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AI Applications for Cerebral Palsy: Focused Review on Diagnosis, Motion Analysis and Rehabilitation

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Abstract

Early diagnosis and effective rehabilitation of cerebral palsy (CP) are essential for improving functional outcomes and reducing long-term complications. CP affects the ability to perform daily physical activities and is often associated with secondary health problems such as obesity and chronic pain. Owing to the complexity of the condition, rehabilitation typically requires continuous supervision by clinical specialists, which can be challenging in environments with limited resources. Recent advances in artificial intelligence (AI) have created new opportunities for enhancing CP healthcare. This review summarises the major applications of AI in diagnosis, clinical decision support, motion classification and rehabilitation systems. AI-based diagnostic tools—including medical-image analysis using MRI and CT—support the early detection of neural abnormalities. Motion-classification systems use physical activity data, functional motor scales and gait analysis features to detect deviations and evaluate treatment progress. In rehabilitation, AI is increasingly integrated into robotic systems, virtual reality environments, video game-based training and metaverse-based therapies, enabling adaptive and engaging therapeutic experiences. This study highlights the shift towards AI-enhanced interventions, discusses the importance of human–computer interfaces for improving interaction between patients and rehabilitation systems and outlines current limitations and challenges. Continued research is required to improve data quality, model generalisability and clinical integration of AI technologies in CP care.

Keywords: *Cerebral palsy; Artificial intelligence; Machine learning; Motion analysis; Rehabilitation systems; Clinical decision support*

1. Introduction

Cerebral palsy (CP) is a developmental disorder that affects posture, movement and motor control. Individuals with CP often face difficulties in coordination, balance and daily activities. Early diagnosis and continuous rehabilitation are essential for improving functional outcomes[1]. CP affects approximately 1.4–1.8 out of every 1,000 live births in developed nations and 2.95–3.4 out of every 1,000 live births in low- and middle-income countries. Amongst the long-term effects of cerebral palsy are reduced freedom in play and minimised engagement in social, educational and communal activities and activities of daily living [2].

According to the Surveillance of Cerebral Palsy in Europe, the three primary classifications of CP are ataxic, dyskinetic (dystonic or choreoathetosis) and spastic (unilateral or bilateral spastic) [3]. Amongst children with cerebral palsy, the most prevalent disabilities include intellectual impairment, sensory abnormalities, seizures, pain, motor impairment, speech impairment and conduct concerns. The main problem is motor deficiencies, which are mostly caused by stiffness. Posture and mobility are altered by abnormal motor functioning. In addition to hand dysfunction and equal deformity, hip pain or dislocation may follow [4]. For children with CP, challenges with selective motor control, strength, balance, coordination and sensory processing are common. In contrast to typically growing children, they are unable to learn motor patterns [2].

The average time to diagnose CP is 2 years, though the signs and symptoms usually start to show in the early stages of infancy. For those with CP, early detection and treatment are crucial because infants are more likely to recover from brain damage compared with adults. Brain scans, motor evaluation and neurological tests can be used to predict CP, track neural development and identify newborns at high risk. Magnetic resonance imaging (MRI) and cranial ultrasound can be used to identify anatomical abnormalities in the baby's brain. These methods are also useful for monitoring the development of lesions and assessing the results of treatment [5]. Despite the lack of treatment for CP, the child can become functionally independent with the help of therapy, medicine, surgery and additional treatments such physical, occupational, speech and psychiatric therapy [4].

Such evaluation can only be performed by certified medical personnel. Medical practitioners frequently evaluate general mobility through visual observations. Accuracy of performance evaluation using visual and physical indicators can be compromised by subjective impressions and fatigue from maintaining observer concentration. Therefore, a systematic model must be designed and created to provide accurate individualised attention and timely and reliable predictive results [6].

Machine learning (ML) has emerged as a powerful instrument with enormous promise in the healthcare industry. This collection of multivariate analytical techniques first finds the salient features or trends in the data that define the training set's classes. The discovered characteristics or trends from the training set are used to classify or forecast the results of fresh data in the test set [6, 7]. ML methods can be utilised for diagnosing conditions, applying classification three in different types to develop tailored intervention strategies and predicting deviations and their outcomes. ML algorithms assist in processing large amounts of data, identifying patterns that are consequential and developing a model that is contextualised to predict an individual patient response to a specified intervention [4]. Random forests (RFs), support vector machines (SVMs), multilayer perceptrons (MLPs), artificial neural networks (ANNs), direct matching, virtual twins and Bayesian causal forests (BCFs) are amongst the ML models that have grown popular in the CP sector [8].

The foundation of ML is the notion that computers can learn from data, identify patterns and make inferences with minimal assistance from humans. Labelled, unused or a combination of both types of datasets can be used to train an algorithm. Labelled data are used in supervised learning (SL) to classify data into predefined categories (classification), predict outcomes using regression techniques and discover the relationships between dependent and independent variables. By contrast, unsupervised learning necessitates that the computers find patterns in the data and form groups using association and clustering analysis without the need for preset outputs. Through trial and error, the computer can discover optimal actions through reinforcement learning (RL), and feedback reinforces successful results [9]. The following are common classification techniques: the neural network, which performs different levels of learning from convolutional neural network (CNN) and feedback; similarity measures involving KNN; vector and margin methods applying SVM; tabular frequent algorithms, such the decision tree, Zero R and One R; and covariance matrix algorithms, including logistic regression and linear discriminant analysis. To create effective prediction models, the ensemble algorithms combine many models using bagging, boosting (AdaBoost) and RF. A probabilistic method for classification that forecasts binary results is called logistic regression (LR). SVM is widely used for data classification and prediction, and KNN classifies data according to their closeness to other data points. Regression and classification tasks can be handled concurrently by neural networks [10].

