.D.F.; Writing—original draft, A.E., I.Z., G.S., S.B., V.S. and M.D.F.; Project administration, M.D.F. All authors have read and agreed to the published version of the manuscript.

Funding: The work is supported by the PRIN 2022 project I-TROPHYTS ("IoT and humanoid RObotics for autonomic PHYsio-Therapeutic monitoring, coaching and supervising in smart Spaces: a feasibility study", id: 20224TAETP) and by the PRIN PNRR 2022 project SORTT ("An IoT-Serviced and Ontology-based Remote human digital Twin for physioTherapy: a feasibility study", id: P2022H74YP). The icons are courtesy of FlatIcon.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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