Computers in Biology and Medicine 166 (2023) 107485

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/compbiomed

A deep learning system to monitor and assess rehabilitation exercises in home-based remote and unsupervised conditions

Ciro Mennella, Umberto Maniscalco *, Giuseppe De Pietro, Massimo Esposito

Institute for High-Performance Computing and Networking (ICAR) - Research National Council of Italy (CNR), Italy

A R T I C L E I N F O

Keywords:
Artificial intelligence
Deep learning
Computer vision
Pose estimation
Movement classification
Rehabilitation

A B S T R A C T

In the domain of physical rehabilitation, the progress in machine learning and the availability of cost-effective motion capture technologies have paved the way for innovative systems capable of capturing human movements, automatically analyzing recorded data, and evaluating movement quality.

This study introduces a novel, economically viable system designed for monitoring and assessing rehabilitation exercises. The system enables real-time evaluation of exercises, providing precise insights into deviations from correct execution. The evaluation comprises two significant components: range of motion (ROM) classification and compensatory pattern recognition. To develop and validate the effectiveness of the system, a unique dataset of 6 resistance training exercises was acquired.

The proposed system demonstrated impressive capabilities in motion monitoring and evaluation. Notably, we achieved promising results, with mean accuracies of 89% for evaluating ROM-class and 98% for classifying compensatory patterns.

By complementing conventional rehabilitation assessments conducted by skilled clinicians, this cutting-edge system has the potential to significantly improve rehabilitation practices. Additionally, its integration in home-based rehabilitation programs can greatly enhance patient outcomes and increase access to high-quality care.

1. Introduction

Physical rehabilitation plays a vital role in improving the functional abilities of patients suffering from physical impairments or disabilities [1–3]. Numerous studies emphasize the significance of physical rehabilitation in enhancing patient outcomes, with exercise intensity being closely linked to the success of rehabilitation programs [4–7]. As part of rehabilitation programs, home-based regimens are often recommended to provide additional flexibility, where clinicians tailor personalized rehabilitation plans consisting of recommended exercises. Surprisingly, over 90% of rehabilitation programs are conducted at home, highlighting the widespread adoption of this approach [8].

However, despite its popularity, home-based rehabilitation faces challenges related to patient motivation and adherence to prescribed exercise regimens, leading to prolonged treatment duration and increased healthcare costs [9,10]. Several factors contribute to reduced patient motivation and engagement, with the lack of timely feedback and real-time supervision by healthcare professionals in the home environment being a prominent issue [11]. Consequently, there is a growing demand for innovative tools and equipment that can support and motivate patients during home-based rehabilitation.

The emergence of digital biofeedback systems marks a new era in rehabilitation technologies, aiming to provide remote guidance and support to patients during their rehabilitation journey [12,13]. Such guidance has been proven to improve the likelihood of patients performing exercises correctly. Nevertheless, achieving real-time motion assessment and live feedback regarding the quality of exercises remains an ongoing challenge. To address the complexities of both home-based and in-clinic rehabilitation programs, the development of reliable systems capable of capturing human movements, automatically analyzing recorded data, and evaluating the quality of movement performance is crucial.

Advancements in low-cost sensors integrated with motion tracking functionality offer a promising avenue for the development of such systems. Additionally, the creation of efficient computational algorithms for modeling and analyzing human motion becomes central to resolving the challenge of evaluating the quality of rehabilitation movements.

Assistive systems play a vital role in supporting patients with in-home exercises [14,15]. To be effective, assistive systems need to be adequate, affordable, and easily accessible, while also ensuring user engagement [16]. Furthermore, it is essential for these systems to assess

* Corresponding author.
E-mail addresses: ciro.mennella@icar.cnr.it (C. Mennella), umberto.maniscalco@icar.cnr.it (U. Maniscalco).

https://doi.org/10.1016/j.compbiomed.2023.107485
Received 12 June 2023; Received in revised form 31 August 2023; Accepted 15 September 2023
Available online 18 September 2023

patients' performance and provide therapists with the necessary data to track progress and make informed clinical decisions [17,18].

Previous studies have explored computer-based solutions for in-home rehabilitation. These emerging systems often feature complex interaction models that offer visual and audio feedback [16,19]. They utilize marker-based motion capture or Kinect-based systems to assess patients' exercise performance through motion kinematic analysis [19, 19]. While these works showcase the potential of computer-based systems in improving movement quality, they are often hindered by technical complexities. Current quantitative assessment methods rely on data kinematic analysis, necessitating specific motion capture sensors. As a result, these systems are less affordable, less accessible, and more challenging to use, making them less ideal for in-home therapy. To address these limitations, there is a need to explore innovative means of assessing patients' performance using built-in cameras on commonly available commercial devices such as smartphones, tablets and laptops. This would lead to more affordable and accessible in-home therapy solutions. However, there has been limited research on low-cost quantitative assessment methods that can provide real-time feedback on motion performances.

The present work introduces an innovative, cost-effective application designed to automatically evaluate rehabilitation exercises within prescribed routines. By unobtrusively monitoring a person's exercises during therapeutic sessions, the system assesses their performances to prescribed motions, distinguishing between correct and incorrect movements. The primary contribution lies in the development of an artificial intelligence system capable of analyzing human motion, providing valuable support to patients without the constant need for supervision during rehabilitation. The proposed technological solution composed of a single laptop with a built-in webcam aims to achieve three main objectives: first, gathering comprehensive data about human motion through exercise monitoring [20,21]; second, evaluating the quality of exercise performance in terms of motion offering corrective feedback to patients [22–25]. In summary, this work addresses the urgent need for assistive evaluation systems for rehabilitation exercises. By leveraging the power of artificial intelligence to analyze human motion, the system can serve as a valuable device for patients to ensure they perform exercises correctly and receive real-time feedback during their sessions.

The paper follows a structured organization to present the research findings coherently. In Section 2, an overview of related works on motion monitoring and exercise evaluation is provided. Section 3 outlines the methodology employed in this study. In Section 4, the retrieved results are presented. Section 5 offers a comprehensive analysis of the existing results and their future implications. Finally, Section 6 concludes the work, summarizing the key contributions and potential avenues for future research.

2. Research background

2.1. Motion capture systems

The efficacy of physical physiotherapy programs relies on the patient's adherence and the correct performance of the prescribed routines. Therefore, there is a need for systematic monitoring of their execution. Recent research has explored the application of technological advances in physical routine monitoring. Video-based and wearable technologies are the main alternatives proposed for the monitoring of exercises [26]. For a practical characterization of physical routines, recent research has investigated the feasibility of IMUs to provide accurate recognition and evaluation of exercises in different human motion fields, such as sports and rehabilitation [27]. Also, video-based solutions are frequently used because of their accuracy and real-time visual feedback. Vision-based methods can be divided into marker-based and markerless. Marker-based methods provide accurate measurements of the position of markers in the space to guide patients during rehabilitation exercises [28]. Body-worn sensors and marker-based systems, despite their accuracy in motion capture, can be very intrusive to a patient's day-to-day activities due to the difficulties related to sensor placement. Moreover, marker-based technologies are limited to those places where the systems are installed, and entail patients' privacy concerns. These motivations make such technologies impractical for implementing successful home-based rehabilitation provided at a distance [29].

For a more practical characterization of physical routines, recent research has investigated the feasibility of marker-less motion capture systems to provide accurate recognition and evaluation of exercises in different human motion fields, such as sports and rehabilitation [26, 30]. Marker-less vision-based human motion modeling has the potential to provide unobtrusive home-based monitoring. This technology is a significantly more practical and easy-to-use solution for the patient that only needs a computing device with one or more cameras attached for performing therapeutic exercises guided by the application [31]. According to recent literature sources, various markerless assistive systems have been proposed, often utilizing specific motion capture sensors such as the Microsoft Kinect [32,33], the BioStage System [34, 35], the DARI Motion system [36], and the 4DBODY System [37]. Microsoft Kinect is the most commonly used markerless system resulting a relatively low-cost and commercially available solution that facilitates the capture and analysis of whole-body movements in comparison to the other sophisticated capture motion devices [38]. An important consideration for potential users of Kinect is that the system has been out of production since 2017, and Microsoft announced that it is no longer supported by the Xbox platform [39]. As a result, for future rehabilitation assessors looking to utilize markerless technology, alternative markerless systems may need to be considered. One such option is the newly developed Azure Kinect, but it is important to note that its cost may not be as accessible, potentially limiting its widespread use.

Consequently, it becomes essential for researchers and practitioners in the rehabilitation field to explore alternative, easily accessible markerless technologies that cater to their specific requirements. In recent years, the integration of machine learning algorithms has revolutionized the extraction of valuable kinematic data directly from standard videos, eliminating the need for additional hardware devices and greatly enhancing the feasibility of motion capturing in natural environments. Notably, pose estimation algorithms and motion analysis techniques have witnessed rapid advancements, enabling precise identification and classification of human joint kinematics through cutting-edge computer vision and deep learning methodologies [40]. There has been an exciting exploration of utilizing time-ordered sequences of angular or position coordinates of the joints extracted from RGB or depth cameras. These sequences are proving to be invaluable for modeling and analyzing human motions with great precision and accuracy [38]. The adoption of these innovative approaches has the potential to revolutionize motion analysis by utilizing portable and low-cost cameras, offering a practical and cost-effective alternative to traditional systems like Kinect, which heavily rely on specialized sensors.

Capitalizing on these cutting-edge advancements, our primary objective is to overcome the limitations of traditional motion capture systems by introducing a practical, cost-effective, and user-friendly solution that revolutionizes motion analysis in rehabilitation programs. To accomplish this, we have seamlessly integrated state-of-the-art machine learning pose estimation with a standard RGB camera, resulting in a remarkably low-cost motion system that stands out from existing methods, such as the Kinect, in the field of motion analysis.

From a clinical practice standpoint, our vision is to implement a single-camera system that can accurately identify the coordinates of all joints, offering an optimal and efficient solution for routine use. With such a system in place, advanced joint movement analysis would become a reality, encompassing the monitoring of various functional movements, including walking, squatting, as well as simple limb joint movements like stretching and bending [41].

By focusing on user-friendliness and minimizing hardware requirements, our solution has the potential to significantly broaden the application of markerless motion capture technology for precise measurement and clinical assessment in rehabilitation. This groundbreaking approach promises to empower researchers and practitioners with an accessible and versatile tool for enhancing the effectiveness of rehabilitation programs.

