A universal real-time validation algorithm for rehabilitation exercises based on spatial pose configuration analysis*

Yaroslav Hladkyi[1,†] , Volodymir Druzhynin[1,†], Myroslava Gladka[1,2,*,†], Sergiy Paliy[1,†] and Rostyslav Lisnevskyi[3,†]

[1] *Taras Shevchenko National University of Kyiv, Volodymyrska Street, 60, Kyiv, 01601, Ukraine*

[2] *National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Prosp. Peremohy, 37, Kyiv, 01601, Ukraine*

[3] *Astana IT University, Mangilik El avenue, 55/11 Business center EXPO, block C1, Astana, 010000, Kazakhstan*

Abstract

This article proposes and substantiates an innovative algorithm for the automated real-time quality control of rehabilitation exercises performance. Existing solutions are frequently constrained by narrow specialisation in particular exercises, substantial computational demands, or the need for extensive training datasets tailored to each new type of movement. Such limitations restrict their applicability in real-world telerehabilitation scenarios. The core of the development is based on the use of the MediaPipe Pose artificial intelligence model for detecting 33 anthropometric key points of the human body. The scientific novelty of the approach lies in the development of a universal configuration space, within which each exercise is formalized as an "ideal cycle" consisting of multiple discrete stages.

The validation methodology is based on comparing the current body posture with a multidimensional vector representing the reference state. The key evaluation parameter is the relative positioning of key points, determined through the calculation of the angles between vectors in the cinematic chain. This approach ensures the algorithm's invariance to the user's anthropometric characteristics and the positioning of the camera. In addition to geometric accuracy, the algorithm performs temporal analysis-monitoring the speed of transitions between discrete stages – which is critical for preventing injury during the rehabilitation process.

The system implements a mechanism of instantaneous biological feedback (biofeedback): in the case of deviations in movement amplitude, sequence, or tempo, the user receives targeted corrective instructions. The proposed solution is universal: an integration of a new exercise requires only the specification of its reference cycle in the appropriate format, without the need for model retraining. The research outcomes demonstrate significant potential for integration into telemedicine platforms and modile applications for self-guided rehabilitation.

Keywords

IT-system, computer vision, MediaPipe Pose, rehabilitation, exercise performance validation, pose detection, real-time feedback, biomechanical analysis

1. Introduction

Physical rehabilitation following injuries, wounds, surgical interventions, or neurological disorders requires prolonged and systematic execution of specialized exercises [1], [2]. The effectiveness of patient recovery is directly dependent on the correct performance of exercises and precise adherence to movement techniques [3]. Traditionally, such control is ensured by a rehabilitation specialist [4]. However, limitations in healthcare system resources, the growing number of patients requiring rehabilitation, the high cost of personalized sessions, and the increasing demand for

*The Third International Conference of Young Scientists on Artificial Intelligence for Sustainable Development: Intelligent Systems and Artificial Intelligence (YAISD-WS 2026:ISAI) May 7-8, 2026, Ternopil, Ukraine

[1,*] Corresponding author.

[†] These authors contributed equally.

hladkky@gmail.com (Y. Hladkyi); volodymir.druzhynin@knu.ua (V. Druzhynin); miragladka@gmail.com (M. Gladka); paliy@fit.knu.ua (S. Paliy); Rostyslav.Lisnevskyi@astanait.edu.kz (R. Lisnevskyi)

0000-0003-2914-8685 (Y. Hladkyi); 0009-0009-5049-0099 (V. Druzhynin); 0000-0001-5233-2021 (M. Gladka); 0000-0001-9742-1116 (S. Paliy); 0000-0002-9006-6366 (R. Lisnevskyi)

© 2026 Copyright for this paper by its authors. Use permitted under Creative Commons License Attribution 4.0 International (CC BY 4.0).

CEUR Workshop Proceedings ceur-ws.org ISSN 1613-0073

published 2026-11-11

CEUR-WS.org/Vol-4326/paper1.pdf

remote medicine (telerehabilitation) necessitate the development of automated monitoring systems for the rehabilitation process [5].