Despite improvements in medical technology and therapeutic techniques, the diagnosis, division and treatment of CP remain difficult, time-consuming and dependent on the knowledge of medical professionals. Accurate diagnoses and specific treatment plans would allow ML to quickly and impartially process massive datasets [11, 12].

This review provides an overview of AI applications related to medical imaging, movement analysis, activity recognition and rehabilitation technologies. The aim is to summarise current approaches and highlight their clinical relevance, benefits and limitations.

2. AI Applications for Cerebral Palsy

A literature search was conducted using PubMed, IEEE Xplore, Scopus and Google Scholar. Keywords included 'cerebral palsy', 'artificial intelligence', 'machine learning', 'motion analysis' and 'rehabilitation'. Studies published between 2010 and 2024 were reviewed. Articles were included if they applied AI methods to diagnosis, motion assessment or rehabilitation in CP. Duplicate and nonrelevant studies were excluded.

According to parent accounts, AI methods for diagnosing CP have produced promising outcomes. Though restrictions in the quantity and quality of information (especially crucial concerning management) may continue to be an issue for efficacy, the recent establishment of well-designed registries4 in many nations will enhance this kind of task, improve prognosis and aid in management selection. A transition from knowledge-intensive to data-intensive applications may lead to the reapplication of the CP concept into potentially pertinent entities5 and categories based on presentation and consequence when additional data eventually become available on big-data platforms. The applications of AI for patients with CP are summarised in Figure 1 as follows:

1) Clinical decision support systems: includes analysing MRI or computed tomography (CT) images [13, 14], movement analysis and handwriting analysis.
2) Motion classification: focuses on *physical activities* [15] and *motor functional scales and indices* [16-19].
3) Rehabilitation systems: includes rehabilitation robots [20-24] and exercise training systems [25-30].

3. Clinical Decision Support Systems

Clinical Decision Support Systems (CDSS) integrate specialized clinical knowledge and patient-specific data to enhance decision-making within the clinical workflow as follows:

3.1. AI in Cerebral Palsy Diagnosis

AI techniques such as CNNs have been used to analyse the MRI and CT images of patients with CP, improving lesion detection and segmentation accuracy. These models help reduce subjective interpretation and support early diagnosis. Other studies used physiological data such as heart rate variability to identify early indicators of neurological impairment using ML algorithms. Overall, AI contributes to consistent and objective diagnosis in CP.

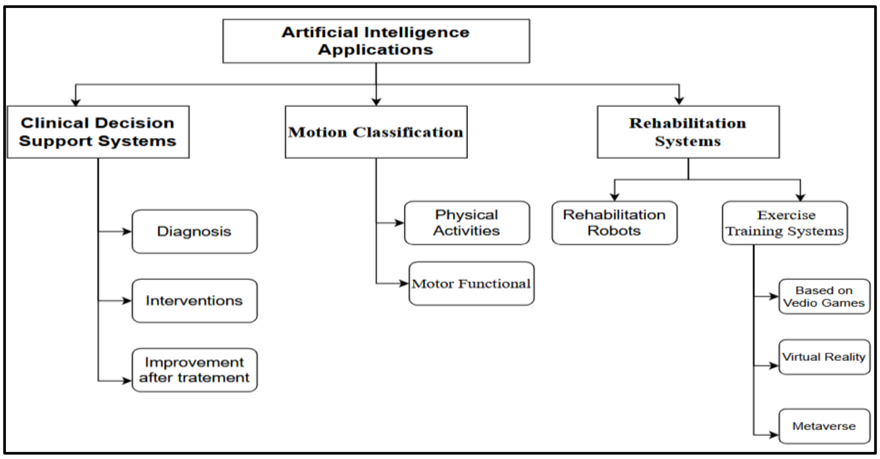

Fig. 1. AI applications for patients with cerebral palsy

Sabina van der Veen et al. [31] studied the utilisation of natural language processing (NLP) methods for standardising the evaluation of motor function in patients with CP to overcome the huge variability between clinical care providers.

In conclusion, ANNs and deep learning methods can enhance the early prediction of CP lesion when used with medical images.

3.2. AI in Determining Interventions

Gait analysis produces an abundance of highly varied data. Van Gestel et al. [32] compared gait classification between the reading of experts and Bayesian networks built based on the motion of ankle and knee in CP (139 patients).

Bertoncelli et al. [33] designed logistic regression models to predict health issues in children with CP. PredictMed is a model that has been trained, validated and tested to predict several conditions including scoliosis, intellectual disability, autistic traits and feeding difficulties requiring a gastrostomy.

Den Hartog et al. [34] explored the possibility of employing smartphone-coupled inertial sensors and ML to monitor dystonia at home and determine its severity. Klobucka et. al. [35] investigated the patient-specific characteristics that modify the efficacy of robot-assisted step instruction in patient role with bilateral spastic CP.

3.3. AI in Evaluation Rehabilitation Progress

Xi Zhang et al. [36] utilised hybrid segmentation network (HSN) to analyse the brain CT images of 73 children with CP and compared it with other CNN methods. The images were randomly allocated into two distinct groups: the AI image group, which utilised a cross-segmentation network model to analyse brain images in support of treatment; and the control group, which utilised the original images for diagnostic and therapeutic purposes. They found that HSN had the highest Dice score amongst all the models as shown in Figure 2 [37, 38].

