Advances in Bioscience and Biotechnology, 2024, 15, 289-309
https://www.scirp.org/journal/abb
ISSN Online: 2156-8502
ISSN Print: 2156-8456

Harnessing the Power of Artificial Intelligence in Neuromuscular Disease Rehabilitation: A Comprehensive Review and Algorithmic Approach

Rocco de Filippis[1]*, Abdullah Al Foysal[2]

[1]Institute of Psychopathology, Rome, Italy
[2]Computer Engineering (AI), University of Genova, Genova, Italy
Email: *roccodefilippis@istitutodipsicopatologia.it, niloyhasanfoysal440@gmail.com

How to cite this paper: de Filippis, R. and Al Foysal, A. (2024) Harnessing the Power of Artificial Intelligence in Neuromuscular Disease Rehabilitation: A Comprehensive Review and Algorithmic Approach. *Advances in Bioscience and Biotechnology*, **15**, 289-309.
https://doi.org/10.4236/abb.2024.155018

Received: February 26, 2024
Accepted: May 14, 2024
Published: May 17, 2024

Abstract

Neuromuscular diseases present profound challenges to individuals and healthcare systems worldwide, profoundly impacting motor functions. This research provides a comprehensive exploration of how artificial intelligence (AI) technology is revolutionizing rehabilitation for individuals with neuromuscular disorders. Through an extensive review, this paper elucidates a wide array of AI-driven interventions spanning robotic-assisted therapy, virtual reality rehabilitation, and intricately tailored machine learning algorithms. The aim is to delve into the nuanced applications of AI, unlocking its transformative potential in optimizing personalized treatment plans for those grappling with the complexities of neuromuscular diseases. By examining the multifaceted intersection of AI and rehabilitation, this paper not only contributes to our understanding of cutting-edge advancements but also envisions a future where technological innovations play a pivotal role in alleviating the challenges posed by neuromuscular diseases. From employing neural-fuzzy adaptive controllers for precise trajectory tracking amidst uncertainties to utilizing machine learning algorithms for recognizing patient motor intentions and adapting training accordingly, this research encompasses a holistic approach towards harnessing AI for enhanced rehabilitation outcomes. By embracing the synergy between AI and rehabilitation, we pave the way for a future where individuals with neuromuscular disorders can access tailored, effective, and technologically-driven interventions to improve their quality of life and functional independence.

Keywords

Neuromuscular Diseases, Rehabilitation, Artificial Intelligence, Machine Learning, Robotic-Assisted Therapy, Virtual Reality, Personalized Treatment, Motor Function, Assistive Technologies, Algorithmic Rehabilitation

1. Introduction

Neuromuscular diseases, comprising ailments such as muscular dystrophy, spinal muscular atrophy, and cerebral palsy, pose formidable obstacles to individuals' motor functions, necessitating innovative rehabilitation approaches. Amidst these challenges, the convergence of artificial intelligence (AI) and rehabilitation emerges as a promising frontier, reshaping the landscape of personalized treatment. This research embarks on a comprehensive journey to explore the transformative impact of AI technologies in the rehabilitation domain, aiming to address the complex needs of individuals grappling with neuromuscular disorders. Over the past decade, rapid technological advancements have ushered in a new era, offering a spectrum of interventions ranging from robotic-assisted therapy to virtual reality rehabilitation. These interventions not only mitigate the limitations imposed by neuromuscular disorders but also empower individuals to regain control and independence over their motor functions. This paper serves as a guide through these advancements, meticulously dissecting their applications and implications within the context of neuromuscular diseases.

At the heart of this exploration lies the intricate interplay of AI algorithms, machine learning models, and innovative rehabilitation technologies. By delving into the nuanced intricacies of these interventions, we aim to provide a holistic understanding of how AI-driven approaches can revolutionize rehabilitation strategies for individuals with neuromuscular disorders. As we unravel the complexities of these technological advancements, this research not only offers a retrospective analysis but also sets the stage for envisioning a future where AI plays a pivotal role in crafting tailored solutions to address the unique challenges posed by neuromuscular disorders. Through this exploration, we seek to pave the way for enhanced rehabilitation outcomes and improved quality of life for individuals facing the complexities of neuromuscular diseases.

2. Literature Review

This comprehensive review meticulously explores the dynamic evolution of rehabilitation robotics and orthotics over the past 15 years, tracing their development from initial applications in manufacturing to their critical role in patient-centred healthcare interventions [1]. The review provides a historical context, illustrating the significant shift from robots primarily used in industrial settings to their reconfiguration for healthcare applications, specifically tailored to address complex neuromuscular disorders. This transition underscores a broader trend towards adapting technology for enhanced human benefit, particularly in medical rehabilitation. A focal point of this analysis is the examination of innovative robotic devices such as the iARM, WREX, and ARMON [2]. These devices are dissected to reveal their functionalities and evaluated for their transformative impact on the daily lives of individuals suffering from debilitating conditions like muscular dystrophy and spinal muscular atrophy [3]. The iARM, for example, offers enhanced mobility through a wheelchair-mounted robotic arm, facilitating greater independence for users [4]. Similarly, the WREX and ARMON provide vital support for limb movement, significantly improving the quality of life for patients with severe muscular limitations [5]. In addition to hardware advancements, this review delves into the integration of sophisticated software solutions, specifically the use of ensemble machine learning algorithms to forecast rehabilitation outcomes. This innovative, data-driven approach not only deepens our understanding of rehabilitation outcomes but also enables the customization of patient-specific therapies, thereby enhancing the precision of treatment plans [6] [7] [8] [9]. The predictive prowess of these AI models, validated through rigorous evaluation metrics such as root mean squared error (RMSE), highlights their capacity to significantly influence and transform the landscape of precision healthcare technologies in rehabilitation medicine. The inclusion of AI and machine learning not only augments the effectiveness of physical robotic systems but also propels the entire field toward more adaptive, responsive, and effective treatment methodologies [10]. This enriched perspective on rehabilitation robotics and orthotics, through both the lens of technological evolution and advanced predictive analytics, offers a multifaceted understanding of their potential to revolutionize rehabilitation practices. The integration of these technologies represents a critical step forward in our ability to meet the complex and varied needs of patients with neuromuscular disorders, ultimately paving the way for more personalized, effective, and technologically integrated healthcare solutions.

3. Applications

3.1. Robotics and Assistive Technology for Neuromuscular Diseases

There is a description of treatments for persons with movement problems, as well as technology that may be utilized to alleviate symptoms. Muscular dystrophy, spinal muscular atrophy, cerebral palsy, and other movement disorders are examples. This study focuses on robotics and other assistive technologies used to treat and aid persons suffering from neuromuscular diseases such as muscular dystrophy (MD), spinal muscular atrophy (SMA), arthrogryposis multiplex congenita (AMC), and cerebral palsy (CP). These conditions make these people's extremities weak, uncontrollable, stiff, or a mix of the three. People suffering from these disorders resort to compensating motions such as ballistic-or swingingmovements, tabletop aid, using both hands or tilting their head forward to eat food directly from the plate. A parent or caregiver may be expected to assist in the feeding process or in other daily life duties, which can strip people of their freedom. Robots, or those, and other technologies can help persons with impairments live independent and dignified lives. Although robots might look mechanical, machine-like, and impersonal in appearance and movement, they can also be of great assistance if they are appropriately matched with the individual and their condition. Over the last 10 - 15 years, there has been considerable development in rehabilitation robotics as technology shrinks and improves and personal machines become more acceptable.