Contemporary computer vision solutions enable human motion tracking using standard RGB cameras. However, most existing systems are either narrowly specialized – being tailored to specific types of exercises – or require significant computational resources and complex training datasets [6], [7]. These limitations hinder the scalability of rehabilitation complexes to include exercises suited for various types of injuries, wounds, and related conditions [8].

Therefore, there is a pressing need for a universal algorithm capable of easily adapting to various rehabilitation protocols and specialist's prescriptions, while ensuring high-precision real-time validation and providing comprehensible feedback to the patient. Such feedback should account not only for the correctness of exercise execution, but also for individual patient characteristics, including anthropometric parameters, performance dynamics, and the presence of progress over time [2].

Recent advances in deep learning, particularly the MediaPipe Pose library developed by Google [9], enabled sub-millimeter tracking of 33 body landmarks on mobile devices. [10]. Research indicates that the application of graph-based models and analysis of joint angular characteristics represent the most promising approach for assessing biomechanics during rehabilitation exercises. However, the issues of constructing a flexible "configuration space" – one that allows for representation of arbitrary exercises as a sequence of discrete stages without reprogramming the system's core – remains insufficiently addressed in recent studies [11].

The aim of this article is to develop and theoretically substantiate a universal algorithm for validation of rehabilitation exercises. The algorithm is based on the model of an ideal motion cycle, in which each stage is validated through multidimensional vectors of relative landmark postitions and corresponding time intervals.

To achieve the stated aim, the following objectives are addressed:

1. Formalization of an exercise structure through a sequence of control stages.
2. Development of a mathematical framework for real-time calculation of deviations in angular parameters between keypoints.
3. Design of a mechanism for monitoring the temporal characteristics (speed) of transitions between exercise stages.
4. Implementation of an interactive feedback system for correcting user actions.

2. Methodology

The proposed methodology is based on the decomposition of an arbitrary rehabilitation exercise into a finite set of stages forming a cyclic directed graph [12]. The validation process is implemented through continuous analysis of the data stream from the MediaPipe Pose model, which monitors and tracks 33 keypoints (Figure 1). In the present work, the MediaPipe Pose model is employed solely as a tool for obtaining normalised coordinates of reference points in real time. The scientific novelty and the authors' original contribution consist in the development of a superstructural algorithmic layer, the formalisation of a universal configuration space of stages, a mathematical model for the validation of angular parameters in 3D, and the implementation of a temporal analysis mechanism that is not part of the library's standard functionality. MediaPipe thus serves as a data acquisition layer, whereas the entire logic of validation, modelling, and adaptivity constitutes the authors' original contribution.

We formalize the structure of each exercise as an ordered sequence of stages:

$$S = \{s_1, s_2, \ldots, s_n\} \quad (1)$$

here s_i — a specific biomechanical state of the body at each moment during the execution of the exercise. A state is considered to be achieved when the current configuration of keypoints P corresponds to the reference configuration P^* within a predefined error tolerance ε epsilon.
Each rehabilitation exercise is described as:

$$E = (S, T, V) \tag{2}$$

here:

- S— a set of stages (static poses, captured during the execution of the exercise);
- T— temporal constraints on transitions between stages of exercise execution $t_{min} < \Delta t < t_{max}$;
- V— constraint vectors for each keypoint (permissible angles).

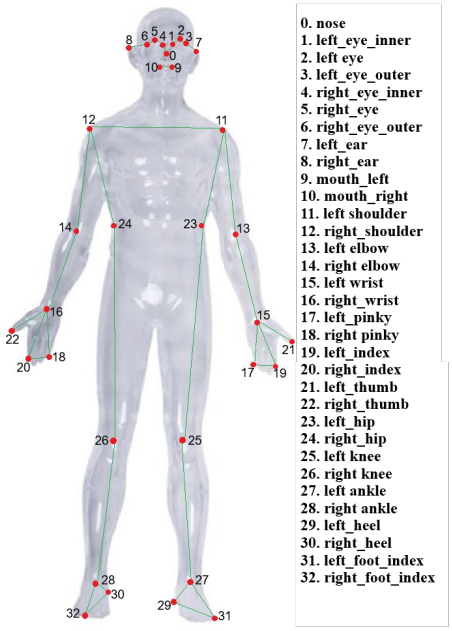


Figure 1: Location of key points of human body used for monitoring rehabilitation exercise performance.