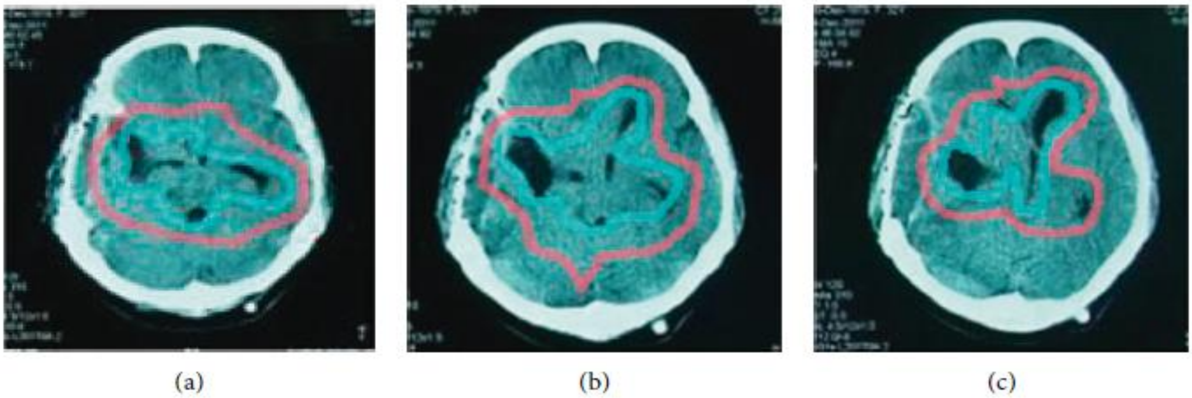

Fig. 2. Outcomes of qualitative segmentation on the test set are represented by the artificial segmentation area in red and the model segmentation area in blue. (a) HSN; (b) HSN-Dice; (c) HSN-S3D [36]

In the between-group comparison, significant changes were observed in VP and PI. Adjustments in the development quotient of two cases earlier and later treatment are shown in Figure (3), and the alteration of GMFM scale scores prior to and later therapy in the two groups of children is depicted in Figure (4) [37].

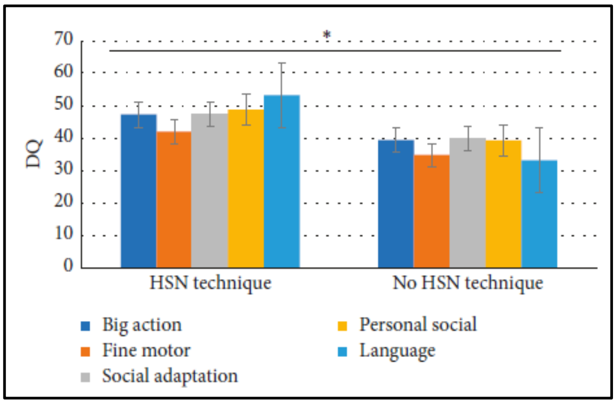

Fig. 3. Development quotient of control and image-based treatment in groups of children with cerebral palsy before and after treatment [36]

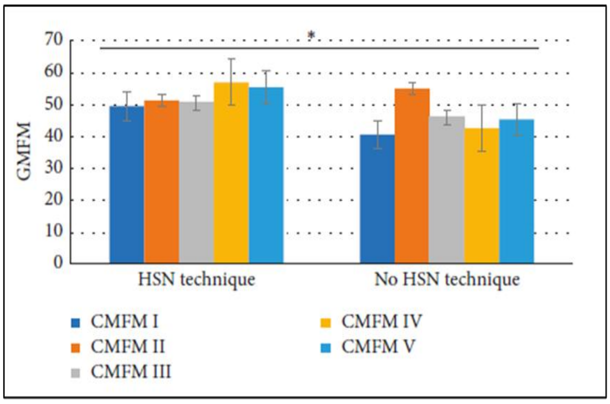

Fig. 4. CMFM scale scores before and after treatment in the studied groups [36]

4. AI in Cerebral Palsy Motion Classification

ML models such as SVM, RF and ANN have been used to classify daily movements and motor patterns in children with CP. These models improve accuracy in identifying sitting, walking, standing and transitional activities. Activity classification supports functional assessment and helps monitor progress during rehabilitation.

4.1. Motor Function Classifiers

The gross motor function classification system (GMFCS) [39], manual ability classification system (MACS) [39] [40], mini-MACS [41] and numerous additional systems are used for the functional classification of CP [42]. These classification systems assess different functions: GMFCS assesses the gross motor function of the patient with CP, and MACS assesses the functions of the upper limb. Most studies consider the walking speed, gross motor function measure (GMFM) or reactive range of activity of the lower extremities (pROM) as evaluation methods that depend on user interpretation [43]. Lisa von Elling-Tammen et al. [44] developed the medical device score calculator and predicted gross motor function GMFM-66 by applying AI models to a dataset of 1581 cerebral palsy cases (children and adolescents).

Duran et al. [45] utilised AI methods to reduce the GMFM-66 items. The performance of RF, SVM and ANN models in estimating the GMFM-66 score was evaluated using a dataset of 1217 motor function evaluations.

Suzuki et al. [46] designed an AI evaluation scheme based on the gross motor action recognition (GM-AR) to classify 13 types of gross motor. Figure 5 shows the system developed by Wang et al. [47] that allows the families of individuals with CP to access and benefit from an automated rehabilitation training program.