Wheelchair-mounted, stationary, and commercial industrial robots have not seen widespread commercial success in healthcare due to a combination of high costs, limited adaptability, and the need for more personalized solutions [11]. The significant financial outlay for development, maintenance, and implementation makes these robots less accessible, particularly in financially constrained healthcare settings. Moreover, robots initially designed for industrial applications often lack the flexibility needed for the dynamic environments of healthcare, which require devices adaptable to the varied needs of individual patients and specific medical conditions [12]. Personalized medicine, which tailors' treatments to individual patient characteristics, demands a level of customization that these robots currently do not offer [13]. Regulatory hurdles also play a role, as healthcare devices undergo stringent scrutiny to ensure patient safety, delaying the integration of robotic technologies into everyday clinical use. Additionally, there are technological limitations in terms of sensor sensitivity and the intelligence of autonomous systems, which can undermine the effectiveness of robots in complex medical scenarios [14]. Cultural and psychological barriers further complicate the acceptance of robotic aids in healthcare, as patients and providers often prefer human interaction, especially in therapeutic contexts. Overcoming these challenges will require focused efforts on enhancing technological capabilities, reducing costs, ensuring safety, and building trust among users to integrate robotics more fully into healthcare systems.

For many years, occupational therapists (OTs) have employed assistive devices and assistive technology (AT) in environmental modification. This might entail employing low-tech equipment like assistive gadgets such as swivel spoons and button hooks, adaptive equipment such as self-feeding gear and overhead slings, and augmentative communication devices [15] [16] [17].

3.2. Rehabilitation Robotics and Orthotics

Robots were used in manufacturing environments, such as automobile assembly, for repetitive tasks that were labour-intensive and required a high degree of accuracy. Towards the end of the century, the possibility of robots interacting with humans became a possibility, including advanced prosthetics, motorized feeding devices, and sentry robots [18]. Another cause was the aging population as the baby boomer generation approached retirement age. Population growth is a global phenomenon.

For example, robot technology in healthcare was more readily accepted in Japan than in many other wealthy countries. Robots originally appeared in research labs [19] as assistive aids to help persons with upper extremity paralysis. Later, wheelchair-mounted and fixed robots, as well as commercial industrial robots, were created and repurposed for healthcare [20]. They were used to treat a wide range of motor disabilities, including neuromuscular illnesses including muscular dystrophy and spinal muscle atrophy. Despite having a significant impact on persons with neuromuscular illnesses, these devices did not achieve broad commercial success. A variety of elements are considered to be involved.

In contrast, the rehabilitation robotics field has moved its emphasis in the previous 10 - 15 years toward treatment robots, with the patient as the primary benefactor. This has been pushed by the enormous number of stroke victims; science demonstrating the brain's ability to adapt through neuroplasticity even in the chronic stage [21], and the desire to control healthcare expenditures. More projects focusing on cerebral palsy and robots have emerged in recent years [22] [23] [24]. The sections that follow are divided into assistive robots, therapeutic robots, and upper extremity orthoses, with an emphasis on devices that are currently on the market and employed therapeutically and as consumer products.

3.3. Orthoses and Assistive Robots

The iARM (previously known as the Manus) is a gadget that has been available for over 20 years. This is a wheelchair-mounted 7-jointed robot arm that helps persons with neuromuscular disorders to move about situations to have access to their surroundings and do a portion of the activities that their normal arm would perform.

Someone can use the iARM to grab a drink or feed themself. A joystick or keyboard can be used to operate it. It may be operated in joint, programmed, or Cartesian mode, which moves the gripper in anXYZ configuration. The wheelchair battery powers the motors, and the iARM sits alongside the wheelchair. The iARM [25] is priced at $20,000. People with muscular dystrophy, spinal muscular dystrophy, spinal cord injury, cerebral palsy, and other motor disabilities utilize the iARM. There are roughly 400 iARM devices in operation across the world. Upper extremity exoskeletons are utilized for those who still have some arm strength. This is common in persons with neuromuscular diseases including MD, SMA, arthrogryposis, and other motor illnesses like ALS and SCI. These exoskeletons are mainly passive, which means they lack external power sources such as motors. They are lightweight and frequently mounted to wheelchairs. The WREX (Wilmington Robotic EXoskeleton) is one such exoskeleton. WREX is a mechanical linkage driven by elastic bands that may be added to a wheelchair [26] [27]. The gadget glides alongside the arm, allowing for easy anti-gravity motions. This is especially effective for persons with muscular dystrophy and spinal muscular atrophy when proximal muscles are weak and distal muscles are not. The WREX enables them to manoeuvre their hand in front of them and carry out regular tasks. The WREX comes in one size and may be altered to fit different-sized persons, as well as the number of elastic bands, which can be varied based on the individual's weight. A balanced forearm orthosis (BFO) or ball-bearing feeder is a mechanical linkage that attaches to a wheelchair and allows individuals to move their arms in the horizontal plane. They can move their hand to their mouth by pivoting around a fulcrum at the midline of their forearm. There is also a variation that permits elevation using an elastic band, however this is rarely utilized. The BFO was invented in the 1950s and is available for around $600 from Patterson Medical. The ARMON, which is marketed in Europe, is a wheelchair-mounted passive exoskeleton that allows the arm to move against gravity. It is designed for persons with neuromuscular diseases such as muscular dystrophy and SMA and is powered by adjustable springs. The ARMON differs from the WREX in that it is not a genuine exoskeleton because it is derived from the wheelchair's base. It has a wide range of gravity-free mobility. It costs around $3000. The DAS (Dynamic Arm Support) is another commercially available gadget. For persons who have arm weakness, this is a spring-loaded upper extremity orthosis. It may also be attached to a wheelchair and is sold in Europe.

3.4. Using Ensemble Machine Learning, a Multifaceted Approach to Predicting Rehabilitation Outcomes

In this groundbreaking study, a multidimensional strategy is employed to forecast the prospective functional improvement of neurological (NP) and orthopaedic (OP) rehabilitation patients, underscoring the importance of precision medicine in patient-centric care. Leveraging a dataset of approximately 4050 hospital discharges from IRCCS San Raffaele (2015-2018), crucial variables from the "Acceptance/Discharge Report for the Rehabilitation Area" (ADR) are meticulously curated, handling missing values and outliers. Four tree-based ensemble machine learning models (xGBT, LightGBM, CatBoost, and gradient boosting) are utilized to evaluate functional ability post-discharge, while a custom-designed stacked ensemble technique combines the strengths of these models with simpler ones like ridge regression and kernel ridge. This approach enhances our understanding of rehabilitation outcomes and offers a novel tool for tailoring patient-specific therapies. Evaluating predictive accuracy using root mean squared error (RMSE), the outstanding performance of the models is confirmed, with RMSE values of 6.58 for OP patients and 8.66 for NP patients, calculated using the equation

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}$$

These results signify a significant advancement in the integration of artificial intelligence and rehabilitation medicine, paving the way for precision healthcare technologies and individualized rehabilitation regimens [28] [29] [30] [31].

