VIRTUAL-PHYSIO: A Virtual Assistant for Home Physiotherapy Rehabilitation

Nicoletta Balletti[1,2], Antonella Cascitelli[4], Patrizia Gabrieli[4], Emanuela Guglielmi[2], Gennaro Laudato[2], Aldo Lazich[1], Marco Notarantonio[1], Rocco Oliveto[2,3], Stefano Ricciardi[2], Simone Scalabrino[2] and Jonathan Simeone[3]

[1]*Center for Biotechnology, Institute of Biomedical Sciences of the Ministry of Defense, Rome, Italy*

[2]*University of Molise, Pesche (IS), Italy*

[3]*Datasound srl, Pesche (IS), Italy*

[4]*Atlantica Digital spa, Rome, Italy*

Keywords: Virtual Assistant, Home Rehabilitation, Artificial Intelligence, Motion Capturing.

Abstract: Mobility impairments reduce the ability of patients to complete daily activities. Physio-therapeutic exercises help patients address such limitations. Correctly executing these exercises is crucial, often requiring a physiotherapist's guidance. To address this need, combining advanced sensors with artificial intelligence offers a promising solution for home rehabilitation, enabling remote monitoring and reducing stress. In this paper, we introduce VIRTUAL-PHYSIO, a virtual assistant for remote rehabilitation integrated into a home-deployable low-cost physiotherapy monitoring system 2VITA-B PHYSICAL. VIRTUAL-PHYSIO provides real-time feedback during rehabilitation exercises and evaluates entire sessions, allowing physiotherapists to focus on critical cases. We experimented with VIRTUAL-PHYSIO on 51 individuals whose performances were also evaluated by a physiotherapist as a reference. The results (i) highlight good patient acceptability for the virtual assistant, and (ii) show that the proposed machine learning approach can effectively perform an automated evaluation of rehabilitative movements.

1 INTRODUCTION

Rehabilitation, like prevention, promotion, treatment, and palliation, is an important health service both in the community and in hospitals. Physical rehabilitation aims to (i) achieve complete recovery, in the case of patients with transient motor deficits, and (ii) relieve suffering and provide a higher level of independence, in the case of patients with permanent dysfunction. The proper execution of rehabilitation exercises is crucial to recover quickly.

Physical therapy has received attention from the computer science research community over the years, with a special focus on home-based rehabilitation. Home rehabilitation allows patients to complete rehabilitation exercises in the comfort of their own homes by reducing the hassle and cost of commuting on a daily or weekly basis. This helps to improve treatment quality and hasten recovery (Maclean et al., 2002), while also lowering hospitalisations and, as a result, healthcare costs (Han et al., 2005). Although remote monitoring of patients solves a logistical problem for patients, this solution still requires the active presence and intervention of a human expert (physiotherapist). The reason is that only a small percentage of patients with motor disabilities complete exercises as recommended (Shaughnessy et al., 2006). The physiotherapist is in charge of carefully observing patients performing the exercises and making them correct their movements when necessary. The natural unbalance between the number of patients and the number of physiotherapists constitutes a problem: The physiotherapist needs to schedule meetings with patients. Ideally, human experts should intervene only when necessary, so that they can better focus on cases that require particular attention.

To tackle this problem, we introduce VIRTUAL-PHYSIO, a virtual assistant for home rehabilitation. We integrated VIRTUAL-PHYSIO in the 2VITA-B PHYSICAL system (Antico et al., 2021a), which uses

Balletti, N., Cascitelli, A., Gabrieli, P., Guglielmi, E., Laudato, G., Lazich, A., Notarantonio, M., Oliveto, R., Ricciardi, S., Scalabrino, S. and Simeone, J.
VIRTUAL-PHYSIO: A Virtual Assistant for Home Physiotherapy Rehabilitation.
DOI: 10.5220/0013127400003911

In *Proceedings of the 18th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2025) - Volume 2: HEALTHINF*, pages 467-474
ISBN: 978-989-758-731-3; ISSN: 2184-4305

a low-cost easy-to-install motion tracking sensor (*i.e.,* the Azure Kinect DK) which proved to be suited to perform physiotherapy monitoring at home(Antico et al., 2021b).

VIRTUAL-PHYSIO aims to (i) guide patients while they perform exercises by giving them feedback about their movement, and (ii) evaluate a whole exercise session so that a physiotherapist can be notified about the cases that might require attention. To achieve the first goal, we use a virtual 3D body model that visually mirrors the patients' movements, possibly highlighting limbs not correctly positioned at a given time. To achieve the second goal, we exploit machine learning algorithms to compare the optimal movement and the actual one to automatically distinguish sessions that a physiotherapist would consider well-performed from the ones containing relevant errors.

