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Machine Learning in Rehabilitation Training: Traditional and Deep Learning Approaches

Yanbo Li

College of Computer and Information Science & College of Software, Southwest University, Chongqing, China

Abstract. This study aims to review and analyze the application of machine learning techniques in rehabilitation training, particularly in motor function recovery after stroke. The methodological framework is classified into two primary categories: traditional machine learning techniques and deep learning approaches. Traditional machine learning methods include: using multiple linear regression to predict gait parameters, applying Support Vector Machines (SVM) combined with surface electromyography (sEMG) signals to recognize upper limb movement intentions, and employing decision trees to assist in developing rehabilitation training plans. Deep learning methods involve using Deep Neural Networks (DNNs) to process electroencephalogram (EEG) signals, Time-series sEMG signals can be effectively captured using Long Short-Term Memory (LSTM) models, and CNN-LSTM hybrid models for skeletal motion sequence recognition. Some methods, such as SVM optimized with genetic algorithms and CNN-LSTM models incorporating attention mechanisms, have achieved recognition accuracy exceeding 90% without manual feature extraction. Although current models perform well in recognizing standard rehabilitation movements, challenges remain in terms of poor interpretability, weak generalization to rare movements, and limited deployability in low-resource environments. Future efforts should focus on interpretable network design, transfer learning strategies, and the application of model distillation algorithms to facilitate the real-world deployment of rehabilitation training systems.

1 Introduction

Rehabilitation encompasses structured interventions intended to improve physical and cognitive function while mitigating disability in individuals experiencing health-related challenges in interaction with their surroundings [1]. Rehabilitation Training (RT), a significant branch of rehabilitation, usually refers to training provided to injured individuals to help them return to their pre-injury fitness levels. Rehabilitation has been demonstrated to be beneficial for individuals. Specifically, rehabilitation has been found effective in improving trunk and lower extremity movement control, hip muscle strength, gait speed, and daily activities in stroke patients [2]. Additionally, significant improvements in insulin

eric0823wtf@email.swu.edu.cn

profile and lipid metabolism were observed when RT was combined with dietary interventions compared to dietary interventions alone [3].

Currently, the quality of rehabilitation training is universally emphasized during training sessions. Investing in quality rehabilitation education and training contributes to more efficient healthcare delivery, potentially reducing overall healthcare costs [1]. Traditional rehabilitation training, which relies solely on medical professionals, often depends primarily on intuitive judgments and estimations [4]. In contrast, the involvement of Artificial Intelligence (AI) algorithms has improved the quality of rehabilitation training today. By supporting tailored treatment strategies, AI-driven approaches contribute to improved rehabilitation efficacy and help bridge the gap between clinical rehabilitation and real-life functional recovery [5]. Introducing AI algorithms to guide rehabilitation training is a viable option for maintaining training quality in the absence of necessary equipment and medical professionals [6].

The formalization concept of rehabilitation training occurred in the 20th century. Rehabilitation gained significant attention during World War I due to the large number of injured soldiers. In the early years, physical medicine was once regarded as synonymous with rehabilitation medicine, which led to the neglect of the psychological aspects of rehabilitation [7]. Rehabilitation training requires certain external conditions. Studies have shown that the setup of the external physical and organizational environment can impact the final rehabilitation outcome [8]. Even for critically ill patients, rehabilitation activities can be considered as adjunct therapy. Experiments have demonstrated that initiating treatment a few days after admission to the Intensive Care Unit (ICU) may improve therapeutic outcomes [9].

In the early stages, rehabilitation training equipment included devices proposed by pioneers aimed at assisting patients in achieving rehabilitation. The general principle behind these devices was to facilitate physical recovery through specific mechanical interventions. Currently, AI is being integrated into rehabilitation training to aid patients more effectively. Specifically, today's AI utilizes machine learning or deep learning algorithms to support rehabilitation training and outcome prediction. For instance, intelligent medical rehabilitation training systems based on motor coordination utilize deep learning to analyze interactive feedback, assisting stroke patients in accomplishing their rehabilitation goals [10]. In recent years, researchers have leveraged structured datasets containing Clinical Reported Outcome Measures (CROM) and Patient-Reported Outcome Measures (PROM) integrating deep learning algorithms to generate outcome prediction models that assess treatment efficacy and risk of failure. Hybrid architectures that fuse CNN and RNN components have been successfully applied to predict rehabilitation efficacy, utilizing structured clinical and patient-reported outcome metrics (CROM and PROM) [11].