We introduce a matematical model for analyzing angular parameters to ensure invariance to image scale and distance from the camera [13], [14]. The primary validation metric is defined as the angle between body segments at each moment of exercise execution.

Let A, B, C— represent three consecutive keypoints (e.g., shoulder, elbow, and wrist).

Let vectors **u** and **v** represent the directional segments formed by three keypoints:

$$u = \vec{AB}, v = \vec{BC} \tag{3}$$

where A, B, C are 3D coordinates of keypoints, and vectors are defined in Euclidean space.

The angle at boint θ is computed using the scalar (dot) product of vectors BA and BC:

$$\theta = \arccos\left(\frac{u * v}{\|u\| * \|v\|}\right) \tag{4}$$

The algorithm compares the computed angle θ_{curr} with the reference angle θ_{ref}, defined in the stage configuration. A deviationg is registered if $|\theta_{curr} - \theta_{ref}| > \delta$ where δ — is sensitivity threshold.

The real-time validation algorithm monitors exercise execution according to the following logic (Figure 2).

- In Step 1, the coordinates (x, y, z) of 33 key points are obtained from the MediaPipe model.
- In Step 2, the system waits for the body to enter the tolerance zone of the target stage .
- In Step 3, the system performs sequence control: if the user attempts to execute stage s_{i+1}, while skipping stage s_i, the system generates an error notification.
- In Step 4, the time Δtbetween reaching stage $s_i$and stage s_{i+1} is measured. If Δt exceeds the predefined thresholds $\left[t_{min}, t_{max}\right]$, a recommendation is provided to adjust the pace (either to speed up or slow down).

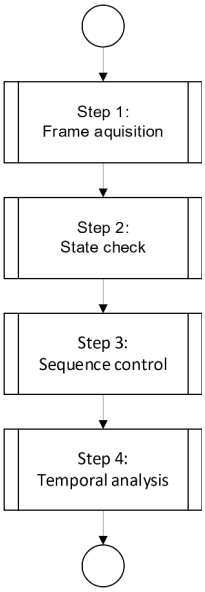


Figure 2: Real-time validation algorithm.

An essential aspect of exercise execution is the biofeedback system [7], [15], in which the algorithm integrates an error-handling module that classifies deviations into three categories:

1. Geometric – mismatch in joint angles;
2. Sequential – skipping control points of the exercise;
3. Dynamic – failure to maintain the correct rhythm or execution speed.

Such a multi-level verification process not only confirms the execution of the exercise but also ensures its therapeutic quality [16].

3. Implementation

The practical implementation of the algorithm is based on a client-oriented architecture that enables all computations to be performed directly on the user's device (on-device processing), thereby ensuring the confidentiality of medical data and minimizing latency [17].

A key feature of the implementation of the exercise configuration space is the separation of exercise logic from the algorithm's source code. Each exercise is described in a JSON configuration file, enabling rapid retrieval and adaptation according to the specific exercise being performed.

The data processing and validation logic are divided into three primary pipelines (Figure 3):

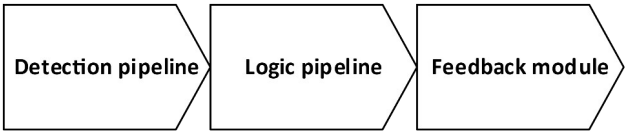


Figure 3: Data processing and validation logic implementation process.

The detection pipeline enables MediaPipe Pose to receive the video stream and returns an array of normalized coordinates $L = \{l_1, l_2, \ldots, l_{33}\}$. Since MediaPipe provides coordinates in the (x, y, z) format, the algorithm utilized the z-coordinate to account for depth, thereby improving the accuracy of angle computations in 3D space.