We verified the effectiveness of VIRTUAL-PHYSIO in a controlled experiment involving 51 participants, who used the virtual assistant during rehabilitation sessions. The results achieved show that (i) the level of real-time audio-visual feedback provided by the system during the remote rehab session greatly increases the patient's confidence in such a system and their willingness to attend a home rehabilitation plan, and (ii) the proposed automated evaluation models, according to the different machine learning techniques considered, achieves up to 84% accuracy.

2 RELATED WORK

In this section, we discuss previous work to support home rehabilitation using machine learning (ML).

Recent advancements in home-based rehabilitation leverage machine learning and sensor technologies to enhance patient outcomes and accessibility. Chae *et al.* (Chae et al., 2020) demonstrated that a system using a smartwatch and machine learning could improve motor function and shoulder mobility in chronic stroke patients, achieving notable accuracy in performance assessments. Similarly, Osgouei *et al.* (Osgouei et al., 2020) explored how different algorithms suit various rehabilitation stages, with Hidden Markov Models excelling in early-stage performance monitoring and Dynamic Time Warping providing detailed analysis later. Adans-Dester *et al.* (Adans-Dester et al., 2020) utilized wearable sensor data and machine learning to estimate functional ability and Fugl-Meyer scores accurately during motor task performance. Imura *et al.* (Imura et al., 2021) identified key variables for predicting home discharge outcomes using a classification and regression tree model. Liao *et al.* (Liao et al., 2020) reviewed machine learning approaches for motion capture systems, emphasizing their effectiveness in quantifying movement quality in home-based settings.

Table 1: Summary of studies on the design and implementation of home rehabilitation systems. The column *Part.* indicates the number of participants involved in each study, *RT-Feed* specifies whether real-time feedback was provided, and *ML* denotes the use of machine learning techniques.

Reference	**Goal of the Study**	**# Part.**	**RT-Feed**	**ML**
(Lee, 2018)	Build computer-assisted stroke rehabilitation using Kinect and ML	26	x	x
(Chae et al., 2020)	Develop and evaluate a web-based upper limb home rehabilitation system using a smartwatch and ML model	38	-	x
(Osgouei et al., 2020)	Use of Motion Sensing and ML to Quantify Exercise Performance in Healthy Volunteers	16	-	x
(Adans-Dester et al., 2020)	Enabling precision rehabilitation interventions using wearable sensors and ML to track motor recovery	37	-	x
(Liao et al., 2020)	Review computational approaches for the evaluation of rehabilitation exercises	54	x	x
(Lee et al., 2020)	Combine machine and human intelligence for personalized rehabilitation assessment	26	-	x
(Ahammad et al., 2020)	Spinal cord disorder classification for patient wellness and remote monitoring	950	-	x
(Kashi et al., 2020)	Automatic detection of movement compensation in stroke patients	30	x	x
(Imura et al., 2021)	Identify stroke patients after rehabilitation using functional and environmental predictors	1125	-	x
(Biebl et al., 2021)	Show that the interrater agreement between physiotherapists and Motion Coach is noninferior to physiotherapists' interrater agreement for exercise evaluations	24	x	x
(Ranasinghe et al., 2021)	Introduce a system for people to perform physical exercise at home	16	x	x
(Seifallahi et al., 2022)	Alzheimer's disease detection based on video data using ML	85	-	x
(Bijalwan et al., 2022)	Guide patients to perform real-time upper limb physiotherapy	25	-	x
This work	Introduce *VIRTUAL-PHYSIO*, a virtual assistant to support home rehabilitation	51	x	x

Interactive machine learning approaches, such as the one described by Lee *et al.* (Lee et al., 2020), combine expert input with data-driven models to assess rehabilitation exercise quality. Ahammad *et al.* (Ahammad et al., 2020) focused on spinal cord disorder classification using sensor data, demonstrating improved efficiency in remote care. Biebl *et al.* (Biebl et al., 2021) validated the MotionCoach app, showing strong agreement with physiotherapist evaluations in osteoarthritis patients.

Other works emphasize innovative feedback mechanisms. Ranasinghe *et al.* (Ranasinghe et al., 2021) proposed a muscle-strength-based exercise difficulty measurement method, enabling remote patient guidance through instructional videos. Kashi *et al.* (Kashi et al., 2020) developed a ML model to provide feedback on stroke patient movements, achieving 85% precision in detecting compensations.

Low-cost systems have also gained traction. Lee *et al.* (Lee, 2018) introduced Virtual Coach, a post-stroke rehabilitation system with 78% agreement with clinicians. Seifallahi *et al.* (Seifallahi et al., 2022) and Bijalwan *et al.* (Bijalwan et al., 2022) applied Kinect v2 sensors to detect Alzheimer's disease and categorize rehabilitation exercises, achieving accuracies of 97.75% and over 98%, respectively.