Given the unparalleled importance of advancements in this field, summarizing and translating these developments is essential for further progress and dissemination.The remainder of this article is structured as follows: Section 2 summarizes how deep learning methods have been utilized by researchers to enhance rehabilitation training. Section 3 discusses potential challenges and future development directions in this field. Finally, Section 4 provides a summary of the article and presents the conclusions.

2 Method

2.1 Traditional machine learning methods

In rehabilitation training research, traditional machine learning methods still play a significant role. The following section categorizes and introduces several representative traditional machine learning methods used in rehabilitation training studies, including multiple linear regression, Support Vector Machines (SVM), and decision trees, along with examples of their applications in different research contexts.

2.1.1 Multiple Linear Regression Model

The multiple linear regression model, as one of the most fundamental machine learning models, has been used to predict lower limb motor function recovery in stroke patients by incorporating practical indicators during rehabilitation training [12]. Specifically, the method involves collecting gait data from healthy individuals and patients who meet the research criteria, and calculating the Gait Time Proportion Parameter, Gait Time Symmetry Parameters, and Gait Time Variability Parameters (GTVP). A corresponding motor function recovery evaluation model is then constructed using a multiple linear regression model. The results indicate that this recovery model can effectively distinguish the severity levels of the patients' conditions [12].

2.1.2 SVM

SVM is one of the traditional machine learning models. Researchers have utilized surface electromyography (sEMG) signals and SVM to control rehabilitation robots assisting stroke patients in upper limb training. This approach has been proven to have good accuracy and can be used to support self-rehabilitation training for stroke patients [13]. The researchers proposed an sEMG-based upper limb intention recognition control framework using an SVM classifier. By optimizing the SVM parameters with a genetic algorithm, the sEMG-based SVM classification control scheme achieved an accuracy rate of over 90% in recognizing five types of movements in healthy individuals, demonstrating its high accuracy [13].

2.1.3 Decision Tree

Decision trees are a traditional supervised learning method that recursively select the most informative features to partition the dataset, thereby constructing a classification or regression model. The study demonstrated that decision tree analysis can serve as an effective tool for selecting the optimal rehabilitation training method for subacute stroke patients [14]. To investigate recovery patterns in post-stroke upper limb function, a cohort of 131 patients was randomly assigned to five therapeutic protocols: MT, IVES, TES, RFEs, and standard therapy. Effectiveness comparisons were conducted through decision tree analysis to determine the optimal intervention. The Fugl-Meyer Assessment (FMA) score for upper limb function at four weeks post-treatment was designated as the variable to be predicted. The analysis incorporated explanatory variables including age, time elapsed since stroke onset, the applied therapy type, and evaluation metrics. The experimental results confirmed that decision tree analysis is an effective tool for identifying the most suitable rehabilitation training method for subacute stroke patients [14].

2.2 Deep learning method

As artificial intelligence technologies continue to evolve, deep learning has gained prominence in rehabilitation research due to its effectiveness in capturing and modeling complex data representations. In recent years, a variety of deep learning architectures have been proposed and applied to stroke rehabilitation, motor function evaluation, and intention recognition. This section introduces representative deep learning models, including Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and other related methods, along with their practical applications in rehabilitation training.

2.2.1 DNN

DNNs are a type of feedforward artificial neural network composed of multiple layers of interconnected neurons [15]. By mimicking the hierarchical structure of the human brain, DNNs extract and abstract features layer by layer, possessing powerful nonlinear modeling capabilities. Deep learning methods were employed to build a stroke rehabilitation system based on EEG signal analysis. Within this model, the LM_SVM utilized a Deep Neural Network (DNN) as its kernel component, allowing for additional feature space mapping of the input data.The output of the DNN was then fed into the LM_SVM, which produced the final classification result of the model. This stroke rehabilitation model has been proven to achieve a higher recognition rate compared to other models and can better assist patients in performing limb movements [16].