Machine Learning Algorithms for Rehabilitation Outcome Prediction: Mathematical Formulation and Clinical Application

1) Tree-Based Ensemble Models (xGBT, LightGBM, CatBoost, Gradient Boosting): In a tree-based ensemble model, such as XGBoost, LightGBM, CatBoost, or Gradient Boosting, predictions are made by aggregating the outputs of multiple individual trees. Given a dataset $D=\{(x_i,y_i)\}$, where $x_i \in \mathrm{R}^m$ represents the features and $y_i \in \mathrm{R}$ represents the target variable for n samples, the prediction $\hat{y}_i$ for the i-th sample is obtained by summing up the predictions of K trees:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i)$$

Here, $f_k(x_i)$ represents the prediction made by the k-th tree for the i-th sample.

This can be conceptualized as follows: for each sample x_i, the model traverses through each tree k in the ensemble and obtains a prediction $f_k(x_i)$. These predictions from all trees are then aggregated to obtain the final prediction $\hat{y}_i$ for the sample x_i. This representation emphasizes the sequential nature of tree-based ensemble models, where each tree contributes its prediction to the final outcome. It also highlights the iterative training process where subsequent trees are trained to correct the errors made by the previous ones, ultimately leading to a more accurate ensemble prediction.

2) Custom Stacked Ensemble Algorithm: At the second level of the custom stacked ensemble algorithm, a meta-learner based on simple ridge regression or kernel ridge regression is utilized. The input for this level is the matrix P produced by the first level. The optimization task involves minimizing a loss function L given by:

$$L = \sum_{i=1}^{n}\left(y_i^{\text{predicted}} - y_i\right)^2 + \lambda \sum_{i=1}^{n} B_i^2$$

Where, predicted is the predicted value obtained from the first level ensemble, y_i is the actual ground truth value, B_i is the penalization term, λ is the regularization parameter. In essence, ridge regression minimizes a residual sum of squares (RSS) plus a squared penalization factor to prevent over fitting and stabilize the solution. Additionally, because there are two distinct groups of patients, NP and OP, tailored models are utilized for each group. This implies that different learners in both the first and second layers are chosen based on their performance on the metric of interest. **Figures 1(a)**, **Figures 1(b)** provided illustrate examples of the models for OP and NP, showcasing slight differences between the models employed in the first and second layers. For instance, LightGBM is utilized in the first layer for OP, along with xGBT and CatBoost. However, for NP, Gradient Boosting is used instead of LightGBM.

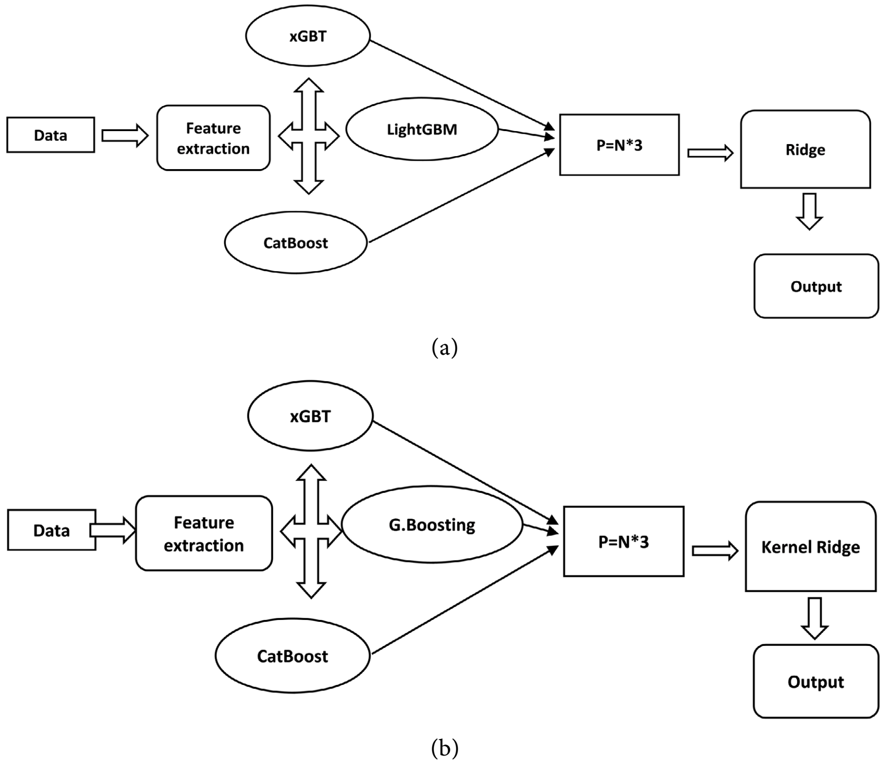

Figure 1. (a) Illustration of customized models for OP model; (b) Illustration of customized models for NP model .

3.5. ML in Low Back Pain Rehabilitation

The main cause of global disability is low back pain (LBP) [32]. LBP prevalence peaks in the third decade of life, declining until around age 60 - 65 [33]. It is a significant health and socioeconomic concern, leading to workforce absenteeism, particularly among individuals engaged in high-intensity work [34] [35] [36]. LBP is characterized by recurrence rates ranging from 24% to 80% within one year, necessitating preventive measures to mitigate its effects. Despite approximately 90% of LBP cases lacking a known explanation [37], various treatment modalities such as education, reassurance, analgesic medications, and non-pharmacological therapies are employed [38]. Machine Learning (ML), a subfield of artificial intelligence, offers computational methods for building and updating knowledge-based models in intelligent systems [39]. ML approaches, particularly supervised and unsupervised learning, have been increasingly investigated in medical sciences, including the prognosis and prediction of clinical outcomes in LBP [40]. Additionally, ML's application in telerehabilitation, particularly through virtual coaching, shows promise in guiding users through exercises and skill acquisition [41].

Algorithmic Approach and Mathematical Formulation:

Predictive Modeling for LBP:

$$\text{Risk Score} = f\left(\text{Demographic Characteristics}, \text{Lifestyle Factors}\right)$$

$$\text{Recurrence Probability} = g\left(\text{Baseline Characteristics}\right)$$

Utilize predictive modeling algorithms to assess the risk of developing LBP based on demographic and lifestyle factors, as well as predict recurrence probabilities using individual baseline characteristics.

Machine Learning in Medical Sciences:

$$\text{Prediction Model} = h(\text{Clinical Markers})$$

Apply supervised and unsupervised machine learning algorithms to analyze clinical markers and their combinations for prognosis and therapeutic planning in LBP, enhancing overall patient care.

Virtual Coaching in Telerehabilitation:

$$\text{Virtual Coach} = i(\text{User Activity}, \text{Skill Acquisition})$$

Implement virtual coaching algorithms to guide users through exercises and skill acquisition in LBP management, providing personalized support and encouragement.

Mathematical Proofs and Justifications:

Predictive Modeling for LBP: Prove the effectiveness of predictive modelling algorithms through cross-validation and performance evaluation metrics such as accuracy, sensitivity, and specificity, demonstrating their ability to accurately predict LBP risk and recurrence probabilities.

Machine Learning in Medical Sciences: Justify the use of supervised and unsupervised machine learning algorithms in medical sciences by demonstrating their ability to identify patterns and extract valuable insights from clinical data, thereby improving diagnosis, prognosis, and treatment planning in LBP.

Virtual Coaching in Telerehabilitation: Provide evidence of the effectiveness of virtual coaching algorithms through user feedback, adherence rates, and improvements in patient outcomes, highlighting their role in promoting engagement and facilitating self-management in LBP rehabilitation. By employing these algorithmic approaches and mathematical formulations, we can enhance our understanding and management of LBP, ultimately improving patient outcomes and reducing the burden of this debilitating condition.