Table 1 shows that the evaluation of VIRTUAL-PHYSIO involved a participant count comparable to prior studies. Unlike previous work, VIRTUAL-

PHYSIO uniquely integrates real-time feedback and automatic exercise evaluation through machine learning, offering a novel approach to home rehabilitation.

3 2VITA-B PHYSICAL IN A NUTSHELL

The 2VITA-B PHYSICAL (Antico et al., 2021a) system is the foundation of the VIRTUAL-PHYSIO, the proposed virtual assistant for home-based physiotherapy. 2VITA-B PHYSICAL is designed to monitor and support the physical rehabilitation process by creating a link between the therapist and the patient. In 2VITA-B PHYSICAL, each user plays a distinct role in ensuring the successful functioning of the rehabilitation process, in which various professionals contribute to the recovery process of the patient.

The **admin** manages access and creates user profiles. The **physiatrist** enrolls new patients and develops an Individual Rehabilitation Project (IRP). The **physiotherapist** designs and updates exercises based on the patient's condition and progress. The **psychologist** monitors the patient's psychological state during rehabilitation. Lastly, the **patient** follows a personalized rehabilitation plan, consisting of exercises tailored to their therapy.

Patient enrollment is the process of designing a personalized rehabilitation plan. When a new patient begins rehabilitation, the physiatrist registers them and creates an Individual Rehabilitation Project (IRP), entering all relevant health information. The physiotherapist then develops the rehabilitation plan by selecting a set of exercises from a manageable list, tailored to the patient's specific needs.

The core of 2VITA-B PHYSICAL is represented by the Rehab Station, a dedicated station used by the patient during rehabilitation activities. Rehabilitation activities are conducted using the Rehab Station, which includes a laptop running 2VITA-B PHYSICAL software, a Microsoft Azure Kinect motion sensor for movement analysis, and a Polar OH1 heart rate monitor. In detail, for each exercise, a physiotherapist must record the ideal execution, which is used by VIRTUAL-PHYSIO to give real-time feedback to the patient and to evaluate the execution. This means that, once a patient has been assigned to a new rehabilitation plan, the 2VITA-B PHYSICAL system could be used also without the presence of the physiotherapist.

The system also registers a video of the movement and the automatic evaluation provided by VIRTUAL-PHYSIO. Such an evaluation is used by the 2VITA-B PHYSICAL to alert the physiotherapist that the patient wrongly executed an exercise. This enables the physiotherapist to review the execution, provide feedback, or reach out to the patient for further clarification. Patients can also provide self-assessments, and both patient and physiotherapist evaluations are used to continuously train VIRTUAL-PHYSIO.

4 THE VIRTUAL ASSISTANT FOR HOME REHABILITATION

VIRTUAL-PHYSIO is a virtual assistant integrated into the 2VITA-B PHYSICAL system, designed to help patients perform rehabilitation exercises correctly and assist physiotherapists by automatically assessing exercise performance. Once the physiatrist creates an Individual Rehabilitation Project (IRP), patients interact with VIRTUAL-PHYSIO through a straightforward, touch-friendly interface. This interface guides them through the rehabilitation process, allowing them to watch a demonstration video of the exercise, perform it, review their performance, and provide a self-assessment.

After the exercise is completed, VIRTUAL-PHYSIO evaluates the execution, enabling physiatrist and physiotherapist oversight to ensure progress and address any issues. A rehabilitation session includes multiple exercises, each consisting of several repetitions. The term exercise refers to the complete set of repetitions, while repetition describes a single instance of the movement, highlighting the structured approach VIRTUAL-PHYSIO brings to the rehabilitation process.

4.1 Guiding Patients in Rehab Exercises

VIRTUAL-PHYSIO provides real-time support to patients during the execution of rehabilitation exercises by utilizing a dual-avatar system. Patients view two 3D avatars: a *real* avatar replicating their movements and an *ideal* avatar showcasing the pre-recorded, correct movements provided by medical staff. These avatars, modeled with a skeleton and rendered skin, are designed to visually guide the patient in aligning their movements with the ideal execution.

Both avatars are 3D models of the human body, composed of a *skeleton* and a *skin*, *i.e.,* a polygonal mesh. The *skeleton* is built of bones (a rigged system controlling the mesh deformation) and the *skin* is the rendered part of the avatar. The motion tracking system, Microsoft Azure Kinect DK, detects 19 key body joints for movement analysis, including arms, legs, spine, and head, while excluding finer details like facial, finger, and toe joints. The customizable interface allows patients to adjust the visualization, such as superimposing avatars or displaying them separately, and to select specific movements to focus on. Additionally, the ideal movement can be displayed in the interface for reference. During the exercise, the sidebar displays essential information, including the number of completed repetitions, elapsed time, and the patient's heart rate. These metrics help monitor progress, assess effort, and identify potential issues such as overexertion, ensuring a comprehensive and user-friendly experience during rehabilitation.