2.2. Approaches for human motions modeling and evaluation

A key prerequisite for the evaluation of patients' progress in home exercise programs is the provision of efficient and comprehensive performance evaluation approach. Mathematical modeling of human motions is a research topic in several scientific fields, and subsequently it has been employed across a wide range of applications. Nevertheless, from a general point of view modeling of human motions remains a challenging problem, due to several aspects related to their intrinsic properties.

First, the selection of the approach for modeling and analyze rehabilitation performance depends on the nature of the exercise, whether it involves a simple or complex movement. A complex movement is characterized by patterns that may differ between individuals due to the specific functional activity being performed [42,43]. These movements involve multiple joints and muscles working together to accomplish a specific task or functional activity. Complex movements are more context-dependent and may vary based on individual capabilities, body mechanics, and motor skills. Activities such as drinking, walking, or picking up objects are examples of complex movements because they require coordination and integration of various body movements to achieve the desired outcome. On the other hand, a simple movement can be defined as a physiological bending and extension along the range of motion of a particular joint or body part [42]. This kind of movement typically follows a standard pattern and is consistent across individuals. Examples of simple movements include basic joint flexion and extension, such as bending and straightening the elbow or knee.

Existing approaches for evaluating rehabilitation exercises can generally be categorized into discrete movement classification approaches, rule-based approaches, and template-based approaches [44]. The class of rule-based approaches utilizes a set of rules for a considered rehabilitation exercise that is defined in advance by clinicians or human movement experts. The rules are used as a gold standard for assessing the level of correctness of the movements. Whereas a smaller number of rules, such as relative angles or distances, may be sufficient for the representation of simpler movements, a more comprehensive set of rules is needed to describe functional exercises. Discrete movement classification approaches classify individual repetitions of rehabilitation exercises into discrete classes, most often in correct and incorrect movements. In template-based approaches, patients' exercise performance is evaluated based on the difference between training motion sequences executed by the patients and template motion sequences, typically obtained from the correct performance of the exercises by healthy subjects, clinicians, or patients under a clinician's supervision.

All above-mentioned approaches present some shortcomings. Template-based approaches provide an automatic evaluation of complex activities, however, contain limited information to provide detailed correction feedback during rehabilitation exercise monitoring. Rule-based approaches and evaluations based on classification of discrete classes of movements lack flexibility and capacity for generalization to new exercises and a larger set of classes are required to describe more complicated exercises.

To achieve the objective of developing a markerless evaluation system that can deliver real-time feedback with highly specific information regarding any deviations from the correct execution, our study proposes a modeling and evaluation method of resistance training rehabilitation exercises. Considering the intrinsic properties of exercise that our system aims to evaluate and also considering shortcomings of existing evaluation approaches, we propose a method based on a discrete movement classification approach that utilizes a neural network algorithm for the evaluation of exercises. Considering that resistance training is typically characterized by the repetition of key movements during a repetition of a certain exercise, the modeling of the evaluation exercise is based on set of predefined categories to describe key movement executions that subjects could accomplish [45,46]. Since a set of categorical correct and incorrect classes of movements could be associated with the corresponding exercise phase of an individual's performance, each exercise repetition could be analyzed at a finer level [46]. In detail, the evaluation will consider two aspects of the performed exercise: the completeness of the range of motion (ROM) and the recognition of compensatory movements.

This approach represents a novel method for modeling and evaluating rehabilitation exercises, with the potential for application in home-based physical therapy and rehabilitation programs. By employing this technology, we aim to mitigate potential risks associated with incorrect exercise performance, ultimately enhancing the safety and effectiveness of rehabilitation procedures.

3. Materials & methods

3.1. Overview of the proposed system

The work presents a system to quantitatively assess motor patterns of rehabilitation exercises through 2D video analysis in real time. The main goal is to monitor unobtrusively the exercise carried out by a person in a therapeutic session and evaluate whether it is being performed according to its prescription (correct performance) or not (wrong performance). The evaluation corresponds to the assessment of the range of motion (ROM) and the compensatory movement patterns that a subject could accomplish during the rehabilitation session.

This section offers a concise overview of our comprehensive proposal, which centers on the development of an advanced assessment system. The primary focus of this system is to meticulously evaluate both valid and incorrect repetitions, with particular attention given to analyzing ROM and identifying compensatory movement patterns.

The proposed system relies on the architecture illustrated in Fig. 1, which comprises five main modules: (i) a 2D human pose network, (ii) data pre-processing; (iii) a ROM-classifier module, (iv) a compensation-classifier module, and (v) a repetition counting and validation module to analyze ROM and compensatory patterns. Throughout the following, let $X(z) = \{X_t, m_t, c_t\}$ denote a labeled sequence of N frames of the considered set of exercises $z \in \{E1, E2, E3, E4, E5, E6\}$, where X_t denotes the acquired RGB image at frame t, m_t represents the current ROM class of the exercise execution, and c_t indicates the class of motion corresponding to physiological or compensatory movement patterns. First, the acquired image X_t is fed through the 2D human pose network to obtain a set of K keypoints coordinates. Second, a ROM-classifier operates on top of skeleton-based features to predict the ROM motion category. Furthermore, ROM-class 3 and ROM-class 4 of each exercise are evaluated to belong to the good or compensatory patterns category via the compensation classifier. Finally, the repetition counting module receives the predicted ROM-class which outputs the current number of valid and invalid repetitions via an internal state machine and the validation module tracks the percentage of erroneous patterns present in each exercise repetition. The internal state machine outputs and increments the current number of valid and invalid repetitions if the following conditions are satisfied: (i-a) there is a transition from the last to the first ROM-class of the exercise (valid repetition), (i-b) there is a transition from the intermediate ROM-classes of the exercise (invalid repetition); (ii) all the ROM-classes of the repetition appear in the right order within the current repetition. This module updates the current number of repetitions at each frame t by having the ROM-class

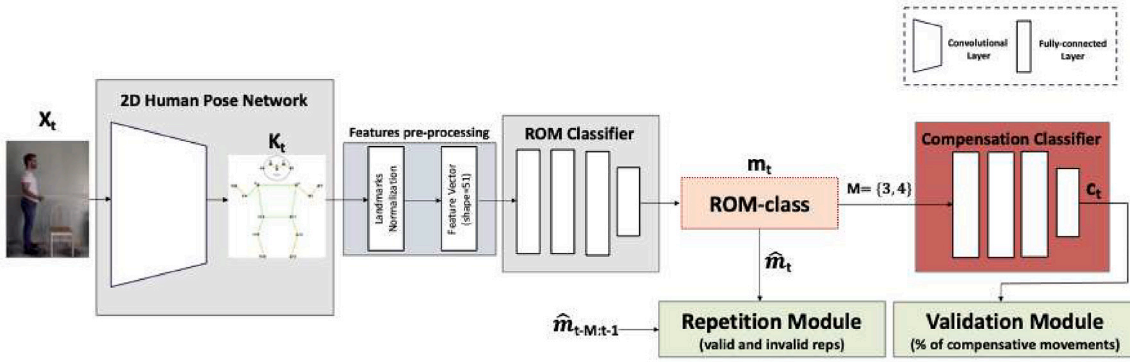


Fig. 1. Proposal of a system that counts valid and invalid repetitions and recognize compensatory motion patterns of the rehabilitation exercises. The architecture is composed of five different modules: (i) a 2D human pose network, (ii) data pre-processing module, (iii) a ROM-classifier module, (iv) a compensation-classifier module, (v) a repetition counting and validation module. $m_t \in C = \{C_j | 1 \leq j \leq 4\}$ represents ROM classes of a given exercise comprising key poses or phases of the exercise. $c_t \in C = \{C_j | 0 \leq j \leq 2\}$ denotes whether the t frame belongs either to a physiological or compensatory motion pattern class.

prediction of the current frame m^t, as well as the M past ROM-class predictions $m_{t-M:t-1}$. Finally, the system counts those repetitions correctly if all the ROM-classes of the exercise appear in the right order in a given time window (3 past frames, current frame, and 3 future frames) [47].

3.2. Movement evaluation approach

The system aims to evaluate the performance quality in two different stages of classification. The proposal divides the complete process of determining the completeness of ROM and the recognition of compensatory movements into two different stages of classification. It is based on the hypothesis that separating the evaluations into two different stages, both classifications would improve their accuracy rates due to the reduction of the number of classes.

Formally, we consider a set of input–output pairs $D = \{(x_i, y_i)\}_{i=1}^{N}$ where $x_i \in R^n$ are the N samples of the input feature space obtained from the 2D video motion analysis and $y_i \in C = \{C_j | 1 \leq j \leq J\}$ are the class to which these features correspond. The number of classes $J \in N$ depends on each proposal. The classification algorithms look for a decision function $f : R^n \rightarrow C$ which given a sample, that in this work contains features of body joints' 2D pose data, determines the output class that includes the kind of execution performed: $x \rightarrow y = f(x, w)$. During the training process, the algorithm finds the parameters w that best fit the given training data set. These methods aim to find a function f capable of generalizing its good accuracy to the given new data, which corresponds in this study to a person's motion features derived from a 2D pose estimation module.

In summary, to assess a patient's exercise performance from 2D videos, the methodology is composed of the following steps: body keypoint extraction, data normalization, and classification. A neural network-based approach was investigated to classify the correctness of the prescribed exercise. The classifier must be robust enough to assign a label to each frame denoting the wrong performance and indicate good movement quality (normal movement patterns without erroneous motion categories such as limited ROM executions or compensatory movements).

Two different models that take the preprocessed landmark coordinates as input and predict the pose class that the person performs were addressed respectively to assess the ROM execution and compensatory movements for each of the 6 rehabilitation exercises. As we intend to identify multiple motion patterns from video frames, we deal with a multilabel classification problem. First, a multilabel classifier assesses the ROM execution to recognize the series performed well from the series erroneously performed. At the same time, a second multilabel classifier determines compensation existence by detecting the class of the patterns related to compensatory movements.

3.3. Experimental setup and data collection

The proposed exercise evaluation method was investigated on a rehabilitation protocol including resistance training exercises. Resistance training is defined as a strength training exercise with the use of progressive overload in which the muscles create the force against external load. Resistance training interventions might be particularly beneficial to reduce the causes (e.g., loss of muscle mass) and consequences (e.g., loss of muscular strength or functionality) that both syndromes usually produce, even at early stages [48,49].