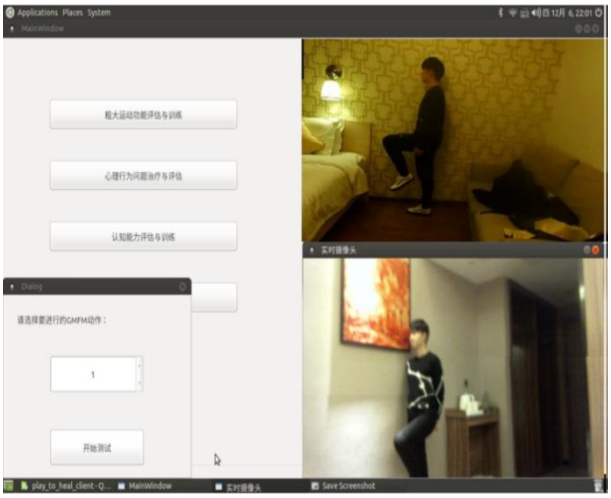

Fig. 5. Evaluation interface of Wang et al.'s system [21]

The server utilises Open Pose to extract the essential points of the individual and generates a body vector. After that, the final test score is based on the 10-layer CNN. Finally, the system compares the subject's motion with the GMFM-66 standard. The scores are added to the located database. Once the data have been managed, the user can access the web platform to review the child's evaluation data [48].

4.2. Physical Activity Recognition

Systems should be able to distinguish between activities. ML is the most suitable AI model for this type of application. Matthew Ahmadi et al. [49] estimated physical activity intensity using various ML models that were designed and tested for ambulant CP (22 children and adolescents).

4.3. Motion Deviations

Each type of CP features different walking patterns. The main goal of developing several gait classifiers for CP is to distinguish gait patterns into clinical categories such as crouch gait, apparent equinus, leap gait and actual equal [46]. Studies utilised AI models to reduce personal error and to benefit from gait analysis systems that play an important role in developing inhouse rehabilitation systems [37, 50, 51]. Zhang et. al. [36] compared seven ML algorithms (ANN, DA, NB, DT, KNN, SVM and RF) for gait classification using the same gait data collected from 200 patients with CP.

Fuzzy logic (FL) shows potential in gait classification. It translates the experiences of experts into objective rules that are triggered by subject data. Researchers built FL inference systems based on gait kinematic, kinetic or time distance parameters [52, 53]. Massoud et al. [54] utilised FL inference system based on ground reaction force to determine the severity of spastic CP of 10 children. Sagawa et al. [55] looked at clinical assessments to determine which assessments would be the most effective in reducing gait indices in individuals with CP, with the aim of using them to improve treatment strategies. For comparison, researchers employed the gait deviation index (GDI) created by Schwartz and Rozumalski and calculated using pelvic, hip, knee, ankle and foot gait kinematic data [56]. The researchers also adopted the principle of blurry windows with three belonging functions to describe clinical and GDI measurements at three levels (low, medium and high) as shown in Figure 6.

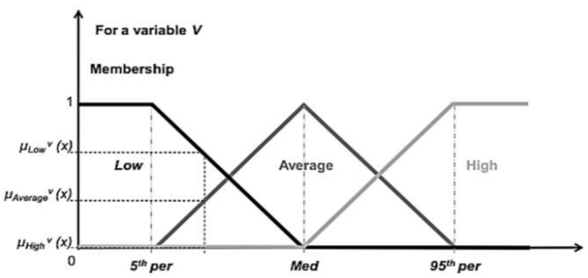

Fig. 6. Use of fuzzy windows with membership functions [51]

5. AI in Rehabilitation

5.1. Robots

AI has been increasingly integrated into robotic rehabilitation systems and virtual reality (VR) environments to provide adaptive exercises and real-time feedback. These systems offer engaging therapy options and allow continuous monitoring of performance. Several studies reported improvements in motor function when using AI-assisted rehabilitation tools. For example, a wearable machine known as the Hybrid Assistive Limb® (HAL®, CYBERDYNE) was built to assist standing, walking and leg movements according to the wearer's planned movement [52].

Through the use of exoskeletons, robot-assisted gait training (RAGT) offers task-based walking assistance. Moll et al. [57] looked into the effects of RAGT on the gait metrics and walking speed of young patients with CP.

5.2. Rehabilitation Training Systems

The field of paediatric neurorehabilitation has substantially changed. Robotics-based rehabilitation and computer-assisted systems can enhance traditional physiotherapeutics or occupational therapies. These technologies seem promising, particularly for younger users for whom engaging and difficult VR scenarios may boost their motivation to exercise hard in an enjoyable therapeutic setting. However, well-designed randomised controlled trials are currently scarce in this area. Meyer-Heim et al. [58] presented the therapeutic implications of these technologies (computer-based and robot-assisted therapy) for children with CP. Galarraga et al. [59] predicted postoperative lower limb kinematics using surgical data, preoperative kinematics and physical examination results. GMFCS is a widely used tool for assessing the mobility of patients with CP. Yoon et al. [60] investigated the association between kinematic gait metrics and GMFCS stages in normal individuals and patients with CP with variable GMFCS levels; they developed a multivariate functional classification method by employing a scant linear functional discrimination basis. This technique is generally applicable to multiclass grouping and multivariate functional data. Chakraborty et al. [61, 62] suggested a low-cost gait analysis system with several Kinect sensors. They gathered 20 CP sufferers and 20 healthy individuals for their study and suggested a data-driven technique to eliminate outlier frames from the collected sensor data.

5.2.1. Video Games

Esfahlani et al. [63] created a user-friendly neurorehabilitation video game using FL, inverse kinematics and ANN data fusion. The player's real-time interaction automatically controls the game's complexity level based on built-in algorithms. As shown in Table 1, 52 participants engaged in the program. Their functional ability was assessed using a motor assessment scale before and after treatment as shown in Table 2.