3.6. Robots for Upper Limb Rehabilitation

End-effector robots, which have the benefits of simple structure, easy control, and great accuracy, initially debuted 30 years ago [42]. The bulk of end-effector robots were built around that time, and numerous rehabilitation experiments with human volunteers have taken place throughout the last two decades. Some end-effector robots are now being used in clinical robotic rehabilitation or therapy. End-effector robots that are commonly used include MITManus, MIME, ARMGuide, GENTLE/S, NeReBot, EMUL, Braccio di ferro, ACT3D, which depicts a new end-effector upper limb rehabilitation robot named EULRR, which consists of a supporting module and a motion assistance module [43]. Two 7-DOF manipulators were employed to support and help the patient's arm in completing rehabilitation training. Each joint was outfitted with a torque sensor and a position encoder for torque control. The assist-as-needed (AAN) controller allows the patient's arm to move freely inside a virtual channel while providing help if the arm deviates from the virtual channel. Wearable exoskeleton robots can aid numerous upper limb joints in performing safe and flexible rehabilitation training, which is becoming increasingly popular in clinics.

In the context of robots for upper limb rehabilitation, machine learning (ML) and artificial intelligence (AI) play crucial roles in enhancing control systems, adapting to patient needs, and improving rehabilitation outcomes. One significant challenge is ensuring trajectory tracking accuracy amidst uncertainties and disturbances. To address this, a neural-fuzzy adaptive controller based on radial basis function neural networks (RBFNN) can be employed:

$$\text{Controller Output} = \sum_{i=1}^{N} w_i \phi\left(\left\|x - c_i\right\|\right)$$

Here, x represents the input state, c_i are the centers of the radial basis functions, w_i are the weights, and ϕ denotes the radial basis function.

Additionally, to recognize and adapt to the patient's motor intentions, machine learning algorithms (MLAs) can be utilized. These algorithms can analyze physiological and physical signals to infer motion intention and adjust training accordingly. One common approach is using support vector machines (SVMs) for classification:

$$\min_{w,b,\xi} \frac{1}{2} w^{\mathrm{T}} w + C \sum_{i=1}^{N} \xi_i$$

Subject to:

$$y_i \left(w^{\mathrm{T}} \phi\left(x_i\right) + b\right) \geq 1 - \xi_i$$

$$\xi_i \geq 0$$

Where w is the weight vector, b is the bias term, ξ are slack variables, and C is the regularization parameter.

Moreover, for adapting control methods, intelligent or adaptive controllers can be employed, combining sophisticated control theory with MLAs. One example is model predictive control (MPC) integrated with reinforcement learning (RL) algorithms:

$$J\left(u\right) = \sum_{k=0}^{N-1} \left\|y_{k+1} - y_{\text{ref}}\right\|^2 + \left\|u_k - u_{\text{ref}}\right\|^2$$

Where $J(u)$ is the cost function to be minimized, y_{ref} and u_{ref} are the reference trajectories for the outputs and inputs, respectively, and N is the prediction horizon.

Finally, MLAs can facilitate quantitative evaluation of patient progress by preprocessing, learning, and categorizing patient data. One approach is using deep learning models, such as convolutional neural networks (CNNs), to process patient data and predict rehabilitation outcomes:

$$\hat{y} = f_\theta\left(x\right)$$

Where $\hat{y}$ is the predicted outcome, f_θ is the CNN model parameterized by θ, and x is the input data.

Through the integration of these ML and AI techniques, robots for upper limb rehabilitation can offer personalized and adaptive therapy, leading to improved patient outcomes and enhanced rehabilitation effectiveness. Furthermore, most present robotic systems still use predetermined control methods, whereasintelligent or adaptive controllers are better suited for tailored rehabilitation. Intelligent control methods that combine sophisticated control theory and MLAs can be offered to better adapt to nonlinear systems and the dynamic environment. Finally, MLAs are appropriate for patient quantitative evaluation by preprocessing, learning, and categorizing patient data during the healing process [39] [40] [41] [42] [43].

3.7. Artificial Intelligence and Rehabilitation Evaluation

Artificial intelligence (AI), particularly machine learning, has revolutionized rehabilitation evaluation, offering sophisticated approaches for assessing both upper and lower limb function. Techniques such as support vector machines (SVM) and artificial neural networks (ANN) have played pivotal roles in tasks like image and speech recognition, enhancing the accuracy and efficiency of rehabilitation assessment [44] [45]. Objective evaluation methods based on AI technology, such as surface electromyogram signal (sEMG) analysis, human motion trajectory tracking, joint motion range assessment, and maximum angular velocity evaluation, have been investigated extensively. The sEMG enables non-invasive measurement of muscle electrical activity during limb movement, providing valuable insights into muscle function and coordination. Meanwhile, human motion trajectory tracking employs image processing technologies to analyze the trajectory of patients' limbs, facilitating precise assessment of movement patterns and abnormalities. Joint mobility range measurement and maximal angular velocity evaluation in patients' upper limbs serve as reliable indicators of rehabilitation progress, reflecting improvements in mobility and function. These objective evaluation approaches offer quantitative insights into patients' progress and can aid clinicians in tailoring rehabilitation interventions to individual needs. Numerous studies have demonstrated the efficacy of AI-based evaluation methodologies in assessing rehabilitation success, underscoring their potential to enhance patient outcomes and optimize rehabilitation strategies [46].

Artificial intelligence (AI), particularly through the use of machine learning and neural networks, has proven to be highly efficient in evaluating rehabilitation effects [47]. The section highlights how AI technologies provide quantitative evaluations that surpass the accuracy and reliability of traditional methods. This advancement significantly improves the assessment of rehabilitation outcomes by enabling more precise tracking of patient progress and the effectiveness of treatment protocols [48]. The enhanced analytical capabilities of AI not only facilitate a deeper understanding of patient responses to various therapies but also allow for the customization of rehabilitation plans to better suit individual patient needs, thereby optimizing recovery trajectories and outcomes [49].

Algorithmic Approach and Mathematical Formulation:

***Surface Electromyogram Signal (sEMG) Analysis*:**

$$\text{sEMG}_{\text{activity}}(t) = f(\text{Muscle Activation})$$

Utilize machine learning algorithms to analyze sEMG signals and quantify muscle activity during limb movement, providing objective measures of muscle function and coordination.

***Human Motion Trajectory Tracking*:**

$$\text{Trajectory}(t) = g(\text{Image Processing})$$

Apply image processing algorithms to track the trajectory of patients' limbs during movement, enabling precise assessment of movement patterns and abnormalities.

Joint Motion Range Assessment:

$$\text{Range}_{\text{joint}} = h(\text{Joint Position})$$

Calculate the range of motion in joints using machine learning algorithms, providing quantitative measures of joint mobility and flexibility.

Maximum Angular Velocity Evaluation:

$$\text{Velocity}_{\max} = i(\text{Angular Displacement}, \text{Time})$$

Determine the maximum angular velocity of limb movement using mathematical algorithms, reflecting the speed and efficiency of rehabilitation progress.

Proofs and Justifications:

***sEMG Analysis*:** Prove the effectiveness of sEMG analysis algorithms through correlation with clinical assessments and rehabilitation outcomes, demonstrating their ability to accurately quantify muscle activation and coordination.