The exercise protocol is proposed as an effective strategy to treat sarcopenia and physical frailty [50–52]. Furthermore, the protocol was developed to be scalable for home-based rehabilitation programs and to fit the needs of a large range of individuals with reduced motor ability such as elderly people [53]. The exercises were selected according to the guidelines of the American College of Sports Medicine (ACSM) for resistance training for older subjects [54]. The protocol consists of 6 rehabilitation exercises: 3 for upper limbs (biceps curl (E1), triceps curl (E2), front raise (E3)), and 3 for lower limbs (squat (E4), leg extension (E5), leg curl (E6)). These exercises targeted the major muscle groups, such as the legs, back, abdomen, chest, shoulders, and arms.

Resistance training exercises are typically characterized by the execution of a muscle contraction (concentric phase) followed by muscle relaxation (eccentric phase) repeated a defined number of times. So, the repetition of a certain exercise corresponds to the period between two consecutive key phases (concentric and eccentric phases) that a subject should accomplish. The concentric and eccentric phases are correctly performed when the subject achieves the full ROM of the joint interested in the exercise. For this reason, it is important to distinguish series performed along the entire ROM as correct executions from the wrong performances that are represented by incomplete executions in concentric/eccentric phases. Furthermore, the patient intending to achieve the target movement during the concentric phase of resistance training exercises could accomplish compensation movements that have a deleterious outcome on the rehabilitation program. A meticulous evaluation should promptly recognize the performance of compensatory movements to preserve the beneficial effects of rehabilitation exercise. A set of pre-defined categories of the compensatory patterns of motion were defined for each exercise in agreement with existing guidelines [42].

Under the scope of the proposed approach, a dataset containing the video of 6 rehabilitation exercises performed in the correct and wrong manner was acquired. The dataset was obtained by recording a rehabilitation expert performing the pre-defined variants of the exercise motion. Five of the 6 exercises requested the person in a stand position (S1). Exercises E2 and E6 were recorded with the therapist in the seated position (S2). Each video was recorded from the best camera perspective which allows us to perfectly monitor the exercise. When selecting

Fig. 2. The figure is a visual description example of a biceps curl (E1) repetition, highlighting: (i) the difference between key poses and phases, (ii) the difference between each class of ROM execution.

the most relevant point of view to describe subjects' movements, we considered three scenarios concerning subject positioning in front of the camera: a lateral view with the right side perpendicular to the camera (V1), a frontal view facing the camera (V2), and a lateral view with the right-side oblique to the camera (V3). For V1 and V3, only the right side is completely visible in the image. All samples were recorded under a resolution of 1280 × 720 at 30 frames per second. All frames of each video were labeled in agreement with a physical rehabilitation expert concerning temporal and categorical motion domains. The labeling process was carefully conducted twice by a rehabilitation expert to ensure accuracy and avoid any errors in labeling. The characteristics of each exercise, the information regarding scenario settings, as well as the classes corresponding to the categories for the evaluation of the completeness of ROM and compensatory movements, are all described in Table 1.

During the repetition of a certain exercise, key poses represent the most important human poses that everyone should accomplish, and phases correspond to the period between two consecutive key poses. Therefore, frames with a common phase or key pose will have the same temporal label accordingly. On the other side, repetitions can also be analyzed in terms of validity at a frame-level, since a set of categorical motion categories of ROM and compensatory movements can be associated with each frame depending on the individual's performance, as shown in Table 1.

The temporal and categorical motion domains to evaluate the valid repetitions taking into account the ROM are visually depicted in Fig. 2.

For instance, during the execution of the frontal raise exercise (E3), individuals might excessively extend the trunk (C1) or bent elbow flexion (C2) in ROM-classes 3–4 instead of following the physiological pattern of movement (see Fig. 3) (see Table 4).

3.4. The 2D human pose estimation network

Pose estimation refers to computer vision techniques that detect human joints in images and videos. It is important to know pose estimation merely estimates where key body joints are and do not recognize a person's identity in an image or video.

To this scope, a convolutional neural network model that runs on RGB images and predicts the human joint locations of a single person was applied for pose estimation.

After a meticulous evaluation of various state-of-the-art pose estimation models, we made the decision to integrate the pre-trained Google-based inference model MoveNet into our motion analysis system to extract joint landmarks. This choice was primarily driven by MoveNet's outstanding accuracy and exceptional performance on edge devices [55]. Further reinforcing our decision, a recent study compared several skeleton-based human pose estimation models, including OpenPose, PoseNet, MoveNet, and MediaPipe Pose. The study's findings revealed that MoveNet exhibited the highest performance in detecting various human poses in static images and videos [56].

Fig. 3. Sample frames used for exemplifying common compensatory movements during the execution of a frontal raise (E3).

MoveNet is a bottom-up estimation model that uses heatmaps to localize human key points. The model is designed to be run in the browser using Tensorflow.js or on devices using TF Lite in real time. The variant MoveNet Thunder resulting in a higher capacity model that performs better prediction quality while still achieving high real-time speed was selected [56].

The MoveNet Thunder version architecture takes in input an RGB frame of video or an image with a resolution of 256 × 256. MoveNet output consists of lists containing the coordinate predictions of COCO's standard 17 keypoint locations, and their corresponding prediction confidence (see Fig. 4).

MoveNet was trained on two datasets: COCO and an internal Google dataset called Active. While COCO is the standard benchmark dataset for general detection, the Active dataset containing yoga, fitness, and dance videos from YouTube makes MoveNet suitable for physical activity and exercise monitoring. The architecture consists of a feature extractor and a set of prediction heads that inference the landmarks of the 17 body joints.

The feature extractor in MoveNet is MobileNetV2 [57] with an attached feature pyramid network, which allows for a high resolution (output stride 4), semantically rich feature map output. There are four prediction heads attached to the feature extractor, responsible for densely predicting: (i) person center heatmap: predicts the geometric center of person instances; (ii) keypoint regression field: predicts a full set of keypoints for a person, used for grouping keypoints into instances; (iii) person keypoint heatmap: predicts the location of all keypoints, independent of person instances; (iv) 2D per-keypoint offset

Table 1
Exercises description and characteristics.

Exercise name (N)	Camera view and scenario	List of ROM-classes	List of compensatory movements
Biceps curl (E1)	Camera view: V1 (frontal), V3 (lateral oblique); Scenario: S1 (standing)	Down (ROM-class 1): elbow extension (<30°) with the forearms parallel to the trunk; Incomplete down (ROM-class 2): incomplete elbow extension; Incomplete up (ROM-class 3): incomplete elbow flexion; Up (ROM-class 4): elbow flexion (>130°) with arms parallel to the trunk.	C1: excessively shoulder flexion with arms not parallel to the trunk during ROM-classes 3–4; C2: excessively trunk extension during ROM-classes 3-4.
Triceps curl (E2)	Camera view: V2 (lateral perpendicular), V3 (lateral oblique); Scenario: S2 (seated)	Down (ROM-class 1): elbow flexion (>130°) with the arms in line to the trunk; Incomplete down (ROM-class 2): incomplete elbow flexion; Incomplete up (ROM-class 3): incomplete elbow extension; Up (ROM-class 4): elbow extension (<30°) with the forearms parallel to the trunk.	C1: excessively shoulder abduction with the arms and trunk not aligned below them during ROM-classes 3-4.
Frontal raise (E3)	Camera view : V1 (frontal), V3 (lateral oblique); Scenario: S1 (standing)	Down (ROM-class 1): shoulder extension with the forearms parallel to the trunk; Incomplete down (ROM-class 2): incomplete shoulder extension; Incomplete up (ROM-class 3): incomplete shoulder flexion; Up (ROM-class 4): shoulder flexion at 90° with elbow aligned to shoulder and wrist joints.	C1: excessively trunk extension during ROM-classes 3-4; C2: elbow flexion not aligned to shoulder and wrist joints during ROM-classes 3-4.
Squat (E4)	Camera view: V1 (frontal), V3 (lateral oblique); Scenario: S1 (standing)	Up (ROM-class 1): standing upright position; Incomplete up (ROM-class 2): incomplete upright position; Incomplete down (ROM-class 3): incomplete squat position; Down (ROM-class 4): squat position with bent knees and hips aligned below them.	C1: excessively trunk flexion during ROM-classes 3-4; C2: knees and ankles joints not aligned below them during ROM-classes 3-4.
Leg extension (E5)	Camera view: V1 (frontal), V3 (lateral oblique); Scenario: S2 (seated)	Down (ROM-class 1): seated position with bent knee (90°); Incomplete down (ROM-class 2): incomplete flexion of knee; Incomplete up (ROM-class 3): incomplete extension of knee; Up (ROM-class 4): seated position with extended knee aligned to hip and ankle joints.	C1: hip flexion with knee not aligned to hip joint during ROM-classes 3-4.
Leg curl (E6)	Camera view: V1 (frontal), V3 (lateral oblique); Scenario: S1 (standing)	Down (ROM-class 1): standing upright position; Incomplete down (ROM-class 2): incomplete flexion of knee; Incomplete up (ROM-class 3): incomplete extension of knee; Up (ROM-class 4): seated position with bent knee aligned to hip joint.	C1: hip extension with knee not aligned to hip joint during ROM-classes 3-4.

field: predicts local offsets from each output feature map pixel to the precise sub-pixel location of each keypoint.

3.5. Body keypoints extraction and data normalization

The selected pose estimation module MoveNet Thunder was used to extract the body joints' pose data from each frame of the video dataset. The 2D position of 17 body keypoints (body skeleton) in the image coordinate system $\{I\}$ (Fig. 4). Each keypoint provided is denoted by $o_k^t = [p_k^t z_k^t]' = [x_k^t y_k^t z_k^t]'$. Here, $p_k^t = [x_k^t y_k^t]'$ denotes the transposed vector of 2D coordinates in the image of a body keypoint k from a set of joints K, t is the frame number, and z_k^t is a confidence score of keypoint detection. A moving average filter with a window of five frames was applied to reduce the noise and measurement errors of the pose estimation module in keypoints inferences [58,59].