VIRTUAL-PHYSIO provides two types of feedback to the patient: (i) a *precision score*, to report how well the exercise is going; (ii) some *correction hints*, to suggest how to improve the movement.

Both the feedback are provided by comparing the ideal movement (*ideal* avatar) with the actual movement of the patient (*real* avatar). The comparison is based on the similarity between the bones of the two avatars, represented as quaternions. Formally, let $B^r(f) = (b^r_1, b^r_2, \ldots, b^r_{19})$ and $B^i(f) = (b^i_1, b^i_2, \ldots, b^i_{19})$ be the set of acquired bones—in a specific frame f—of the *real* avatar and the *ideal* avatar, respectively. Given two quaternions, qr and qi, representing the j^{th} bone of both *real* (b^r_j) and *ideal* (b^i_j) avatar, respectively, we can compute the similarity between the two bones through the cosine similarity between the two quaternions.

Once obtained the Δ for each bone it is possible to define the *precision score* for a specific frame f.

The *precision score* evaluates movement accuracy at specific moments (frames) during an exercise, offering continuous feedback to patients. This score is visually represented using emoticons based on its value: a smile emoticon for scores above 0.7, a neutral face for scores between 0.5 and 0.7, and a sad face for scores below 0.5. This system allows patients to easily interpret their performance and make adjustments in real-time during rehabilitation (Figure 1).

As said before, VIRTUAL-PHYSIO also provides some *correction hints* during the execution of a movement. Such hints include (i) suggestions, in the form of both natural language statements and audio messages, and (ii) visual feedback (see Figure 1). The less correctly moving bone b_{bad} is the bone with the highest Δ that is also higher than a fixed threshold t.[1] If the identified less correctly moving bone b_{bad} remains the same for more than five seconds, a warning is generated. Specifically, we mark in red b_{bad} on the *real* avatar and we display an arrow showing how to correct the movement (Figure 1). We also generate a suggestion by reporting the name of the bone b_{bad} (*e.g.,* "right arm") and the action that needs to be taken, based on the pointing direction of the arrow (*e.g.,* "raise").

[1] If the highest Δ is lower than the threshold t, we do not generate any hints. Such a threshold has been empirically defined through a *trial* & *error* approach.

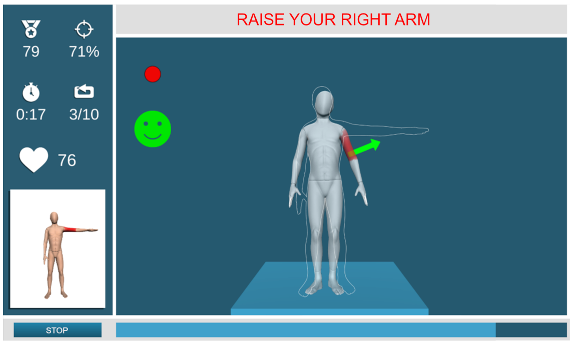

Figure 1: An example of feedback provided by VIRTUAL-PHYSIO during the execution of an exercise.

4.2 Evaluating Rehabilitation Exercises

The machine learning pipeline of VIRTUAL-PHYSIO is composed of several steps. The first step of the pipeline is the extraction—for each bone—of the motion tracks from the recording. At the end of the extraction process, we have 19 tracks, one for each tracked bone.

After completing an exercise, VIRTUAL-PHYSIO automatically evaluates the patient's performance and assigns a numeric score. This evaluation is powered by a machine learning model trained on expert-evaluated exercises, utilizing features derived from comparisons between the ideal and patient movements. Detailed information about the model and its accuracy is available in Section 5.

The evaluation pipeline begins by extracting motion tracks for each of the 19 tracked bones. These tracks undergo pre-processing to ensure reliability. **Smoothing filters** reduce noise caused by environmental factors, while **synchronization** aligns the patient's movements with the ideal execution, accounting for potential timing delays. The recording is then **sectioned** into individual repetitions, excluding the first and last repetitions, which are often incomplete or imprecise, as advised by physiotherapists. Incomplete repetitions due to missing frames are also discarded, ensuring the evaluation focuses on high-quality data for accurate scoring.