***Human Motion Trajectory Tracking*:** Justify the use of trajectory tracking algorithms by comparing tracked trajectories with manual assessments by clinicians, validating their accuracy and reliability in assessing movement patterns.

***Joint Motion Range Assessment*:** Provide evidence of the reliability of joint motion range assessment algorithms through comparison with standardized clinical measures, demonstrating their validity in quantifying joint mobility and flexibility.

***Maximum Angular Velocity Evaluation*:** Demonstrate the utility of maximum angular velocity evaluation algorithms by correlating measured velocities with patient-reported functional outcomes, highlighting their relevance in assessing rehabilitation progress and functional improvements.

By leveraging these algorithmic approaches and mathematical formulations, AI-based rehabilitation evaluation methodologies offer objective and quantitative insights into patients' progress, enabling personalized and effective rehabilitation interventions.

3.8. Advances in the Evaluation of Motor Function Rehabilitation

With the increased emphasis on evidence-based clinical treatment, it is more critical than ever to create objective and efficient procedures for accurately assessing Patients with motor dysfunction who have functional impairments. For realistic rehabilitation goal-setting and effective allocation of therapy resources following motor dysfunction, an accurate and quantitative assessment method for evaluating and forecasting patients' functional state is required. Clinicians currently use a variety of subjective assessment scales to assess neurological deficits, motor patterns, motor performance, balance, and activities of daily living. The reliability of these measures is primarily determined by physicians' experience and skill. As a result, it is difficult to track functional changes during the recovery process and alter rehabilitation treatment accordingly. To augment and enhance conventional evaluation, objective assessment methods such as biomechanical testing, electrophysiological measures, and neuroimaging have been increasingly developed and practically implemented.

Biomechanical Testing:

$$\text{Muscle Strength} = f\left(\text{Biomechanical Parameters}\right)$$

Utilize ML algorithms to analyze biomechanical parameters and objectively evaluate muscle strength under isometric conditions, providing quantitative measures of motor impairments, particularly in stroke patients.

Electrophysiological Measures:

$$\text{Neuromuscular Status} = g\left(\text{Electrophysiological Data}\right)$$

Implement AI techniques such as electromyography (EMG), mechanomyography (MMG), and motor-evoked potentials (MEPs) to objectively assess neuromuscular status, aiding in the evaluation of motor function and recovery outcomes.

Proofs and Justifications:

Biomechanical Testing: Prove the effectiveness of ML algorithms in biomechanical testing by comparing results with standardized clinical assessments, demonstrating their ability to accurately quantify muscle strength and motor impairments.

Electrophysiological Measures: Justify the use of AI techniques in electrophysiological measures by correlating findings with clinical outcomes and recovery results, validating their utility in objectively evaluating neuromuscular status and predicting rehabilitation outcomes.

To improve the accuracy of assessing patients with motor dysfunction who have functional impairments, healthcare professionals can integrate artificial intelligence (AI) technologies into their evaluation processes [50]. Specifically, the use of ensemble machine learning models and neural networks offers a way to enhance precision and objectivity [51]. These AI-driven approaches provide more accurate and detailed analyses of motor functions than traditional methods, allowing for tailored treatments and better tracking of rehabilitation progress [52]. By leveraging these sophisticated algorithms, clinicians can gain deeper insights into the nuances of motor impairments, leading to more effective and personalized patient care.

By integrating ML and AI algorithms into the evaluation of motor function rehabilitation, clinicians can enhance the accuracy and objectivity of assessments, leading to more personalized and effective rehabilitation interventions. These advancements pave the way for improved patient outcomes and optimized allocation of therapy resources in motor dysfunction rehabilitation. Muscle strength may be reliably evaluated under isometric situations using biomechanics to determine the extent of motor impairments in stroke patients. Electromyography, mechanomyography, and motor-evoked potentials are electrophysiological methods that may be used in the clinic to objectively evaluate neuromuscular status. The existence or absence of motor-evoked potentials in paretic limbs after a few hours or days of motor dysfunction are often related to recovery results [53].

3.9. Rehabilitation with Virtual Reality

VR systems offer a multidimensional experience from an immersive, semi-immersive, or non-immersive viewpoint. In stroke therapy settings, individuals can engage with virtual simulated surroundings [54]. VR-based rehabilitation intervention has been widely used in the treatment of neurological illnesses, with usually favorable results [55]. VR systems record users' motions, which are subsequently represented in various ways on the computer screen, a process known as movement visualization. The three basic types of movement visualization are indirect, abstract, and augmented reality [56]. Movement visualization helped stroke patients observe limb movement, which triggered the mirror neuron system in the frontoparietal cortical region. Furthermore, fMRI revealed that whether the virtual limb was shown on the screen or not, mirror neuron activity was increased in healthy participants during the movement observation task. These findings suggested a link between VR systems and the mirror neuron system. The VR system was usually complemented or combined with other stroke therapy treatments. The combination of kinetic-based VR with a cognitive method enhanced motor function and vocational performance in chronic stroke patients. Chronic stroke patients were given kinetic-based VR and physical therapy to test upper extremity function, and the findings were compared to those of a group that only received physical therapy; motor function and active range of motion of the upper extremities were dramatically improved. To stimulate appropriate contraction of wrist and digit extensors, FES of the wrist and finger extensors was integrated into a VR-based wearable system [57]. VR has also been incorporated into a BCI, which employed electroencephalography and synchronized electromyography of peripheral muscle activity to identify attempts at upper extremity movement in the brain. Patients with severe impairment benefitted the most from virtual movements of the upper extremity in VR based on the patient's volition. VR-FES and BCIVR both formed a neural loop by connecting the central and peripheral nervous systems, potentially facilitating cortical excitability and neuroplasticity. Similarly, constraint-induced mobility therapy was administered to chronic stroke patients at home using a VR game, and the results were encouraging with no side effects [58]. VR-based technologies are beneficial as an additional therapy for movement disorders. When compared to isolated treatments, the effect of rehabilitation approaches might be improved and enhanced using VR training systems to obtain better outcomes for individuals with neurological disorders.

3.10. Home-Based Shoulder Rehabilitation Using Technology

Numerous medical innovations are now in the works, with many of them intended for usage in clinical or hospital settings due to their inherent complexity. Certain equipment and technologies, on the other hand, are quite simple to operate, making them ideally suited for home usage and allowing patients to regain autonomy and independence in their rehabilitation journey [59]. **Figure 2** depicts an overview of these fundamental technologies, which are divided into physical and virtual applications, each of which plays an important role in home-based rehabilitation. Wearable devices, often known as wearables, have emerged as a transformational tool in modern medicine within the area of physical technology. These devices include sensors that collect data from the patient and/or the environment, allowing for continuous monitoring outside of standard healthcare settings. Wearables offer event prediction, prevention, and intervention through the use of powerful computer algorithms, transforming the sector [60].