In a real-world setting, subjects have body parts of different sizes and occupy different locations regarding the camera. Accordingly, landmarks were normalized and scaled to a constant pose size based on the torso's length size and the maximum distance of a landmark from the pose center. Each keypoint was transformed from the image coordinate

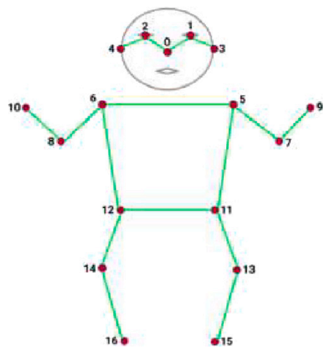


Fig. 4. COCO Keypoints used in MoveNet (nose = 0, left eye = 1, right eye = 2, left ear = 3, right ear = 4, left shoulder = 5, right shoulder = 6, left elbow = 7, right elbow = 8, left wrist = 9, right wrist = 10, left hip = 11, right hip = 12, left knee = 13, right knee = 14, left ankle = 15, right ankle = 16).

Table 2
MLP model configuration in Keras library.

Model architecture	Parameters/Activation function
Input layer	34
Hidden layer	128/ReLU
Drop out layer	0.5
Hidden layer	64/ReLU
Drop out layer	0.5
Output layer	$C = \{C_j \mid 1 \leq j \leq J\}$ / Softmax
Train configuration	**Parameters**
Epochs	200
Batch size	16
Early stopping	monitor='val accuracy' patience=5
Optimizer	Adam
Loss	Categorical cross entropy
Metrics	Accuracy

system $\{I\}$ to the body coordinate system $\{B\}$. The image coordinate system $\{I\}$ represents the Cartesian pixel coordinate system with its origin (0,0) located in the upper left corner. Conversely, the body coordinate system $\{B\}$ is also a Cartesian pixel coordinate system, but with its origin at the midpoint between the left hip ($k = 11$) and right hip ($k = 12$) ($c^t(p^t_{11}, p^t_{12})$ see Eq. (1)). The introduction of the body coordinate system $\{B\}$ aims to address variations in subject positions when facing the camera. To further account for differences in body part dimensions, each keypoint coordinate in the $\{B\}$ system was normalized based on the subject's spine length ($d^t(p^t_0, p^t_c)$ see Eq. (2)) measured at each time step t. This method allows the algorithm to generalize with different users' body length measurements, distance from the camera, as well as other relative factors.

$$c^t = \left(\frac{x^t_{11} + x^t_{12}}{2}, \frac{y^t_{11} + y^t_{12}}{2}\right) \tag{1}$$

$$d^t = \sqrt{(x^t_0 - x^t_c)^2 + (y^t_0 - y^t_c)^2} \tag{2}$$

3.6. Movement classification algorithm

A feedforward fully connected multilayer perceptron (MLP) classification algorithm was implemented in the Keras library to address the movement classification tasks [60]. Some studies recently evidenced that MLP achieves high accuracy in classification movement tasks for evaluation purposes in rehabilitation [61–63]. Each model was built using Python libraries such as TensorFlow, Keras, NumPy, and Scikit Learn [64,65].

The comprehensive configuration details of the neural network models used for the ROM classifier and the compensation classifier are summarized in Table 2. To arrive at the best configuration, we systematically explored various model architectures, ranging from one to three layers, with hidden units varying from 16 to 512. Additionally, we employed an adaptive learning rate approach with multiple initial learning rate values, including 0.001, 0.005, 0.01, 0.05, 0.1. This extensive exploration of hyperparameters was conducted using the Keras library, ensuring an optimized configuration for our neural network models.

The used MLP architecture consists of an input layer of 128 neurons, a hidden layer of 64 neurons, and an output layer (size depending on the number of classes to predict).

Preprocessed landmarks have been flattened in a feature vector representation used to feed the input layer. A batch size of 16 was used to train the model over epochs. Adam algorithm was selected for the model optimization and the early stopping technique was used to stop model training once its performance stops improving on the hold-out validation dataset (15% of the total of the training dataset).

Dropout regularization for reducing overfitting and improving the generalization of the model was used in the input and hidden layers by setting the hyperparameter at 0.5.

Rectified Linear Unit (ReLU) activation functions were used in the input and hidden layer. Softmax activation function was used in the output layer. About the classification task addressed by the model the categorical cross-entropy loss function was selected, and the accuracy metric (3) was used to assess the general model's performance.

Also, a set of metrics appropriated to a multi-class problem to evaluate our classification models' performance was adopted: Precision, Recall, and F1 score [66]. Precision (4) is the percentage of predicted labels truly significant for the sample. Recall (5) expresses the classifier's ability to detect all positive samples. Score F1 (6) is a weighted harmonic mean Precision and Recall, which measures classification accuracy.

$$acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$prec = \frac{TP}{TP + FP} \tag{4}$$

$$rec = \frac{TP}{TP + FN} \tag{5}$$

$$F1 = \frac{2TP}{2TP + FP + FN} \tag{6}$$

True positive (TP), true negative (TN), false positive (FP), and false negative (FN) were used in the above equations to denote the performance of the classification model.

The evaluation of performance metrics was conducted on test sets obtained by employing a stratified method to divide the original dataset into train and test subsets. This approach effectively maintains the class distribution from the original dataset in both subsets, making it particularly valuable when dealing with imbalanced datasets, where certain classes may have significantly fewer samples than others.

3.7. Data augmentation

In deep learning, artificial neural network models need a considerable number of samples for training to obtain satisfactory results, or else there may be overfitting, and the model's generalization ability may drastically decrease. However, for certain actions, it is difficult to obtain a quantity of available and quality samples, so data augmentation methods are used to enlarge the dataset. A data augmentation strategy is proposed to generate new frame samples and prevent the MLP model from overfitting and generalizing in various configuration settings. The strategy consists of mimicking a person acting in different places and sides in the field of view and at different distances from

Table 3
Data augmentation parameters used in Keras library.

Argument	Parameter value
Width shift range	0.2
Height shift range	0.2
Zoom range	[0.9,1.8]
Horizontal flip	True
Fill mode	'nearest'

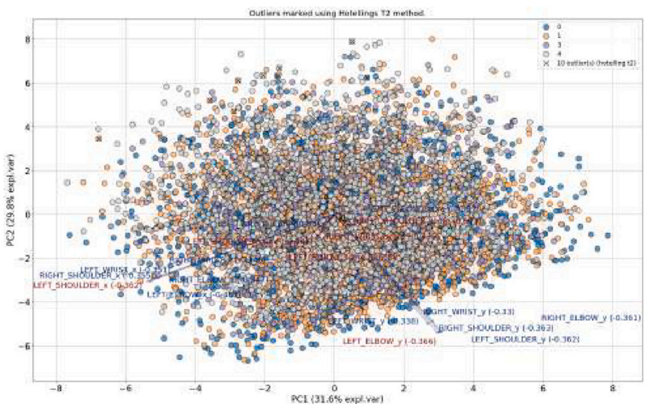


Fig. 5. Example of outliers detection plot using Hotelling T^2 statistics for ROM-classes in E1 dataset.

the camera view. The Keras 'Image Data Generator' library was used to apply transformations to obtain augmented data [65]. Horizontal and vertical shifts were applied to simulate an action performed in different places of view. A horizontal flip was applied to simulate the exercise also performed with the left body side and not only performed by the right side as obtained in the video dataset. A range for zooming in and out each frame of the dataset was applied to simulate the various distances from the camera that the subject could accomplish. The parameters of the arguments of each transformation are synthesized in Table 3.

Noteworthy is to highlight that each exercise dataset was split into train and test sets and therefore data augmentation was applied on each split set, including the test dataset. The dataset was splitted in train and test sets using a stratified method, which effectively preserves the class distribution from the original dataset in both subsets. This approach enhances the model's ability to generalize well to new, unseen data and ultimately contributes to the robustness of our findings. In this way, the model's performance was evaluated taking into account both the original test dataset (not augmented), containing the frames acquired in an optimal setup configuration, and a generated test dataset containing the augmented frame used to simulate a real application that no expects setup configurations. This method allows us to assess whether setup configurations should be necessary to consider in the development process of the system that integrates the proposed system to monitor and assess rehabilitation exercises at home.

Some of the applied transformations introduced some measurement errors during the inference of the 2D human pose network so an outlier detection method was applied to the train dataset before compiling the model. Considering the multivariate characteristics of the dataset a principal component analysis (PCA) was used to reduce the dimensionality of the data and the Hotelling T^2 test was applied to detect outliers across the multidimensional space of PCA [67–69]. The Hotelling T^2 computes the chi-square tests and P-values (level of significance fixed at $\alpha < 0.05$) across the top five PCA components which allows to determine the detection of outliers with its ranking (strongest to weak). A visual example of the outlier detection algorithm is shown in Fig. 5.

4. Results

The datasets containing images of a healthy subject labeled for ROM classes and compensatory movement categories were pre-processed by MoveNet to obtain kinematic data of the 17 body joints detected along with the ground truth class labels. The characteristics of each dataset used for the ROM classifier and the compensation movement classifier are presented in Table 4. Also, in Table 4 is synthesized information regarding the number of samples synthesized from data augmentation and the number of frames that the 2D human pose estimation module effectively succeeded to process.

The proposed MLP classification algorithm showed good performance in classifying both ROM classes and also compensatory movements. Classification results obtained for the ROM classifier and the compensation classifier are reported in Table 5 in terms of accuracy, precision, recall, and F1-score.

Classification performances of each model over ROM-classes and compensation movements categories are respectively reported in detail in Tables 6 and 7.

The confusion matrix of each model is presented in Tables 8 and 9.

To better understand each model's performance on each exercise, incorrect samples predicted by the ROM classifiers and compensation classifiers are plotted respectively in Fig. 6 and Fig. 7.

5. Discussion

Providing qualitative and quantitative evaluation of rehabilitation exercises to patients is fundamental for supporting the effective implementation of at-home rehabilitation programs.

The advances in machine learning and computer vision techniques have inspired an increased interest in the automated evaluation of rehabilitation exercises. Despite the progress, there are still open questions and numerous challenges to overcome before the broad deployment of these systems in home-based and in-clinic settings.

An innovative deep learning-based system for monitoring and assessing resistance training exercises has been proposed in this work.