The logic pipeline (State Machine) implements the program as a finite-state machine [18]. A transition to state s_{i+1} occurs only when the validation function returns True for the current frame over a predefined filtering interval, to avoid false positive caused by noise.

The feedback module is implemented through a system of triggers. If the angle θ exceeds the permissible threshold, the systems activates a visual indicator (changing the skeleton color on the screen from green to red) and displays a textual prompt, such as: "Straighten your elbow".

To ensure stable real-time performance and optimize computational efficiency, the following measures were implemented:

1. Adaptive smoothing using a low-pass filter to stabilize key points (landmarks jitter reduction);
2. Frame Skipping for biomechanical parameter computation on every second frame, which reduces CPU load without comprimising monitoring quality.

A key aspect of monitoring rehabilitation of exercise performance is the universal video processing function applicable to any exercise. This function aggregates the exercise configuration instance, the pose estimation model (MediaPipe), and the parameters for handling the video stream (Figure 4).

- Step 1: Retrieve keypoints from the pose estimation model.
- Step 2: Perform a visibility check of critical keypoints; if any keypoints are occluded or lost, a warning message is generated.
- Step 3: Determine the current stage of exercise execution based on the configuration file.
- Step 4: Validate transitions between stages, ensuring the correctness of state changes during execution and verifying the number of required cycles (repetitions) for the exercise.
- Step 5: Validate the current stage by continuously monitoring angular and coordinate parameters throughout the execution.
- Step 6: Verify general exercise-specific requirements such as postural stability and body symmetry.
- Step 7: Visualize the execution process in real time.

At each step, the system performs video output recording, real-time monitoring with instant signaling, and the delivery of appropriate notifications.

The video processing function condludes by generating a comprehensive report detailing the results of the rehabiliation exercise execution.

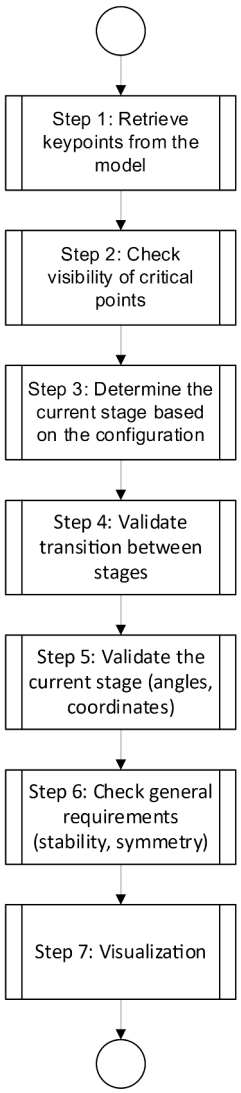


Figure 4: Universal video processing function.

4. Discuss and Results

To verify the functionality of the algorithm, a series of tests were conducted using the "Dead Bug" [19], [20] exercise, which is fundamental to the rehabilitation of the lumbar spine. In accordance with the proposed methodology, the exercise was configured as a cycle consisting of five key stages.

The experimental validation involved N = 12 participants aged between 18–49 years. The sample included individuals with varying anthropometric characteristics, including differences in: body mass index (BMI), height, limb proportions, level of physical fitness (sedentary to moderately active). To test the algorithm's invariance with respect to the sample, the study included individuals with different body types (ectomorphs, mesomorphs) and varying levels of physical fitness (from beginners to experienced users). To evaluate robustness, the algorithm was tested under varying conditions: different camera angles (±20°), varying distances from the camera, diverse execution speeds. No participants had acute musculoskeletal injuries at the time of testing; however, the exercise corresponds to standard rehabilitation protocols [20], [21].

The consistently high accuracy (94.8%–97.4%) confirms the system's robustness to anthropometric differences among the participants.

4.1. Exercise description

5. *Initial Position (Stage 0 – REST) (Figure 5 a):*

- The user lies supine.
- Both arms are raised vertically upward (perpendicular to the torso).
- Both knees are bent at approximately 90° (i.e., thighs are perpendicular to the floor).
- The lumbar spine is pressed against the floor.

