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SCUOLA DI INGEGNERIA INDUSTRIALE E DELL'INFORMAZIONE

# A Kinematic-based Intention Detection Strategy for Robotic Assistance: A Real-Time Approach to Upper Limb Rehabilitation

Tesi di Laurea Magistrale in Biomedical Engineering - Ingegneria biomedica

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**Abstract:** Upper limb motion impairment resulting from neurological disorders significantly hinders individuals in their interactions with the environment and performing activities of daily living (ADL). Effective rehabilitative therapies can greatly enhance the quality of life for people living with such disabilities. Rehabilitation robotics has proven to be a valuable complement to traditional therapies, enabling a high volume of training sessions in a safe and controlled environment. When combined with an efficient Intention Detection Strategy (IDS), motor recovery potential can be maximized, enabling individuals affected by neurological disorders to regain their autonomy and perform ADL with precision and consistency in task execution. An IDS is a method or approach used to identify an individual's volitional movements or intentions. It acts as the crucial link between human intention and the response generated by technology. In cases where a person has suffered a neurological injury or has a disability affecting their motor functions, such as arm or leg movements, the ability to detect their intention to move and translate it into a action thanks to the innovative technology, can be life-altering. The study conducted experiments with healthy subjects wearing an exoskeleton on their rigth arm, named "AGREE", to detect the intention of various movements, with a particular focus on reaching tasks. The collected data, acquired with the built-in sensors of the exoskeleton, were then used to train machine learning architectures. Then, a real time evaluation has been performed by testing four subjects with the same protocol directly in the robotic platform. The results demonstrated that the exoskeleton is capable of recognizing the intention to move in an impressively short timeframe, with a latency of 5.2 milliseconds with an accuracy of 84%. Future developments in this field will involve expanding the range of exercises for which intention detection is possible. This includes tasks like bringing the hand to the mouth or lateral elevation, thereby allowing the exoskeleton to assist patients with a wide variety of movements. Such advancements in the fusion of rehabilitation robotics and IDS hold the potential to significantly improve the lives of individuals affected by neurological disorders.

**Key-words:** rehabilitation, upper limb, exoskeleton, Intention detection strategies, hybrid systems

# 1. Introduction

## 1.1. Neurological disorders and motion impairment

Our upper limbs are indispensable for a wide range of daily activities, enabling us to engage physically and socially with our surroundings. When functional limitations in the upper limbs occur, often stemming from neurological injuries or diseases, they can profoundly affect the independence, health, and overall well-being of individuals. These limitations extend beyond the physical realm, impacting emotional, cognitive, and behavioural aspects of their lives. Neurological diseases have become more present among the society rather than the past, this is due to the aging of population, sedentary and the current lifestyle. Furthermore, thanks to the advance medical technologies and therapies, more people can survive from such disorders and so more rehabilitation robotic techniques are needed. Neurological disorders represent the primary cause of disability and the second cause of death worldwide [11]. Furthermore, people affected by these disabilities present strong disadvantages regarding the daily life activities (DLA), social activities and relationships. Simple actions, such as drinking a glass of water, results strongly hostile and difficult due to the motion limitation because of the disorders. Deeper, the Neurological disorders are a broad category of medical conditions that affect the nervous system, including the brain, spinal cord, and peripheral nerves. These disorders can impact the normal function of the nervous system and cause a wide range of symptoms and health issues. Some examples of neurological disorders include epilepsy, stroke, Alzheimer's disease, Parkinson's disease, multiple sclerosis, peripheral neuropathy, spinal cord injury and many other conditions [20]. Each disorder has specific causes, symptoms, and treatments, and managing such disorders often involves neurologists and other healthcare professionals specialized in the field of neurology. [22] Stroke is a neurological condition resulting from a sudden injury to the central nervous system, typically caused by vascular issues. According to data from the World Health Organization (WHO), it stands as a significant contributor to long-term disability, impacting 15 million individuals globally, with about one-third of them facing permanent disability. Consequently, stroke carries substantial social and economic consequences for society. A majority (77%) of stroke survivors experience a decline in motor function, leading to mobility issues and a subsequent decrease in their quality of life [1]. The mobility-related impacts of a stroke often manifest as muscle weakness (known as spastic paresis) and the development of contractures. Specifically addressing spasticity, it is recognized as one of the outcomes of upper motor neuron syndrome. Spasticity is defined as a sensorimotor disorder that affects the ability to voluntarily activate certain muscle groups. The process of motor recovery following brain injury is intricate, dynamic, and influenced by various factors. These factors include genetics, pathophysiology, sociodemographic elements, and therapeutic interventions, all of which collectively shape the overall trajectory of recovery [1, 9]. Currently, a wide range of techniques is available to enhance the rehabilitation process following the manifestation of a neurological pathology. According to the current state of the art, it is feasible to stimulate the reacquisition of motor skills by increasing the intensity of the exercise, involving the patient's volitional aspect, and ensuring that the exercise is performed correctly; these aspects represent the benefits of applying functional electrical stimulation (FES) and rehabilitation robotics [8, 23]. Among the field of neurological disorders, the rehabilitation robotics is regarded as a fundamental and innovative technique in order to promote the motor recovery, as it is able to limit the disabilities and the difficulties of the interaction between the subjects and the environment itself and most importantly, it is able to personalize the training for the specific patients regarding the different features of the disorder and the motor characteristics of the subject. In the following chapter a better explanation of the powerful, and limitations of the rehabilitation robotics is described.

## 1.2. Neural plasticity and neurorehabilitation

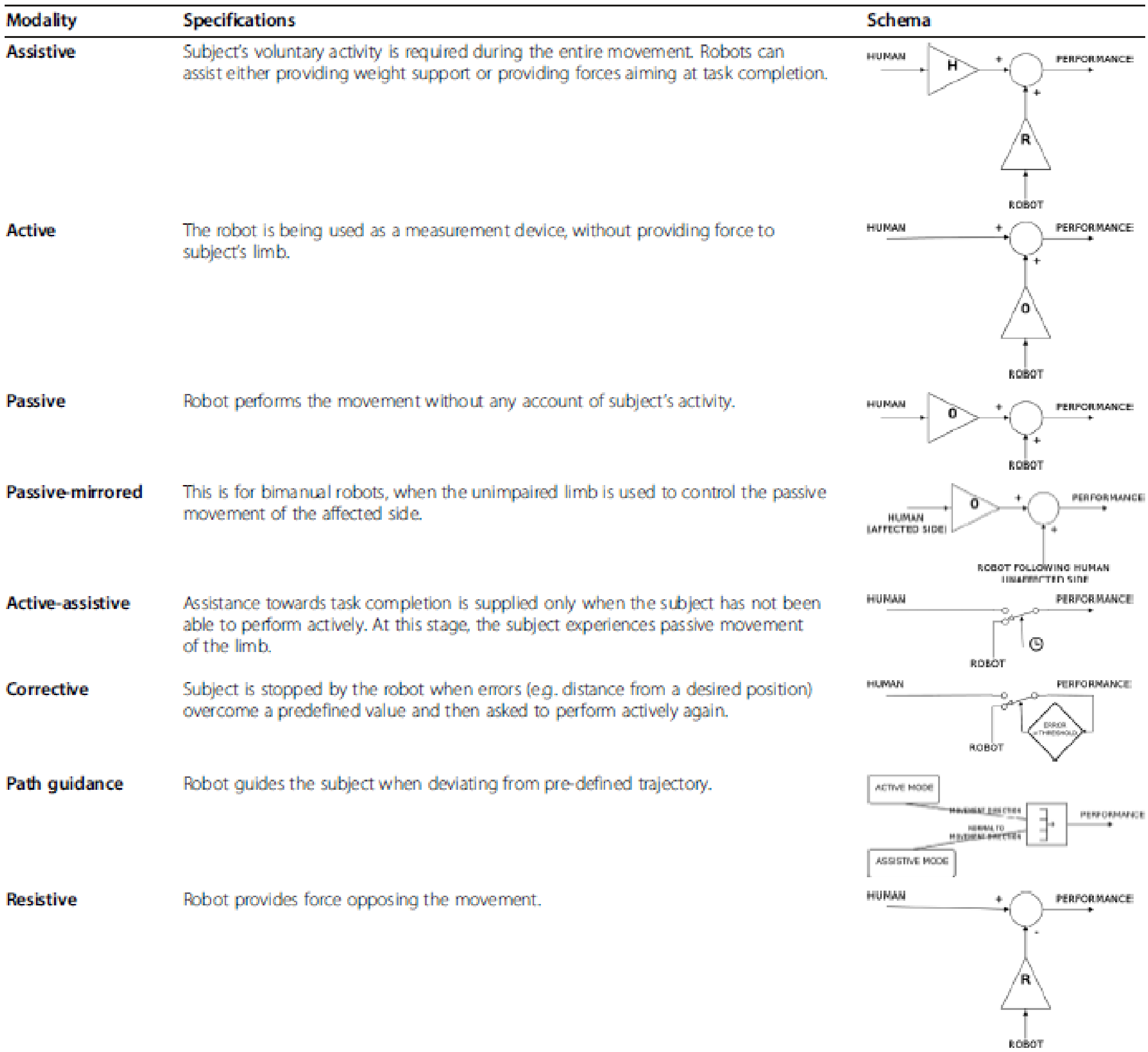
Regarding the literature [9], the brain is able to change or reorganize itself to recover after disorders or injures. This is called neuroplasticity, and it is a very powerful brain adaption that can promote the motor relearning. Neuroplasticity encompasses all the changes in the arrangement of neural elements that take place in the central nervous system throughout a person's entire lifespan. It has been well-established that the cerebral cortex demonstrates spontaneous instances of brain plasticity when responding to injuries [17]. Damage to specific brain areas prompts a restructuring of neural connections, and the extent of this rewiring is greatly influenced by the experiences following the injury. These plastic changes primarily affect the tissue surrounding the injured area in the same hemisphere, but they can also impact the opposite hemisphere, as well as subcortical and spinal regions. [20]
According to the period following a neurological injury two different phases can be distinguished:

- In the short-term plasticity phase, we observe biochemical, biophysical, vascular, and neurovegetative changes.
- During the long-term plasticity phase, we primarily observe morphological and functional neuroplastic changes.

The primary aim of rehabilitation is to leverage neuroplasticity to achieve the best possible outcome for each patient. However, it's important to note that many patients tend to reach a plateau in their recovery, typically at around 70-80% of their initial impairment [19].
Neurorehabilitation encompasses a range of goals: preventing further losses, reversing damage when feasible, restoring function, developing new strategies for compensation, and adapting to functional impairments resulting from neurological injury or disease. These efforts often extend beyond immediate clinical care and continue to play a significant role throughout a patient's lifetime. Therefore, neurological rehabilitation should be a vital and ongoing component within systems of care for individuals dealing with neurological disorders. Currently a lot of techniques for motor rehabilitation are present: the usage of a treadmill, virtual environments, Functional Electrical Stimulation (FES) and rehabilitation robotics are examples. The key role of the neurorehabilitation is the constant activity of the patient during the rehabilitation treatment. In fact, it has been demonstrated that people actively involved during the exercises are more subjected to promote the motor relearning and, as mentioned before, the rehabilitation robotics results a fundamental principle of the motor recovery.[21]

## 1.3. Rehabilitation robotics

Rehabilitation robotics aims to understand and enhance recovery through the application of robotic devices. The main aspect is the use of robots as therapy tools rather than mere assistive devices [7, 8, 32]. Furthermore, there are currently different types of modalities through which rehabilitation robotics can work.
The exoskeleton represents a category of wearable robots in which the kinematic chain of the exoskeleton overlaps harmoniously with the anatomy of human limbs. There is a two-way correspondence between human anatomical joints and robot joints or sets of joints. Its main purpose is to enhance, assist or recover the functionality of human limbs [31].
Exoskeletons can be considered as a viable and highly valued solution for providing assistance to individuals with varying degrees of upper-limb motor impairment. These devices can operate in different modalities. Passive devices are the most prevalent among current solutions, but they may not be suitable for severely impaired patients as they require users to have some remaining ability to initiate movement. The only effective means of assisting patients in severe conditions is through the use of a fully active exoskeleton. Active exoskeletons are powered systems that are more complex than their passive counterparts. This complexity arises from the need to devise a strategy for precisely controlling joint movements in accordance with the patient's needs. Additionally, in terms of usability, accurately interpreting the user's desire to move and using it as a trigger to initiate the intended exoskeleton movement is crucial. Exoskeletons can be a valuable supplement to therapist-based training for post-stroke patients. These robotic devices enable individuals to engage in functional, high-dosage, and repetitive exercises that are crucial for their recovery.[16, 33]



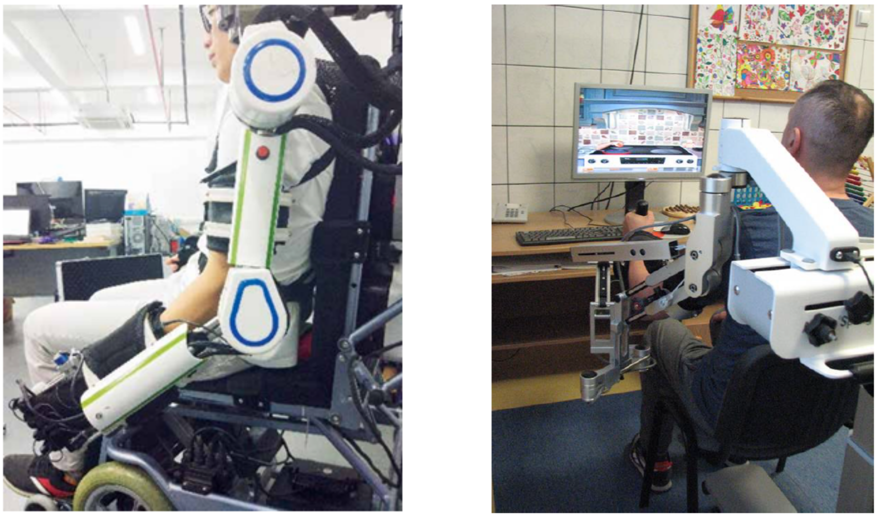
| Modality | Specifications | Schema |
|---|---|---|
| **Assistive** | Subject's voluntary activity is required during the entire movement. Robots can assist either providing weight support or providing forces aiming at task completion. | |
| **Active** | The robot is being used as a measurement device, without providing force to subject's limb. | |
| **Passive** | Robot performs the movement without any account of subject's activity. | |
| **Passive-mirrored** | This is for bimanual robots, when the unimpaired limb is used to control the passive movement of the affected side. | |
| **Active-assistive** | Assistance towards task completion is supplied only when the subject has not been able to perform actively. At this stage, the subject experiences passive movement of the limb. | |
| **Corrective** | Subject is stopped by the robot when errors (e.g. distance from a desired position) overcome a predefined value and then asked to perform actively again. | |
| **Path guidance** | Robot guides the subject when deviating from pre-defined trajectory. | |
| **Resistive** | Robot provides force opposing the movement. | |