Since the 1990s, the incorporation of rehabilitation robots has been a vital part of therapy, providing a helpful aid in giving treatment to patients. These robots use electronic interfaces to help people do activities, providing not just physical assistance but also emotional encouragement and incentive. Numerous studies have shown that robot-assisted training improves arm function and overall performance in daily tasks. Exoskeletons, which are wearing robotic systems meant to augment and increase human physical capabilities, have also gained popularity, particularly among those with limited mobility [61]. The use of machine learning in virtual rehabilitation systems has revolutionized process automation, enabling real-time adaptability and individualized treatments based on user and environmental information. Deep learning, in particular, has aided progress in picture identification and behavior prediction in the field of rehabilitation. There has been an increase in the usage of virtual and augmented reality systems, indicating a change toward a more e-health-focused approach in both medical and social rehabilitation [62]. These devices may recreate realistic scenarios, giving vital assistance to people with impairments throughout the recovery process. Notably, the literature contains several examples of virtual and augmented reality technology being successfully used to improve rehabilitation results. These technologies, by immersing users in interactive and lifelike worlds, provide new pathways for treatments and allow individuals to engage in meaningful and immersive rehabilitation experiences [63].

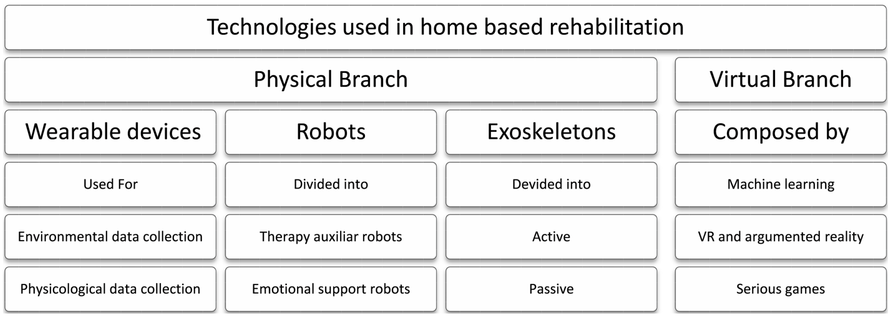

Figure 2. Technologies used for home-based shoulder rehabilitation.

4. Conclusions

In conclusion, this paper traverses the landscape of robotics and assistive technologies within the realm of neuromuscular diseases, showcasing the evolution from compensatory motions to the integration of advanced devices that signifies a paradigm shift in enhancing the quality of life for affected individuals. The convergence of artificial intelligence (AI) and machine learning (ML) algorithms further propels the field towards personalized rehabilitation, marking a significant stride towards precision healthcare. Through the application of ensemble machine learning techniques, rehabilitation strategies can be tailored to the unique needs of individuals, offering unprecedented levels of customization and effectiveness.

The integration of AI, ML, and virtual reality holds immense promise for the future of rehabilitation, promising even more effective and tailored solutions. By harnessing the power of AI-driven algorithms, rehabilitation devices can adapt in real-time to the changing needs and abilities of patients, providing dynamic and responsive assistance. Additionally, virtual reality technologies offer immersive environments for therapeutic interventions, enabling individuals to engage in rehabilitative activities in a safe and controlled manner. As the field continues to advance, the synergy between robotics, AI, ML, and virtual reality promises to revolutionize rehabilitation practices, offering hope for improved outcomes and increased autonomy for individuals with neuromuscular disorders. By embracing these cutting-edge technologies and innovative approaches, we can pave the way towards a future where individuals facing neuromuscular challenges can lead fulfilling and independent lives, empowered by personalized and effective rehabilitation interventions tailored to their unique needs.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Lusardi, M.M., Jorge, M. and Nielsen, C.C. (2012) Orthotics and Prosthetics in Rehabilitation-E-Book. Saunders, Philadelphia.

[2] Proietti, T., Crocher, V., Roby-Brami, A. and Jarrasse, N. (2016) Upper-Limb Robotic Exoskeletons for Neurorehabilitation: A Review on Control Strategies. *IEEE Reviews in Biomedical Engineering*, **9**, 4-14. https://doi.org/10.1109/RBME.2016.2552201

[3] Thring, M.W. (1983) Robots and Telechirs: Manipulators with Memory, Remote Manipulators, and Machine Limbs for the Handicapped (Ellis Horwood Series in Engineering Science). Halsted Press, Chichester.

[4] Petrich, L.C. (2023) Advancing the Acceptance and Use of Wheelchair-Mounted Robotic Manipulators. Master's Thesis, University of Alberta, Edmonton.

[5] Demers, M., Rowe, J. and Prochazka, A. (2022) Passive Devices for Upper Limb Trainin. In: Reinkensmeyer, D.J., Marchal-Crespo, L. and Dietz, V., Eds., *Neurorehabilitation Technology*, Springer, Cham, 525-547. https://doi.org/10.1007/978-3-031-08995-4_23

[6] Santilli, V., Mangone, M., Diko, A., Alviti, F., Bernetti, A., Agostini, F., Palagi, L., Servidio, M., Paoloni, M., Goffredo, M. and Infarinato, F. (2023) The Use of Machine Learning for Inferencing the Effectiveness of a Rehabilitation Program for Orthopedic and Neurological Patients. *International Journal of Environmental Research and Public Health*, **20**, Article 5575. https://doi.org/10.3390/ijerph20085575

[7] Chen, T. and Guestrin, C. (2016) XGBoost: A Scalable Tree Boosting System. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Francisco, 13-17 August 2016, 785-794. https://doi.org/10.1145/2939672.2939785

[8] Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q. and Liu, T.-Y. (2017) LightGBM: A Highly Efficient Gradient Boosting Decision Tree. *Proceedings of the 31st Conference on Neural Information Processing Systems*, Long Beach, 4-9 December 2017, 3149-3157.

[9] Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A.V. and Gulin, A. (2018) Catboost: Unbiased Boosting with Categorical Features. *Proceedings of the 32nd Conference on Neural Information Processing Systems*, Montreal, 3-8 December 2018, 6638-6648.

[10] Khan, J.I., Khan, J., Ali, F., Ullah, F., Bacha, J. and Lee, S. (2022) Artificial Intelligence and Internet of Things (AI-IoT) Technologies in Response to COVID-19 Pandemic: A Systematic Review. *IEEE Access*, **10**, 62613-62660. https://doi.org/10.1109/ACCESS.2022.3181605

[11] Van der Loos, H.F., Reinkensmeyer, D.J. and Guglielmelli, E. (2016) Rehabilitation and Health Care Robotics. In: Siciliano, B. and Khatib, O., Eds., *Springer Handbook of Robotics*, Springer, Cham, 1685-1728. https://doi.org/10.1007/978-3-319-32552-1_64

[12] Heng, W., Solomon, S. and Gao, W. (2022) Flexible Electronics and Devices as Human-Machine Interfaces for Medical Robotics. *Advanced Materials*, **34**, Article 2107902. https://doi.org/10.1002/adma.202107902

[13] Liefaard, M.C., Lips, E.H., Wesseling, J., Hylton, N.M., Lou, B., Mansi, T. and Pusztai, L. (2021) The Way of the Future: Personalizing Treatment Plans through Technology. *American Society of Clinical Oncology Educational Book*, **41**, 12-23. https://doi.org/10.1200/EDBK_320593

[14] He, H., Gray, J., Cangelosi, A., Meng, Q., McGinnity, T.M. and Mehnen, J. (2021) The Challenges and Opportunities of Human-Centered AI for Trustworthy Robots and Autonomous Systems. *IEEE Transactions on Cognitive and Developmental Systems*, **14**, 1398-1412. https://doi.org/10.1109/TCDS.2021.3132282

[15] Shepherd, J., Procter, S. and Coley, I.L. (1996) Self-Care and Adaptations for Independent Living. In: Allen, A.S., Pratt, P.N. and Case-Smith, J., Eds., *Occupational Therapy for Children*, 3rd Edition, Mosby, St. Louis, 461-503.