Table 1,
Description of participants [63]

Variables	Results
Age	60.1 (11.02)*
Gender	Male 26 (%65.0) vs. Female 14 (%35.0)
Time since the outset of MS symptoms (months)	59.9 (14.8)*
Subjects for rehabilitation of right upper limb	Sum= 17, 0.425 (0.406)*
low muscle tone	3 (2.3)*

The user controls and communicates with the game in real-time by inputting the system via Microsoft Kinect with a skeleton framework that provides built-in 3D motion capture capability. Figure 7 shows the anatomical planes for upper limbs and trunk with the joint progressive system, in addition to the diagram of FL classification in the game [64].

Table 2,
MAS scores pre- and postrehabilitation [64].

Motor Assessment Scale	Item	Pretreatment		Posttreatment	
		X	SD	X	SD
Upper Arm Function					
	1	2.08	0.94	3.98	1.03
	2	2.45	0.90	4.20	0.76
	3	2.25	0.87	4.13	0.88
	4	2.43	0.87	4.24	0.71
	5	2.33	0.76	4.38	0.63
	6	2.00	0.68	3.53	0.51
Hand Movements					
	1	2.03	0.70	3.55	0.64
	2	2.48	0.85	3.70	0.76
	3	3.03	0.62	4.43	0.59
	4	2.60	0.84	4.40	0.74
	5	1.95	0.68	4.15	0.66
	6	2.60	0.93	4.15	0.70
Advanced Hand Activities					
	1	1.48	0.85	2.60	0.74
	2	1.45	0.88	2.88	0.69
	3	1.75	1.03	3.00	0.99
	4	1.80	1.11	3.03	1.00
	5	1.88	1.16	3.55	0.93
	6	1.33	0.69	3.25	0.67

The findings supported the efficacy of utilising nonlinear autoregression for categorising and illustrating the target groups. The accuracy of prediction surpassed 94% [65].

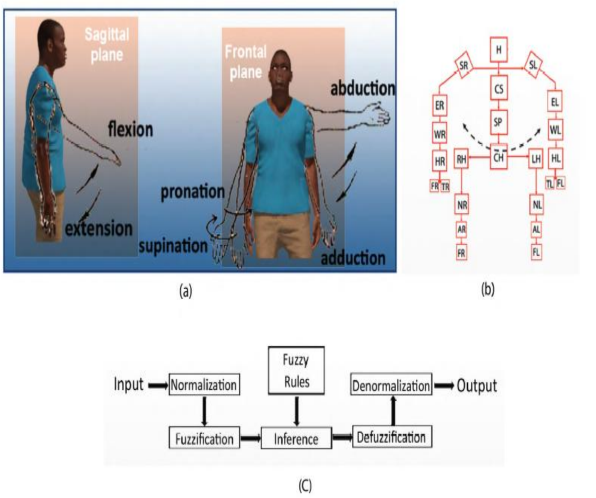

Fig. 7. (a) Anatomical motion. (b) Kinect tracks the joints of the skeleton and the stick figure. (c) Fuzzy logic classification diagram in the game [65]

5.2.2. Training Systems

Researchers utilised AI in training systems to evaluate a child's performance during the training session to guide the training program depending on the child's interaction with the system. Zhenli Lu et al. [66] developed a communication interface that depends on emotional recognition and supports the rehabilitation care of children with CP. The goal of the interface is to maintain the capability of the rehabilitation psychotherapist and provide appropriate guidance for training children. Figure 8 presents the interface module, which consists of a main panel and some panels with cartoon pictures (smile, blink and muscle nose). The interface was specifically created with an action button to aid therapists in adjusting the sequence of training exercises in response to real-time situations during children's training sessions.

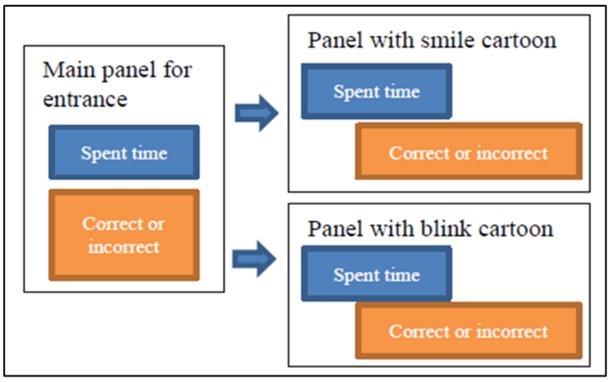

Fig. 8. Zhenli Lu et al.'s interface structure [67]

Figure 9 displays the data flow from a brain-computer interface that utilises the data from 14 sensors attached to the patient to the Emotiv program used to 3D visualise the brain.

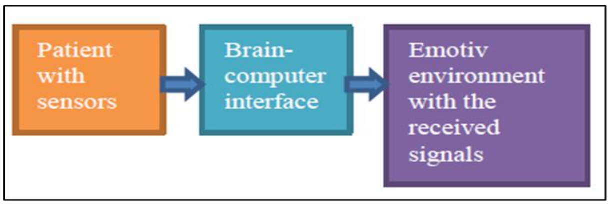

Fig. 9. Data flow from the patient to the Emotiv environment [67].

The data are organised according to the structure presented in Table 3, which provides a breakdown of the results of emotion recognition based on the child's facial expressions, specifically smiling, blinking and nasal muscle movements.