2.2.2 RNN

Recurrent Neural Networks (RNNs) are a class of neural network architectures designed for processing sequential data. By incorporating recurrent connections, RNNs maintain a hidden state that captures temporal dependencies, allowing information from previous time steps to influence the current output [17]. LSTM, a popular architecture under the RNN family, excels in modeling sequence-dependent information present in data streams like numeric time series, textual data, and audio recordings [18]. The dataset, comprising both real and simulated sEMG signals, was segmented into training, validation, and testing sets, with no preliminary feature extraction applied. Trained with the Adaptive Moment Estimation (Adam) algorithm [19], the LSTM model demonstrated superior performance over traditional approaches, including the Teager–Kaiser Energy Operator (TKEO) [20], and the double-threshold statistical detector [21], achieving classification accuracies exceeding 90% across both real and synthetic datasets [22].

2.2.3 CNN and LSTM

Designed for processing data with spatial regularity, CNNs employ convolutional layers with shared kernels to learn local patterns across the input [6], thereby achieving feature extraction with reduced parameter complexity. To reduce spatial resolution and promote translational invariance, pooling layers are applied to downsample feature maps. LSTMs are specifically designed to mitigate issues such as vanishing and exploding gradients that often hinder traditional RNNs when capturing long-range temporal dependencies [23]. LSTMs have been widely applied in tasks such as time series prediction, action recognition, speech processing, and physiological signal modeling in rehabilitation training, particularly for analyzing sequential data [23]. Researchers leveraged Mediapipe [24], a real-time pose estimation tool, to extract 33 keypoints representing the skeletal structure of human posture simultaneously. In parallel, the researchers proposed a hybrid LSTM-CNN model comprising two Long Short-Term Memory (LSTM) layers. The initial LSTM layer is responsible for dimensionality reduction, capturing salient temporal features from the input sequence and thereby reducing the computational load for the subsequent processing. In contrast, the second LSTM layer performs dimensionality expansion, projecting the high-dimensional feature space into a more compact hidden state representation. Equipped with a pair of convolutional layers and a max-pooling layer, the CNN architecture leverages 3×3 kernels to efficiently identify spatial patterns and learn weights indicative of diverse movement trajectories. By integrating temporal modeling through LSTMs with spatial feature extraction via CNNs, the model is capable of effectively processing skeletal sequence data for the purpose of action detection and classification. Experimental results indicate that the model achieves an accuracy exceeding 95% in recognizing standard movements based on the Fugl-Meyer upper limb motor function assessment, while maintaining high classification stability across different action categories. The results show that the proposed model yields notable improvements in accurately detecting standard upper limb rehabilitation movements and holds practical applicability in stroke patient training scenarios [25].

3 Discussion

3.1 Limitations and challenges

Although the aforementioned methods have achieved fairly excellent results in practical rehabilitation training scenarios—demonstrating high accuracy in motion recognition across multiple models—these approaches still face certain challenges. The main issues include: a limited number of training and testing samples, a lack of investigation into the transferability of individual models to other rehabilitation movements, and low interpretability of the models.

Surface electromyography (sEMG) signals consist of action potentials from groups of muscle fibers. Prior investigations have revealed that surface electromyography (sEMG) signals embed significant motor control cues and user intention, making them ideal candidates for controlling upper limb rehabilitation systems [26]. However, sEMG signals are influenced by many factors and tend to be unstable. Given the patient-specific differences in data consistency and reliability, assembling robust training datasets remains difficult [27], thereby impeding the practical implementation of deep learning models.

Another issue, apart from the acquisition of training data, is the interpretability of the model. In deep learning, interpretability has become a widely discussed topic. Due to the inherent "black-box" nature of deep neural networks and the difficulty in understanding their prediction outcomes, these models often exhibit poor interpretability [28]. Interpretability plays a vital role in lower limb rehabilitation models, given that patient care and quality of life are directly affected by their outputs [29]. If patients are unable to understand why a particular rehabilitation plan is suggested, they may lose confidence in the system. Such uncertainty can result in poor compliance with prescribed exercises [30].

