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Design and Evaluation of an Augmented Reality Posture Guidance System for Marching Exercises in Older Adults: A Pilot Study

Charlee Kaewrat,[1,2] Kanjana Haruehansapong,[1] Thanawat Sriwilai,[1] Phongnaphat Chuchuai,[1] M. Arif Efendi[3] and Bukhoree Sahoh[1,2,*]

Abstract

Incorrect movements during marching exercises among older adults can result in acute injuries and chronic complications, highlighting the need for precise and real-time feedback from exercise specialists to mitigate further risks. This study proposes an automated detection system designed to address these challenges by leveraging a convolutional neural network (CNN)-based pre-trained model integrated with a cosine-based formula algorithm derived from the dot product. The system extracts anatomical movement data from key joints-specifically the hip, knee, and ankle—to calculate joint angles θ, thereby emulating the evaluative capabilities of exercise specialists. Furthermore, augmented reality (AR)-based techniques are incorporated to visualize the results, offering a practical solution to the scarcity of physiotherapists. The proposed approach is experimentally validated through a study involving 90 elderly participants, 30 in controlled laboratory settings and 60 in real-world environments. The system demonstrates robust performance in detecting marching postures across diverse body weight statuses and genders, achieving F-measure scores exceeding 98%. These findings suggest that the system is highly suitable for real-world applications, providing a self-assessment tool that enables older adults to exercise safely and effectively by simulating continuous professional supervision.

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1. Introduction

Proper exercise postures are crucial for enhancing physical health in older adults.[1] However, incorrect movement patterns during exercise can lead to immediate injuries and chronic complications, particularly compromising balance and mobility in this population.[2] Age-related declines in balance, muscle strength, and movement control further exacerbate the challenge of maintaining correct exercise.[3] Older adults often perform exercises incorrectly, particularly without specialists' supervision, which diminishes the intended health benefits and increases the risk of musculoskeletal problems.[4] Even though specialist guidance has been shown to improve exercise form effectively, limited access to rehabilitation specialists remains a significant barrier to sustaining regular and safe exercise routines among older adults.[5] Addressing this gap is essential to ensure the safety and efficacy of exercise interventions in promoting healthy aging.

An automatic posture detection system integrates motion sensing, analysis, and real-time feedback to track human movement and can be applied to a posture guidance system for exercise. These systems employ two primary technological approaches for motion sensing and analysis. The first approach utilizes RGB cameras combined with advanced pose estimation frameworks, enabling skeleton tracking and real-time action recognition.[6-8] Motion data can be processed through advanced image processing techniques such as histogram analysis and skeletonization, and these systems are particularly well-suited for home-based exercise programs.

[1] *School of Informatics, Walailak University, Nakhon Si Thammarat, 80160, Thailand*
[2] *Informatics Innovation Center of Excellence (IICE), Walailak University, Nakhon Si Thammarat, 80160, Thailand*
[3] *Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering, Universitas Gadjah Mada, Yogyakarta, 55281, Indonesia*
**Email:* bukhoree.sa@wu.ac.th (B. Sahoh)

The second approach incorporates RGB-depth cameras, such as LiDAR (light detection and ranging) sensors, for motion sensing,[9] alongside analysis algorithms that process both color and depth information to enable precise three-dimensional movement tracking, joint angle measurement, and limb position monitoring.[10] These systems may leverage augmented reality (AR), a three-dimensional technology that overlays digital content onto the real world. AR enhances user understanding by providing real-time feedback through visualizations, reference lines, and movement trajectories. It enables users to better comprehend and correct their actions within their field of view.[11,12]