6. *Stage 1 – LEFT_PHASE (Figure 5 b):*

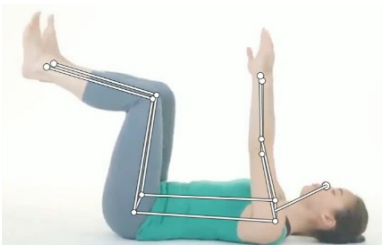
- The left leg extends and lowers toward the floor (hip angle approaches 180°).
- The right arm moves backward over the head toward the floor.
- The right leg remains bent (~90° at the knee).
- The left arm remains vertical.

7. *Stage 2 – RETURN_TO_REST:*

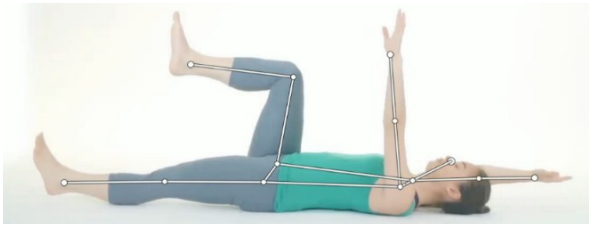
- Return to the initial position (Stage 0).

8. *Stage 3 – RIGHT_PHASE (Figure 5 c):*

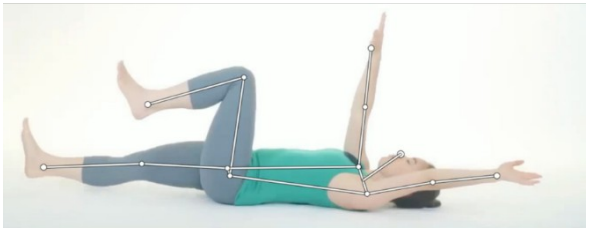
- The right leg extends and lowers toward the floor (hip angle approaches 180°).
- The left arm moves backward over the head.
- The left leg remains bent.
- The right arm remains vertical.



a



b



c

- **Figure 5:** Execution stages of the «Dead bug» exercise [19].
- a - initial position; b – left phase; c – right phase.

9. *Stage 4 – RETURN_TO_REST:*

- Return to the initial position (Stage 0).

10. *Cycle summary: Stage 0 ⟶ Stage 1 ⟶ Stage 0 ⟶ Stage 3 ⟶ Stage 0.*

4.2. Definition of Constraints for Stage

11. 0: REST (Initial/Resting Position)
12. *Keypoints (MediaPipe BlazePose indices):*

- 11: left_shoulder, 12: right_shoulder.
- 13: left_elbow, 14: right_elbow.
- 15: left_wrist, 16: right_wrist.
- 23: left_hip, 24: right_hip.
- 25: left_knee, 26: right_knee.
- 27: left_ankle, 28: right_ankle.

13. *Angular Constraints:*

1. Left Elbow (shoulder ⟶ elbow ⟶ wrist):

- Points: (11, 13, 15).
- Ideal angle: 170°–180° (arm extended upward).
- Tolerance: ±15°.

2. Right Elbow (shoulder ⟶ elbow ⟶ wrist):

- Points: (12, 14, 16).
- Ideal angle: 170°–180°.
- Tolerance: ±15°.

3. Left Knee (hip ⟶ knee ⟶ ankle):

- Points: (23, 25, 27).
- Ideal angle: 80°–100° (leg bent).
- Tolerance: ±20°.

4. Right Knee (hip ⟶ knee ⟶ ankle):

- Points: (24, 26, 28).
- Ideal angle: 80°–100°.
- Tolerance: ±20°.

5. Arm Verticality Relative to the Torso:

- Arm vector: (13 – 11) ⟶ from shoulder to elbow.
- Torso vector: (23 – 11) ⟶ from shoulder to hip.
- Ideal angle: 70°–110° (approximately perpendicular).
- Tolerance: ±20°.

6. Right Arm:

- Arm vector: (14 – 12).

- Torso vector: (24 – 12).
- Ideal angle: 70°–110°.
- Tolerance: ±20°.