*Figure 1: Training modalities in robot-mediated therapy. [23]*

Robots can be exploited with an active participation with the patient or just coaching without any interaction. Inside these "active" category the key word is the assistance: studies and research have recently demonstrated that the active participation of the subject is fundamental for a powerful motor relearning, thus the robots have to assist the patient in a proper way to exploit the maximum volitional movement of the injury muscles. The objective of control algorithms in robotic therapy is to govern robotic devices specifically designed for rehabilitation exercises. The aim is to ensure that the exercises selected for participants stimulate motor plasticity, thereby enhancing motor recovery. Consequently, control algorithms for robotic therapy are typically developed on a case-by-case basis, often drawing inspiration from principles found in the fields of rehabilitation, neuroscience, and motor learning literature.[3, 23] According to the state of the art there are four categories of robots: Assistive controller, Challenge-based controllers, Haptic stimulation with Virtual Reality and the non-contact coaching. The most significant one to be mentioned within this article belongs to the first category in which the goal of the robot is to help the participant to move the limb in the desired pattern through a physical assistance to the patience. This recovery modalities shows interesting advantages: prevention muscle stiffness, spasticity reduction, moreover the robot can help the patient doing the correct task in safety conditions. Furthermore, the medical device is able to change the difficulty of the training with phycological benefit like the rewarding of the subject. Therefore, this kind of solution described powerful gains for the subjects affected by neurological injures. One key point that is always well highlighted in literature is that the rehabilitation robotics does not want to replace the rule of the physiotherapist, but they have to collaborate each other in order to give to the patience best training recovery as possible.[29] Conversely, there are certain limitations to consider. The primary objective is to assist the patient in achieving the correct physical movements, as they might not be able to perform these movements without assistance. It is also essential to address the "slacking hypothesis" where individuals may passively rely on the robot to complete tasks if they realize that minimal

effort on their part will suffice.
The concept known as "assistance as needed" has gained significance in active rehabilitation strategies. The primary aim is to stimulate the user's active participation and provide assistance as necessary to help them successfully complete the task. According to the state of the art different categories of assistance as needed are present, in this article the focus is on the impedance base controller and performance-based. The key idea is to modulate the level of assistance provided by the robot dynamically. To achieve this, various parameters based on the individual's contribution are adjusted. When the patient is performing well, the robot decreases assistance or increases the task's difficulty. The common idea of the assistance as needed is that when the subjects moves along a desired trajectory the robot should not provide any assistance while when the the participant deviates from the trajectory, the exoskeleton provides assistance through a resistive force which is created from a mechanical impedance. In the case of controller base, the resisting force increases as the participant deviates from the desired trajectory. For instance, in the case of a position feedback controller utilizing proportional and derivative components, when the participant deviates from the intended trajectory, the force generated by the controller rises proportionally. This behavior can be likened to the controller's response resembling that of a damped spring. The control strategy employed by robotic aids plays a pivotal role in the therapy's effectiveness and is typically designed to tailor the technology to the patient's specific requirements. While there are non-motorized passive devices that merely support the limb without facilitating movement, the integration of active motors is generally favoured. This approach allows for a more substantial and dynamic contribution to the rehabilitation process, enhancing its overall impact. In the following chapter the intention detection strategy is described, this is a fundamental strategy that aims to capture the initial volitional movement of the patient in order to start the task, thus, to define the trigger point for the beginning of the robot assistance. When a patient possesses some remaining capabilities, it becomes crucial for the patient to be alert and actively engage in attempting movements rather than remaining passive. This approach is essential for stimulating neural plasticity as it activates motor planning pathways. [6, 23, 29]



(a) Powered exoskeleton.

(b) Armeo Spring.

*Figure 2: Examples of rehabilitation robots for upper limb:(a) Powered exoskelton [26], (b) Armeo Spring.[28]*

## 1.4. Intention detection strategies

In addition to the development of rehabilitation devices, there is significant emphasis on identifying the most effective Intention Detection Strategy (IDS) to detect a subject's voluntary movements and initiate the assistance provided by rehabilitation robots. Researchers and engineers face the challenge of selecting the most suitable IDS tailored to the specific task, as it plays a pivotal role in designing training protocols aimed at promoting motor recovery. Thus, IDS is a vital component of various applications, particularly in the context of rehabilitation robotics and assistive technologies. Therefore, IDS is a method or approach used to recognize the volitional movements or intentions of an individual. It serves as the bridge between human intention and technological response. In a scenario where someone suffers a neurological injury or is living with a disability that affects their motor functions, such as moving their arm or legs, in these cases the ability to detect their intention to move and translate it into action through technology can be life changing. In essence, IDS is about enabling individuals to regain control and independence in their lives. It empowers them to interact with the world and carry out daily activities. An often-underestimated advantage is the restoration of dignity and the enhancement of the overall quality of life. When Intention Detection Strategies are effectively applied, they not only enable individuals to regain control over their movements but also grant them a sense of dignity by fostering independence. Moreover, this technology can significantly improve the day-to-day experiences and well-being of those who benefit from it, highlighting the profound impact it has on the human spirit and sense of self-worth. Furthermore, IDS is not limited to physical rehabilitation alone. It has the potential to revolutionize various fields, from gaming and virtual reality to smart homes and human-computer interaction. By accurately detecting human intention, IDS can make technology more responsive, intuitive, and user-friendly.

According to the literature, different types of intention detection strategies can be performed.[5, 12, 13, 34, 35]

- **Bio-Signal-Based IDS:** This approach relies on detecting biological signals, such as brain activity through EEG, thanks to scalp electrodes, or muscle activity through EMG, thanks to superficial electrodes. Bio-signal-based IDS enables direct control of devices through the brain or muscles, opening the door to solutions like mind-controlled prosthetics and brain-computer interfaces. In the field of assistive technology, electromyography (EMG) signals generated during muscle activation are commonly used for control. EMG signals are employed in 40.2% of the studies due to their ease of acquisition using standard hardware and wearable technology like Myo armbands or sleeves. However, EMG signals have limitations, including sensitivity to changes in electrode placement, skin impedance, sweat, and muscle fatigue.
- **Vision-Based IDS:** These IDS use cameras and artificial vision systems to detect body movements. They are often used in applications like gesture recognition and motion tracking in video games. Gesture recognition technology is becoming increasingly common in our daily lives. Eye movement is a critical component in human motion planning as it gathers information about the environment and objects before initiating movement. Visual input, obtained through tracking eye motion or gaze, can be used to guide upper limb movements in tasks like reaching and grasping. This is especially relevant for individuals with limited upper limb functionality due to neurological deficits, as eye movement is typically unaffected. Various eye-tracking techniques are available, such as video-oculography and electrooculography (EOG), making it feasible for a broad target population.
- **Inertial Sensor-Based IDS:** These devices, like gyroscopes and accelerometers, monitor body orientation and acceleration. They are often integrated into wearables like smartwatches and smartphones, but they also find applications in rehabilitation for motion monitoring and assessment. They exploit the property of inertia; the goal is to find the volitional movement of the patient tanks to value of the kinematics chain of the limb. IMUs are easy to wear, not codependent on skin conductivity and they provide a wide range of detection. However, they are sensitive to possible electronic interference, sensitive to the mounted position and they require the process of calibration.
- **Voice-Based IDS:** This type of IDS relies on the analysis of vocal sounds and voice commands. They are widely used in voice assistant systems, allowing us to control devices and obtain information through voice recognition. It can be used by a broad range of people with impairments, as long as their speech abilities are not severely affected. The potential number of distinguishable states with voice control is theoretically infinite, but it is practically limited by computational power, software capabilities, and the need for internet connectivity. However, the accuracy of voice control may be affected in noisy environments with interfering sounds.
- **Upper limb movement IDS:** This approach stands on identifying the volitional movement of the patient through the joint rotation or kinematics of the upper limb segments. The goal of upper limb movement IDS is to facilitate more natural and intuitive interaction between individuals and technology, especially in cases where individuals may have limited upper limb function due to injury, disability, or other factors. Intention detection systems (IDS) that rely on joint rotation or the kinematics of upper limb segments offer a natural and easy way to control devices. However, they are primarily suitable for users with sufficient residual upper-limb function, making them ideal for devices designed to augment neurologically intact individuals or orthoses to assist those with limited but residual upper limb functionality. These IDS are not practical alternatives for individuals with more severe impairments or full paralysis.

The focus of this the article regards the upper limb movement strategy and the interaction between this IDS and the rehabilitation robotics therapy for the upper limb after neurological disorders.

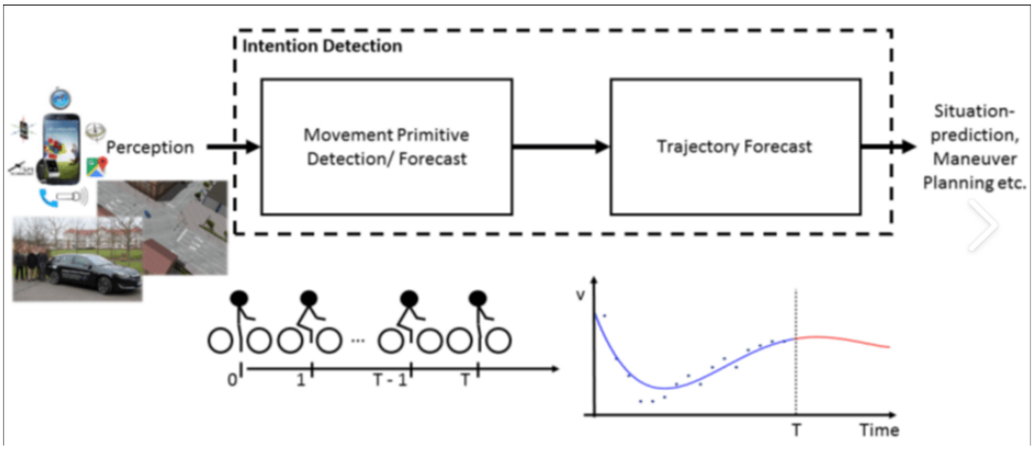
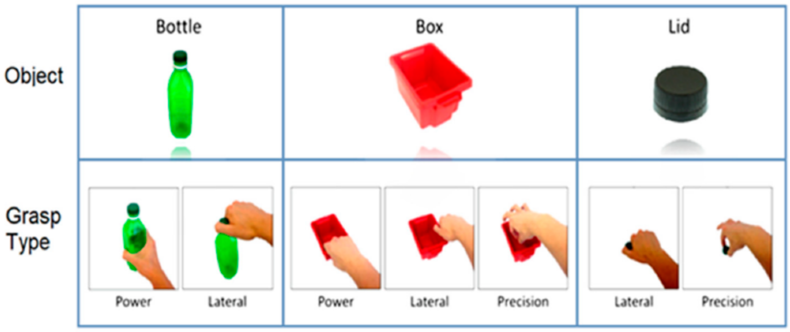


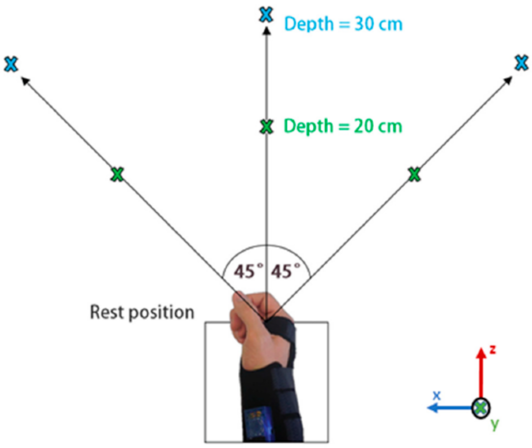

*Figure 3: Schematic representation of intention detection model. [4]*

## 1.5. Example of upper limb movement IDS from literature

This study initially focused on the exploration of artificial intelligence classifiers and the identification of effective parameters within guided research studies in the field of robotic rehabilitation. The primary objective of [14] is to assess the real-time classification accuracy for reaching tasks performed with an upper limb robotic prosthesis equipped with inertial sensors and a camera-based vision system. Each object was systematically tested at all 18 possible locations, with data recorded for the object placed at angular orientations of -45 degrees, 0 degrees, and +45 degrees, as well as at depths of 20 cm and 30 cm. Data have been gather from ten healthy subjects.




(a) Experimental protocol.




(b) Objects locations.

*Figure 4: Experimental protocol (a) and object location (b) of the rehabilitation exercises of the study. [14]*

Following it is possible to see the different classifiers used and their performances:

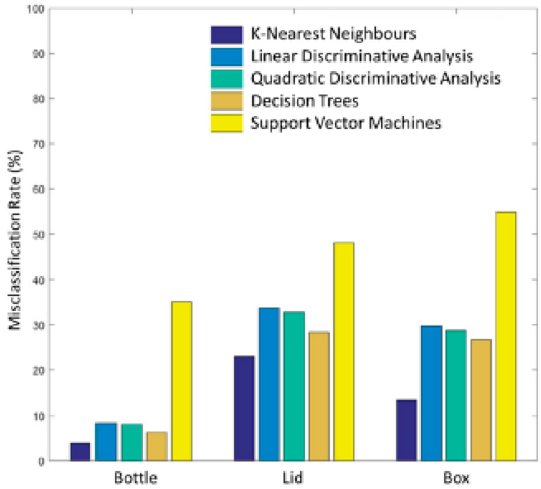
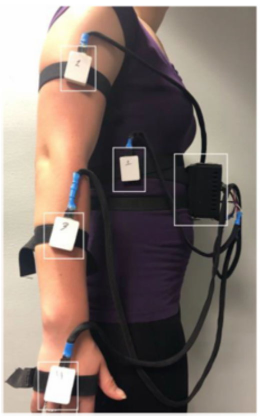



*Figure 5: Comparison of the misclassification errors of the different classifiers for each task. [14]*

Thus, in this experiment the best model is the KNN with an average accuracy of 86% for the grasping task. In the study [18] the aim is to assess the performance of machine learning models in categorizing nine distinct upper extremity exercises using kinematic data collected from a device that relies on Inertial Measurement Units (IMUs). Fifty participants executed a series of exercises, comprising one compound exercise and eight isolation exercises, all using their right arm. Each exercise was repeated ten times, resulting in a total of 4,500 trials. Joint angles were determined by employing IMUs positioned on the hand, forearm, upper arm, and torso. Participants were instructed to perform a set of nine exercises, which included: Standing row, External rotation with the arm abducted 90°, External rotation, Bicep curl, Forearm pronation/supination, Wrist curls, Lateral arm raise, Front arm raise, Horizontal abduction.