Although AR-based feedback mechanisms integrated with motion-sensing technologies hold significant potential to enhance exercise efficacy, older adults often require closer and more direct supervision from specialists to identify incorrect movements and provide corrective guidance. Unfortunately, limited access to these specialists poses a substantial barrier for older adults striving to maintain proper exercise techniques. This highlights a critical research gap at the intersection of older adult exercise, posture detection, AR technology, and specialist-guided interventions. Howard and Davis conducted a comprehensive investigation into AR-based feedback systems with motion-sensing technologies,[13] emphasizing the need for future research to focus on methodological implementations incorporating expert recommendations for real-time mobile applications rather than stationary systems. Similarly, Kiani *et al*.[14] analyzed recent studies and confirmed that AR-based feedback mechanisms can address this gap by enabling remote healthcare delivery with improved efficiency. To address this challenge, our study proposes an AR-based posture guidance system designed to simulate expert validation procedures following specialist assessment standards. This system enables older adults to visualize correct movements, receive real-time feedback, and maintain proper form, ensuring optimal muscle engagement, balance, and safety. The primary contributions of this research are as follows:

1. To introduce a new system architecture for an AR-based posture guidance system designed to assist older adults in performing marching exercises correctly, providing real-time feedback, and ensuring proper exercise form.

2. To develop a detection approach to track and analyze movements during marching exercises and present information in an age-appropriate manner, making it accessible and understandable for older adults.

3. To validate the effectiveness of the proposed detection approach by comparing the system's measurements and feedback to expert-based procedures, demonstrating its potential for real-world application.

Section 2 investigates marching techniques, posture assessment methodologies, and AR applications for elderly exercise. Section 3 illustrates the overview system of AR-based posture guidance. Section 4 concentrates on the design and methodology for posture analysis acquisition, while Section 5 focuses on the detection model for marching exercise prediction. Section 6 evaluates the effectiveness of the posture guidance model using quantitative experiments, and Section 7 presents conclusions and future directions.

2. Related works and background knowledge

This section examines related works and background knowledge of exercise posture detection approaches and their application of expert-based measurements and AR technologies for marching exercises.

2.1 Marching exercises

Marching exercise involves standing upright with feet positioned hip-width apart and alternately lifting the knees toward the chest while swinging the arms in a coordinated motion parallel to the ground. This movement effectively engages the hip flexors and core muscles while promoting stability and balance. It is important to note that marching exercise primarily mobilizes the hip and knee joints, with a knee lift height typically less than 90 degrees. However, a 90-degree knee lift may not be suitable for some older adults due to muscle strength and bone health limitations. To address this issue, Sitthiracha *et al*.[15] recommended exercises involving knee lifts higher than 45 degrees, structured into a program conducted five times weekly for 35–45 minutes per session. This program provides a balanced combination of physical activity and safety measures tailored to the physical capabilities of older adults, emphasizing the importance of regular and manageable exercise routines.

Furthermore, Rikli and Jones investigated the assessment of lower body strength and endurance, concluding that the two-minute step test is suitable for evaluating physical function in older adults.[16] Subsequent studies by Vallabhajosula *et al*.[17] and Pinheiro *et al*.[18] have further validated the effectiveness of the two-minute step test for assessing physical function in this population. Building on these findings, our proposed system incorporates the two-minute step test as a standardized metric for evaluating marching exercises, ensuring alignment with established assessment protocols, and promoting safe, effective exercise practices for older adults.

2.2 Posture estimation for exercises in older adults

Incorrect exercise techniques can reduce muscle activation and increase the risk of musculoskeletal injuries, balance impairments, and falls among older adults.[19,20] Implementing effective exercise posture detection and correction programs for this population presents significant challenges.[21] Many existing systems rely on sensor-based technologies, which can be intrusive, require costly installation and maintenance, and are often impractical for home use due to affordability and accessibility issues.[22,23]

In contrast, the pose estimation approach offers a promising solution by leveraging video streaming analysis to provide an accessible, cost-effective alternative.[24,25] This

Table 1: Summary of recent studies on AR-based exercise guidance systems for older adults.