[16] Trombly, C.A. (2002) Managing Deficit of First Level Motor Control Capacities. In: Trombly, C.A. and Radomski, M.V., Eds., *Occupational Therapy for Physical Dysfunction*, 5th Edition, Lippincott Williams & Wilkins, Baltimore, 571-584.

[17] Rahman, T., Basante, J. and Alexander, M. (2014) Robotics and Assistive Technology to Improve Function in Neuromuscular Diseases. *Acta Mechanica Slovaca*, **18**, 50-57. https://doi.org/10.21496/ams.2014.007

[18] Singer, P.W. (2009) Wired for War: The Robotics Revolution and Conflict in the 21st Century. Penguin Books, London.

[19] LeBlanc, M. and Leifer, L. (1982) Environmental Control and Robotic Manipulation Aids. *IEEE Engineering in Medicine and Biology Magazine*, **1**, 16-22. https://doi.org/10.1109/EMB-M.1982.5005839

[20] Burgar, C.G., Lum, P.S., Shor, P.C., *et al.* (2000) Development of Robots for Rehabilitation Therapy: The Palo Alto VA/Stanford Experience. *Journal of Rehabilitation Research and Development*, **37**, 863-873.

[21] Krebs, H.I., Hogan, N., Aisen, M.L., *et al.* (1998) Robot-Aided Neurorehabilitation. *IEEE Transactions on Rehabilitation Engineering*, **6**, 75-87. https://doi.org/10.1109/86.662623

[22] Fasoli, S.E., Fragala-Pinkham, M., Hughes, R., *et al.* (2008) Upper Limb Robotic Therapy for Children with Hemiplegia. *American Journal of Physical Medicine & Rehabilitation*, **87**, 929-936. https://doi.org/10.1097/PHM.0b013e31818a6aa4

[23] Fasoli, S.E., Fragala-Pinkham, M., Hughes, R., *et al.* (2008) Robotic Therapy and Botulinum Toxin Type A: A Novel Intervention Approach for Cerebral Palsy. *American Journal of Physical Medicine & Rehabilitation*, **87**, 1022-1025. https://doi.org/10.1097/PHM.0b013e31817fb346

[24] Cioi, D., Kale, A., Burdea, G., *et al.* (2011) Ankle Control and Strength Training for Children with Cerebral Palsy Using the Rutgers Ankle CP: A Case Study. 2011 *IEEE International Conference on Rehabilitation Robotics*, Zurich, 29 June-1 July 2011, 1-6. https://doi.org/10.1109/ICORR.2011.5975432

[25] Assistive Innovations (2012) Assistive Innovations Product Listing. https://www.assistive-innovations.com/

[26] Rahman, T., Sample, W., Seliktar, R., *et al.* (2007) Design and Testing of a Functional Arm Orthosis in Patients with Neuromuscular Diseases. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **15**, 244-251. https://doi.org/10.1109/TNSRE.2007.897026

[27] Haumont, T., Rahman, T., Sample, W., *et al.* (2011) Wilmington Robotic Exoskeleton: A Novel Device to Maintain Arm Improvement in Muscular Disease. *Journal of Pediatric Orthopaedics*, **31**, e44-e49. https://doi.org/10.1097/BPO.0b013e31821f50b5

[28] De Melo, W.C., Granger, E. and Lopez, M.B. (2021) MDN: A Deep Maximization-Differentiation Network for Spatio-Temporal Depression Detection. *IEEE Transactions on Affective Computing*, **14**, 578-590. https://doi.org/10.1109/TAFFC.2021.3072579

[29] Arai, H., Onga, Y., Ikuta, K., Chayama, Y., Iyatomi, H. and Oishi, K. (2021) Disease-Oriented Image Embedding with Pseudo-Scanner Standardization for Content-Based Image Retrieval on 3D Brain MRI. *IEEE Access*, **9**, 165326-165340.

https://doi.org/10.1109/ACCESS.2021.3129105

[30] Pinto, J.T., Brachkova, M.I., Fernandes, A.I. and Pinto, J.F. (2016) Evaluation of the Ability of Powdered Milk to Produce Minitablets Containing Paracetamol for the Paediatric Population. *Chemical Engineering Research and Design*, **110**, 171-182. https://doi.org/10.1016/j.cherd.2016.04.014

[31] Yuan, Y. (2021) Observer Metamerism Quantification and Visualization. Master's Thesis, Rochester Institute of Technology, Rochester.

[32] Vos, T., *et al.* (2012) Years Lived with Disability (YLDs) for 1160 Sequelae of 289 Diseases and Injuries 1990-2010: A Systematic Analysis for the Global Burden of Disease Study 2010. *The Lancet*, **380**, 2163-2196. (In English)

[33] Hoy, D., Brooks, P., Blyth, F. and Buchbinder, R. (2010) The Epidemiology of Low Back Pain. *Best Practice & Research Clinical Rheumatology*, **24**, 769-781. (In English) https://doi.org/10.1016/j.berh.2010.10.002

[34] Serranheira, F., Sousa-Uva, M., Heranz, F., Kovacs, F. and Sousa-Uva, A. (2020) Low Back Pain (LBP), Work and Absenteeism. *Work*, **65**, 463-469. https://doi.org/10.3233/WOR-203073

[35] Karunanayake, A.L., Pathmeswaran, A., Kasturiratne, A. and Wijeyaratne, L.S. (2013) Risk Factors for Chronic Low Back Pain in a Sample of Suburban Sri Lankan Adult Males. *International Journal of Rheumatic Diseases*, **16**, 203-210. (In English) https://doi.org/10.1111/1756-185X.12060

[36] Metgud, D.C., Khatri, S., Mokashi, M.G. and Saha, P.N. (2008) An Ergonomic Study of Women Workers in a Woolen Textile Factory for Identification of Health-Related Problems. *Indian Journal of Occupational and Environmental Medicine*, **12**, 14-19. (In English) https://doi.org/10.4103/0019-5278.40810

[37] Bardin, L.D., King, P. and Maher, C.G. (2017) Diagnostic Triage for Low Back Pain: A Practical Approach for Primary Care. *Medical Journal of Australia*, **206**, 268-273. (In English) https://doi.org/10.5694/mja16.00828

[38] Maher, C., Underwood, M. and Buchbinder, R. (2017) Non-Specific Low Back Pain. *The Lancet*, **389**, 736-747. (In English) https://doi.org/10.1016/S0140-6736(16)30970-9

[39] Tack, C. (2019) Artificial Intelligence and Machine Learning Applications in Musculoskeletal Physiotherapy. *Musculoskeletal Science & Practice*, **39**, 164-169. (In English) https://doi.org/10.1016/j.msksp.2018.11.012

[40] Amorim, P., Paulo, J.R., Silva, P.A., Peixoto, P., Castelo-Branco, M. and Martins, H. (2021) Machine Learning Applied to Low Back Pain Rehabilitation—A Systematic Review. *International Journal of Digital Health*, **1**, 10. https://doi.org/10.29337/ijdh.34

[41] Tropea, P., *et al.* (2019) Rehabilitation, the Great Absentee of Virtual Coaching in Medical Care: Scoping Review. *Journal of Medical Internet Research*, **21**, e12805. (In English) https://doi.org/10.2196/12805