First, a dataset of rehabilitation exercises was obtained to provide an extensive list of key poses in terms of ROM classes and compensatory movements that are associated with every single frame that was acquired. Specifically, a set of conditions described in Table 1 were used to label each single frame. Secondly, a state-of-the-art 2D pose estimation network was used to extract landmark coordinates from each sample in the dataset to obtain kinematic data in terms keypoints of the 17 body joints. Finally, a movement classification approach based on the MLP algorithm was implemented to recognize correct and compensatory movements under the scope of assessing the rehabilitation exercise.

The results of each stage of this method were individually evaluated: first, the ones corresponding to the exercises ROM-class recognition and then, those results obtained during the compensation evaluation. The proposed method showed high precision to recognize both ROM classes and compensatory movement patterns, following recent findings evidencing the high performance of the MLP model in classification tasks applied to the movement analysis [61–63]. Concerning its metrics, most models achieved accuracy, F1-score, precision, and recall above 90% when the best setup configuration is provided for the exercise monitoring (compare the results between test original and test augmented in Table 5).

The results presented in Table 5 demonstrate that our approach achieves comparable performance to state-of-the-art discrete movement classification methods used for exercise evaluation. For instance, in existing literature, certain approaches have shown high accuracy in classifying movements into correct or erroneous execution classes [32,33,70].

For example, in the work by [32], the authors achieved an accuracy above 90% in classifying error movements using a support vector

Table 4
Datasets characteristics in terms of number of samples at all the stages of the experimental process.

Exercise	ROM class	Data original		Data augmented		Data processed		
		Train	Test	Train	Test	Train augmented	Test augmented	Test original
E1	Down (M = 1)	439	109	2634	654	2579	636	109
	Incomplete down (M = 2)	369	92	2214	552	2189	546	92
	Incomplete up (M = 3)	530	132	3180	792	3159	789	132
	Up (M = 4)	316	78	1896	468	1879	458	78
E2	Down (M = 1)	378	94	2268	564	2259	564	94
	Incomplete down (M = 2)	333	83	1998	498	1983	494	83
	Incomplete up (M = 3)	620	155	3720	930	3693	926	155
	Up (M = 4)	452	113	2712	678	2698	673	113
E3	Down (M = 1)	465	116	2790	696	2756	683	116
	Incomplete down (M = 2)	598	149	3588	894	3548	880	149
	Incomplete up (M = 3)	432	107	2592	642	2755	634	107
	Up (M = 4)	410	102	2460	612	2443	601	102
E4	Up (M = 1)	369	92	2214	552	2175	547	92
	Incomplete up (M = 2)	728	181	4368	1086	4315	1066	181
	Incomplete down (M = 3)	723	180	4338	1080	4298	1067	180
	Down (M = 4)	240	60	1440	360	1425	356	60
E5	Down (M = 1)	715	178	4290	1068	4141	1060	178
	Incomplete down (M = 2)	411	102	2466	612	2414	601	102
	Incomplete up (M = 3)	311	77	1866	462	1827	457	77
	Up (M = 4)	252	62	1512	372	1489	368	62
E6	Down (M = 1)	900	225	5400	1350	5308	1324	225
	Incomplete down (M = 2)	301	75	1806	450	1790	446	75
	Incomplete up (M = 3)	252	63	1512	378	1494	376	63
	Up (M = 4)	220	54	1320	324	1308	323	54
Exercise	Compensation class	Data original		Data augmented		Data processed		
		Train	Test	Train	Test	Train augmented	Test augmented	Test original
E1	C1 (shoulder flexion)	903	225	5418	1350	5363	1332	225
	C2 (trunk extension)	659	164	3954	984	3797	963	164
	Good patterns	845	211	5070	1266	5021	1257	211
E2	C1 (shoulder abduction)	878	219	5268	1314	5098	1293	219
	Good patterns	1075	268	6450	1608	6394	1603	268
E3	C1 (trunk extension)	984	245	5904	1470	5703	1383	245
	C2 (elbow flexion)	734	183	4404	1098	4266	1032	183
	Good patterns	841	210	5046	1260	5011	1241	210
E4	C1 (trunk flexion)	927	231	5562	1386	5232	1312	231
	C2 (knees displacement)	511	127	3066	762	2960	742	127
	Good patterns	963	240	5778	1440	5744	1423	240
E5	C1 (hip flexion)	800	200	4800	1200	4583	1157	200
	Good patterns	571	142	3426	852	3378	839	142
E6	C1 (hip extension)	913	228	5478	1368	5460	1366	228
	Good patterns	460	115	2760	690	2731	686	115

Table 5
Classification results in terms of accuracy, precision, recall, and F1-score obtained for the ROM classifiers and the compensation classifiers.

Model performance	Test set	ROM classifier				Compensation-classifier			
		Accuracy	*Precision*	*Recall*	*F1-score*	*Accuracy*	*Precision*	*Recall*	*F1-score*
E1	Original	0.94	0.95	0.93	0.94	0.97	0.98	0.97	0.97
	Augmented	0.90	0.93	0.88	0.89	0.95	0.96	0.94	0.94
E2	Original	0.85	0.85	0.85	0.85	1.00	1.00	1.00	1.00
	Augmented	0.76	0.79	0.75	0.75	0.97	0.98	0.97	0.97
E3	Original	0.95	0.96	0.95	0.95	0.95	0.95	0.95	0.95
	Augmented	0.93	0.94	0.93	0.93	0.90	0.91	0.90	0.90
E4	Original	0.88	0.87	0.91	0.88	0.99	0.99	0.99	0.99
	Augmented	0.86	0.84	0.87	0.85	0.98	0.98	0.96	0.97
E5	Original	0.86	0.81	0.81	0.81	1.00	1.00	1.00	1.00
	Augmented	0.81	0.76	0.78	0.76	0.99	0.99	0.99	0.99
E6	Original	0.89	0.86	0.86	0.86	1.00	1.00	1.00	1.00
	Augmented	0.87	0.83	0.81	0.81	0.98	0.98	0.97	0.98

machine (SVM) algorithm. Similarly, in [33], authors used a Hidden-Markov Model approach to classify correct and incorrect movements with an accuracy of 92%. In [70], a k-nearest neighbors classifier was applied for exercise classification after filtering the data noise and applying dimensionality reduction, resulting in a classification accuracy of 96%.

Some other works focus on evaluating the phase of each exercise to monitor subjects' performance in a detailed and highly accurate

Table 6
Classification results in terms of accuracy, precision, recall, and F1-score obtained for each class of the ROM classifiers.

Model performance	ROM class	Test original			Test augmented		
		Precision	*Recall*	*F1-score*	*Precision*	*Recall*	*F1-score*
E1	Down (M = 1)	0.91	0.97	0.94	0.89	0.98	0.93
	Incomplete down (M = 2)	0.96	0.89	0.93	0.98	0.86	0.92
	Incomplete up (M = 3)	0.92	1.00	0.96	0.84	1.00	0.91
	Up (M = 4)	1.00	0.86	0.92	0.99	0.68	0.81
E2	Down (M = 1)	0.84	0.96	0.90	0.82	0.95	0.88
	Incomplete down (M = 2)	0.76	0.73	0.75	0.72	0.63	0.67
	Incomplete up (M = 3)	0.84	0.87	0.86	0.68	0.87	0.77
	Up (M = 4)	0.95	0.82	0.88	0.93	0.54	0.68
E3	Down (M = 1)	0.94	1.00	0.97	0.92	0.96	0.94
	Incomplete down (M = 2)	0.93	0.95	0.94	0.91	0.93	0.92
	Incomplete up (M = 3)	0.96	0.90	0.93	0.92	0.91	0.92
	Up (M = 4)	1.00	0.96	0.98	0.99	0.93	0.96
E4	Up (M = 1)	0.84	0.90	0.91	0.79	0.99	0.88
	Incomplete up (M = 2)	0.99	0.78	0.87	0.96	0.79	0.87
	Incomplete down (M = 3)	0.86	0.91	0.89	0.87	0.88	0.87
	Down (M = 4)	0.79	0.95	0.86	0.74	0.80	0.77
E5	Down (M = 1)	0.99	0.97	0.98	0.99	0.92	0.95
	Incomplete down (M = 2)	0.87	0.86	0.87	0.76	0.81	0.78
	Incomplete up (M = 3)	0.64	0.71	0.67	0.60	0.50	0.55
	Up (M = 4)	0.75	0.71	0.73	0.67	0.87	0.76
E6	Down (M = 1)	0.95	0.94	0.95	0.93	0.97	0.95
	Incomplete down (M = 2)	0.74	0.81	0.78	0.79	0.72	0.76
	Incomplete up (M = 3)	0.86	0.76	0.86	0.83	0.63	0.71
	Up (M = 4)	0.88	0.93	0.90	0.76	0.91	0.83

Table 7
Classification results in terms of accuracy, precision, recall, and F1-score obtained for each category of the compensation classifiers.

Model performance	Compensation class	Test original			Test augmented		
		Precision	*Recall*	*F1-score*	*Precision*	*Recall*	*F1-score*
E1	C1	0.94	1.00	0.97	0.88	1.00	0.94
	C2	1.00	0.91	0.95	1.00	0.82	0.90
	Good patterns	1.00	1.00	1.00	1.00	1.00	1.00
E2	C1	1.00	1.00	1.00	1.00	0.94	0.97
	Good patterns	1.00	1.00	1.00	0.95	1.00	0.98
E3	C1	0.98	0.96	0.97	0.98	0.87	0.92
	C2	1.00	0.88	0.94	0.95	0.87	0.91
	Good patterns	0.89	1.00	0.94	0.80	0.96	0.87
E4	C1	0.98	1.00	0.99	0.94	1.00	0.97
	C2	1.00	0.97	0.98	1.00	0.89	0.94
	Good patterns	1.00	1.00	1.00	1.00	1.00	1.00
E5	C1)	1.00	0.99	1.00	1.00	0.99	1.00
	Good patterns	0.99	1.00	1.00	0.99	1.00	0.99
E6	C1	1.00	1.00	1.00	0.97	1.00	0.99
	Good patterns	1.00	1.00	1.00	1.00	0.94	0.97

manner, as proposed in our study [71,72]. In [71], the authors achieved an overall accuracy of 87% in classifying segmented motions occurring during a shoulder rehabilitation exercise. Moreover, [72] utilized multi-label classifiers to detect subtle errors in exercise performances, achieving a sensitivity of 75%, specificity of 90%, and accuracy of 80%.