(a) Imu set-up.

| | Accuracy | Train time (s) | Test time (s) |
|---|---|---|---|
| RF (flattened) | 98.6% | 12.4 | .678 |
| RF (ROM) | 91.9% | 1.35 | 0.116 |
| 3-NN (flattened) | 97.4% | 0.820 | 13.264 |
| 3-NN (ROM) | 91.8% | 0.003 | 0.063 |
| MLP (flattened) | 95.7% | 1920.15 | 0.549 |
| MLP (ROM) | 89.3% | 360.57 | 0.004 |
| Linear SVC (ROM) | 75.6% | 0.048 | 0.001 |
| Flattened average | 97.2% | | |
| ROM average | 91.0% | | |
| Total average | 94.1% | | |

(b) Classification models' accuracy.

*Figure 6: Imu set-up (a) and classification models'accuracy (b) of the rehabilitation exercises of the study. [18]*

In conclusion, for both the previous experiments described the best accuracy for the upper limb exercises results with the KNN and random forest classifier and while for the classifiers as support vector machine and linear classifier the results cannot be considered reliable for a real time classification.

Furthermore, also the latency of the task recognition has been investigated; regarding the study [24] aims to design a novel embedded algorithm to perform accurate human activity in real-time. The exercises like standing, running and walking have been tested by two participants who wore three IMU sensors on bust, thigh and tibia. Data processing is characterized by a windows length of 450 ms (1080 samples). The machine learning models tested were the KNN, SVM with radial kernel and spherical normalization. The K-Nearest Neighbours (KNN)

model is a simple and effective supervised learning algorithm that can be used to solve both classification and regression problems. The KNN algorithm operates on an intuitive principle: similarity between objects. In other words, similar objects exist in close proximity to each other.
Instead, the Support Vector Machine (SVM), initially presented by Vapnik, encompasses a collection of supervised learning algorithms employed for tasks such as classification, regression analysis, and outlier detection. It operates as a binary classifier. This method of machine learning is designed to minimize empirical risks while maximizing the margin between the delineating hyperplanes and the data representing two distinct classes. Non-linear classification is attainable through various kernel methods like RBF or polynomial kernels. These kernel methods transition data from the original data domain into a higher dimensional domain known as the feature space. Spherical Normalization (SN) emerges as a normalization technique initially introduced in the realm of Speaker Verification. It serves as a preconditioning phase that utilizes a transformation to position each feature vector on the surface of a unit hypersphere.
The best accurate model results the SVM with the radial kernel, and from the figure below it is possibe to see that the average latency is of 107.1 ms with a standard deviation of 8,5 ms.

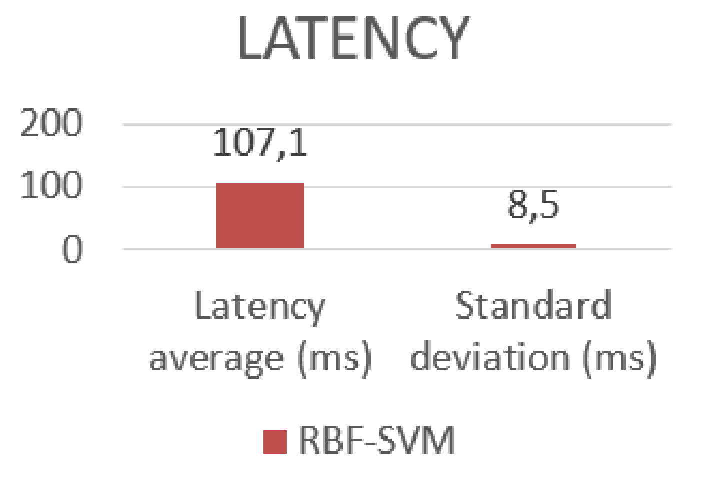



*Figure 7: Latency and standard deviation of the SVM radial base model [24]*

## 1.6. Limitation of robotics and IDS

So far, the strengths of Intention Detection Strategies (IDS) in the rehabilitation therapy process have been highlighted. However, it is crucial to consider all the attributes and features that influence the selection and limitations of different IDS. The first attribute to address is reliability, which measures how effectively a strategy performs its designated functions under specified, unchanging conditions. In real-time scenarios, adhering to non-varying conditions can be challenging, emphasizing the distinction between reliability and robustness. This attribute can be quantified through qualitative user feedback or by calculating the percentage of successes and errors. Additionally, the temporal delay between the user's actual intent and its detection is of paramount importance in effective rehabilitation training; this is known as "temporal workload." It can be assessed by considering factors such as task duration and task speed, accounting for the inherent mechanical delay of the medical robotic device. Another crucial aspect is the user's ease of controlling the device using the IDS. Research has shown that the more user-friendly and comfortable the IDS, the greater the user's active participation. In contrast to reliability, robustness hinges on how well an IDS performs under different conditions, including variations, invalid user inputs, and environmental factors. Furthermore, the setup of the IDS is a critical discussion point. Sensor placement and straightforward calibration are essential requirements for an effective and efficient strategy. Lastly, regarding the exoskeleton itself, other vital characteristics include the cost of the device, which reflects the financial investment, and the comfort or ergonomics perceived by users during usage. Considering these attributes and features ensures a comprehensive evaluation of IDS and its application in the context of rehabilitation and medical robotics.
Therefore, a trade-off between all the parameters mentioned above should be find in order to encompasses the best option of IDS possible for the specific task and injury.

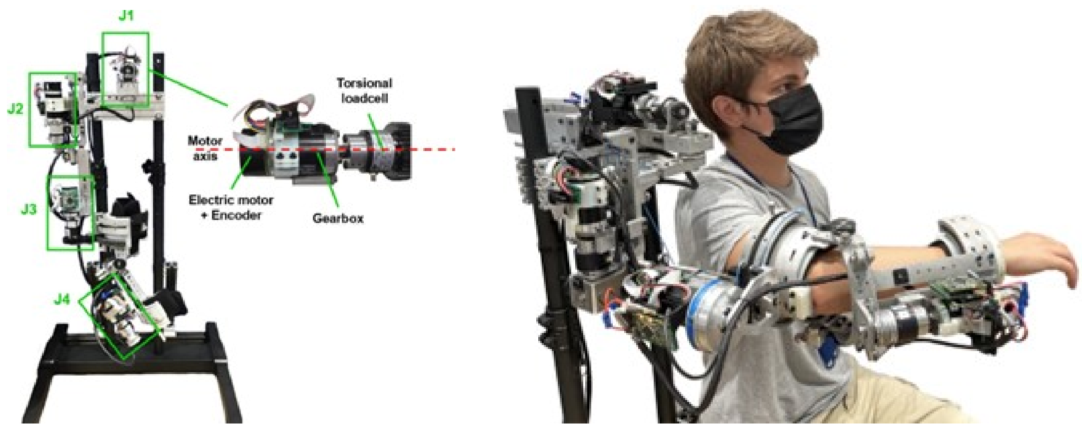
## 1.7. Objectives

The aim of this study is to develop an effective intention detection strategy for robot assisted exoskeleton and validate its accuracy and reliability for the motor recovery during rehabilitation therapy for upper limb movements in real time, based on kinematics data. This strategy combines the strengths of the best available Intention Detection Systems (IDS) with a robotic platform designed for upper limb rehabilitation. The hybrid system's primary function is to recognize three distinct tasks and, upon identification through the IDS, initiate specific upper limb movements to assist individuals with their rehabilitation therapy. The three tasks begin from a "resting position" where the exoskeleton remains stationary. From this starting point, the exoskeleton can move to three different final positions, each corresponding to a different upper limb movement. The study involved healthy subjects who wore the exoskeleton and performed these tasks while data were collected from specific sensors integrated into the hybrid system. The collected data were then analysed to develop the most effective intention detection strategy possible, which was subsequently tested. Once the best machine learning model, trained on data acquired from the subjects, was identified, it was implemented in AGREE and tested in real-time to verify its correct performance and proper usage. The following chapters of the study provide in-depth information on the robotic platform used (AGREE), including details on the materials and methods employed. Additionally, the study outlines the hybrid control system's design and operation. The development of the IDS is a critical component of this research, and the subsequent chapters provide a comprehensive overview of the steps taken in its implementation. In summary, this study seeks to create an intention detection strategy that combines IDS technology with a robotic platform to assist in upper limb rehabilitation. The study involves collecting data from healthy subjects and uses them to develop and test different models such as KNN, Random Forest (RF), Gradient Boosting (GB), Extremely Randomized Trees (Extra Trees), Extreme Gradient Boosting (Xgboost) and Long Short-Term memory (LSTM). Once they were compared, the best one was chosen for real-time evaluation on AGREE. Finally, the final results were compared with the state of the art in the literature. Detailed descriptions of the robotic platform and the IDS development phases are given in the following chapters.

# 2. Material and methods

## 2.1. AGREE robotic platform: exoskeleton design.

The device known as "AGREE" (Arm exoskeleton and Grip assistance for REhabilitation and indipEndent living) is a powered exoskeleton designed to assist neurological patients during seated rehabilitative exercises such as hand-to-mouth, lateral elevation, and arm reaching ones. This advanced device has been developed through collaboration between several high-tech healthcare companies, including Ab.Acus, STAM S.r.l, Sapra Elettronica, and EMAC S.r.l. Additionally, the project involved the Department of Electronics, Information, and Bioengineering (DEIB) and the Department of Mechanics at Politecnico di Milano, including the NearLab and WeCobot laboratories. It can easily be re-organized to work differently with right upper limb and the left one.




(a) Mechanical structure.
(b) Wearability (rigth side).

*Figure 8: Degrees of freedom of the AGREE system. J1: shoulder horizontal abduction/adduction, J2: shoulder flexion/extension, J3: intra/extra humeral rotation abduction, and J4: elbow flexion/extension (a) Wearability of the esxoskeleton (b).[15]*

The goal of AGREE is to provide advanced support during rehabilitation exercises, helping patients to improve their mobility and independence in daily activities. This exoskeleton has been developed by combining expertise in healthcare and advanced technology, enabling the integration of engineering and medical knowledge to create a highly specialized and effective rehabilitation device for neurological patients in the recovery phase. Deeper, the device is characterized by four degrees of freedom which feature three actuated joints at the shoulder one actuated joint for the elbow and one passive joint for the forearm.
Thus, the mechanical design is embodied with four active joints:

- **J1:** shoulder horizontal abduction/adduction
- **J2:** shoulder flexion/extension
- **J3:** intra/extra humeral rotation abduction
- **J4:** elbow flexion/extension

The shoulder flexion/extension joint is equipped with a passive anti-gravity system based on springs to counteract the gravitational forces acting on the arm. The exoskeleton's design is aligned with the natural human joint structure and provides support for the user's arm at two interface points, located on the upper arm and forearm. Unlike traditional exoskeletons, this design does not include a handle at the end-effector, allowing the user to perform grasping tasks with real objects. Each joint of the exoskeleton is driven by an actuation unit that relies on load cells for precise measurement and control of human-robot interaction torques. This design ensures that the exoskeleton can respond compliantly to both forces generated by the user and forces applied by the therapist. Additionally, mechanical end-stops are incorporated into each joint to prevent the arm from moving beyond its natural range of motion, prioritizing safety during rehabilitation exercises.[10, 15]
Exoskeleton rehabilitation robots typically employ electric motors combined with high transmission ratio gearboxes to enhance the output torque generated at each joint. However, this design limits the mechanical back drivability of the actuation unit.
For each joint of the exoskeleton the parameters angular position, rotational velocity and generated output torque are acquired. Position and velocity are recorded using incremental encoders, specifically MILE encoders

| Joint | Range of Motion (ROM) [deg] | Nominal Torque [Nm] | Loadcell Range [Nm] | Transmission Ratio |
|---|---|---|---|---|
| J1 | -50:30 | 3.48 | 5.65 | 26:1 |
| J2 | 10:110 | 20 | 22.6 | 156:1 |
| J3 | 0:60 | 3 * 3.48 | 3 * 5.65 | 3 * 26:1 |
| J4 | 0:125 | 10.85 | 22.6 | 81:1 |

*Table 1: Specificationoftheright-sidedAGREEexoskeletonactivejoints. ROM:rangeofmotion.[10]*

from Maxon Motor in Switzerland. Output torque is acquired through torsional load cells located at the output shaft of the actuator, using TRT load cells from Transducer Techniques in the United States. By measuring the joint load cell torque and subtracting the gravitational torque due to the robot's weight, the resulting value represents the human-robot interaction effort. This measurement provides a good estimate of the assistance provided by the robot at each joint. Additionally, the system offers the option to connect an EMG (Electromyography) and EEG (Electroencephalography) device, specifically the Sessantaquattro device from OTBioelettronica in Italy, for monitoring muscular and brain activity across a total of 64 channels.
In the context of a hand-to-mouth exercise, the signals acquired during a sample trial include the position profile showing movement amplitude and speed, the torque profile indicating robot support with torque up to 14 Nm at the shoulder level, and electromyographic signals demonstrating the contraction of the anterior deltoid during the ascending phase and relaxation during the descending phase of the exercise. Moreover, the system incorporates a visual feedback component designed to assist both therapists during rehabilitation sessions and subjects as they perform specific movement tasks on a table. This visual feedback system utilizes a cost-effective LED-based mat, constructed using semi-plastic materials with dimensions of 100x50 cm. The mat is equipped with a grid of 450 LEDs, evenly spaced at intervals of 3.3 cm, and their colour and light intensity can be controlled via a microcontroller. During the reaching tasks phase of rehabilitation, this visual feedback system is employed to illuminate the target points that need to be reached. This feature serves to enhance the spatial and temporal understanding of the desired movements, aiding both therapists and subjects in achieving the rehabilitation goals effectively.[10, 15]