14. *Minimum Hold Duration for the Stage: at least 0.3 seconds*

Following the same logic, parameters and constraints were defined for all subsequent stages of the exercise. In addition to the stage-specific constraints, a set of transition rules between stages was established, specifically:

15. *Allowed Transitions:*

- REST (0) ⟶ LEFT_PHASE (1): transition time 1.0–2.0 seconds.
- LEFT_PHASE (1) ⟶ REST (0): transition time 1.0–2.0 seconds.
- REST (0) ⟶ RIGHT_PHASE (3): transition time 1.0–2.0 seconds.
- RIGHT_PHASE (3) ⟶ REST (0): transition time 1.0–2.0 seconds.

16. *Disallowed Transitions (Violations):*

- LEFT_PHASE (1) ⟶ RIGHT_PHASE (3) without returning to REST (0).
- Any transition completed in less than 0.8 seconds (too fast).
- Any transition exceeding 3.0 seconds (too slow).

17. *General Execution Requirements*

1. Torso Stability:

- The lumbar spine must remain pressed against the floor.
- Check: The distance between the shoulders (points 5–6) and hips (points 11–12) should remain stable.
- Tolerance: ±10% of the initial value.

2. Shoulder Alignment:

- The left and right shoulders must remain level (symmetrical).
- Check: |Y-coordinate(5) – Y-coordinate(6)| < 20 pixels

3. Hip Alignment:

- The left and right hips must remain level.
- Check: |Y-coordinate(11) – Y-coordinate(12)| < 20 pixels

4. Minimum Keypoint Visibility:

- All critical keypoints must have a confidence score greater than 0.5.
- If visibility is lost — validation is paused and a warning is issued

The tolerance values ±15° were selected based on a combination of: biomechanical variability reported in rehabilitation literature [21], empirical observations during pilot testing, recommendations from physiotherapy practice guidelines regarding acceptable deviations in controlled therapeutic movements.

These ranges ensure a balance between safety (preventing harmful movement patterns) and adaptability to individual anatomical differences.

During the experiment, analysis of the accuracy of angular parameter validation revealed that the use of MediaPipe Pose model in combination with vector-based analysis enabled the detection of deviations in elbow and knee joints with an accuracy ranging from 3° to 5° (Table 1).

Table 1
Angular parameter validation accuracy while exercise execution

Validation parameter	Value		
	Reference value	Tolerance	Reference value
Elbow angle (extension)	180°	± 10°	97.4%
Knee angle (extension)	90°	± 7°	96.2%
Phase transition time	2.5 sec/stage	± 0.5 сек	94.8%

The algorithm successfully identified insufficient limb extension, instantly generating both textual and visual warnings for the user.

One of the principal advantages of the developed algorithm is its universality. Unlike classical neural network-based classifiers, which require throusands of video samples to train each new exercise, the proposed approach relies solely on the specification of a JSON-based configuration describing the exercise stages.

Identified operational charactertics include the following:

- The itroduction of transition spped verification between stages eliminates the issue of “inertial execution”, where patients perform exercises too rapidly, thereby reducing the therapeutic effect; this functionality effectively implements temporal control;
- The use of relative joint angles instead of absolute x, y coordinates ensured stable system performance even when the camera viewing angle varied by 15-20°;
- The algorithm demonstrates high computational efficiency (exceeds 30 FPS on average mobile devices), making it suitable for large-scale deployment.

However, limitations were identified under conditions of severe occlusion, when one limb significantly overlaps another (for example, when the recording is captured strictly from a lateral viewpoint). This indicates the necessity of providing users with recommendations regarding optimal camera placement prior to instantiating a rehabilitation session.

A limitation of the study is the relatively limited sample size, which may affect the generalizability of the results. Future work will involve larger and clinically diverse populations, including patients undergoing rehabilitation.

5. CONCLUSIONS

During this study, a universal algorithm for validating rehabilitation exercises following injuries and wounds was developed and experimentally validated. The algorithm is based on real-time analysis of spatial body configurations. The obtained results allow the following conclusions to be drawn:

1. The concept of an “ideal exercise cycle” was proposed as a sequence of multidimensional state vectors. This approach made it possible to move away from rigidly hard-coded scenarios toward a flexible configuration space, thereby rendering the system adaptable to virtually any physical therapy protocol.
2. The use of relative angular parameters between keypoints of the MediaPipe Pose model ensured high error detection accuracy (exceeding 95%), validation efficiency, and

algorithmic invariance to users' anthropometric differences and camera viewpoint variations.