Participants	AR intervention	Key outcomes	Limitations	Paper
45 (18-59 years)	ARkanoidAR: Kinect sensor, 2m distance setup; text/image/audio feedback for movement correction in-game interface	Movement success rate; SUS scores	The system was not concerned with marching exercise assessment	[30]
27 females (65+ years)	3D motion sensor system, PC, software, real-time feedback, personalized training modules for the elderly	Increased Muscle mass; improved physical performance (SFT)	AR requires technological experts with modern technologies and may not fit with daily use application	[31]
7 (66-88 years)	Microsoft HoloLens: AR headset, holographic display, and visual-interactive tools for balance training supervised by physiotherapists	Improved Balance; Decreased Fear of falling	Microsoft HoloLens comes at an expensive cost and requires maintenance, which makes it difficult for ordinary people.	[32]
15 females (65+ years)	LiDAR-based AR: LiDAR sensors for precise foot movement tracking; six exercise modalities, including tap steps, balloon pathfinding, and catching bugs	Improved TUG, 5TSTS, 1MSTS; enhanced respiratory & cognitive function	The approach overlooked the marching exercises assessment for general application.	[33]
56 females (73.7 years average)	AR Senior Fitness Test: Kinect v2 sensor, AR glasses; fitness assessment system for elderly evaluation	SFT battery; reliability tests (ICC, Cronbach's alpha)	The approach worked well for lower body assessment but did not consider upper body posture, especially for the marching exercises evaluation.	[34]
27 females (76.4 years average)	AR glasses vs tablets: Nreal AR glasses, tablets, smartphones; visual/audio feedback for tele-exercise programs	UEQ analysis; UX comparison	The study compared UX technologies rather than marching exercise assessment.	[35]

method can be customized for specific exercises and older adult populations, enabling real-time posture feedback without needing wearable devices or intrusive equipment. These systems can integrate simultaneous tracking and user engagement by utilizing an RGB camera. Recent advancements in this field include innovative pose estimation-based posture classifier systems that use video streaming analysis to assess exercise postures accurately. For instance, Vijayaprabakaran *et al*.[26] developed a system employing convolutional neural networks (CNNs) to recognize older adults' activities through video streaming, achieving an accuracy of 79.94% in image classification. Additionally, progress has been made in intelligent robotic knee rehabilitation devices, which can perform various functional exercises on the knee joint with precise measurement and control capabilities.[27] The integration of series elastic actuators and dual motor designs has further enhanced these systems, improving torque control, stiffness adjustment, separate limb movement tracking, and overall comfort during knee lifting exercises.[28,29]

Despite these advancements, challenges persist in computer vision and pose estimation. These include the need for the physical installation of equipment in specific locations and the absence of a comprehensive posture detection and exercise guidance system tailored for marching exercises in general home settings. Addressing these limitations is critical to developing accessible and effective solutions for older adults to maintain proper exercise form and safety.

2.3 AR for posture estimation for exercises

AR offers an innovative approach to posture detection and exercise guidance for marching by interactively visualizing the real-world environment. AR systems can be installed on general mobile devices, enabling older adults to receive real-time feedback and instructions seamlessly integrated into their field of view. These are particularly beneficial for older adults who may require clear and immediate guidance. Table 1 provides a comprehensive overview of recent research advancements in AR-based exercise guidance systems tailored for older adults, highlighting their potential to improve exercise safety, efficacy, and accessibility in home-based settings.[30-35]

Table 1 highlights a growing trend in recent studies on AR-based exercise guidance systems for older adults, showcasing a shift from basic movement tracking to comprehensive posture analysis and personalized exercise guidance. Advanced technologies, such as 3D motion sensors, Microsoft HoloLens, Kinect v2 sensors, and AR glasses, have played a pivotal role in these systems, demonstrating positive outcomes in improving physical function, increasing exercise adherence, and enhancing motivation among older adults. However, these systems often come with high costs, require complex installation, and depend on expert supervision, which limits their accessibility and practicality for daily use by older adults.