Table 3,
Facial emotion recognition results for the subject [61]

Time	Smile	Blink
1	Correct	Incorrect
2	Incorrect	Correct
3	Incorrect	Correct
4	Correct	Incorrect
5	Correct	Correct
6	Correct	Correct
7	Correct	Correct
8	Correct	Correct
9	Correct	Correct
10	Incorrect	Correct

5.2.3. Virtual Reality

VR is a mathematical machinery scheme that provides artificial sensory response, granting the user to visualise, practice and apply activities and experiences that mimic those in real life. VR has also been incorporated with 3D vision, which makes motor capabilities similar to the real world [68]. The results are generally affordable, mainly because of the elimination of pain and fear and the escape from the real world. Leap motion can effectively control upper limb rehabilitation treatments in virtual environments, leading to significant results. This approach has significant applications in the rehabilitation of individuals who have suffered from strokes [69].

Juliana M. de Oliveira et al. [70] introduced an immersive digital simulation called Rehab Fun, which can be used to aid in the therapy of children with CP between the ages of 3 and 8 years. As demonstrated in Figure (10), the suggested methodology consists of six stages constituting the implemented procedures.

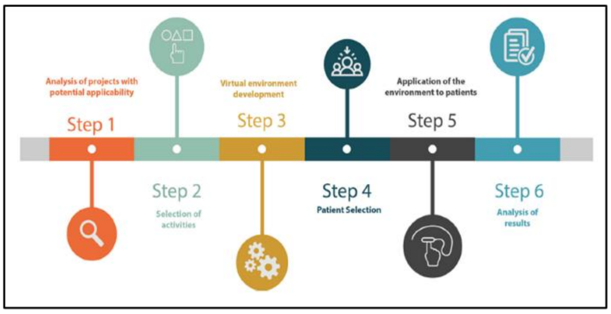

Fig. 10. Work methodology [70]

Figure 11 shows the system architecture, which was develop as two integrated systems. The first system focuses on the implementation of a serious game developed using the Unity engine called Rehab Fun. The second system develops the web to process patients' data, graphs and reports. Rehab Fun has demonstrated efficacy as a motivational tool for patients. By utilising the gathered data, experts can customise therapy strategies for individuals, resulting in enhanced efficacy and efficiency in motor rehabilitation.

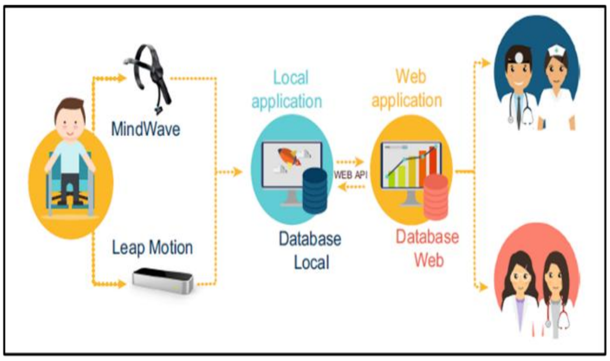

Fig. 11. Developed work methodology [70]

5.2.4. Meta Verse

As demonstrated in Figure 12, metaverse physical therapy (MPT) is an adjuvant technique that has achieved recognition in the clinical sector, especially in CP motor rehabilitation. In 2023, Ilyoung Moon et al. [71] studied the therapeutic benefits of MPT rehabilitation for CP. They also assessed the effects of MPT and conventional physical therapy (CPT) on gross motor function, daily life activities, daily activities, cardiopulmonary function and the threat of transmission of coronavirus disease (COVID-19).

Fig. 12. Metaverse rehabilitation [71]

Table 4,
Characteristics of patients who received different therapies [71]

	CPT[a] Group (n=13)	MPT[b] Group (n=13)	p-Value
Sex (male/female)	6/7	6/7	1.00
Age (years)	16.15±3.16	17.43±2.88	0.36
Body height (cm)	133.17±21.41	140.21±18.11	0.14
Body mass (kg)	38.44±16.08	42.56±20.37	0.10
[c]CP classification			
Spastic/ataxic	10/3	11/2	0.64

MPT was found to be useful in improving perceived COVID-19 transmission risk, cardiopulmonary function and gross motor function. In terms of clinical outcomes, the results offer positive evidence that MPT was superior to CPT in terms of managing children with CP. The results might serve as a helpful blueprint for designing a potent model for paediatric rehabilitation designed for children with CP.

6. AI in the Early Detection and Diagnosis of Cerebral Palsy

The evolving power of AI and ML technologies brings with it the promise of revolutionising early diagnosis in healthcare. AI provides powerful tools that can analyse huge datasets for subtle patterns and make accurate predictions that cannot be provided by humans. In the case of CP, AI can investigate medical imaging, movement patterns or genetic data to spot some early signs of neurological anomalies.

Various ML models were considered for the task of classifying gait patterns to predict joint movement and CP [14]. Assessment of the level of gross motor impairment is amongst the topics covered in Table 5. The more precise the classification of gait patterns, the more targeted the treatment. Once gait abnormalities specific to an individual are identified, clinicians can work towards interventions that address these specific problems and potentially improve the quality of life and mobility of patients with CP. This approach could lead to the development of targeted physical therapy and rehabilitation programs. Additionally, it lays the groundwork for future investigations into the fundamental causes of various gait problems, which may enhance patient outcomes and guide therapeutic approaches. Amongst the ML-based studies in the field of CP are the classification of kinematic data obtained from an IMU-based device whilst performing nine different upper extremity exercises [72], the identification of gait abnormalities in children with CP [73] and the computation of the average treatment effect of medical and neurological approaches.