Once the pre-processing is complete, features are extracted for the ML model using cosine and Euclidean distances between the ideal and real movements, calculated at the bone level for every frame. These values are aggregated (mean, maximum, standard deviation), resulting in 114 features (19 (bones) x 2 (distance metrics) x 3 (aggregations)). Since not all bones are equally important for every exercise, physiotherapists classify bones as relevant or irrelevant based on the exercise. Based on this consideration, for each exercise, we divide the bones into two sets B^r (*i.e.,* the relevant bones) and B^I (*i.e.,* the irrelevant bones). Then, we added other features that consider the overall similarity of bones belonging to these two sets. Especially, for each set of bones, we compute the mean, maximum, and standard deviation of the similarity of the bones. This results in the addition of other 12 features, 2 (sets of bones) x 2 (distance metrics) x 3 (aggregations). Therefore, in total, we considered 126 features. The machine learning model uses these features to assign a score from 1 (lowest) to 5 (highest), reflecting movement accuracy. A score of 1 indicates compensatory movements, 2 highlights deficiencies in important bones, 3 suggests partial execution, 4 denotes slight inaccuracies, and 5 represents perfect execution. This scoring system provides a detailed assessment of performance accuracy.

5 EMPIRICAL EVALUATION

This section reports the design and the results of the empirical study we run to validate VIRTUAL-PHYSIO. The experimentation was approved by the Ethics Committee of *Celio Army Medical Center (Rome, Italy)*—Prot.n. *CE/2021u/03/a-31/03/2021-08.a.*

5.1 Study Definition and Context

The *goal* of our study is to understand to what extent VIRTUAL-PHYSIO is able to help the two types of users it is aimed at, *i.e.,* patients and physiotherapists. This study is steered by the following research questions:

- RQ_1: *To what extent is* VIRTUAL-PHYSIO *able to* ***identify*** *imperfections in the execution of an exercise?*
- RQ_2: *To what extent is* VIRTUAL-PHYSIO *able to* ***quantify*** *imperfections in the execution of an exercise?*

The controlled experiment involved 51 participants (32 males and 19 females). All the subjects were healthy and without any motor disabilities. Participants were selected by using convenience sampling. All the participants were recruited from the *Institute One* and from the *Institute Two* (see Table 2).

Table 2: Age, height, and weight of the participants.

	Mean	Median	Std. Dev.	Min	Max
Age	35	30	13	19	63
Height (cm)	174	175	8	156	191
Weight (kg)	74	74	13	50	101

5.2 Experimental Procedure

The equipment required to conduct the experiment included a workstation[2], the Azure Kinect, the Polar heart-rate wrist band, an adjustable ankle weights kit, and a classical gym step. We set up the system, including both hardware and software components, at the *Institute One* in a dedicated room big enough to allow participants to perform all the exercises.

The experimental protocol provided for the execution of five rehabilitative exercises was:

- **Shoulder rehabilitation**: standing, with the weight on the wrist and keeping the arm straight, abduct up to reach 90 degrees, without exceeding shoulder height. Slowly return to the starting position;
- **Elbow rehabilitation**: standing, with your hands crossed behind your neck, take your hands away from your head, extending the elbows upwards, hold for 4 seconds and return to the starting position and hold the position for 4 seconds;
- **Hip rehabilitation**: standing, with the weight at the ankle, flex the hip until it reaches 90 degrees and return to the starting position;
- **Knee rehabilitation**: standing, with a weight on both wrists, step forward with the right foot, resting it on a step. Focus on the left leg, bending it down until your knee touches the floor. The leg to be bent is the left and the right leg flexes consequently, not the other way. Return to the starting position by pushing with the front foot;
- **Vertebral column rehabilitation**: standing, with your arms at your sides, slide your left hand along the left thigh, tilting the trunk, up to the maximum possible width, maintain for 4 seconds and return to the starting position. Repeat on the right.

Participants were asked to repeat each exercise ten times, always in the same order. The execution started with the participant placed in front of the motion tracking sensor. Before beginning the exercise, a human assistant explained the VIRTUAL-PHYSIO GUI and the steps that the participant would have executed.

[2]AMD Ryzen 7 3800X 8-core 3.9 GHz, 32 GB RAM, Nvidia GTX 1660 6GB, with Windows 10 PRO

After that, the human assistant—through VIRTUAL-PHYSIO—played the execution video to let the participant understand the movement to be performed for each repetition. Once the participant was ready, the execution started. From that moment on, the human assistant did not give any feedback to the participant living this task to VIRTUAL-PHYSIO. The human assistant was allowed to take action only in case of very bad movements that could impact the participants' health. When the exercise was completed, the human assistant showed the participant the recorded movement. At the end of each exercise, the participant was asked to rate her execution giving a score from 1 to 5 stars.

5.3 Analysis Procedure

To answer RQ_1 and RQ_2, we first collected all the executions of the participants and we asked a physiotherapist with more than ten years of experience to manually evaluate all of them both with a binary classification (with/without imperfections, for RQ_1) and on a scale from 1 to 5 (RQ_2). As expected, the majority of the labels are located in the most positive label since all the participants were health.