In contrast to these limitations, our proposed study aims to develop an AR-driven posture guidance system tailored for older adults. It focuses on accessibility through mobile applications and minimizes the need for physical installations, providing older adults with a practical and sustainable solution for maintaining proper exercise form and improving overall physical health.

3. An overview of the posture guidance system architecture

The architecture outlines the design and evaluation of an AR-driven posture guidance system to promote effective exercise among older adults. This system operates in real-time, tracking human movements, detecting postures, and providing user feedback through AR technology. The architecture is structured into two primary components: the environment and the computing system. The computing system is divided into four key modules: 1) data gathering, 2) feature engineering, 3) marching detection, and 4) presentation. The graphical representation of the interaction between these components is illustrated in Fig. 1.

Fig. 1 illustrates the graphical process that connects the computing system and the environment, forming a cyclical and repetitive loop that continues until the marching exercise is completed. This setup configures the environment for older adults to practice marching exercises, requiring only general mobile devices (smartphones based on iOS or Android) equipped with a camera. The posture guidance system initiates with the data gathering component, which captures real-time video from the environment. The video is then compressed and resampled to reduce computational costs while retaining critical information. The feature engineering component normalizes the video frames into standard scales and extracts body pose landmarks from each frame. Joint identification utilizes these landmarks to determine marching exercise postures by analyzing the relationships between key lower-body joints, including the ankles, knees, and hips. The marching exercise detection component computes the flexion angles of the ankles, knees, and hips based on predefined time-dependency rules, analyzing lower-body movements to assess whether the exercise is performed correctly. Finally, the presentation component translates the numerical outcomes into a graphical demonstration, making the computational output understandable for older adults. This graphical feedback is augmented into the original video stream, allowing users to visualize corrections directly in their environment. The architecture operates in a closed-loop manner, with feedback-augmented video streaming continuously sent back to the initial components to refine and improve the system's effectiveness. This iterative design enables precise posture guidance tailored to the needs of each older adult, ensuring accurate assessment and correction of marching exercises.

A key research challenge in this architecture lies in designing and developing a practical approach to detect marching exercise poses, as the system's overall effectiveness and usability depend on its ability to identify and analyze these movements accurately. The following section will detail the design and development of joint identification and marching exercise detection, which are critical components for ensuring the success of the proposed AR-based posture guidance system for older adults.

4. Proposed posture analysis

This section outlines the design and development of the AR posture guidance system, which is structured around four key sub-processes: 1) environment setup and data gathering design, 2) feature engineering, 3) detection approach, and 4) presentation. Each sub-process is critical in ensuring the system's functionality and effectiveness.

4.1 Environment setup and data gathering design

Data gathering is the intermediary connecting the real-world environment with the computing system. To facilitate this, we established a real-world environment chamber at the Digital Medical Informatics Laboratory in Academic Building 6 of the School of Informatics at Walailak University, Thailand. The experimental chamber was designed to replicate a residential