Our results demonstrate that our approach is competitive with these state-of-the-art methods in accurately classifying exercise movements, which is crucial for effective rehabilitation monitoring.

The analysis reveals consistent differences in model performance across exercises. Table 5 shows that exercises involving more distinct motion classes achieve superior metrics in ROM-class classification. For instance, the ROM classifiers for E1 and E3 exercises exhibit accuracy levels above 95%, primarily attributed to the substantial variations in motion features observed within each movement category. This finding is also supported by the models' performance in recognizing compensatory movements, where little substantial difference exists between exercises, as shown in Table 7. The high accuracy in distinguishing between correct and compensatory performances for each exercise is attributed to the markedly distinct features they exhibit. Conversely, exercises with minor differences in motion features between movement classes show poorer classification performance. Consequently, consecutive ROM classes in these exercises are closer together compared to exercises with well-distinguished motion classes [73]. A clear illustration of this can be seen in the varying metrics of the ROM classifier for exercises E5 and E6, as presented in Table 6. Notably, the confusion matrix in Table 8 indicates that incorrect sample predictions made by the ROM classifier typically belong to classes of consecutive motion classes.

Moreover, the ROM classifier's classification metrics might be negatively impacted by partially occluded and incorrectly detected body joints, as observed in exercises E2, E5, and E6 (Fig. 6). To address this concern, we applied a mean average filter with a five-frame window, effectively smoothing the data and yielding more dependable results.

Additionally, the system demonstrates remarkable generalizability across various conditions, successfully simulating patients placed at different angles and distances in front of the camera. Nevertheless, to ensure precise evaluations of exercises E2, E5, and E6, which displayed decreased performance in the augmented dataset compared to the

Table 8
Confusion matrix of ROM classifiers.

Confusion matrix	True labels	Test original				Test augmented			
		Predicted labels				Predicted labels			
E1	Down	106	3	0	0	624	12	0	0
	Incomplete down	10	82	0	0	75	471	0	0
	Incomplete up	0	0	132	0	0	0	786	3
	Up	0	0	11	67	0	0	146	312
E2	Down	90	4	0	0	535	29	0	0
	Incomplete down	17	61	5	0	114	311	69	0
	Incomplete up	0	15	135	5	0	92	808	26
	Up	0	0	20	93	0	0	310	363
E3	Down	116	0	0	0	657	26	0	0
	Incomplete down	7	142	0	0	61	818	1	0
	Incomplete up	0	11	96	0	0	51	577	6
	Up	0	0	4	98	0	0	45	556
E4	Up	91	1	0	0	541	6	0	0
	Incomplete up	17	141	23	0	148	847	71	0
	Incomplete down	0	1	164	15	0	31	937	99
	Down	0	0	3	57	0	0	70	286
E5	Down	172	6	0	0	953	87	0	0
	Incomplete down	1	88	13	0	7	485	109	0
	Incomplete up	0	7	55	15	0	66	230	161
	Up	0	0	18	44	0	0	47	321
E6	Down	212	13	0	0	1287	37	0	0
	Incomplete down	10	61	4	0	104	323	19	0
	Incomplete up	0	8	48	7	0	49	236	91
	Up	0	0	4	50	0	0	30	293

Table 9
Confusion matrix of compensation classifiers.

Confusion matrix	True labels	Test original			Test augmented		
		Predicted labels			Predicted labels		
E1	C1	225	0	0	1331	1	0
	C2	15	145	0	178	785	0
	Good patterns	0	0	211	0	0	1257
E2	C1	219		0	1212		76
	Good patterns	0		268	0		1601
E3	C1	235	0	10	1212	0	184
	C2	6	161	16	12	904	119
	Good patterns	0	0	210	7	43	1198
E4	C1	223	0	0	1309	3	0
	C2	4	118	0	80	662	0
	Good patterns	0	0	240	2	0	1421
E5	C1	191		1	1146		11
	Good patterns	0		142	0		839
E6	C1	228		0	1366		0
	Good patterns	0		115	39		647

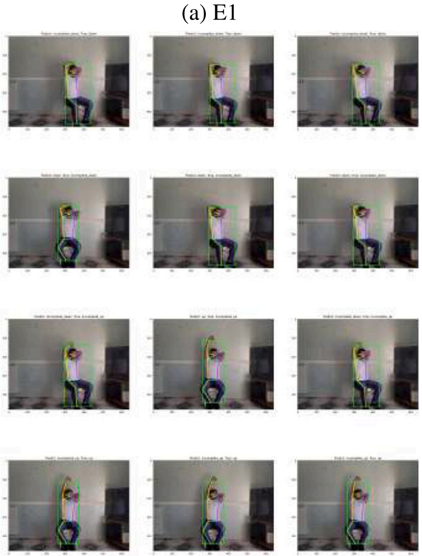
optimal condition, fine-tuning the patient's configuration in front of the camera becomes critical. This setup will significantly improve result reliability when assessing these specific exercises.

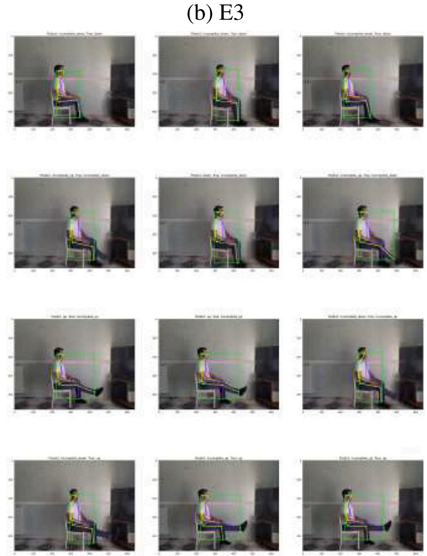
The proposed system presents two major advantages for future applications: one from the technical side and the other from the side of the exercise assessment.

The used 2D pose estimation network is an accurate model that runs well on hardware accelerators supported by TensorFlow Lite, including CPU and GPU. MoveNet is a model deployable on edge device running in real-time (30+ FPS) on most modern desktops, laptops, and phones, which proves crucial for live fitness, sports, and health applications. Also, the MLP model introduced for movement classification is easier to develop, not requiring preliminarily feature engineering like the other machine learning methods, and to adopt in smart assistant applications due to its relatively low computational costs. All mentioned characteristics make the proposed deep learning pose estimation and classification approach very useful to develop low-cost and smart applications for healthcare purposes such as the monitoring and assessment of rehabilitation exercises in home-based settings.

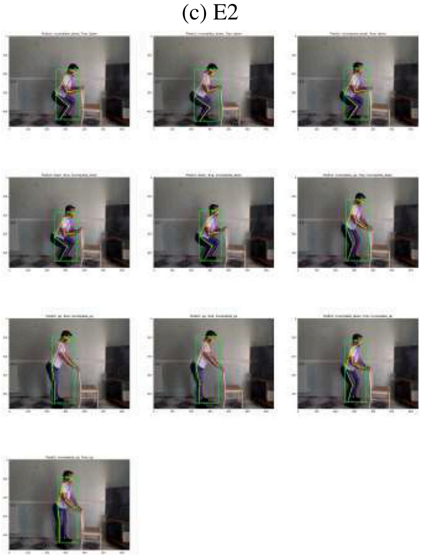
The other relevant aspect of the proposed methods is related to their applicability in clinical practice. The proposed method can promptly provide feedback regarding an individual's performance during exercise, simulating the routine activities of a rehabilitation expert. While a patient is performing a rehabilitation exercise, the data captured by the camera will be processed by the pose estimation algorithm to extract landmark features that are fed into a movement classification engine frame-by-frame for a detailed motion analysis based on predefined evaluation rules. The model trained to recognize correct concentric and eccentric key poses may be used to extract individual repetitions from a continuous motion sequence of an exercise to evaluate them in terms of completely or incompletely executed repetitions. Furthermore, the classifiers that recognize compensatory poses may provide real-time feedback with much more specific information regarding exactly how the motion deviates from the correct execution and quantify the quality of the overall exercise performance by analyzing the pose validity at each frame level. At last, the proposed approach avoids privacy issues related to clinical practice [74]. The pose estimation module elaborates only landmarks features from monocular RGB images for

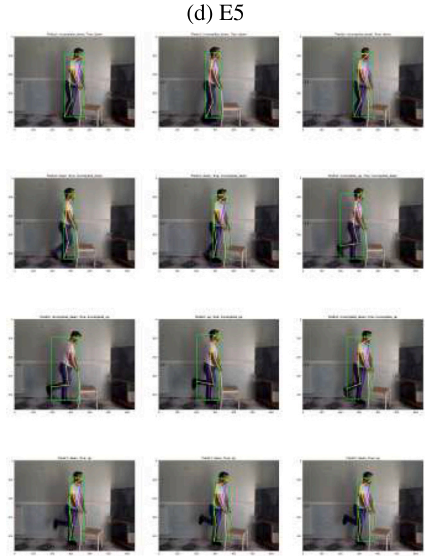
(a) E1 (b) E3





(c) E2 (d) E5





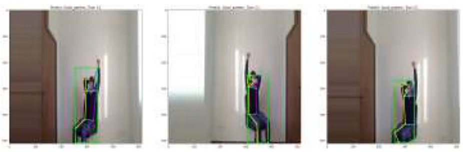
(e) E4 (f) E6

Fig. 6. Incorrect classes predicted by the ROM classifier for each exercise.

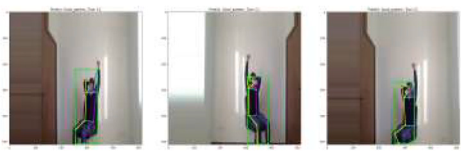
motion analysis [75]. This characteristic makes the approach highly robust for preserving subjects' privacy in their environment during decentralized rehabilitation treatments.

Before testing the presented approach in a relevant clinical application, future studies are required to investigate the performance of the proposed technique deployed on a prototype system that provides real-time evaluation of resistance training rehabilitation exercises. Further, setup configurations of the patient in front of the camera should be considered necessary for correctly monitoring and assessing in-home rehabilitation exercises in future validation studies. Moreover, also the

(a) E1

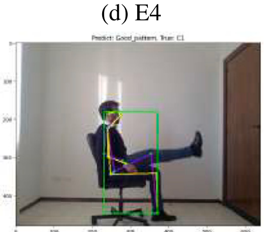


(b) E2

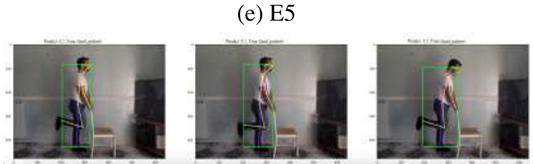


(c) E3

(d) E4



(e) E5



(f) E6

Fig. 7. Incorrect classes predicted by the compensation classifier for each exercise.

efficiency and user-friendliness of this type of system also should be discussed as crucial research topics in the next studies.