Once obtained the ground truth, *i.e.,* a dataset of movement manually labelled, we trained VIRTUAL-PHYSIO in two different scenarios: (i) a binary classification problem (RQ_1), in which VIRTUAL-PHYSIO aims at distinguishing *perfectly conducted* exercises from the ones *conducted with imperfections*; (ii) a regression problem (RQ_2), in which VIRTUAL-PHYSIO aims at providing a score from 1 to 5 which embeds the type of imperfection, *i.e.,* compensatory or deficitary movements (see Section 4.2).

We experimented with seven different machine learning models (Alpaydın, 2021) for each exercise: (i) random forest (RF), (ii) multi-layer perceptron (MLP), (iii) logistic regression (RG), (iv) Gaussian Naive Bayes (GNB), (v) Linear Support Vector Classification/Regression (LSVM), (vi) C-Support Vector Classification/Regression (CSVC), and (vii) k-Nearest Neighbors (KNN). Note that we decide to have a prediction model for each exercise (local prediction) instead of a single model for each exercise (global prediction) because of the differences among the exercises. This choice was supported also by the physiotherapists. To mitigate the problems due to class imbalance we experimented with the use of the SMOTE (Chawla et al., 2002) oversampling technique. Also, we experimented with several automatic feature selection techniques and correlation analysis to filter the features correlated to each other with a correlation index greater than 0.95.

The validation process was based on the leave one out cross validation (Alpaydın, 2021). This process consists in iterating over each instance (participant), using the i-th instance as a test set, and using the remaining as a train set.

For the binary classification, we measure the quality of the classification of VIRTUAL-PHYSIO through the following metrics widely used for machine learning models (Alpaydın, 2021): (i) accuracy; (ii) recall; (iii) precision; (iv) F1-score. While for the regression problem, we evaluate the performance of VIRTUAL-PHYSIO through the Mean Absolute Error (MAE) (Alpaydın, 2021).

5.4 Analysis of the Results

Table 3: Performance of VIRTUAL-PHYSIO in classifying an exercise as correct or incorrect (RQ_2).

Exercise	Model	Accuracy	Recall	Precision	F1
Shoulder	MLP or KNN	0.84	0.84	0.91	0.86
Elbow	MLP	0.76	0.76	0.76	0.76
Hip	KNN	0.82	0.82	0.82	0.81
Knee	MLP	0.57	0.57	0.32	0.41
Vertebral column	MLP	0.71	0.71	0.71	0.69

Table 4: Performance of VIRTUAL-PHYSIO in evaluating an exercise on a five-point score (RQ_3).

Exercise	Model	MAE
Shoulder	Random forest or KNN	0.31
Elbow	MLP	0.47
Hip	GNB	0.29
Knee	SVM	1.16
Vertebral column	Random forest	0.63

The results in Table 3 and Table 4 show the performance of VIRTUAL-PHYSIO in classifying exercises as correct or incorrect (RQ_1) and scoring exercises on a five-point scale (RQ_2). No single machine learning model consistently outperforms others. MLP and KNN perform best for classification without oversampling, while Random Forest achieves top results for regression in two exercises. These findings support the use of exercise-specific models over a global model for all exercise types.

The achieved results indicate that VIRTUAL-PHYSIO has accuracy in evaluating the correctness of an exercise (RQ_1) higher than 70%, with the exception of knee rehabilitation exercise where the accuracy is 57%. Similar results were achieved when evaluating the exercise on a five-point scale: In this scenario, VIRTUAL-PHYSIO achieved an error always lower than 0.5, with the exception of the knee and vertebral column rehabilitation exercises where the MAE is 1.16 and 0.63, respectively.

The knee rehabilitation exercise presented the highest error rate, while the shoulder rehabilitation showed the fewest errors. This discrepancy may result from the greater complexity of movements in the knee and spine exercises, which involve more joints, making the evaluation more challenging for the machine learning model. In addition, the different reasons why the physical therapists negatively evaluated the knee exercises resulted in fewer similar instances evaluated negatively in the training set, complicating the model's ability to identify incorrect execution patterns.

5.5 Case Analysis and Discussion

This section analyzes specific cases to explore factors behind VIRTUAL-PHYSIO's correct and incorrect predictions.

A correct exercise classified by VIRTUAL-PHYSIO as correct. In Figure 4 (Balletti et al., 2024) VIRTUAL-PHYSIO identified a correctly performed exercise, as no abnormalities were observed in the leg or pelvis graphs, indicating proper leg extension and absence of compensatory movements.