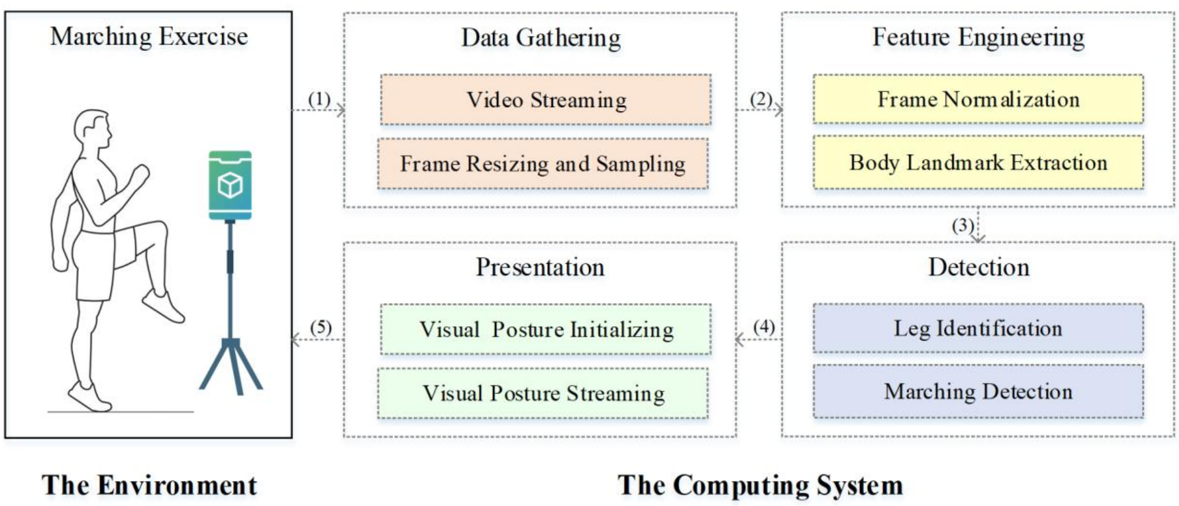


Fig. 1: The architecture of an AR-driven posture guidance system for a marching exercise in older adults.

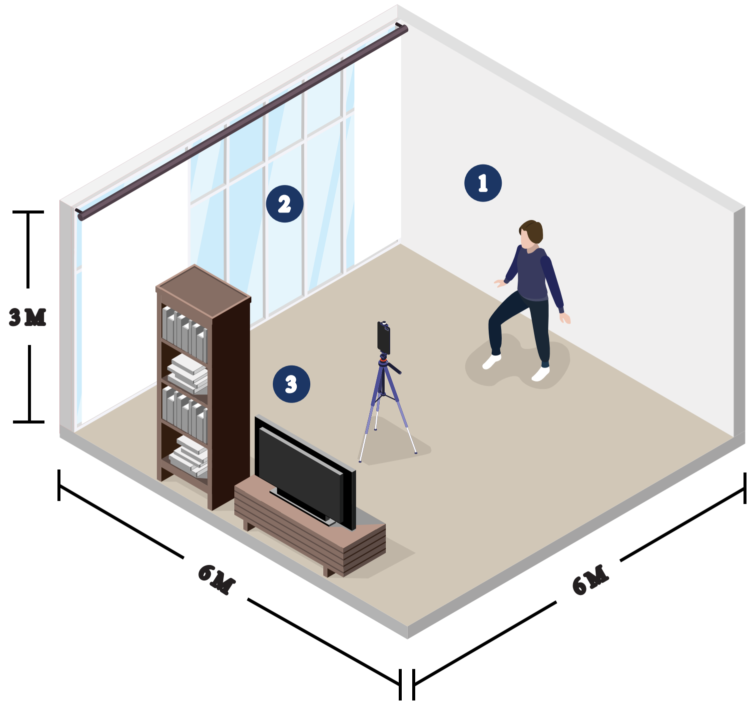


Fig. 2: The chamber is designed for effective marching exercise testing in older adults. It features three distinct backgrounds to accommodate computer vision perspectives: (1) a plain white wall, (2) a bright glass wall, and (3) a simulated living room environment with basic furniture.

living space with multimedia displays and storage furniture. The chamber simulates a residential living space, featuring multimedia displays, storage furniture, and a floor plan of 6 × 6 × 3 meters (L × W × H). Lighting conditions were standardized using six ceiling-mounted light-emitting diode (LED) panels (28 W each), providing an average illuminance of 600 ± 100 lux. Climate control was achieved via an on-off Heating, Ventilation, and Air Conditioning (HVAC) system (20,000 BTU), maintaining stable thermal conditions (25 ± 2 °C, 60 ± 5% RH) to eliminate thermal discomfort during experiments. This optimized setup was specifically designed to study marching exercise actions for older adults, ensuring reproducibility and environmental realism, as illustrated in Fig. 2.