Although the model performs well in identifying typical rehabilitation movement patterns, its accuracy diminishes when applied to atypical or rare movement sequences, indicating that further improvements are needed in handling such cases [31].

Model portability is also a current research hotspot in Human Activity Recognition (HAR) and its application in rehabilitation training. Due to the complex structure of traditional deep learning models and their high dependence on computational resources, they are often difficult to deploy in remote or resource-constrained rehabilitation environments, resulting in poor portability [32]. This limits the widespread application of such models in practical rehabilitation scenarios, especially in home-based rehabilitation or on mobile terminal devices.

3.2 Future prospects

Improving model interpretability is expected to become a key direction in the future development of HAR in rehabilitation training. While traditional machine learning models—such as linear regression and support vector machines—offer good interpretability, the modeling of intricate, nonlinear rehabilitation patterns remains a challenge for such methods, often leading to compromised prediction accuracy. Therefore, relying solely on these conventional models is no longer sufficient to meet the dual demands for high accuracy and robustness in practical applications [33]. In response, researchers have begun exploring ways to enhance the interpretability of deep learning models without compromising their predictive performance.

One such approach involves the adoption of network architectures designed for interpretability. For example, researchers have proposed an interpretable dual-branch electromyography (EMG) network. This architecture incorporates SincNet—a feature extraction method known for its inherent interpretability—at the shallow feature extraction stage, and integrates bottleneck blocks with stochastic attention mechanisms in the deep feature extraction stage [34]. This type of architecture enables the development of models that simultaneously deliver high prediction accuracy and enhanced interpretability.

In addition, another practical improvement is the integration of domain expertise during the model development process. Establishing a feedback mechanism between clinicians and AI systems allows for the generation of more personalized and trustworthy rehabilitation plans, ultimately contributing to better patient outcomes and strengthening the relationship between patients and healthcare providers.

Beyond interpretability, model generalization is another critical factor in the design of rehabilitation training systems. Transfer learning—a machine learning paradigm that facilitates the application of knowledge gained from one task to another—has shown promise in enhancing model adaptability across diverse rehabilitation contexts when combined with deep learning techniques. This strategy not only reduces reliance on large-scale training datasets but also improves the deployment efficiency of models in new environments.

While improving model interpretability and generalization, enhancing model portability will also become a key focus in the future design of rehabilitation training systems. Given its effectiveness in reducing model complexity, knowledge distillation is increasingly recognized as a valuable tool in advancing intelligent rehabilitation systems. This method involves training a lightweight "student model" to mimic the outputs of a more powerful "teacher model," thereby significantly reducing model complexity while retaining as much recognition accuracy and generalization capability as possible. By incorporating knowledge distillation strategies, AI systems in rehabilitation training are expected to achieve smooth migration from high-performance servers to edge devices, enhancing system flexibility and universality.

At the same time, data privacy and ethical considerations must be given full attention. In the process of collecting patient-specific data for personalized rehabilitation training, stringent data protection measures must be implemented, including data anonymization, end-to-end encryption, and secure access protocols. These practices are essential to ensure the confidentiality and security of patient information, especially as data-driven AI systems become more widely adopted in healthcare.

4 Conclusion

This paper presents a comprehensive review of the application of machine learning in rehabilitation training, encompassing both traditional machine learning techniques and advanced deep learning frameworks. The authors systematically surveyed the literature to assess recent achievements and highlight prevailing trends in the use of these algorithms across the field. This review emphasizes a range of representative algorithms, from classical models such as multiple linear regression, support vector machines, and decision trees to advanced architectures like deep neural networks, convolutional neural networks, and long short-term memory networks, evaluating their effectiveness in stroke rehabilitation, electromyographic signal processing, and upper and lower limb motor function prediction .In the discussion section, the authors highlight the major challenges currently faced, including weak model interpretability, poor generalization to rare rehabilitation movements, and limited portability in resource-constrained environments. Addressing these issues will be a critical direction for optimizing machine learning-assisted rehabilitation training systems in the future.

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