Given that prompt intervention depends on the early and precise diagnosis of gait abnormalities, these studies on ML models for CP are important. A simpler approach is to develop corrective actions that can be taken whilst the child is still developing and prevent symptoms from worsening if these abnormalities are discovered early. By improving early diagnosis, this innovation helps doctors administer treatment sooner. Additionally, it facilitates the continuous evaluation of interventions' efficacy, enabling modifications to treatment regimens in response to up-to-date information. Predictive analytics offers important information about which treatments are most likely to work best for specific patients, resulting in improved patient outcomes and an effective and efficient use of medical resources. The ability to forecast treatment outcomes makes specific therapy feasible. It can also improve the overall effectiveness of CP care by reducing needless therapies, cutting down on trial-and-error procedures and concentrating efforts on strategies that have been proven effective by statistics.

Table 5,
Summary of studies using classification and regression models

Study	Algorithm	data	Objectives	Outcome	Accuracy
[6]	CNN, self-normalizing neural networks, RF, DT	Gait data	Classification of gait patterns in individuals with cerebral palsy (CP).	Decision trees and random forests identified important clinical areas and enhanced results.	93.40%
[10]	TT-PredictMed	Clinical data	Predictive modelling for children with cerebral palsy who have postural instability	The model's 82% accuracy rate was in line with recent clinical machine learning studies.	82%
[74]	MLP, Naïve Bayes (NB), Random tree (RT) and SVM	Clinical data	Machine learning for the classification of children with cerebral palsy	The multilayer perceptron (MLP) classifies cerebral palsy correctly.	84%
[9]	Direct matching, virtual twins, and Bayesian causal forests	Clinical data	Using causal inference techniques, the average treatment effects of 13 common medical and neurological treatments are predicted.	BCF did exceptionally well and provided more accurate and precise	74%
[72]	RF, LinearSVC, KNN and MLP	IMU data	finding machine learning models to classify kinematic information from upper extremity exercises based on IMUs.	The most accurate kinematic data classification from IMU-based upper extremity activities was demonstrated by RF models.	98.60%
[35]	SVM, DT, RF and KNN	Clinical data	creating a machine learning-based automated method for evaluating limb exercises.	Every model classified proper exercise execution with 100% accuracy.	100%
[75]	SVM, single and double-NN, boosted decision trees and dynamic time warping (DTW)	Clinical data	to forecast an exercise's quality and determine if it was "good" or "bad."	The Ada Boosted tree performed the best, demonstrating the feasibility of evaluating the quality of exercise.	94.68%
[46]	CNN models	Gait data	Kinematics-based joint moment prediction	Children with cerebral palsy may have their joint movement kinematics predicted using the CNN model.	nRMSE = 18.02–13.58%
[12]	Feed-forward neural net (FNN), RF, SVM, extreme gradient boosting (XG Boost)	Clinical data	Determining the extent of gross motor disability in children and adolescents with cerebral palsy	The random forest method was the most accurate.	nRMSE = 10.1%
[76]	SVR, ADA Boost regressor, RF, linear regression and	Clinical data and EEG data	To forecast the outcomes of treatment programs for kids with cerebral palsy	The most accurate approach was the random forest method.	All have low RMSE than

Bayesian regression	who have hand function issues	Clinical tests

7. Limitations and Challenges

Multiple AI models have been utilised for different applications in CP healthcare. Deep learning models, which are a subset of ML models, are mainly applied in clinical decision support systems and rehabilitation robot systems because they are commonly used in image analysis and recognition tasks [46] [37] [16]. Meanwhile, RL is suitable for optimising robot movements and adapt to the patient's needs. Supervised learning algorithms have great potential in classification application. For instance, a model can be trained to recognise different stages of CP using previous patient data [73] or classify movement types or dysfunctions. By contrast, unsupervised learning algorithms is useful in identifying unique movement patterns in patients with CP [77]. AI applications in CP rehabilitation face several challenges and limitations. The main challenges are as follows:

1. **Data Management**: The development of efficient AI tools necessitates meticulous planning in terms of data collection, processing, model training and result interpretation [50].
2. **Clinical Workflow Integration**: The design and integration of AI into the clinical workflow can encounter potential obstacles.
3. **Information Quality and Volume**: The quantity and quality of information could still pose challenges for effectiveness. Unfortunately, AI systems lack flexibility because they rely on specific measurement systems and patient groups [78].
4. **Customised Care Plans**: Many strategies and interventions can be formulated using the patterns determined by AI to enhance customised care at the patient level.
5. **Ethical Issues**: As big-data platforms accumulate data over time, the CP concept may be redefined into potentially pertinent entities, transitioning from knowledge-intensive to data-intensive applications.
6. **Explainable Results:** Difficulties are faced in relation to tracking and understanding how a model reaches a specific conclusion, how it is based on the input data and what kind of patterns and rules it creates.

8. Conclusions

This thorough examination of several ML models highlights their potential for enhancing CP diagnosis, treatment and detection. From the early detection of anomalies to the creation of specific treatment plans, this work shows the versatility of ML models in handling different aspects of CP treatment. For the identification of motions and disease-related characteristics in children with CP, RF models usually attain high accuracy. CP categories have been successfully classified by decision tree (DT) and RF models, which is crucial for creating focused treatment plans.

In current CP research, clinical data (47%) and gait data (26%) constitute the majority of utilized datasets. These are typically processed using ML architectures like DT, MLP, and RF to handle diverse predictive tasks. Clinical datasets are primarily applied in models such as DT, MLP and RF, showing they can accommodate a range of data types. Most predictive tasks in CP, such as early CP prediction, treatment response prediction and illness progression prediction, are conducted by ML models.