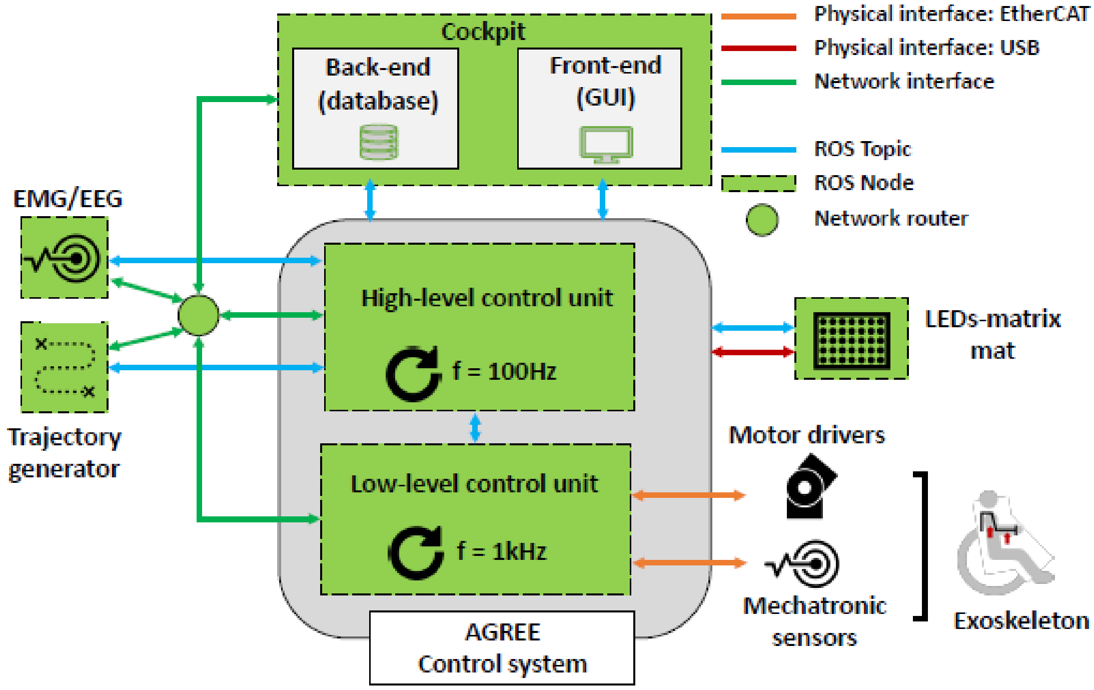



*Figure 9: The AGREE modular concept.[15]*

The exoskeleton system is managed by a real-time control unit based on Linux. This control unit utilizes C++ libraries that are built upon the Simple Open-Source EtherCAT Master (SOEM) framework. SOEM is employed to facilitate communication with the motor drivers and sensors, ensuring precise and real-time control of the exoskeleton's movements and interactions. Furthermore, communication between the middle-level and high-level components of the system is established through the Robotic Operating System (ROS) [10, 15].

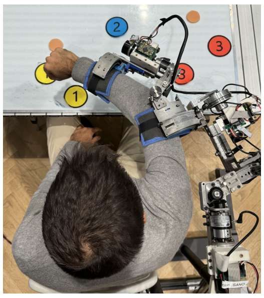
## 2.2. Data Acquisition and Segmentation for Movement Start Identification

One of the fundamental aspects of an effective rehabilitation program is the inclusion of goal-oriented activities that optimize the engagement of the participant. In clinical assessment and within the rehabilitation context, one of the most studied movements is the reaching task, where the subject is asked to reach a point in space [25]. This type of exercise was already implemented in the AGREE platform.

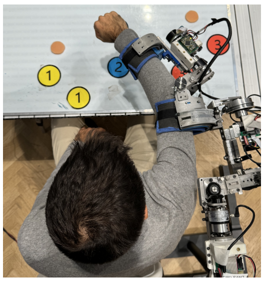
| Subject | Gender | Age |
|---|---|---|
| S1 | F | 26 |
| S2 | M | 24 |
| S3 | M | 23 |
| S4 | F | 25 |
| S5 | M | 23 |
| S6 | F | 24 |
| S7 | M | 24 |
| S8 | M | 24 |
| S9 | F | 23 |
| S10* | F | 24 |
| S11* | M | 24 |
| S12* | M | 24 |
| S13* | M | 24 |

*Table 2: Information about the subjects that were recruited in this study. (*)The asterisk indicates the subjects used for the real-time evaluation on AGREE.*

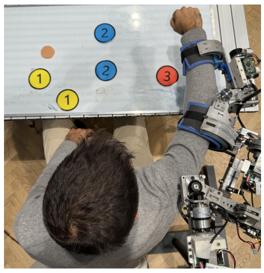
The data collection was conducted on 9 healthy subjects who donned the exoskeleton and were positioned seated at a table. Additionally, for the real-time evaluation using the AGREE system, four more subjects were involved. The reaching movement was executed as follows: the subject started from a rest position and was required to reach a point on the table. Upon reaching the point of interest, they were to return to the rest position where they were to remain for at least 3 seconds.
There were three reaching tasks: the contralateral, where the point of interest was placed to the left of the subject; the frontal, where the point was placed directly in front; and finally, the ipsilateral, where the point of interest was placed to the right of the subject. As can be seen in Figure 10. They were required to perform 15 movements for each task, totaling 45 reaching movements per subject. The acquisition protocol was conducted with the approval of the ethical committee of Politecnico di Milano. The rest position and the three different destinations were determined in accordance with the arm model integrated into the AGREE platform.
The movements were carried out with the exoskeleton in transparent mode in which the exoskeleton compensates only for the weight of its own arm and the movement was performed only by the propulsive force of the subject; thus, the subject was not required to follow a predetermined trajectory and could execute the movement at their preferred speed, aiming to provide as much variability as possible and furthermore making the movement as similar as possible to an ADL (Activities of Daily Living). Once all 15 repetitions for a task were completed, before executing the next task, AGREE was set to gravity mode where it compensates for the weight of its own arm and for the gravity force. The data from the encoders positioned respectively on the 4 joints of AGREE (J1, J2, J3, J4) [15] were saved at a frequency of 1KHz in a CSV file.



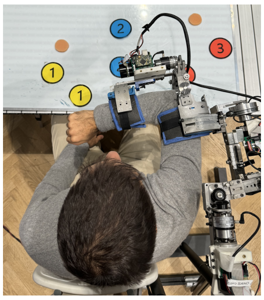
(a) Controlateral



(b) Frontal



(c) Ipsilateral



(d) Rest

*Figure 10: The 3 tasks performed by the subjects and the rest position they had to assume between one repetition and the next.*

## 2.3. Data processing

The CSV file contained information regarding the kinematics for each of the joints of the exoskeleton and had a column where the motion command was saved, which through identifying codes separates the different modes in which AGREE is set, thus allowing the division between the weight compensation mode, where the tasks were performed, and the gravity mode, which was set to prepare the subject for the subsequent movement. This allowed for the separation of the three tasks to process them independently from each other as they have different characteristics.
The processing was carried out in Matlab.
The main objective of this study, as previously described, is to recognize the initiation of the movement by the subject, and once recognized, change the operation mode of the exoskeleton to assist the subject in completing the movement. To do this, the most crucial part of this processing is extracting time windows to be used for training machine learning models. So, the initial instants at which each repetition began for each task were first identified and, of course, also the position of rest.

What was done in this study is based on the idea that by identifying the points where all the velocities of the exoskeleton joints are equal to zero, the resting phases between one repetition and another are identified, and moreover, the forward and return movements for every single repetition can also be distinguished, although for the objective of this study it is not strictly necessary. Since the velocities will never instantaneously be equal to zero, a rounding to the first digit after the decimal point was performed to facilitate the identification of the resting phases. This corresponds to setting a threshold on speeds of 0.05, so all values below this value are set to zero. Obviously, the same process was done for negative values. For this operation, only 3 of the 4 joints representing the exoskeleton were used since J3 is held fixed, thus considering it would have only introduced variations due to noise. The figure 11 shows the graph resulting from this operation.

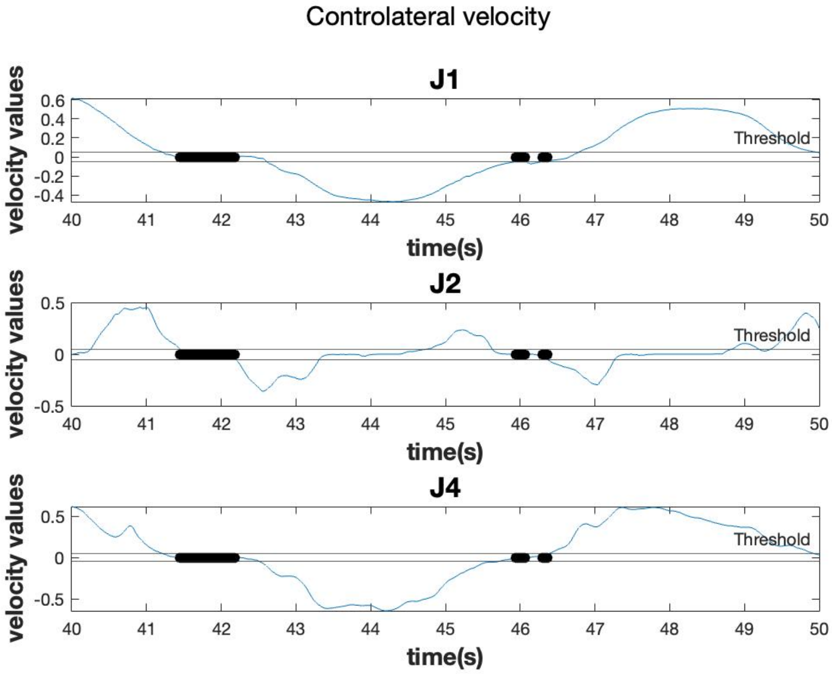



*Figure 11: This figure represents the velocities of the three considered joints (J1, J2, J4). The threshold is the value below which all three velocities are set equal to zero. While the dots represent the instants at which all three velocities are zero simultaneously.*

In this way, all time intervals where velocities are zero were identified. Time intervals are understood to be both the moments when the subject was in the rest position ready to start the movement, and the moments when the subject reached the target point in each repetition, i.e. the point separating the outward from the return. Having identified all the points where the velocities are simultaneously zero, only the last point for each identified interval was taken, by searching for where there was a temporal jump in the points found.

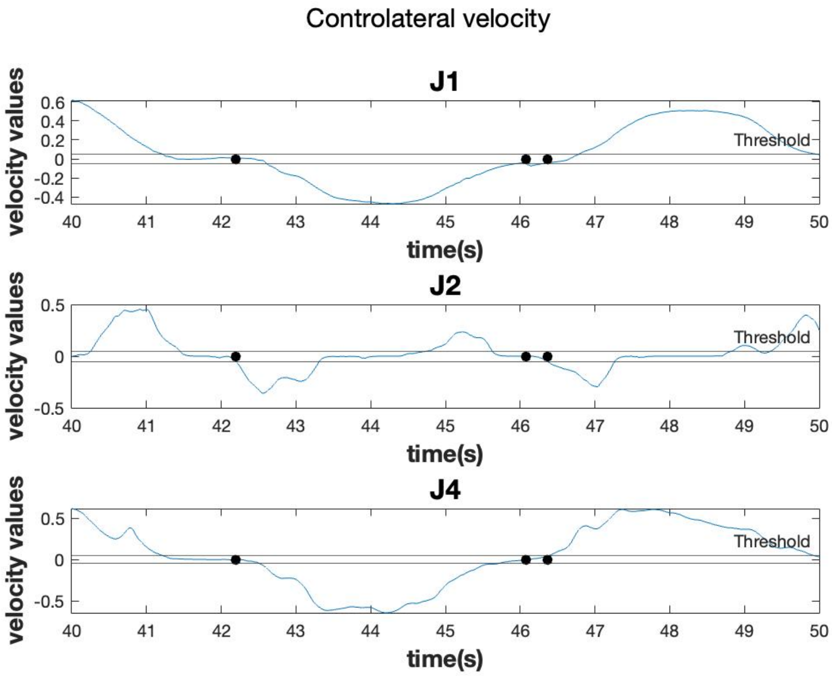



*Figure 12: Representation of points where all joint velocities are zero at the same time after applying the first step in which the number of points went down to select the last one for each time interval.*

In the process of data analysis, it was observed that the number of identified time intervals exceeded the actual count. This discrepancy is likely attributable to the fact that a subject, despite being in a resting position, exhibited minute movements that were captured as distinct time intervals. To address this, the differences between consecutive data points were plotted. Based on this visual representation, a threshold was established corresponding to the longest observed time span between two consecutive differences. Points falling below this threshold were subsequently eliminated to retain only the final data point for each genuine time interval.

Upon identification of the threshold value, it was incorporated into an algorithm designed to refine data segmentation. Within this algorithm, the foundational premise was that if the disparity between two consecutive values fell below the threshold, they were deemed to belong to the same time interval. In such instances, only the bigger value was retained. Conversely, if the difference between two consecutive data points exceeded the threshold, it was interpreted as an indication that they originated from distinct time intervals, prompting the retention of both values.