An incorrect exercise classified by VIRTUAL-PHYSIO as incorrect. In Figure 5 (Balletti et al., 2024) several abnormalities can be found. The leg graphs revealed incomplete movements in repetitions 3, 5, and 8, and the pelvis graph showed compensatory torso rotation throughout the exercise, aligning with the physiotherapist's evaluation.

A correct exercise classified by VIRTUAL-PHYSIO as incorrect. From the analysis of the leg graphs in Figure 6 (Balletti et al., 2024), it is possible to observe approximately complete movements for most of the repetitions. Although most repetitions were performed correctly, a temporary loss of balance in the second repetition caused abnormal movements, which the physiotherapist disregarded when assessing overall performance. Instead, VIRTUAL-PHYSIO weighted the abnormal movements more heavily, leading to an imperfect rating.

An incorrect exercise classified by VIRTUAL-PHYSIO as correct. In Figure 7 (Balletti et al., 2024) VIRTUAL-PHYSIO incorrectly classified an exercise as correct, despite the physiotherapist identifying consistent failure to achieve 90-degree leg extension and trunk flexion. This execution defect, absent in other exercises, likely contributed to the model's inability to classify it negatively.

A perfect exercise evaluated by VIRTUAL-PHYSIO correctly. In Figure 8 (Balletti et al., 2024) the physiotherapist and VIRTUAL-PHYSIO assigned to the exercise a score equals to 5. From the analysis of the graphs of shoulder and arm movement, it is possible to observe no serious differences between actual and ideal movements.

A good exercise evaluated by VIRTUAL-PHYSIO correctly. In this case (Figure 9 (Balletti et al., 2024)), a good but imperfect exercise was correctly rated 4 by both VIRTUAL-PHYSIO and the physiotherapist. The model identified an incomplete arm extension in the initial phase, visible in the graphs, demonstrating its capability to detect and score minor imperfections accurately.

A bad exercise evaluated by VIRTUAL-PHYSIO as perfect. VIRTUAL-PHYSIO misclassified a bad exercise as perfect in Figure 10, assigning a score of 5 while the physiotherapist rated it 3. The physiotherapist noted incomplete shoulder movement in the first repetitions. The graphs indicated near-perfect arm movement, likely influencing the model's overly positive rating, but confirmed the physiotherapist's observation of minimal vertical shoulder movement.

5.6 Threats to Validity

The main threats to the validity of this study resulted from the ML techniques used and the population of participants. Regarding the models, while not all ML approaches were explored, the study included representatives from key algorithm categories, such as tree-based models, logistic regression, Support Vector Machines, and neural networks. Concerning participants, the sample may not be fully representative, a common challenge in human-involved studies due to the time commitment required for participation. However, as discussed above, our study involved a number of participants in line with the other studies in the literature. Another limitation is that the study considers only a single session, whereas rehabilitation typically involves multiple sessions.

6 CONCLUSION

In this paper, we presented VIRTUAL-PHYSIO, a virtual assistant integrated into 2VITA-B PHYSICAL system, designed to guide patients during exercises by providing feedback and evaluating entire sessions to notify physiotherapists about cases requiring attention. Leveraging affordable motion tracking devices, visual feedback, and machine learning-based evaluation, VIRTUAL-PHYSIO aims to enhance home rehabilitation. A controlled experiment with 51 participants demonstrated high confidence and willingness to use VIRTUAL-PHYSIO for home rehabilitation. These results provide a valid premise for the further enhancement of home rehabilitation using motion capture and ML technologies. As a future work, we plan to integrate into 2VITA-B PHYSICAL a hand tracking device aiming at supporting specific hand rehabilitation exercises. Furthermore, we aim to improve the motion-tracking capabilities by incorporating multiple Kinect sensors.

ACKNOWLEDGMENTS

This research was funded by Ministry of Defence grant number 20536 (December 13, 2019) "2VITA-B PHYSICAL: Veteran Virtual Training for Aging Blockchain" – Proposal a2018.137.

REFERENCES

Adans-Dester, C., Hankov, N., O'Brien, A., Vergara-Diaz, G., Black-Schaffer, R., Zafonte, R., Dy, J., Lee, S. I., and Bonato, P. (2020). Enabling precision rehabilitation interventions using wearable sensors and machine learning to track motor recovery. *NPJ digital medicine*, 3(1):1–10.

Ahammad, S. H., Rahman, M. Z. U., Rao, L. K., Sulthana, A., Guptha, N., and Lay-Ekuakille, A. (2020). A multi-level sensor based spinal cord disorder classification model for patient wellness and remote monitoring. *IEEE Sensors Journal*.

Alpaydın, E. (2021). *Machine Learning, Revised And Updated Edition*. The MIT Press.