3. For the first time, a simultaneous verification of pose geometry, stage sequence, and temporal (speed-related) movement characteristics was integrated as a comprehensive control mechanism. This approach enables not only quantitative counting of repetitions but also qualitative control of execution technique, which is critical for medical rehabilitation. Unlike existing solutions, the proposed approach eliminates the need for dataset collection and model retraining for each new exercise, which significantly reduces deployment complexity.
4. The implemented architecture enables computations to be performed on low-power client devices (such as smartphones and laptops) while providing instantaneous feedback. This opens broad opportunities for deploying the system in the fields of telemedicine and home-based rehabilitation and constitutes the practical significance of the proposed algorithm.

Further development of the project involves the integration of depth analysis (3D space) to correct errors occurring in planes parallel to the camera lens, as well as the development of an intelligent recommendation system based on accumulated statistical data regarding typical errors of a specific patient [22], [23].

Acknowledgements

The author team expresses its gratitude to the company manager and the head of the implementation department of company "Test" LLC for the opportunity to conduct experimental research.

Declaration on Generative AI

Grammarly was used to translate the article text from Ukrainian to English.

References

[1] Payedimarri AB, Ratti M, Rescinito R, Vanhaecht K, Panella M. Effectiveness of Platform-Based Robot-Assisted Rehabilitation for Musculoskeletal or Neurologic Injuries: A Systematic Review. *Bioengineering*. 2022; 9(4):129. doi: https://doi.org/10.3390/bioengineering9040129

[2] Y. Hladkyi, M. Gladka, M. Kostikov, R. Lisnevskyi. An IoT Solution: A Fitness Trainer. Information Technology and Implementation: IT&I-WS-2021. Selected Papers of the VIII International Scientific Conference "Information Technology and Implementation" (IT&I-2021). Workshop Proceedings. Kyiv, Ukraine, December 1-3, 2021. P 215-226 http://ceur-ws.org/Vol-3179/

[3] Joke Schuermans, Alena Van Hootegem, Margo Van den Bossche, Marjolein Van Gendt, Erik Witvrouw, Evi Wezenbeek, Extended reality in musculoskeletal rehabilitation and injury prevention - A systematic review, Physical Therapy in Sport, Volume 55,2022, Pages 229-240, ISSN 1466-853X, doi: https://doi.org/10.1016/j.ptsp.2022.04.011

[4] Jamie King, Theresa L Burgess, Candice Hendricks, and Fraser Carson. The coach's role during an athlete's rehabilitation following sports injury: A scoping review. International Journal of Sports Science & Coaching. Volume 18, ssue 3. doi: https://doi.org/10.1177/17479541221150694

[5] Khalid, U. bint, Naeem, M., Stasolla, F., Syed, M. H., Abbas, M., & Coronato, A. (2024). Impact of AI-Powered Solutions in Rehabilitation Process: Recent Improvements and Future Trends. International Journal of General Medicine, 17, 943–969. doi: https://doi.org/10.2147/IJGM.S453903

[6] R. Lisnevskyi, V. Oderiieva, M. Gladka, O. Kravchenko and O. Kolesnikov. Development of a System for Monitoring Health and Patient Care Based on IoT Technologies. 9th International Conference Digital Technologies in Education, Science and Industry. 2025, 3966. Almaty. Ceur Workshop Proceedings, https://ceur-ws.org/Vol-3966/W2Paper1.pdf

[7] Banyai, Adriana Daniela, and Cornel Brișan. 2024. "Robotics in Physical Rehabilitation: Systematic Review" Healthcare 12, no. 17: 1720. doi: https://doi.org/10.3390/healthcare12171720