ML is making predictive analytics possible by personalising treatment interventions for every patient using the patient's characteristics to increase treatment effectiveness and promote the proper use of healthcare resources. However, predictive model performance is dependent on the quality or completeness of the datasets. Obtaining specifically selected datasets for CP is difficult, thus hindering the model from exhibiting good performance or generality. Additionally, the absence of imaging data, longitudinal data on patients or rich clinical data limits the translation of these models in practice for many healthcare facilities.

The use of ML for personal therapeutic recommendations raises additional ethical concerns, particularly regarding data-privacy concerns and informed consent with patients. Solutions to these issues must be explored before ML is implemented in clinical settings. Other models can avoid trial-and-error and adjust therapies depending on patient information to potentially enhance intervention success.

Evaluating ML models in a wide range of patient populations is vital to assess robustness and generalisability. Moreover, the models must be tested in the real world, either through assessments or actual integration in the clinical realm, to evaluate their utility and effect on patient care. This integration of advanced ML into routine clinical practice is contingent upon these processes.

Overall, AI has significant potential to support clinical decision-making and enhance rehabilitation outcomes for individuals with CP. Continued research and validation are needed to ensure safe and effective clinical implementation.

9. Future Directions

New and large versions of datasets are needed to advance new research in the diagnosis and treatment of CP. The availability of large and diverse datasets is vital because their absence limits the ability to build accurate and broadly generalisable models. Creating datasets which relate to different age groups and different intended clinical uses is important and is easy as long as a consistent approach to data collection is employed and appropriate data annotations are made. The established datasets can be used to construct reliable models, which can then be validated and implemented in treatment contexts.

Feature selection and model architecture are equally important. Recurrent neural networks extract temporal dependencies necessary for keeping track of movement patterns, and CNNs extract spatial features from posture data. The use of both these approaches along with transfer learning from a pretrained model has considerably improved feature extraction. Techniques such as domain adaptation or adversarial training will be needed to use models created from artificial or controlled datasets in real-world scenarios. The combination of multimodal data, such as those from accelerometer, electromyography, electroencephalography and pose signals, can further improve predictive performance, particularly when these data are absorbed into attention mechanisms. Data augmentation methods, simulation, or generative adversarial networks for synthetic data generation can improve model robustness.

Frameworks such as federated learning (FL) need to be created to address privacy concerns and access limitations on data. FL supports privacy whilst enabling organisations to develop effective models through collaborative global machine learning model training without the distribution of raw data. FL fulfils health local laws, maintains data sovereignty and supports the safety of AI in clinical practice.

Attention to specifics is another essential goal. CP has a wide range of symptoms and severity requiring different therapies with unique approaches. AI-driven systems can be beneficial for computing patient condition, tracking movement changes and assigning individualised treatment possibilities through specific metrics. They can be helpful to multidisciplinary teams with a team of people including therapists, medical doctors and neurologists to facilitate an understanding of each patient's care options.

Finally, early CP screening is critically needed, especially for preterm infants. Current diagnostic methods at birth have poor specificity, which delays interventions. Research into detection methods for preterm and term newborns should aim to identify CP early by evaluating brain plasticity during early development to enable effective and timely planning treatments.

Conflicts of Interest

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

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تطبيقات الذكاء الاصطناعي في علاج الشلل الدماغي: مراجعة مركزة على التشخيص وتحليل الحركة وإعادة التأهيل

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المستخلص

يُعد التشخيص المبكر وإعادة التأهيل الفعال للشلل الدماغي أمرًا بالغ الأهمية؛ لتحسين النتائج الوظيفية والحد من المضاعفات طويلة الأمد. يؤثر الشلل الدماغي على القدرة على أداء الأنشطة البدنية اليومية، وغالبًا ما يرتبط بمشاكل صحية ثانوية كالسمنة والألم المزمن. ونظرًا لتعقيد هذه الحالة، تتطلب إعادة التأهيل عادةً إشرافًا مستمرًا من قبل أخصائيين سريريين، وهو ما قد يُمثل تحديًا في البيئات ذات الموارد المحدودة.

وقد أتاحت التطورات الحديثة في مجال الذكاء الاصطناعي فرصًا جديدة لتحسين الرعاية الصحية للشلل الدماغي. تُوجز هذه المراجعة أهم تطبيقات الذكاء الاصطناعي في التشخيص، ودعم القرارات السريرية، وتصنيف الحركة، وأنظمة إعادة التأهيل. تدعم أدوات التشخيص القائمة على الذكاء الاصطناعي - بما في ذلك تحليل الصور الطبية باستخدام التصوير بالرنين المغناطيسي والتصوير المقطعي المحوسب - الكشف المبكر عن التشوهات العصبية. تستخدم أنظمة تصنيف الحركة بيانات النشاط البدني، ومقاييس الوظائف الحركية، وخصائص تحليل المشية للكشف عن الانحرافات وتقييم التقدم المُحرز في العلاج. في مجال إعادة التأهيل، يتزايد دمج الذكاء الاصطناعي في الأنظمة الروبوتية، وبيئات الواقع الافتراضي، والتدريب القائم على ألعاب الفيديو، والعلاجات القائمة على الميتافيرس، مما يُتيح تجارب علاجية تكيفية وجذابة.

تُسلّط هذه الورقة الضوء على التحوّل نحو التدخلات المُعزّزة بالذكاء الاصطناعي، وتناقش أهمية واجهات التفاعل بين الإنسان والحاسوب لتحسين التفاعل بين المرضى وأنظمة إعادة التأهيل، وتُحدّد القيود والتحديات الحالية. ولا يزال البحث مستمرًا لتحسين جودة البيانات، وقابلية تعميم النماذج، والتكامل السريري لتقنيات الذكاء الاصطناعي في رعاية مرضى الشلل الدماغي.