Antico, M., Balletti, N., Ciccotelli, A., Ciccotelli, M., Laudato, G., Lazich, A., Oliveto, R., Notarantonio, M., Ricciardi, S., Scalabrino, S., et al. (2021a). 2ViTA-B Physical: An intelligent home rehabilitation system based on Microsoft Azure Kinect DK. *Frontiers in Human Dynamics*, page 54.

Antico, M., Balletti, N., Laudato, G., Lazich, A., Notarantonio, M., Oliveto, R., Ricciardi, S., Scalabrino, S., and Simeone, J. (2021b). Postural control assessment via Microsoft Azure Kinect DK: An evaluation study. *Computer Methods and Programs in Biomedicine*, 209:106324.

Balletti, N., Cascitelli, A., Gabrieli, P., Guglielmi, E., Laudato, G., Lazich, A., Notarantonio, M., Oliveto, R., Ricciardi, S., Scalabrino, S., and Simeone, J. (2024). Appendix figure. https://bit.ly/3DnLPkT. 18 dicembre 2024.

Biebl, J. T., Rykala, M., Strobel, M., Bollinger, P. K., Ulm, B., Kraft, E., Huber, S., and Lorenz, A. (2021). App-based feedback for rehabilitation exercise correction in patients with knee or hip osteoarthritis: Prospective cohort study. *Journal of Medical Internet Research*, 23(7):e26658.

Bijalwan, V., Semwal, V. B., Singh, G., and Mandal, T. K. (2022). Hdl-psr: Modelling spatio-temporal features using hybrid deep learning approach for post-stroke rehabilitation. *Neural Processing Letters*, pages 1–20.

Chae, S. H., Kim, Y., Lee, K.-S., and Park, H.-S. (2020). Development and clinical evaluation of a web-based upper limb home rehabilitation system using a smartwatch and machine learning model for chronic stroke survivors: prospective comparative study. *JMIR mHealth and uHealth*, 8(7):e17216.

Chawla, N. V., Bowyer, K. W., Hall, L. O., and Kegelmeyer, W. P. (2002). Smote: synthetic minority oversampling technique. *Journal of artificial intelligence research*, 16:321–357.

Han, D., Kuschner, D., and Wang, Y.-f. (2005). Upper limb position sensing: A machine vision approach. In *Conference Proceedings. 2nd International IEEE EMBS Conference on Neural Engineering, 2005.*, pages 490–493. IEEE.

Imura, T., Iwamoto, Y., Inagawa, T., Imada, N., Tanaka, R., Toda, H., Inoue, Y., Araki, H., and Araki, O. (2021). Decision tree algorithm identifies stroke patients likely discharge home after rehabilitation using functional and environmental predictors. *Journal of Stroke and Cerebrovascular Diseases*, 30(4):105636.

Kashi, S., Polak, R. F., Lerner, B., Rokach, L., and Levy-Tzedek, S. (2020). A machine-learning model for automatic detection of movement compensations in stroke patients. *IEEE Transactions on Emerging Topics in Computing*, 9(3):1234–1247.

Lee, M. H. (2018). A technology for computer-assisted stroke rehabilitation. In *23rd International Conference on Intelligent User Interfaces*, pages 665–666.

Lee, M. H., Siewiorek, D. P., Smailagic, A., Bernardino, A., and Bermúdez i Badia, S. (2020). Interactive hybrid approach to combine machine and human intelligence for personalized rehabilitation assessment. In *Proceedings of the ACM Conference on Health, Inference, and Learning*, pages 160–169.

Liao, Y., Vakanski, A., Xian, M., Paul, D., and Baker, R. (2020). A review of computational approaches for evaluation of rehabilitation exercises. *Computers in biology and medicine*, 119:103687.

Maclean, N., Pound, P., Wolfe, C., and Rudd, A. (2002). The concept of patient motivation: a qualitative analysis of stroke professionals' attitudes. *Stroke*, 33(2):444–448.

Osgouei, R. H., Soulsby, D., and Bello, F. (2020). Rehabilitation exergames: Use of motion sensing and machine learning to quantify exercise performance in healthy volunteers. *JMIR Rehabilitation and Assistive Technologies*, 7(2):e17289.

Ranasinghe, I., Dantu, R., Albert, M. V., Watts, S., and Ocana, R. (2021). Cyber-physiotherapy: Rehabilitation to training. In *2021 IFIP/IEEE International Symposium on Integrated Network Management (IM)*, pages 1054–1057. IEEE.

Seifallahi, M., Mehraban, A. H., Galvin, J. E., and Ghoraani, B. (2022). Alzheimer's disease detection using comprehensive analysis of timed up and go test via kinect v. 2 camera and machine learning. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 30:1589–1600.

Shaughnessy, M., Resnick, B. M., and Macko, R. F. (2006). Testing a model of post-stroke exercise behavior. *Rehabilitation nursing*, 31(1):15–21.