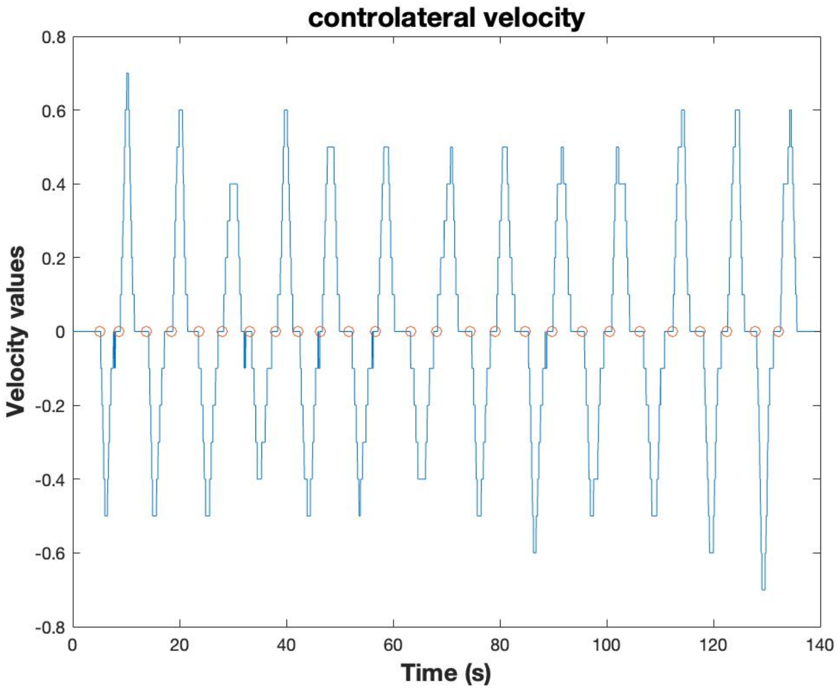



*Figure 13: Final result obtained after implementing all necessary steps to isolate a single point for each time interval. In this context, the points denote moments in time when the subject remained stationary, both prior to initiating the movement and upon reaching the target point during the execution of the reaching movement.*

After this fundamental step, a point was obtained, ideally the last, for each resting interval. From these points, only one out of every two points was selected to derive a vector that contains the last point and exclude those points representing the instance between the onward and return movement, or the instance immediately preceding the beginning of the movement, for every single repetition.

This all process was replicated for each of the three tasks considered.

To experimentally validate the adopted approach, a graph was generated that correlates the position of a joint with its velocity, also highlighting the instances designated as the beginning of the movement. This graphical representation helps provide a clear and direct visualization of the correlation between the position and velocity of the joint, along with the considered initial instances, thus facilitating the analysis and interpretation of the obtained results.

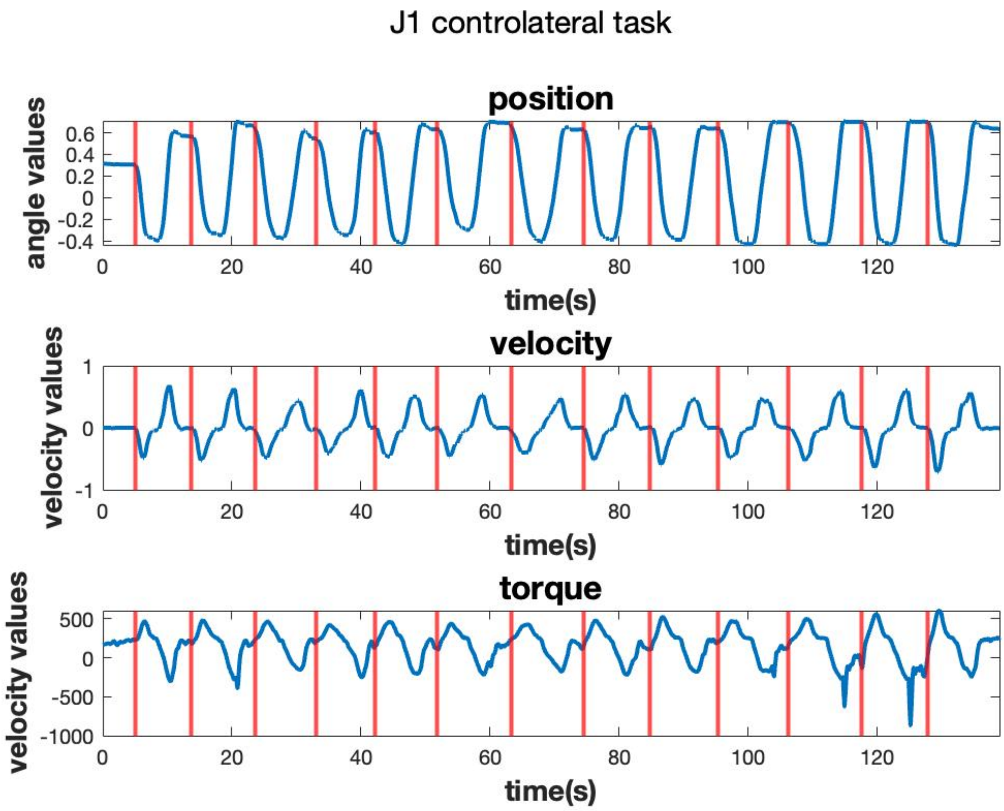



*Figure 14: This figure depicts the comparison between the position of an exoskeleton joint, in this case J1, its velocity and its torque. These three quantities were the pieces of information, for each joint, that were saved in the dataset extracted from MATLAB for subsequent training of the machine learning models.*

## 2.4. Windows creation

The primary objective of this study pertains to the identification of movement intention, as well as the recognizability of the task executed by the subject. To accomplish this aim, the creation of a dataset for training the selected machine learning models for this analysis was necessary. Consequently, the processing of temporal windows was conducted, each containing a set of data, starting from the data point following the one identified in the previous processing phase. This allowed for obtaining a window for each repetition of every task. For example, in [24] they use machine learning models to perform motion recognition, achieving a latency of 107.5ms. Moreover, in this article [27], they perform the same task but with a latency of 10ms. For this reason, it was decided to create and subsequently test different window sizes, to allow for performance evaluation across all of them. The dimensions of the windows examined varied, including: 10ms, 20ms, 30ms, 50ms, 100ms, 150ms, 200ms, and 300ms.

The flow followed for their creation was as follows: for each repetition, the point identifying the instant at which the subject began the movement was taken, and from that point a window was extracted, containing a quantity of values allowing the identification of the beginning of the movement by the automatic classifiers and therefore each point in the window has been associated with the same class. Furthermore, to allow the models to recognize the rest position, the same window was extracted to the left of the instant at which the movement began to contain all points at which the velocities of the joints were zero and in this case each value was associated with the 'REST' class. Figure 16. For each type of window created, the same number of samples were extracted and then cleaned to form the dataset extracted from MATLAB.

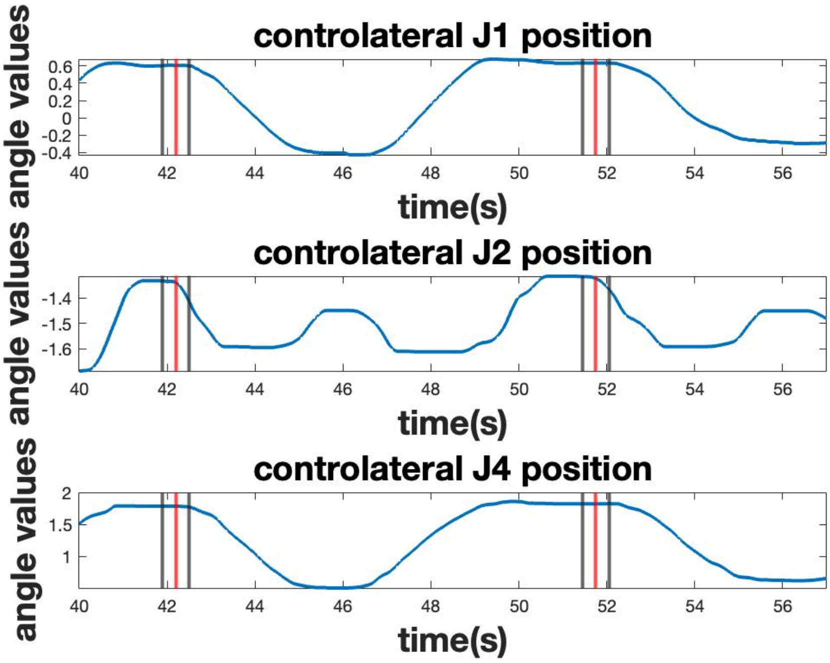



*Figure 15: In this image, a portion of the signal pertaining to the position of the three joint of the exoskeleton selected over time in the controlateral movement are represented. In the figure, the red vertical lines identify the points determined as the beginning of the movement, while the black ones represent the windowing considered for each repetition. In this case, the windowing of 300ms is shown, but the steps are the same for every chosen interval*

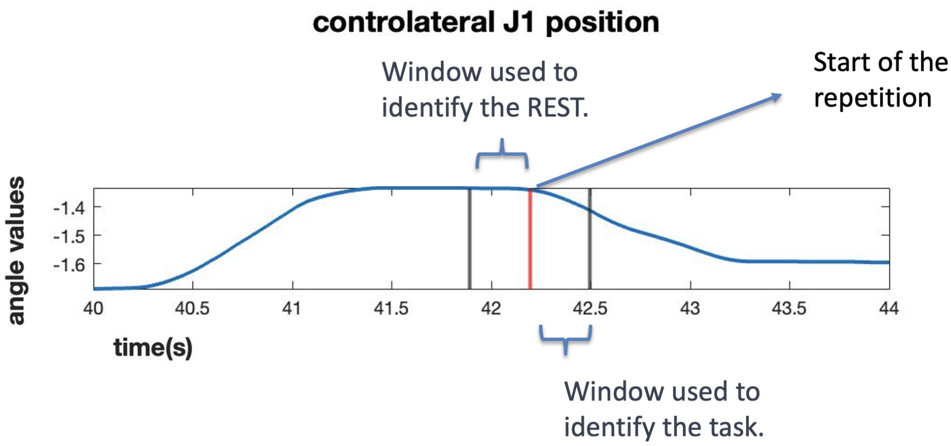



*Figure 16: In this image, a portion of the signal pertaining to the position of a single joint of the exoskeleton selected over time in the contralateral movement is represented. In the figure, the red vertical lines identify the points determined as the beginning of the movement, while the black ones represent the windowing considered for each repetition. In this case, the windowing of 300ms is shown, but the steps are the same for every chosen interval*

Given that the signal obtained from the encoders was sampled at 1000Hz, selecting a window of 10ms entails the acquisition of 10 samples for each repetition, plus 10 identifying samples of the resting phase for each repetition of movement. This procedure was replicated for every window size, for every task, and for every subject.

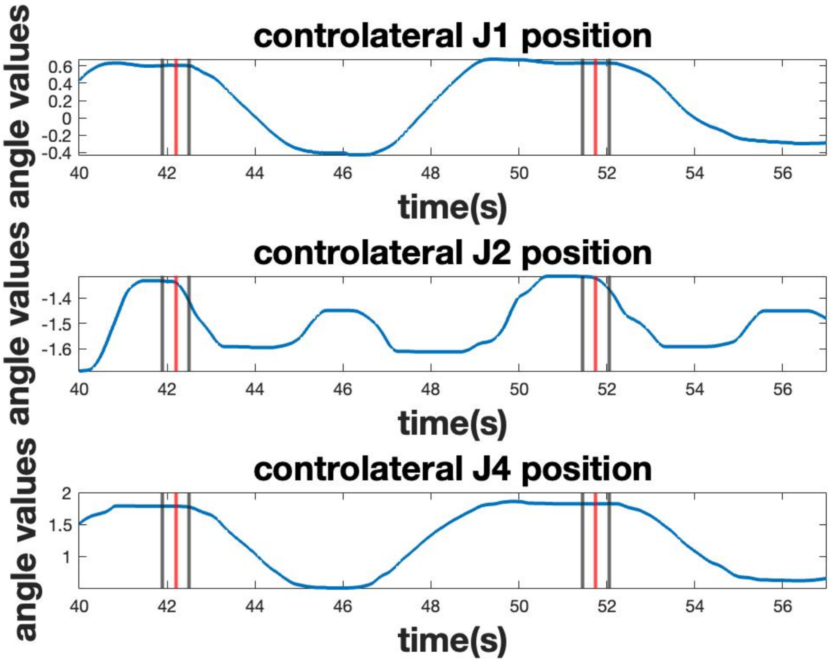



*Figure 17: In this image, a portion of the signal pertaining to the position of the three joint of the exoskeleton selected over time in the controlateral movement are represented. In the figure, the red vertical lines identify the points determined as the beginning of the movement, while the black ones represent the windowing considered for each repetition. In this case, the windowing of 300ms is shown, but the steps are the same for every chosen interval*

In the concluding phase, only the columns deemed most informative were selected for the compilation of a CSV file, designated for export from MATLAB for use in training. The selected columns included: the velocities of joints J1, J2, and J4; the respective positions of the three joints and the torque recorded for every instance on the same. Additionally, a column named 'labels' was included, to which an integer value representing the specific class of each task was associated: '1' for contralateral movement, '2' for frontal movement, '3' for ipsilateral movement, and '0' for the resting mode.

| Pos J1 | Pos J2 | Pos J4 | Torque J1 | Torque J2 | Torque J4 | Velocity J1 | Velocity J2 | Velocity_J4 | Label |
|---|---|---|---|---|---|---|---|---|---|
| 0.306531 | -1.33999 | 1.77517 | 227.868 | -8630.17 | 993.735 | -0.000786496 | -0.0382213 | -0.00196535 | 0 |
| 0.306531 | -1.34009 | 1.77513 | 227.93 | -8630.09 | 994.087 | -0.00078453 | -0.0394906 | -0.00214388 | 0 |
| 0.306472 | -1.34109 | 1.77493 | 228.707 | -8628.95 | 997.002 | -0.000911922 | -0.0506099 | -0.00302225 | 1 |
| 0.306472 | -1.3412 | 1.77492 | 228.796 | -8628.95 | 997.285 | -0.000909643 | -0.0518007 | -0.00306972 | 1 |
| 0.548634 | -1.31349 | 1.90294 | 218.037 | -8327.57 | 1016.3 | 0.00053716 | -0.0501928 | 0.00682989 | 2 |
| 0.548634 | -1.31355 | 1.90294 | 217.808 | -8327.12 | 1016.15 | 0.000535817 | -0.0504597 | 0.00679575 | 2 |
| 0.316591 | -1.30821 | 1.81959 | 241.876 | -8517.85 | 1095.13 | -0.014304 | -0.0520803 | 0.000794319 | 3 |
| 0.316561 | -1.30828 | 1.81959 | 242.013 | -8517.67 | 1094.81 | -0.014342 | -0.0523095 | 0.000790347 | 3 |

*Table 3: This is an example of a dataset extracted from MATLAB at the end of the data processing that will be used to train the models. The columns representing the features were joint positions, velocities, and torques. Additionally, a column representing the label was added.*

## 2.5. Learning model

The CSV files generated in MATLAB, at the end of all the processing operations, were structured in tables segmented by subject and time interval, containing several samples equivalent to the width of the time windows. Once acquired, these data were imported into Python for the training of Machine Learning and Deep Learning models, with the aim of identifying the type of task performed with the highest accuracy and the lowest possible latency. The models that were tested were chosen from those most frequently used in the literature, like [24], [27], [2] and [30].