6. Conclusions

The field of rehabilitation technologies is increasingly focused on developing digital assistive systems to support and motivate patients during home sessions. A significant challenge for researchers lies in creating automated approaches for assessing patient performance and functional recovery. While deep learning has been widely studied for motion modeling, there has been limited research on movement evaluation in rehabilitation exercises.

This article introduces a deep learning-based application designed specifically for assessing rehabilitation exercises. The architecture encompasses five modules, each serving a unique purpose in the evaluation process. Importantly, the use of low-cost hardware to record human motion makes this approach highly attractive for future home-based rehabilitation applications.

As the future unfolds, we can expect ubiquitous systems offering remote assistance in rehabilitation procedures, significantly complementing traditional approaches for evaluating home rehabilitation programs. For instance, also the integration of AI-based voice assistants could profoundly impact patient engagement during remote exercise by providing instructions on movement sequences, posture correctness, and even offering suggestions to enhance exercise quality and identify areas requiring improvement.

These advancements hold immense potential in elevating patient outcomes and optimizing the overall efficacy of rehabilitation practices. The seamless integration of technology and healthcare is paving the way for a transformative era in medicine, revolutionizing patient care.

CRediT authorship contribution statement

Ciro Mennella: Supervision, Writing – original draft, Writing – review & editing, Formal analysis, Conceptualization, Methodology. **Umberto Maniscalco:** Supervision, Writing – review & editing, Conceptualization, Methodology. **Giuseppe De Pietro:** Conceptualization, Review and editing. **Massimo Esposito:** Supervision, Writing - Review and editing, Conceptualization, Methodology.

Declaration of competing interest

All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version. This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue. The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.

Acknowledgment

Ciro Mennella is a Ph.D. student enrolled in the National PhD in Artificial Intelligence, XXXVII cycle, course on Health and life sciences, organized by Università Campus Bio-Medico di Roma (Via Alvaro del Portillo 21, 00128 Roma, Italy).

References

[1] R.P. Van Peppen, G. Kwakkel, S. Wood-Dauphinee, H.J. Hendriks, P.J. Van der Wees, J. Dekker, The impact of physical therapy on functional outcomes after stroke: What's the evidence? Clin. Rehabil. 18 (8) (2004) 833–862.

[2] C. Burtin, B. Clerckx, C. Robbeets, P. Ferdinande, D. Langer, T. Troosters, G. Hermans, M. Decramer, R. Gosselink, Early exercise in critically ill patients enhances short-term functional recovery, Crit. Care Med. 37 (9) (2009) 2499–2505.

[3] P. Langhorne, J. Bernhardt, G. Kwakkel, Stroke rehabilitation, Lancet 377 (9778) (2011) 1693–1702.

[4] D.U. Jette, R.L. Warren, C. Wirtalla, The relation between therapy intensity and outcomes of rehabilitation in skilled nursing facilities, Arch. Phys. Med. Rehabil. 86 (3) (2005) 373–379.

[5] M.J. Bade, J.E. Stevens-Lapsley, Early high-intensity rehabilitation following total knee arthroplasty improves outcomes, J. Orthopaedic Sports Phys. Therapy 41 (12) (2011) 932–941.

[6] T.L. Chmielewski, S.Z. George, S.M. Tillman, M.W. Moser, T.A. Lentz, P.A. Indelicato, T.N. Trumble, J.J. Shuster, F.M. Cicuttini, C. Leeuwenburgh, Low-versus high-intensity plyometric exercise during rehabilitation after anterior cruciate ligament reconstruction, Am. J. Sports Med. 44 (3) (2016) 609–617.

[7] C. Sherrington, A. Tiedemann, N. Fairhall, J.C. Close, S.R. Lord, Exercise to prevent falls in older adults: An updated meta-analysis and best practice recommendations, South Wales Public Health Bull. 22 (4) (2011) 78–83.

[8] R. Komatireddy, A. Chokshi, J. Basnett, M. Casale, D. Goble, T. Shubert, Quality and quantity of rehabilitation exercises delivered by a 3-D motion controlled camera: A pilot study, Int. J. Phys. Med. Rehabil. 2 (4) (2014).

[9] S.F. Bassett, H. Prapavessis, Home-based physical therapy intervention with adherence-enhancing strategies versus clinic-based management for patients with ankle sprains, Phys. Therapy 87 (9) (2007) 1132–1143.

[10] K. Jack, S.M. McLean, J.K. Moffett, E. Gardiner, Barriers to treatment adherence in physiotherapy outpatient clinics: A systematic review, Manual Therapy 15 (3) (2010) 220–228.