As illustrated in Fig. 2, the environmental chamber was designed to validate the application's functionality across various settings that approximate typical living conditions for older adults. This validation was conducted through three distinct scenarios: (1) a plain white wall representing an ideal location with minimal noise and unrelated objects, (2) a bright glass wall simulating a dynamic background with potential movement outside the room, and (3) a simulated living room environment with ordinary furniture representing static objects that may appear in camera frames. The primary objective of this setup is to establish a collaborative framework between AR technology and expert-based measurement, ensuring that both methods can measure and assess marching exercises in older adults to the same standard.

To achieve this, the experiment was co-designed by two computational engineers and two physiotherapists, combining medical procedures with scientific digital evaluation processes. Engineers utilized a high-quality web camera, the MAXHUB UC W21 model, with a 1080p resolution sensor and a frame rate of 25 frames per second (FPS) for video recording. The recorded videos were used for data understanding and resized and downsampled to optimize processing efficiency. It was determined that a resolution of 480p with 10 FPS effectively captured critical body localization while maintaining computational feasibility. The OpenCV API, an open-source computer vision and machine learning library based on Python, was employed for video processing and analysis.

On the other hand, physiotherapists utilized medical-grade measuring tools, including a 360-degree goniometer physical therapy protractor, to accurately measure and mark joint angles based on international standards for range of motion. This collaboration ensured that engineers and physiotherapists could consistently measure and assess the recorded data. Specifically, they guided and labeled the postures in the marching exercises, determining whether they were correct or incorrect based on the streaming video.

4.2 Feature engineering

Feature engineering aims to uncover critical features hidden in complex streaming videos that help automation systems identify practical exercises. For instance, specialists determine the effective postures of marching exercises based on three lower body components: the ankle, knee, and hip flexions. The proper movement (degree ° of angle: θ) between them is vital information to detect the marching exercises, as shown in Fig. 3.

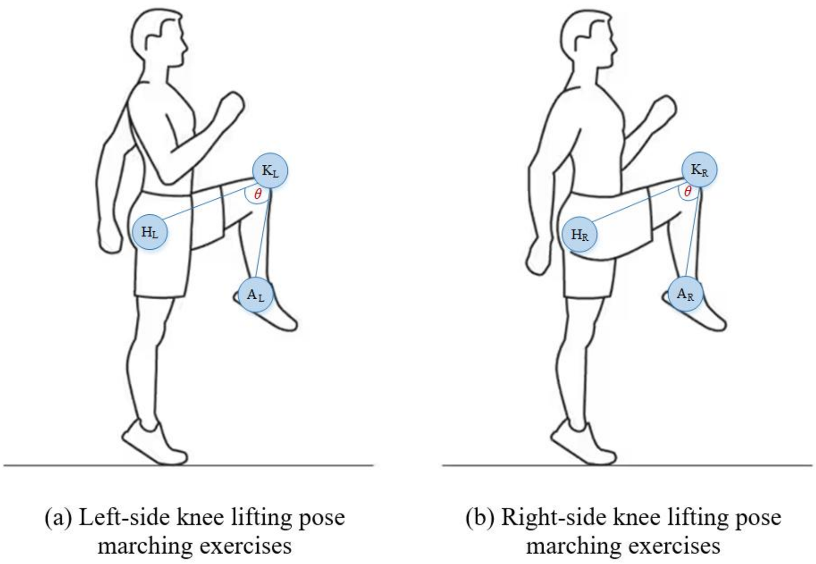


Fig. 3: Left (a) and right (b) knee lifting postures for marching exercises by considering θ between three lower body components: the ankle, knee, and hip flexions.

Fig. 3 illustrates that θ represents the angle between the shin (the length between the hip and knee) and the thigh (the length between the knee and ankle). The marching exercise's effectiveness depends on the action's correctness, which is determined by the specific θ and the lengths of the shin and thigh. To assess this, feature engineering mimics expert-like intelligence by extracting the positions of the hip, knee, and ankle, which are then used to calculate the lengths of the shin and thigh. These measurements are critical for evaluating the proper θ required for practical marching exercises in older adults.