Initially, the data were imported, and all the necessary libraries were installed. Subsequently, the division of the training set and the test set was carried out as follows: of the 13 subjects selected for analysis, 8 were included in the training set, 1 in the test set, while the other 4 subjects were used for real-time model evaluation, once the training and testing phases were completed. For the optimization of the parameters of the considered classifiers, a Grid Search was employed, which conducted a search for optimal parameters over a predefined range, using cross-validation and adopting accuracy as the evaluation metric. Moreover, in the grid search process, the generation of the normalized confusion matrix was also included, to analyze the model's performance in terms of correct and incorrect classification for each class. All the models examined belong to the category of supervised models, since labels related to the tasks under examination were available.

The first model evaluated was the K-Nearest Neighbors (KNN) model for its simplicity of implementation, having only two parameters to configure: the number of neighbors to consider for classification and the distance metric to adopt. In this model, the data was used without scaling, and moreover, a varying number of neighbors was used depending on the tested window. This number ranged from 95 to 400 and all points in each neighborhood are weighted equally. Instead, the Euclidian distance was used as the distance measure.

The second model considered was the Random Forest (RF) model for its proven validity in various studies present in the literature involving human movements, both upper and lower limb. Furthermore, the RF algorithm can autonomously perform a selection of the most relevant features in the creation of decision trees, and is also more robust against overfitting, taking into account an average among the predictions of multiple decision trees. In this model, the parameter values employed varied based on the specific window under analysis. On average, the number of estimators, or more precisely, the simpler trees utilized, was set at 70. The criterion adopted to gauge the quality of data splits was the Gini index. The maximum tree depth was configured to 3 for certain windows and 4 for others. Additionally, both the minimum number of samples mandated to divide an internal node and those required for a node to become a leaf differed across windows, averaging 5 for each criterion.

Another model explored was Gradient Boosting which, unlike RF, seeks to correct the errors made by previous trees through the calculation of residuals for each simple tree used. This model shares several parameters with the RF. The number of estimators employed ranged from 50 to 100, contingent upon the specific window under analysis. The learning rate was set at 0.1. The maximum depth of each tree was capped at 1. The minimum number of samples required to split an internal node, as well as the minimum samples required for a node to become a leaf, varied across each window, with an average of 8. Moreover, to expedite the model's training process, the subsample parameter was configured to 0.8. This configuration allowed for 80% of the data to be utilized for training each individual tree, which also contributed to mitigating the potential for overfitting.

The Extremely Randomized Trees (Extra Trees) model was also evaluated, which, unlike RF, determines the split of the features in a completely random manner, making the decision trees even more randomized, and is particularly useful in scenarios where training speed is crucial. This model shares numerous parameters with the Random Forest. Specifically, the number of estimators used ranged between 50 and 200, varying based on the specific window under consideration. The maximum depth of the tree was set at 7. Regarding the splitting criteria, the minimum number of samples required for a split in an internal node, and the minimum number needed for a node to be considered a leaf varied across windows, averaging at 9. Similarly, to the Random Forest, the criterion adopted to determine the quality of data splits in relation to the label was the GINI criterion.

The eXtreme Gradient Boosting classifier was tested as it represents an optimized implementation of Gradient Boosting, made more efficient, faster and, thanks to the inclusion of a regularization term in its objective function, more robust compared to a standard Gradient Boosting. In this model, several parameters were finely tuned, among which include: the learning rate, which was set to 0.01 up to the 50ms window and then adjusted to 0.001; the maximum depth of a tree, which was configured to 2; and lastly, the subsample, which was set at 0.8 to mitigate overfitting.

Lastly, after exploring all models that learn in a pointwise manner, the Long Short-Term Memory (LSTM) model was tested, a recurrent neural network capable of handling and learning from data with long-term temporal dependencies. For this model, the data was scaled using a standard scaler. Additionally, depending on the window considered, the network had a number of layers ranging from 2 to 4, with the number of neurons varying from layer to layer based on the window.

## 2.6. Online Testing

Once the results of the models listed above were compared, the best one was integrated on AGREE to perform the real-time evaluation. it is important to note that the model performs a pointwise recognition. This means that for each set of velocity, torque and position values of each joint it will make a prediction. To make the result more robust, logic was used such that the model had to perform a series of consecutive predictions of the same class to effectively classify the direction of movement made by the subject. In order to choose the number of consecutive predictions to be performed, different quantities of samples were tested using one subject: 5, 10, 20, 30, 40 and 50. They were evaluated according to the resulting accuracy, as shown in Figure 18. The result showed that the accuracy remained the same for the number of samples ranging from 5 to 30 and decreased in 40 and 50. With the same results, 5 was chosen as the number of samples used to predict the class as the speed of direction recognition is a key point in real-time applications. Thus, in addition to evaluating the performance of the movement direction recognition and REST phase by accuracy and confusion matrix, latency was also evaluated, calculated as the time taken by the model to make five consecutive predictions of the same class was calculated.

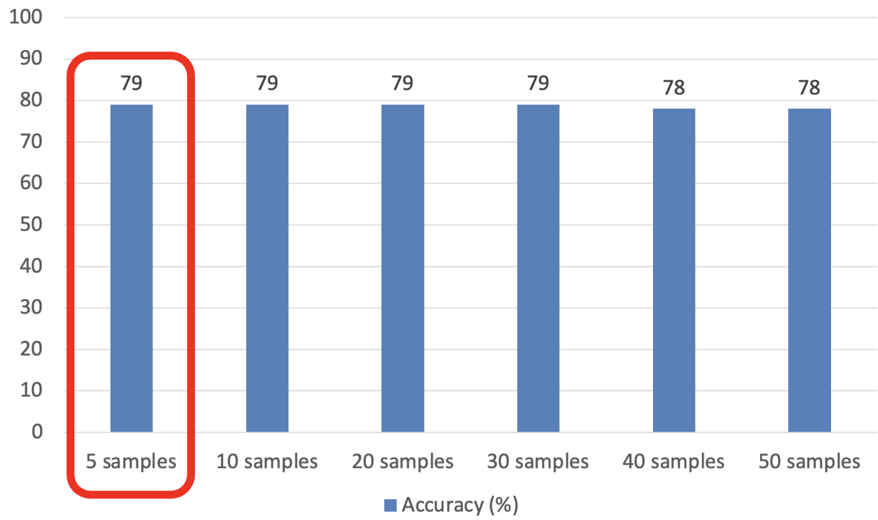



*Figure 18: The figure displays the accuracy calculated for the different latencies tested for real-time evaluation. In this context, latency is defined as the time in which the model must consecutively predict the same class to allow the recognition of the movement's direction.*

# 3. Result and Discussion

## 3.1. Models result

The models under discussion were trained on a training set composed of data from 8 subjects, while a test set was derived from a single subject. Details regarding the training outcomes are illustrated in Figure 19, where bar charts are presented comparing the training set accuracy with that of the test set for different time windows.

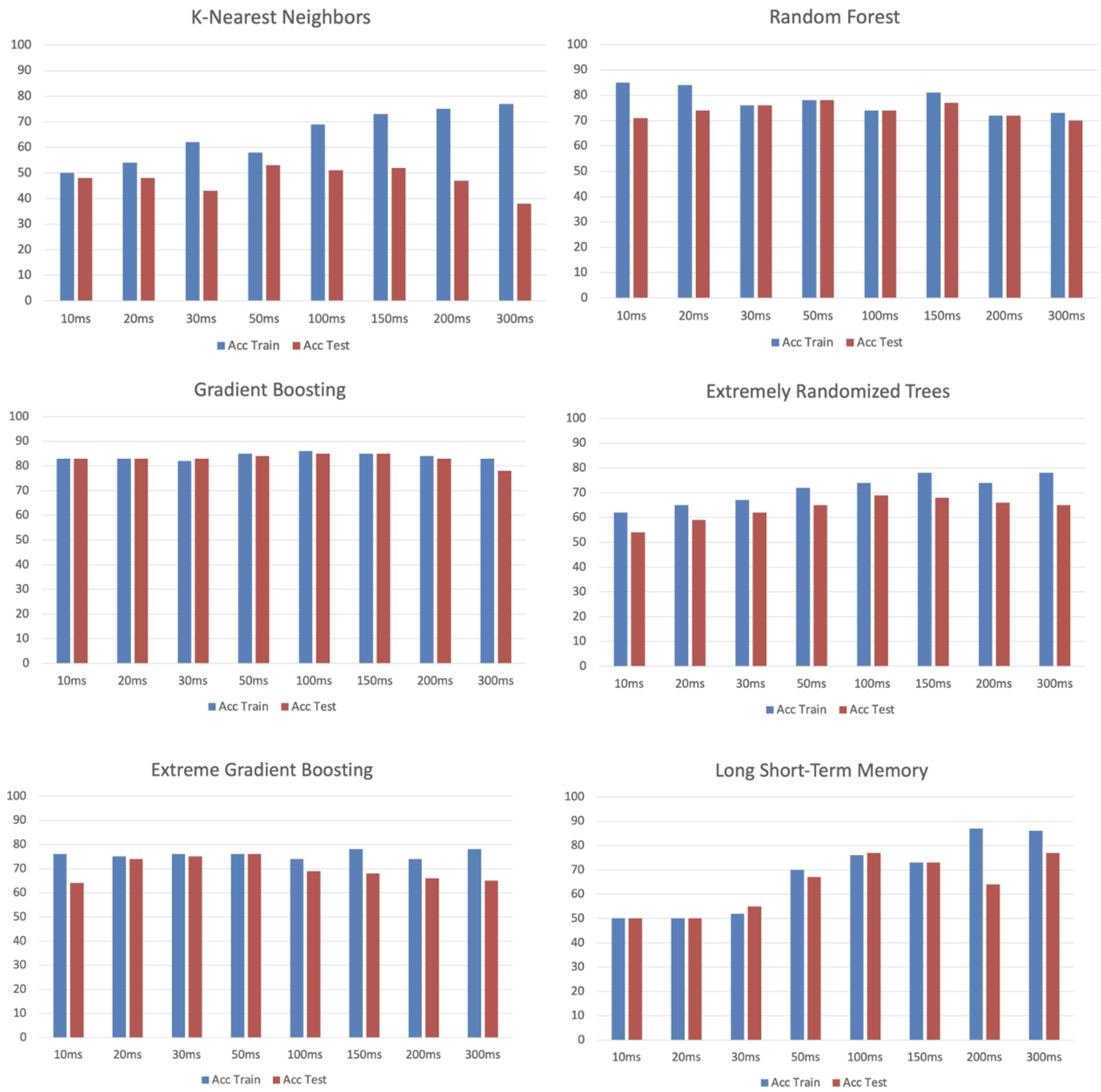



*Figure 19: The figure displays the results of the models for each created time window: K-Nearest Neighbors, Random Forest, Gradient Boosting, Extremely Randomized Trees, Extreme Gradient Boosting, and Long Short-Term Memory, respectively.*

The analysis of the K-Nearest Neighbors (KNN) model reveals a higher training accuracy compared to the test accuracy, indicating the presence of overfitting, which becomes more pronounced with the increase in the size of the time window. The 50 ms window was identified as optimal for this model, with an overall accuracy exceeding 50%. It is noteworthy that the chance level is 25%, as there are four classes to predict.

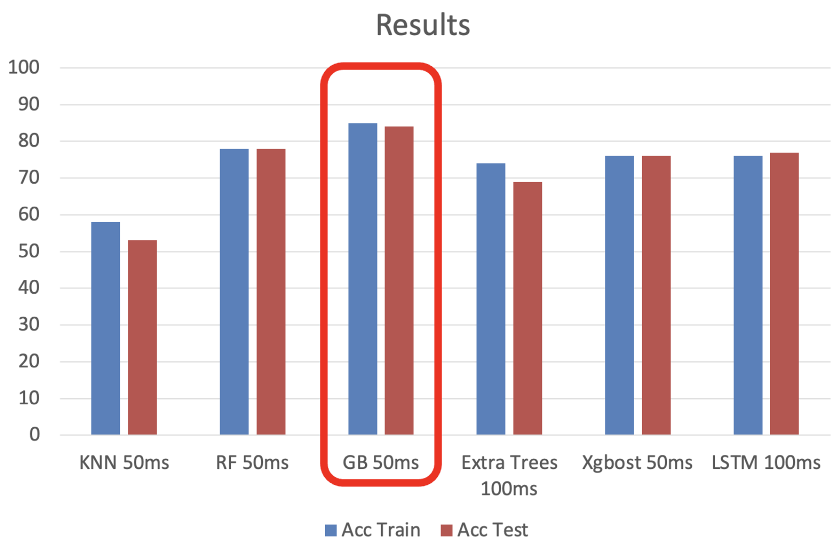
The Random Forest (RF) model displays an overall accuracy higher than KNN, exceeding 70%. Overfitting is also reduced in this context. For RF, the optimal time window is 50 ms, with an accuracy of 78%.

Gradient Boosting surpasses the other models with an overall accuracy above 80%. The introduction of sub-sampling has mitigated overfitting. Similar to other models, the 50 ms time window was chosen as the most suitable.