[8] M.Gladka, A. Kuchansky, M. Kostikov and R. Lisnevskyi. A model of the application of IoT devices based on RFID to ensure the safety of the military and civilian population under war conditions. Information Technology and Implementation: IT&I-WS-2022. Selected Papers of the IX International Scientific Conference “Information Technology and Implementation" (IT&I-2022). Workshop Proceedings Kyiv, Ukraine, November 30 – December 02, 2022. P269-278 https://ceur-ws.org/Vol-3347

[9] Pose landmark detection guide. https://ai.google.dev/edge/mediapipe/solutions/vision/pose_landmarker

[10] Pose detection. https://developers.google.com/ml-kit/vision/pose-detection?hl=en

[11] Shubham Garg, Aman Saxena, Richa Gupta. Yoga pose classification: a CNN and MediaPipe inspired deep learning approach for real-world application. Journal of Ambient Intelligence and Humanized Computing 14(4) June 2022. doi: https://doi.org/10.1007/s12652-022-03910-0

[12] Francesco Lanotte, Megan K. O’Brien, Arun Jayaraman. AI in Rehabilitation Medicine: Opportunities and Challenges. Ann Rehabil Med 2023;47(6):444-458. doi: https://doi.org/10.5535/arm.23131

[13] Watier, N. Measures of angularity in digital images. Behav Res 56, 7126–7151 (2024). doi: https://doi.org/10.3758/s13428-024-02412-5

[14] Haotong Lin, Sili Chen, Junhao Liew, Donny Y. Chen, Zhenyu Li, Guang Shi, Jiashi Feng, Bingyi Kang. Depth Anything 3: Recovering the Visual Space from Any Views. Computer Vision and Pattern Recognition. arXiv:2511.10647. 13 Nov 2025. doi: https://doi.org/10.48550/arXiv.2511.10647

[15] Reddy, K. Jayasankara. "Motor Rehabilitation and Biofeedback." Innovations in Neurocognitive Rehabilitation: Harnessing Technology for Effective Therapy. Cham: Springer Nature Switzerland, 2025. 231-266. doi: https://doi.org/10.1007/978-3-031-88117-6_11

[16] Lee, J. W., Antonellis, P., Fino, P. C., Peterka, R. J., Wilhelm, J. L., Scanlan, K. T. & King, L. A. (2026). Wearable technology to characterize and treat mild traumatic brain injury subtypes: Study protocol for a randomized controlled trial on biofeedback-based precision rehabilitation (SuBTyPE). PLoS One, 21(1), e0340867. Doi: https://doi.org/10.1371/journal.pone.0340867

[17] Vitalina Holubenko, Paulo Silva, Carlos Bento. Intelligent Mechanisms for Monitoring and Intrusion Detection in IoT Devices. MS thesis. Universidade de Coimbra (Portugal), 2022. Doi: https://doi.org/10.48550/arXiv.2306.17187

[18] Reddy, Naveen Reddy Singi, and Mahitha Adapa. "AI-Driven Data Integration: Transforming Enterprise Data Pipelines through Machine Learning." Journal of Computer Science and Technology Studies 7.12 (2025): 110-119. doi: https://doi.org/10.32996/jcsts.2025.7.12.16

[19] Core Exercise: Dead Bug https://www.youtube.com/watch?v=g_BYB0R-4Ws

[20] Rehab Protocol Forms. https://www.codyregionalhealth.org/our-services/orthopedics/rehab-protocol-forms/

[21] Essential Protocols for Functional Rehabilitation https://kinvent.com/blog/essential-protocols-for-functional-rehabilitation/

[22] Jennifer Sumner, Hui Wen Lim, Lin Siew Chong, Anjali Bundele, Amartya Mukhopadhyay, Geetha Kayambu. Artificial intelligence in physical rehabilitation: A systematic review. Artificial Intelligence in Medicine. Volume 146, December 2023. doi: https://doi.org/10.1016/j.artmed.2023.102693

[23] Nazeer, Afreen. "Post-Injury Rehabilitation Reimagined: Integrating AI into Personalized Recovery Pathways." (2025). https://www.ijstjournal.com/papers/volume-2/issue-2/ijst241027/