CNNs serve as the primary technique in feature engineering, enabling the extraction of key body landmarks—such as the hip, knee, and ankle—from video streams. CNNs process raw video data and automatically identify meaningful information for detecting marching exercises. The CNN model focuses on six specific landmarks: the right hip (H_R), left hip (H_L), right knee (K_R), left knee (K_L), right ankle (A_R), and left ankle (A_L). Fortunately, significant advancements have been made in recognizing human body landmarks using CNNs, resulting in high-performance models capable of accurately detecting these landmarks in video data.

In this study, we utilize MediaPipe, a CNN-based pre-train model with over 90% accuracy, to detect the keypoint localization of the six landmarks relevant to marching exercises. Specifically, we implement feature engineering using the MediaPipe Pose Landmarker, an artificial intelligence-based Python library, to extract the essential features required for exercise detection. The outputs for each landmark are represented in three dimensions (3D). For example, the right hip (H_R) is represented as $H_R = (x_{hr}, y_{hr}, z_{hr})$, where x_{hr}, y_{hr}, and z_{hr} denote the right hip landmark's horizontal, vertical, and depth coordinates. These detailed outputs are transferred to the marching exercise detection process, enabling precise and accurate posture analysis. This approach ensures a robust and reliable system for guiding older adults in performing marching exercises correctly and safely.

4.3 Detection approach for elderly marching exercise

The proposed detection system for elderly marching exercises begins with leg identification, focusing on two primary components: the lower part, represented by the shins, and the upper part, represented by the thighs. This division is essential because the angle θ between the shins and thighs can be calculated once their magnitudes are determined. For instance, the left-side angle θ_L of the leg is formed between the landmarks A_L, K_L, and H_L. The relationship between these points forms a triangle θ, as illustrated in Fig. 4, where the lengths corresponding to A_L, K_L, and H_L are used to compute θ_L.

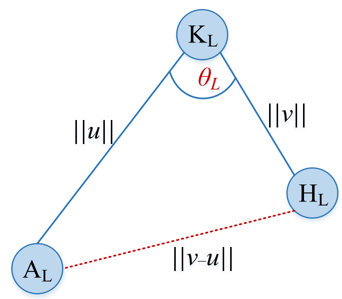


Fig. 4: The angle θ between two vectors u and v, where $\| u \|$ represents the length of the thigh and $\| v \|$ represents the length of the shin, and the length of the opposite side of an angle θ can be determined by $\| u - v \|$.

Fig. 4 shows the angle θ_L between two vectors u and v, non-zero vectors in $\mathbb{R}$, where $\| u \|$ represents the magnitude of the thigh and $\| v \|$ represents the magnitude of the shin. The magnitude of the opposite side of an angle θ can be determined by $\| u - v \|$. The u and v are the lengths between the hip, knee,

Algorithm 1: Evaluating the correctness of marching exercises based on the angle θ between the shin and thigh.

Input: angle θ—the measured angle between shin and thigh in degrees (real number)

Output: String indicating the evaluation result (correct posing: CP, over posing: OP, and under posing: UP)

```
// global constants
ideal_angle ← 45          // target angle θ in degrees
tolerance ← 5             // acceptable deviation from ideal angle θ
runtime_duration ← 120    // total runtime in seconds

// global variables
lower_bound ← ideal_angle – tolerance
upper_bound ← ideal_angle + tolerance

// data structure for result tracking
struct result_counter:
  cp_count: integer     // correct posing count
  up_count: integer     // under posing count
  op_count: integer     // over posing count

// main functions
function evaluate_angle(angle: real) → string
  begin
    if angle ∈ [lower_bound, upper_bound] then
      return "CP"   // correct posing
    else if angle < lower_bound then
      return "UP"   // under posing
    else
      return "OP"   // over posing
    end if
  end

function initialize_counter() → result_counter
  begin
    counter ← new result_counter
    counter.cp_count ← 0
    counter.up_count ← 0
    counter.op_count ← 0
    return counter
  end

function update_counter(counter: result_counter, result: string)
  begin
    if result = "CP" then
      counter.cp_count ← counter.cp_count + 1
    else if result = "UP" then
      counter.up_count ← counter.up_count + 1
    else
      counter.op_count ← counter.op_count + 1
    end if
  end

procedure continuous_angle_assessment(initial_angle: real)
  begin
    counter ← initialize_counter()
    start_time ← current_time()
    end_time ← start_time + runtime_duration
```

```
    while current_time() < end_time do
      // perform angle evaluation
      result ← evaluate_angle(initial_angle)
      update_counter(counter, result)

      // output current status
      output_status(initial_angle, result, counter)
    end while

    output_final_results(counter)
end
```