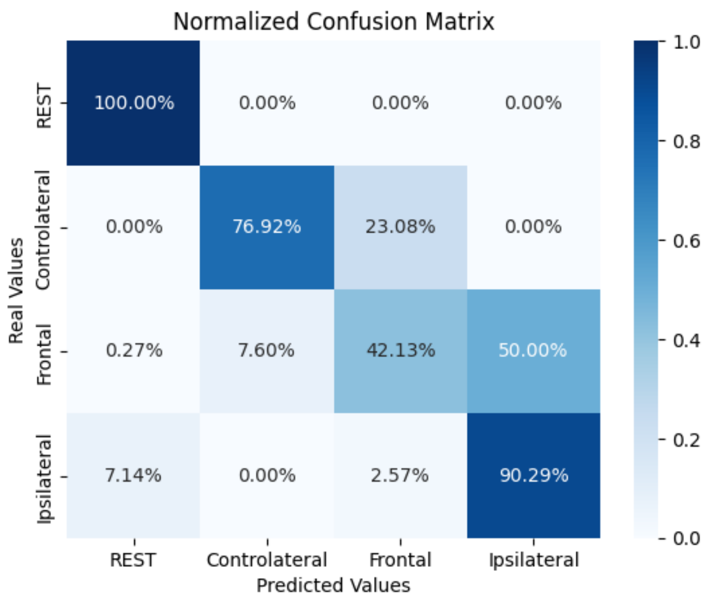
Regarding the Extra Trees, the model shows a lower overall accuracy compared to RF and Gradient Boosting for the same time windows. Consequently, for this model, the 100 ms time window was considered the most suitable.

The XGBoost model, although being a variant of Gradient Boosting, has reduced accuracy and increased overfitting with the rise in the size of the window. The 50 ms window showed the best results with an accuracy of 76%.

The LSTM model, although designed to emphasize the importance of temporal sequencing, produced an overall accuracy lower than RF and Gradient Boosting. Once again, there is an increase in overfitting with the enlargement of the time window. The 100 ms window provided the best results for this model.




(a) Gradient Boosting result.




(b) Normalized confusion Matrix.

*Figure 20: (a) Comparison of the models used in this study among the windows with the best results. The circled model is the one that was chosen as the best and that was used in the real-time evaluation. (b) Displays the normalized confusion matrix by the sum of its row*

Figure 20a presents a comparison between the best time windows of each model considered in this analysis. It is evident that Gradient Boosting stands out as the most accurate model, achieving an accuracy of 84% on the test set, using only a 50ms time window. By examining the normalized confusion matrix, shown in Figure 20b, one can observe that the model accurately classifies the "Rest" class and the "ipsilateral" direction. However, it faces challenges in classifying movement in the frontal direction.

It is crucial to highlight that such discrepancies might be attributed to data acquisition conditions. The variable positioning of the table, not standardized among subjects, might have influenced data collection. Besides, interindividual variations in movement mechanics, particularly concerning shoulder movement, could have impacted classification. For instance, a subject performing a frontal movement emphasizing the use of the shoulder could be mistakenly classified as a contralateral or ipsilateral movement.
The Gradient Boosting model was employed for real-time evaluation, thus determining the latency time between the start of the subject's movement and the model's detection of the movement direction.

## 3.2. Real-time evalutation

The real-time evaluation was conducted by implementing the Gradient Boosting algorithm, chosen as the most effective model, within the AGREE system. This approach was adopted in order to enable the system to predict in real time the direction of the movement performed by the participants. Once the movement was recognized, the system assisted the subjects in completing the undertaken trajectory and returning them to the resting position. For the execution of this evaluation, four individuals were involved, following the same protocol used during the data collection phase. The confusion matrix, based on data from the subjects, is depicted in Figure 21
.

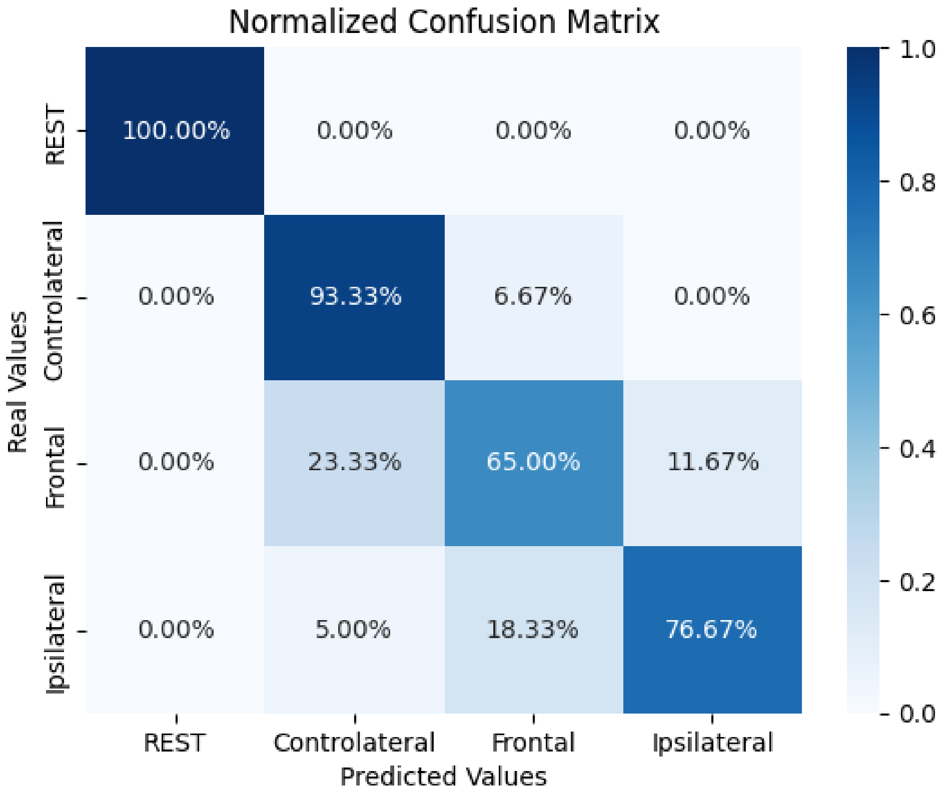



*Figure 21: Normalized confusion matrix of the Gradient Boosting model used on the four subjects for real-time assessment.*

It is observed that the model has a perfect ability to identify the "rest" position. Contrary to the results obtained with the test set, in this assessment, the model displayed significant precision in classifying movement in the contralateral direction. However, suboptimal performance is recorded for movements in frontal and ipsilateral directions. A possible explanation, as previously mentioned, could be due to the peculiarities of the movement performed by the subject: in the frontal movement, the emphasis on shoulder movement might have made it similar to the ipsilateral movement and controlateral movement, causing difficulties for the model in precisely distinguishing between the two classes. The time required for the model to classify 5 consecutive times the direction of movement was 5.2 milliseconds. Thus, the overall accuracy associated with a latency of 5.2ms milliseconds is 84%, similar to the training result.

### 3.3. Comparison with literature

Once the accuracy of the real-time evaluation by the best-performing model in this study, the Gradient Boosting, was calculated, it was compared with the results found in the state of the art through the literature review conducted prior to the study. The articles in question are [14] and [18], where machine learning models are used to respectively perform a real-time classification assessment of reaching tasks performed with an upper limb prosthesis and to evaluate the performance of learning models to categorize different exercises. These studies are further described in the paragraph 1.5

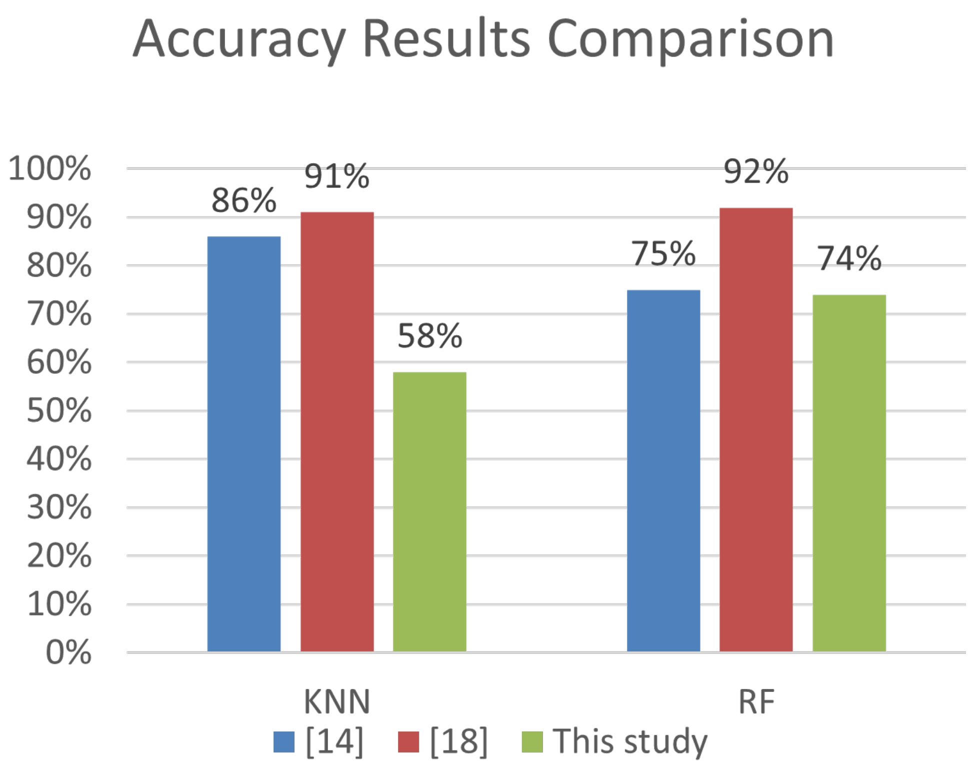



*Figure 22: Comparison between the accuracy found in the K-Nearest Neighbors and Random Forest models present in the analyzed literature and that of the same models in this study. The first study is indicated by: [14]. The second study is indicated by: [18].*

As highlighted in Figure 22, when comparing the accuracies of the KNN and RF models found in the literature with those from the current study, it is observed that in this study the same models show lower performance. However, when comparing the accuracy of these same models with that of the Gradient Boosting model, identified as the best in our study, it is noted that the latter is in the range of the standards reported in the state of the art. This can be seen in Figure 23.

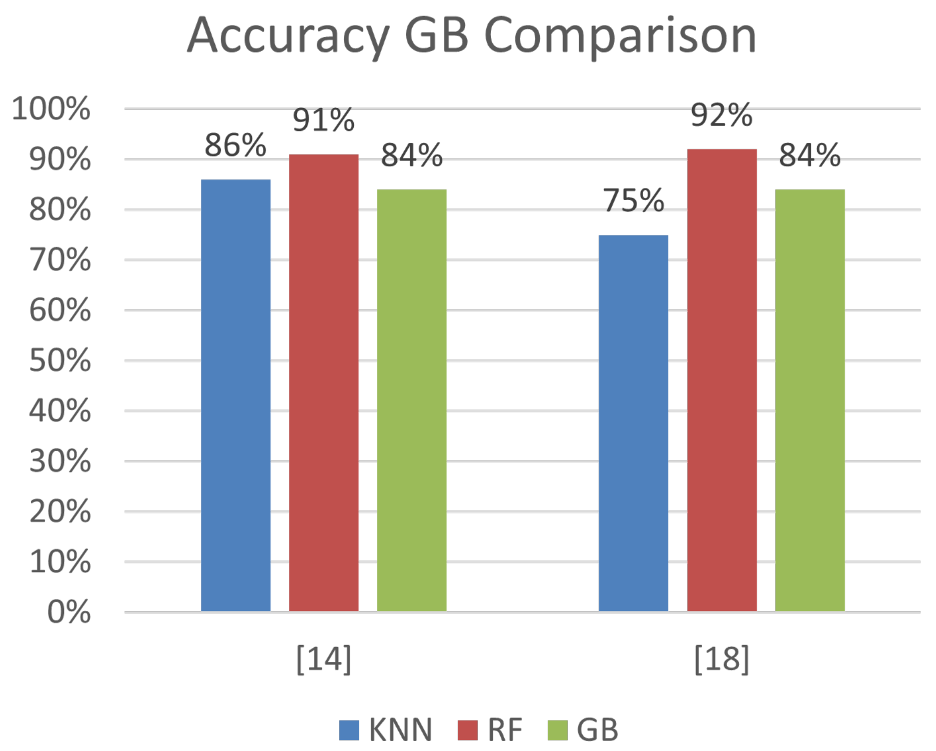



*Figure 23: Comparison between the accuracy found in the K-Nearest Neighbors and Random Forest models present in the analyzed literature and the accuracy of the Gradient Boosting, chosen in this study as the best. The first study is indicated as: [14]. The second study is indicated as: [18].*

Regarding the latency, understood as the time interval between real-time data recording and the moment when the model predicts the movement direction, the Gradient Boosting model, identified as the most efficient in this study, has shown superior performance compared to what is reported in the literature. For the analysis of this parameter, we used a comparison based on another scientific study [24] identified during the literature review, in which a Support Vector Machine model is used for the classification of 8 total body movements.

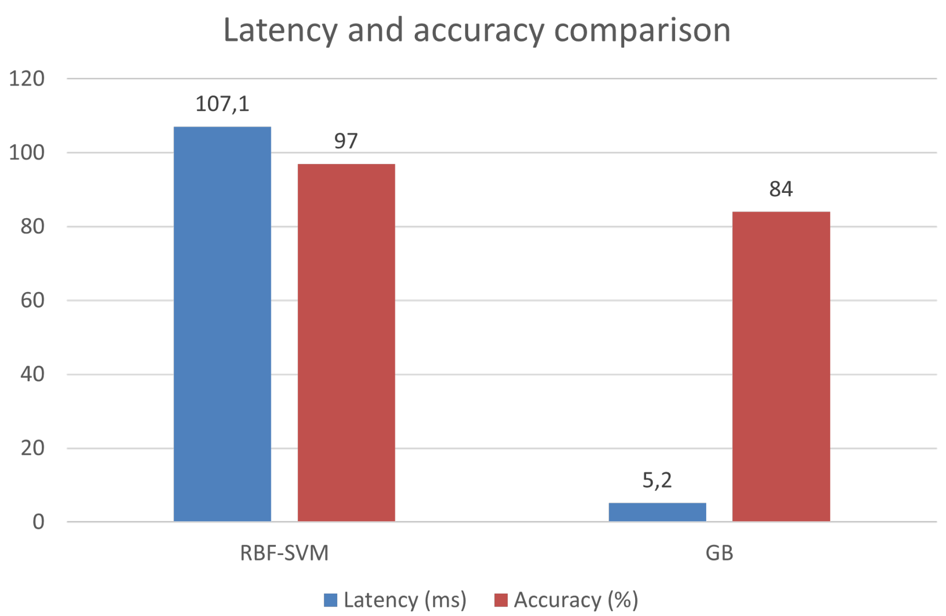



*Figure 24: Comparison using accuracy value and latency parameter between an SVM model present in the literature [24] and the model presented in this study.*

From the analysis of figure 24, it can be observed that the accuracy reported in the cited literature surpasses that achieved in the current study. However, focusing on the latency parameter, the proficiency of the Gradient Boosting model in accurately predicting movement direction becomes evident. In fact, this model ensures support to the subject while performing the specified task with a latency of only 5ms, significantly lower than the 107.1ms latency mentioned in the literature.