[11] K.K. Miller, R.E. Porter, E. DeBaun-Sprague, M. Van Puymbroeck, A.A. Schmid, Exercise after stroke: Patient adherence and beliefs after discharge from rehabilitation, Topics Stroke Rehabil. 24 (2) (2017) 142–148.
[12] O.M. Giggins, U.M. Persson, B. Caulfield, Biofeedback in rehabilitation, J. Neuroeng. Rehabil. 10 (1) (2013) 1–11.
[13] H. Huang, S.L. Wolf, J. He, Recent developments in biofeedback for neuromotor rehabilitation, J. Neuroeng. Rehabil. 3 (1) (2006) 1–12.
[14] D. Siewiorek, A. Smailagic, A. Dey, Architecture and applications of virtual coaches, Proc. IEEE 100 (8) (2012) 2472–2488.
[15] F. Gimigliano, S. Negrini, The world health organization" rehabilitation 2030: A call for action", Eur. J. Phys. Rehabil. Med. 53 (2) (2017) 155–168.
[16] T. Rikakis, A. Kelliher, J. Choi, J.-B. Huang, K. Kitani, S. Zilevu, S.L. Wolf, Semi-automated home-based therapy for the upper extremity of stroke survivors, in: Proceedings of the 11th PErvasive Technologies Related To Assistive Environments Conference, 2018, pp. 249–256.
[17] E.V. Olesh, S. Yakovenko, V. Gritsenko, Automated assessment of upper extremity movement impairment due to stroke, PLoS One 9 (8) (2014) e104487.
[18] Y.X. Zhi, M. Lukasik, M.H. Li, E. Dolatabadi, R.H. Wang, B. Taati, Automatic detection of compensation during robotic stroke rehabilitation therapy, IEEE J. Transl. Eng. Health Med. 6 (2017) 1–7.
[19] M. Duff, Y. Chen, L. Cheng, S.-M. Liu, P. Blake, S.L. Wolf, T. Rikakis, Adaptive mixed reality rehabilitation improves quality of reaching movements more than traditional reaching therapy following stroke, Neurorehabil. Neural Repair 27 (4) (2013) 306–315.
[20] L. Bavan, K. Surmacz, D. Beard, S. Mellon, J. Rees, Adherence monitoring of rehabilitation exercise with inertial sensors: A clinical validation study, Gait Posture 70 (2019).
[21] M. Mancini, M. El-Gohary, S. Pearson, J. McNames, H. Schlueter, J.G. Nutt, L.A. King, F.B. Horak, Continuous monitoring of turning in Parkinson's disease: Rehabilitation potential, NeuroRehabilitation 37 (1) (2015) 3.
[22] A. Pereira, D. Folgado, R. Cotrim, I. Sousa, Physiotherapy exercises evaluation using a combined approach based on sEMG and wearable inertial sensors, in: Biosignals, 2019, pp. 73–82.
[23] L.V. Gauthier, C. Kane, A. Borstad, N. Strahl, G. Uswatte, E. Taub, D. Morris, A. Hall, M. Arakelian, V. Mark, Video game rehabilitation for outpatient stroke (VIGoROUS): Protocol for a multi-center comparative effectiveness trial of in-home gamified constraint-induced movement therapy for rehabilitation of chronic upper extremity hemiparesis, BMC Neurol. 17 (1) (2017) 1–18.
[24] P. Maciejasz, J. Eschweiler, K. Gerlach-Hahn, A. Jansen-Troy, S. Leonhardt, A survey on robotic devices for upper limb rehabilitation, J. Neuroeng. Rehabil. 11 (1) (2014) 1–29.
[25] S. Kyriazakos, H. Schlieter, K. Gand, M. Caprino, M. Corbo, P. Tropea, E. Judica, I. Sterpi, S. Busnatu, P. Philipp, et al., A novel virtual coaching system based on personalized clinical pathways for rehabilitation of older adults—requirements and implementation plan of the vCare project, Front. Digital Health 2 (2020) 546562.
[26] E.E. Cust, A.J. Sweeting, K. Ball, S. Robertson, Machine and deep learning for sport-specific movement recognition: A systematic review of model development and performance, J. Sports Sci. 37 (5) (2019) 568–600.
[27] V. Camomilla, E. Bergamini, S. Fantozzi, G. Vannozzi, In-field use of wearable magneto-inertial sensors for sports performance evaluation, in: ISBS-Conference Proceedings Archive, 2015.
[28] H.M. Fardoun, P. Gamito, V.M. Penichet, D.M. Alghazzawi, Proceedings of the 3rd 2015 Workshop on ICTs for improving Patients Rehabilitation Research Techniques, ACM, 2015.
[29] R.M. Viglialoro, S. Condino, G. Turini, M. Carbone, V. Ferrari, M. Gesi, Review of the augmented reality systems for shoulder rehabilitation, Information 10 (5) (2019) 154.
[30] C. Mennella, U. Maniscalco, G. De Pietro, M. Esposito, The role of artificial intelligence in future rehabilitation services: A systematic literature review, IEEE Access (2023).
[31] T. Hellsten, J. Karlsson, M. Shamsuzzaman, G. Pulkkis, The potential of computer vision-based marker-less human motion analysis for rehabilitation, Rehabil. Process Outcome 10 (2021) 11795727211022330.
[32] W. Wei, C. McElroy, S. Dey, Towards on-demand virtual physical therapist: Machine learning-based patient action understanding, assessment and task recommendation, IEEE Trans. Neural Syst. Rehabil. Eng. 27 (9) (2019) 1824–1835.
[33] Y. Rybarczyk, C. Cointe, T. Gonçalves, V. Minhoto, J.K. Deters, S. Villarreal, A.A. Gonzalo, J. Baldeón, D. Esparza, On the use of natural user interfaces in physical rehabilitation: A web-based application for patients with hip prosthesis, J. Sci. Technol. Arts 10 (2) (2018) 15–24.
[34] F. Sá, A. Marques, N.B. Rocha, M.J. Trigueiro, C. Campos, J. Schröder, Kinematic parameters of throwing performance in patients with Schizophrenia using a markerless motion capture system, Somatosens. Motor Res. 32 (2) (2015) 77–86.
[35] J.A. O'Keefe, A.A.E. Orías, H. Khan, D.A. Hall, E. Berry-Kravis, M.A. Wimmer, Implementation of a markerless motion analysis method to quantify hyperkinesis in males with fragile X syndrome, Gait Posture 39 (2) (2014) 827–830.
[36] H.R. Martinez, A. Garcia-Sarreon, C. Camara-Lemarroy, F. Salazar, M.L. Guerrero-González, Accuracy of markerless 3D motion capture evaluation to differentiate between On/Off status in parkinson's disease after deep brain stimulation, Parkinson's Dis. 2018 (2018).
[37] K. Krasowicz, J. Michoński, P. Liberadzki, R. Sitnik, Monitoring improvement in infantile cerebral palsy patients using the 4DBODY system—a preliminary study, Sensors 20 (11) (2020) 3232.
[38] W.W. Lam, Y.M. Tang, K.N. Fong, A systematic review of the applications of markerless motion capture (MMC) technology for clinical measurement in rehabilitation, J. Neuroeng. Rehabil. 20 (1) (2023) 1–26.
[39] M. Weinberger, The rise and fall of kinect: Why microsoft gave up on its most promising product, Bus. Insider 3 (2018).
[40] S. Sardari, S. Sharifzadeh, A. Daneshkhah, B. Nakisa, S.W. Loke, V. Palade, M.J. Duncan, Artificial intelligence for skeleton-based physical rehabilitation action evaluation: A systematic review, Comput. Biol. Med. 158 (2023) 106835.
[41] G.M. Difini, M.G. Martins, J.L.V. Barbosa, Human pose estimation for training assistance: A systematic literature review, in: Proceedings of the Brazilian Symposium on Multimedia and the Web, 2021, pp. 189–196.
[42] M. Clark, S. Lucett, et al., NASM Essentials of Corrective Exercise Training, Lippincott Williams & Wilkins, 2010.
[43] A. de los Reyes-Guzmán, I. Dimbwadyo-Terrer, F. Trincado-Alonso, F. Monasterio-Huelin, D. Torricelli, A. Gil-Agudo, Quantitative assessment based on kinematic measures of functional impairments during upper extremity movements: A review, Clin. Biomech. 29 (7) (2014) 719–727.
[44] Y. Liao, A. Vakanski, M. Xian, D. Paul, R. Baker, A review of computational approaches for evaluation of rehabilitation exercises, Comput. Biol. Med. 119 (2020) 103687.
[45] W. Kraemer, K. Adams, E. Cafarelli, G. Dudley, C. Dooly, M. Feigenbaum, S. Fleck, B. Franklin, A. Fry, J. Hoffman, R. Newton, J. Potteiger, M. Stone, N. Ratamess, T. Triplett-McBride, Position stand: Progression models in resistance training for healthy adultsAmerican college of sports MedicineMed Sci sports exerc20023436438011828249, Med. Sci. Sports Exercise 34 (2002) 364–380.
[46] J. Keogh, J. Lake, P. Swinton, Practical applications of biomechanical principles in resistance training: Moments and moment arms, J. Fitness Res. 2 (2013) 39–48.
[47] B. Ferreira, P.M. Ferreira, G. Pinheiro, N. Figueiredo, F. Carvalho, P. Menezes, J. Batista, Deep learning approaches for workout repetition counting and validation, Pattern Recognit. Lett. 151 (2021) 259–266.
[48] E.V. Papa, X. Dong, M. Hassan, Resistance training for activity limitations in older adults with skeletal muscle function deficits: A systematic review, Clin. Intervent. Aging (2017) 955–961.
[49] K. Talar, A. Hernández-Belmonte, T. Vetrovsky, M. Steffl, E. Kałamacka, J. Courel-Ibáñez, Benefits of resistance training in early and late stages of frailty and sarcopenia: A systematic review and meta-analysis of randomized controlled studies, J. Clin. Med. 10 (8) (2021) 1630.
[50] E. Marzetti, R. Calvani, M. Tosato, M. Cesari, M. Di Bari, A. Cherubini, M. Broccatelli, G. Savera, M. D'Elia, M. Pahor, et al., Physical activity and exercise as countermeasures to physical frailty and Sarcopenia, Aging Clin. Exper. Res. 29 (2017) 35–42.
[51] S.-Z. Yoo, M.-H. No, J.-W. Heo, D.-H. Park, J.-H. Kang, S.H. Kim, H.-B. Kwak, Role of exercise in age-related Sarcopenia, J. Exerc. Rehabil. 14 (4) (2018) 551.
[52] J.C. Mcleod, T. Stokes, S.M. Phillips, Resistance exercise training as a primary countermeasure to age-related chronic disease, Front. Physiol. 10 (2019) 645.
[53] J. Hong, J. Kim, S.W. Kim, H.-J. Kong, Effects of home-based tele-exercise on Sarcopenia among community-dwelling elderly adults: Body composition and functional fitness, Exper. Gerontol. 87 (2017) 33–39.
[54] M.E. Nelson, W.J. Rejeski, S.N. Blair, P.W. Duncan, J.O. Judge, A.C. King, C.A. Macera, C. Castaneda-Sceppa, Physical activity and public health in older adults: Recommendation from the American college of sports medicine and the American heart association, Circulation 116 (9) (2007) 1094.
[55] R. Votel, N. Li, Next-generation pose detection with MoveNet and TensorFlow.js, 2021, http://blog.tensorflow.org/2021/05/next-generation-pose-detection-with-movenet-and-tensorflowjs.html.
[56] J.-L. Chung, L.-Y. Ong, M.-C. Leow, Comparative analysis of skeleton-based human pose estimation, Future Internet 14 (12) (2022).
[57] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, L.-C. Chen, Mobilenetv2: Inverted residuals and linear bottlenecks, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 4510–4520.
[58] A.R. Cóias, M.H. Lee, A. Bernardino, A low-cost virtual coach for 2D video-based compensation assessment of upper extremity rehabilitation exercises, J. Neuroeng. Rehabil. 19 (1) (2022) 1–16.
[59] M.H. Lee, D.P. Siewiorek, A. Smailagic, A. Bernardino, S.B. Badia, Learning to assess the quality of stroke rehabilitation exercises, in: Proceedings of the 24th International Conference on Intelligent User Interfaces, 2019, pp. 218–228.
[60] J. Han, J. Pei, M. Kamber, Data Mining: Concepts and Techniques, Elsevier, 2011.
[61] V.C.E. Bernal, S.V. Hiremath, B. Wolf, B. Riley, R.J. Mendonca, M.J. Johnson, Classifying and tracking rehabilitation interventions through machine-learning algorithms in individuals with stroke, J. Rehabil. Assist. Technol. Eng. 8 (2021) 20556683211044640.

[62] H. Sarwat, H. Sarwat, S.A. Maged, T.H. Emara, A.M. Elbokl, M.I. Awad, Design of a data glove for assessment of hand performance using supervised machine learning, Sensors 21 (21) (2021).
[63] A. Macintosh, N. Vignais, E. Desailly, E. Biddiss, V. Vigneron, A classification and calibration procedure for gesture specific home-based therapy exercise in Young people with cerebral palsy, IEEE Trans. Neural Syst. Rehabil. Eng. 29 (2021) 144–155.
[64] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, E. Duchesnay, G. Louppe, Scikit-learn: Machine learning in Python, J. Mach. Learn. Res. 12 (2012).
[65] F. Chollet, et al., Keras, 2015.
[66] F. Herrera, F. Charte, A. Rivera Rivas, M.J. Del Jesus, Multilabel classification, 2016, http://dx.doi.org/10.1007/978-3-319-41111-8.
[67] P. Filzmoser, V. Todorov, Robust tools for the imperfect world, Inform. Sci. 245 (2013) 4–20.
[68] P. Filzmoser, V. Todorov, Review of robust multivariate statistical methods in high dimension, Anal. Chim. Acta 705 (1–2) (2011) 2–14.
[69] N.D. Tracy, J.C. Young, R.L. Mason, Multivariate control charts for individual observations, J. Qual. Technol. 24 (2) (1992) 88–95.
[70] S.-k. Jun, S. Kumar, X. Zhou, D.K. Ramsey, V.N. Krovi, Automation for individualization of kinect-based quantitative progressive exercise regimen, in: 2013 IEEE International Conference on Automation Science and Engineering, CASE, IEEE, 2013, pp. 243–248.
[71] L. Brennan, A. Bevilacqua, T. Kechadi, B. Caulfield, Segmentation of shoulder rehabilitation exercises for single and multiple inertial sensor systems, J. Rehabil. Assist. Technol. Eng. 7 (2020) 2055668320915377.
[72] P.E. Taylor, G.J. Almeida, J.K. Hodgins, T. Kanade, Multi-label classification for the analysis of human motion quality, in: 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE, 2012, pp. 2214–2218.
[73] S.G. de Villa, D. Casillas-Pérez, A. Jiménez-Martín, J.J. García-Domínguez, Simultaneous exercise recognition and evaluation in prescribed routines: Approach to virtual coaches, Expert Syst. Appl. 199 (2022) 116990.
[74] K.M. Chong, Privacy-preserving healthcare informatics: A review, in: ITM Web of Conferences, Vol. 36, 2021, p. 04005.
[75] T. Cao, M.A. Armin, S. Denman, L. Petersson, D. Ahmedt-Aristizabal, In-bed human pose estimation from unseen and privacy-preserving image domains, in: 2022 IEEE 19th International Symposium on Biomedical Imaging, ISBI, IEEE, 2022, pp. 1–5.