[42] Fasoli, S.E., Krebs, H.I. and Hogan, N. (2004) Robotic Technology and Stroke Rehabilitation: Translating Research into Practice. *Topics in Stroke Rehabilitation*, **11**, 11-19. https://doi.org/10.1310/G8XB-VM23-1TK7-PWQU

[43] Ai, Q., Liu, Z., Meng, W., Liu, Q. and Xie, S.Q. (2021) Machine Learning in Robot-Assisted Upper Limb Rehabilitation: A Focused Review. *IEEE Transactions on Cognitive and Developmental Systems*, **15**, 2053-2063. https://doi.org/10.1109/TCDS.2021.3098350

[44] Veerbeek, J.M.V., Langbroek-Amersfoort, A.C.L., Van Wegen, E.E.V., Meskers,

C.G.M. and Kwakkel, G.K. (2017) Effects of Robot-Assisted Therapy for the Upper Limb after Stroke: A Systematic Review and Meta-Analysis. *Neurorehabilitation and Neural Repair*, **31**, 107-121. https://doi.org/10.1177/1545968316666957

[45] Mu, P., Dai, M. and Ma, X. (2021) Application of Artificial Intelligence in Rehabilitation Assessment. *Journal of Physics*: *Conference Series*, **1802**, Article 032057.

[46] Kaelin, V.C., Valizadeh, M., Salgado, Z., Parde, N. and Khetani, M.A. (2021) Artificial Intelligence in Rehabilitation Targeting the Participation of Children and Youth with Disabilities: Scoping Review. *Journal of Medical Internet Research*, **23**, e25745. https://doi.org/10.2196/25745

[47] Lo, K., Stephenson, M. and Lockwood, C. (2017) Effectiveness of Robotic Assisted Rehabilitation for Mobility and Functional Ability in Adult Stroke Patients: A Systematic Review. *JBI Database of Systematic Reviews and Implementation Reports*, **15**, 3049-3091.

[48] Sardari, S., Sharifzadeh, S., Daneshkhah, A., Nakisa, B., Loke, S.W., Palade, V. and Duncan, M.J. (2023) Artificial Intelligence for Skeleton-Based Physical Rehabilitation Action Evaluation: A Systematic Review. *Computers in Biology and Medicine*, **158**, Article 106835. https://doi.org/10.1016/j.compbiomed.2023.106835

[49] Dobkin, B.H. and Dorsch, A. (2011) The Promise of mHealth: Daily Activity Monitoring and Outcome Assessments by Wearable Sensors. *Neurorehabilitation and Neural Repair*, **25**, 788-798. https://doi.org/10.1177/1545968311425908

[50] Turchi, T., Prencipe, G., Malizia, A., Filogna, S., Latrofa, F. and Sgandurra, G. (2024) Pathways to Democratized Healthcare: Envisioning Human-Centered AI-as-a-Service for Customized Diagnosis and Rehabilitation. *Artificial Intelligence in Medicine*, **151**, Article 102850. https://doi.org/10.1016/j.artmed.2024.102850

[51] Patel, U.K., Anwar, A., Saleem, S., Malik, P., Rasul, B., Patel, K., Yao, R., Seshadri, A., Yousufuddin, M. and Arumaithurai, K. (2021) Artificial Intelligence as an Emerging Technology in the Current Care of Neurological Disorders. *Journal of Neurology*, **268**, 1623-1642. https://doi.org/10.1007/s00415-019-09518-3

[52] Jozdani, S.E., Johnson, B.A. and Chen, D. (2019) Comparing Deep Neural Networks, Ensemble Classifiers, and Support Vector Machine Algorithms for Object-Based Urban Land Use/Land Cover Classification. *Remote Sensing*, **11**, Article 1713. https://doi.org/10.3390/rs11141713

[53] Rahman, S., Sarker, S., Haque, A.K.M.N., Uttsha, M.M., Islam, F. and Deb, S. (2022) AI-Driven Stroke Rehabilitation Systems and Assessment: A Systematic Review. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **31**, 192-207. https://doi.org/10.1109/TNSRE.2022.3219085

[54] Di Pino, G., Pellegrino, G., Assenza, G., Capone, F., Ferreri, F., Formica, D., Ranieri, F., Tombini, M., Ziemann, U., Rothwell, J.C. and Di Lazzaro, V. (2014) Modulation of Brain Plasticity in Stroke: A Novel Model for Neurorehabilitation. *Nature Reviews Neurology*, **10**, 597-608. https://doi.org/10.1038/nrneurol.2014.162

[55] Laver, K.E., George, S., Thomas, S., Deutsch, J.E. and Crotty, M. (2015) Virtual Reality for Stroke Rehabilitation. *Cochrane Database of Systematic Reviews*, No. 2, Article No. CD008349. https://doi.org/10.1002/14651858.CD008349.pub3

[56] Tak, S., Choi, W. and Lee, S. (2015) Game-Based Virtual Reality Training Improves Sitting Balance after Spinal Cord Injury: A Single-Blinded, Randomized Controlled Trial. *Medical Science & Technology*, **56**, 53-59.

[57] Dos Santos, L.F., Christ, O., Mate, K., Schmidt, H., Krüger, J. and Dohle, C (2016) Movement Visualisation in Virtual Reality Rehabilitation of the Lower Limb: A Systematic Review. *BioMedical Engineering OnLine*, **15**, Article No. 144.

https://doi.org/10.1186/s12938-016-0289-4

[58] Lee, S.H., Lee, J.Y., Kim, M.Y., Jeon, Y.J., Kim, S. and Shin, J.H. (2018) Virtual Reality Rehabilitation with Functional Electrical Stimulation Improves Upper Extremity Function in Patients with Chronic Stroke: A Pilot Randomized Controlled Study. *Archives of Physical Medicine and Rehabilitation*, **99**, 1447-1453. https://doi.org/10.1016/j.apmr.2018.01.030

[59] Borstad, A.L., Crawfis, R., Phillips, K., Lowes, L.P., Maung, D., McPherson, R., Siles, A., Worthen-Chaudhari, L. and Gauthier, L.V. (2018) In-Home Delivery of Constraint-Induced Movement Therapy via Virtual Reality Gaming. *Journal of Patient-Centered Research and Reviews*, **5**, 6-17. https://doi.org/10.17294/2330-0698.1550

[60] Gallagher, J.F., Sivan, M. and Levesley, M. (2022) Making Best Use of Home-Based Rehabilitation Robots. *Applied Sciences*, **12**, Article 1996. https://doi.org/10.3390/app12041996

[61] Seneviratne, S., Hu, Y., Nguyen, T., Lan, G., Khalifa, S., Thilakarathna, K., Hassan, M. and Seneviratne, A. (2017) A Survey of Wearable Devices and Challenges. *IEEE Communications Surveys & Tutorials*, **19**, 2573-2620. https://doi.org/10.1109/COMST.2017.2731979

[62] Gull, M.A., Bai, S. and Bak, T. (2020) A Review on Design of Upper Limb Exoskeletons. *Robotics*, **9**, Article 16. https://doi.org/10.3390/robotics9010016

[63] Cunha, B., Ferreira, R. and Sousa, A.S.P. (2023) Home-Based Rehabilitation of the Shoulder Using Auxiliary Systems and Artificial Intelligence: An Overview. *Sensors*, **23**, Article 7100. https://doi.org/10.3390/s23167100