The primary objective of these models is their real-time implementation to assist rehabilitative sessions, making the minimization of temporal delay paramount. A reduced latency offers optimal synchronization between the patient and the exoskeleton, ensuring smooth movements and preventing unnatural or abrupt actions, which could be potentially harmful. This synchronicity is crucial to avoid injuries from uncoordinated movements and makes each rehabilitative session more effective. Timely assistance instills confidence in the patient throughout the rehabilitation process, fostering a perception of greater autonomy. If the patient suddenly changes the direction or speed of the movement, low latency allows the exoskeleton to respond instantly, ensuring consistent support. From a clinical perspective, this responsiveness allows therapists to better assess the patient's progress, enhancing the quality of the rehabilitative treatment.

# 4. Conclusions

The aim of this study was to investigate the feasibility of using a kinematics and torque-based identification (ID) node for recognizing different directions of frontal reaching movements through the robotic platform AGREE. Several machine learning models were tested for three different tasks: contralateral, frontal, and ipsilateral. The best-performing architecture was the gradient boosting technique, achieving an accuracy of 85%. However, the frontal task had a lower accuracy of approximately 42% compared to the other tasks. This discrepancy could be attributed to non-standardized table positions during data acquisition and variations in how healthy subjects executed the shoulder movements.

Additionally, four final subjects were tested for real-time evaluation of the gradient boosting model, which yielded a final accuracy of 84% and a low latency of 5,2ms. The final accuracy had decreased compared to the offline evaluation, and the accuracy of the ipsilateral movement also decreased, though it did not perform as well as in the offline evaluation, where it achieved an accuracy of 85%.
These results deviate from what is found in the literature, where the best models used EMG and IMU sensors, while this study focused solely on kinematics and torques data from the built-in exoskeleton sensors. The latency observed in this study was significantly lower (5,2ms) compared to the literature (107,1ms).

In summary, the best model in this study exhibited a similar accuracy compared to models in the literature but offered a much faster ability to recognize the intended movement. This discrepancy may be attributed to differences in data sources (kinematics vs. EMG and IMU and built-in sensors) and the emphasis on low latency in this study.
In terms of future developments for this study, several improvements and expansions can be considered:

- **Increased Data Diversity:** Expanding the dataset by including more healthy subjects is a positive step. A larger and more diverse dataset can help improve the generalizability of the machine learning models and increase their accuracy. It's important to include subjects with varying characteristics, such as age, gender, and physical abilities, to ensure that the models can be applied to a wider population.
- **Standardized Table Position:** Standardizing the table position during data acquisition is crucial for reducing variability in the data. This can help improve the accuracy, particularly for the frontal movement category, which showed lower performance in the current study due to non-standardized table positions.
- **Evaluation of Additional Movement Categories:** Expanding the scope of the study to include other movement categories, such as hand-to-mouth and lateral elevation, is a valuable extension. This can provide a more comprehensive assessment of the capabilities of the robotic platform AGREE and the machine learning models in recognizing a broader range of movements.
- **Fine-Tuning Machine Learning Models:** While gradient boosting showed promise in the current study, further optimization and fine-tuning of machine learning models should be explored to achieve even better accuracy. Experiment with different model architectures, hyperparameters, and feature engineering techniques.
- **Real-Time Performance:** Continue to focus on low latency for real-time movement recognition. Reducing latency is critical for practical applications of this technology, especially in the context of assistive devices or rehabilitation.

By addressing these aspects and iteratively improving the study, you can enhance the accuracy, reliability, and practical applicability of the kinematics-based ID node for recognizing various movements through the robotic platform AGREE.

# References


[1] A Alawieh, J Zhao, and W Feng. Factors affecting post-stroke motor recovery: Implications on neurotherapy after brain injury. *Behav Brain Res*, 2016.

[2] F Attal, S Mohammed, M Dedabrishvili, F Chamroukhi, L Oukhellou, and Y Amirat. Physical human activity recognition using wearable sensors. *Sensors*, 2015.

[3] A Basteris, SM Nijenhuis, AH Stienen, JH Buurke, GB Prange, and F Amirabdollahian. Training modalities in robot-mediated upper limb rehabilitation in stroke: a framework for classification based on a systematic review. *J Neuroeng Rehabil*, 2014.

[4] M. Bieshaar, G. Reitberger, S. Zernetsch, B. Sick, E. Fuchs, and K. Doll. Detecting intentions of vulnerable road users based on collective intelligence. 2018.

[5] Domenico Buongiorno, Michele Barsotti, Francesco Barone, Vitoantonio Bevilacqua, and Antonio Frisoli. A linear approach to optimize an emg-driven neuromusculoskeletal model for movement intention detection in myo-control: A case study on shoulder and elbow joints. *Frontiers in Neurorobotics*, 2018.

[6] RS Calabrò, M Russo, A Naro, D Milardi, T Balletta, A Leo, S Filoni, and P Bramanti. Who may benefit from armeo power treatment? a neurophysiological approach to predict neurorehabilitation outcomes. *PM R*, 2016.

[7] A Cancrini, P Baitelli, M Lavit Nicora, M Malosio, A Pedrocchi, and A Scano. The effects of robotic assistance on upper limb spatial muscle synergies in healthy people during planar upper-limb training. *PLoS One*, 2022.

[8] WE Clark, M Sivan, and RJ O'Connor. Evaluating the use of robotic and virtual reality rehabilitation technologies to improve function in stroke survivors: A narrative review. *J Rehabil Assist Technol Eng*, 2019.

[9] ER Coleman, R Moudgal, K Lang, HI Hyacinth, OO Awosika, BM Kissela, and W Feng. Early rehabilitation after stroke: a narrative review. *Curr Atheroscler Rep*, 2017.

[10] S Dalla Gasperina et al. Agree: A compliant-controlled upper-limb exoskeleton for physical rehabilitation of neurological patients. *IEEE Transactions on Medical Robotics and Bionics*, 2023.

[11] V. L. Feigin, T. Vos, E. Nichols, M.O. Owolabi, W.M. Carroll, M. Dichgans, G. Deuschl, P. Parmar, M. Brainin, and C. Murray. The global burden of neurological disorders: translating evidence into policy. *The Lancet Neurology*, 2020.

[12] M Gandolla, B Luciani, DE Pirovano, A Pedrocchi, and F Braghin. A force-based human machine interface to drive a motorized upper limb exoskeleton. a pilot study. In *IEEE Int Conf Rehabil Robot*, 2022.

[13] J Gantenbein, J Dittli, JT Meyer, R Gassert, and O Lambercy. Intention detection strategies for robotic upper-limb orthoses: A scoping review considering usability, daily life application, and user evaluation. *Front Neurorobot*, 2022.

[14] M. Gardner, C.S. Mancero Castillo, S. Wilson, D. Farina, E. Burdet, B.C. Khoo, S.F. Atashzar, and R. Vaidyanathan. A multimodal intention detection sensor suite for shared autonomy of upper-limb robotic prostheses. *Sensors (Basel)*, Oct 2020.

[15] SD Gasperina, V Longatelli, M Panzenbeck, B Luciani, A Morosini, A Piantoni, P Tropea, F Braghin, A Pedrocchi, and M Gandolla. Agree: an upper-limb robotic platform for personalized rehabilitation, concept and clinical study design. In *IEEE Int Conf Rehabil Robot*, 2022.

[16] R Gassert and V Dietz. Rehabilitation robots for the treatment of sensorimotor deficits: a neurophysiological perspective. *J NeuroEngineering Rehabil*, 2018.

[17] Y. Hara. Brain plasticity and rehabilitation in stroke patients. *Journal of Nippon Medical School*, 2015.

[18] A. Hua, P. Chaudhari, N. Johnson, J. Quinton, B. Schatz, D. Buchner, and M.E. Hernandez. Evaluation of machine learning models for classifying upper extremity exercises using inertial measurement unit-based kinematic data. *IEEE J Biomed Health Inform*, 25(9), Sep 2020.

[19] A. Keci, K. Tani, and J. Xhema. Role of rehabilitation in neural plasticity. *Open Access Macedonian Journal of Medical Sciences*, 2019.

[20] F. Khan, B. Amatya, M.P. Galea, R. Gonzenbach, and J. Kesselring. Neurorehabilitation: applied neuroplasticity. *Journal of Neurology*, 2017.

[21] MO Krucoff, S Rahimpour, MW Slutzky, VR Edgerton, and DA Turner. Enhancing nervous system recovery through neurobiologics, neural interface training, and neurorehabilitation. *Frontiers in Neuroscience*, 2016.

[22] Martina Maier, Ballester Belén Rubio, and Paul F. M. J. Verschure. Principles of neurorehabilitation after stroke based on motor learning and brain plasticity mechanisms. *Frontiers in Systems Neuroscience*, 2019.

[23] L Marchal-Crespo and DJ Reinkensmeyer. Review of control strategies for robotic movement training after neurologic injury. *J Neuroeng Rehabil*, 2009. Jun.

[24] Q Mascret, M Bielmann, C L Fall, LJ Bouyer, and B Gosselin. Real-time human physical activity recognition with low latency prediction feedback using raw imu data. In *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2018.

[25] PH McCrea, JJ Eng, and AJ Hodgson. Biomechanics of reaching: clinical implications for individuals with acquired brain injury. *Disability and Rehabilitation*, 2002.

[26] Q. Meng, Q. Xie, H. Shao, W. Cao, F. Wang, L. Wang, H. Yu, and S. Li. Pilot study of a powered exoskeleton for upper limb rehabilitation based on the wheelchair. *Biomed Res Int*, Dec 2019.

[27] A Narayan, FA Reyes, M Ren, and Y Haoyong. Real-time hierarchical classification of time series data for locomotion mode detection. *IEEE J Biomed Health Inform*, 2022.

[28] A. Olczak, A. Truszczyńska-Baszak, and A. Stępień. The use of armeo®spring device to assess the effect of trunk stabilization exercises on the functional capabilities of the upper limb-an observational study of patients after stroke. *Sensors (Basel)*, 27(6):2289, Jun 2022.

[29] Alessandra Pedrocchi. *Neuroengineering Compendium - Rehabilitation Robotics*. 2021.

[30] C Pew and GK Klute. Turn intent detection for control of a lower limb prosthesis. *IEEE Trans Biomed Eng*, 2018.

[31] Jose L. Pons. *Wearable Robots: Biomechatronic Exoskeletons*. John Wiley & Sons Inc, 2008.

[32] GB Prange, MJ Jannink, CG Groothuis-Oudshoorn, HJ Hermens, and MJ Ijzerman. Systematic review of the effect of robot-aided therapy on recovery of the hemiparetic arm after stroke. *J Rehabil Res Dev*, 2006.

[33] T Proietti, V Crocher, A Roby-Brami, and N Jarrasse. Upper-limb robotic exoskeletons for neurorehabilitation: A review on control strategies. *IEEE Rev Biomed Eng*, 2016.

[34] E Trigili, L Grazi, S Crea, et al. Detection of movement onset using emg signals for upper-limb exoskeletons in reaching tasks. *J NeuroEngineering Rehabil*, 2019.

[35] C Zhao, X Lu, T Zhang, Y Feng, and W Chen. Multi-channel separated encoder based convolutional neural network for locomotion intention recognition. In *2022 34th Chinese Control and Decision Conference (CCDC)*, 2022.

# Abstract in lingua italiana

Le persone affette da disturbi neurologici sperimentano notevoli difficoltà nell'interagire con l'ambiente circostante a causa della ridotta capacità di movimento degli arti superiori e nell'esecuzione delle attività quotidiane (ADL). Terapie riabilitative efficaci possono notevolmente migliorare la qualità della vita delle persone affette da tali disabilità. La robotica riabilitativa si è dimostrata un complemento prezioso alle terapie tradizionali, consentendo un alto numero di sessioni di allenamento in un ambiente sicuro e controllato. Quando combinata con una strategia di rilevamento delle intenzioni efficiente (IDS), il potenziale di recupero motorio può essere massimizzato, consentendo alle persone affette da disturbi neurologici di riguadagnare l'autonomia e di eseguire le ADL con precisione e coerenza. Un IDS è un approccio o un metodo utilizzato per identificare e comprendere le intenzioni di un individuo in base ai suoi comportamenti o azioni. Essa costituisce il collegamento essenziale tra la volontà dell'individuo e la risposta prodotta dalla tecnologia. Nei casi in cui una persona abbia subito una lesione neurologica o abbia una disabilità che influisce sulle funzioni motorie, come i movimenti degli arti superiori o inferiori, la capacità di rilevare l'intenzione di muoversi e tradurla in un'azione tecnologica può cambiare radicalmente la vita. Lo studio si riconduce a esperimenti con soggetti sani che indossavano un esoscheletro sul braccio destro, chiamato "AGREE", per rilevare l'intenzione di vari movimenti, con particolare attenzione alle attività di raggiungimento. I dati raccolti, acquisiti con i sensori integrati dell'esoscheletro, sono stati quindi utilizzati per addestrare architetture di apprendimento automatico. Successivamente, quattro soggetti sono stati utilizzati per una valuatione in tempo reale eseguendo lo stesso protocollo direttamente sulla piattaforma robotica. I risultati hanno dimostrato che l'esoscheletro è in grado di riconoscere l'intenzione di muoversi in un breve lasso di tempo, con una latenza di 5,2 millisecondi con una accuratezza dell' 84%. Sviluppi futuri in questo campo comporteranno l'espansione della gamma di esercizi per i quali è possibile rilevare l'intenzione di movimento da parte del soggetto. Ciò include attività come portare la mano alla bocca o l'innalzamento laterale, consentendo così all'esoscheletro di assistere i pazienti in una vasta gamma di movimenti. Tali progressi nella fusione tra la robotica riabilitativa e l'IDS hanno il potenziale per migliorare significativamente la vita delle persone affette da disturbi neurologici.



**Parole chiave:** Riabilitazione, arto superiore, esoscheletro, Strategie di detezione dell'intenzione, sistemi ibridi