and ankle, and the magnitudes of shin and thigh can be subtracted from their vectors as follows in Eqs. (1) and (2):

$$u = \mathrm{A_L} - \mathrm{K_L} \quad (1)$$

$$v = \mathrm{K_L} - \mathrm{H_L} \quad (2)$$

where $\mathrm{A_L} = (x_{al}, y_{al}, z_{al})$, $\mathrm{K_L} = (x_{kl}, y_{kl}, z_{kl})$, and $\mathrm{H_L} = (x_{hl}, y_{hl}, z_{hl})$. The angle θ_L can be calculated using the principal law of cosine for dot product based on the magnitudes of two vectors, u and v, which are $\| u - v \|^2 = \| u \|^2 + \| v \|^2 - 2\| u \| \| v \| \cos\theta_L$, and can be calculated as follows Eq. (3):

$$cos\,\theta_L = \frac{u \cdot v}{||u||v||} \quad (3)$$

The result a from Eq. (3) can be converted into the degree using $\cos^{-1}(a)$, which can be used to interpret whether the marching exercise is satisfied or needs improvement. We developed the computation of θ for elderly marching exercises based on NumPy, the standard library for scientific computing in Python, which can produce reliable results.

The ideal angle θ between the shin and thigh is 45°, as discussed in Section 2.1. A preliminary comparison was conducted between the results generated by the system and those measured by physiotherapists using medical-grade measuring tools under controlled laboratory conditions to evaluate the accuracy of the proposed approach. A pre-evaluation process involving 20 participants—10 males and 10 females—was performed to assess the acceptability of the outcomes. The results revealed slight discrepancies between the proposed approach and manual measurements based on physiotherapists, with variations ranging from ±3° to 5°. These findings indicate that the proposed approach is suitable for real-world applications, as deviations within this range maintain a balance between precision and safety. Deviations lower than this range could compromise the accuracy of exercise ability measurements. In contrast, deviations higher than this range might pose safety risks, particularly for older adults.

4.4 Presentation

This section introduces an AR posture guidance system based on the proposed detection approach, serving as the final computing system process that bridges the gap between computational analysis and real-world application. The system is designed to be accessible and understandable for ordinary users, particularly older adults. It is implemented based on the two-minute step test, a validated method for assessing physical function in older adults (as outlined in Section 2.2). The presentation component utilizes rule-based statements to evaluate whether the marching exercises performed by older adults are correct. This evaluation is achieved by applying the cosine function, as described in the previous section, and is detailed in Algorithm 1.

The outputs generated by the proposed algorithm serve as a guide to remind older adults when their actions need adjustment or correction. These results are delivered through a web-based responsive interface that can be rendered on mobile devices. The system requires specific hardware specifications to ensure optimal performance: a front-facing camera with a minimum resolution of 480p and 10 FPS, a processor equivalent to Snapdragon 662 or higher, and at least 3GB of random access memory (RAM). The AR interface simulates outcomes using a graphical marching dial, a familiar daily life symbol for older adults, implemented using A-Frame, a web framework for building AR experiences. For example, "OP" and "UP" indicate over and under actions during marching exercises, prompting real-time recommendations for users to decrease or increase their knee lifts accordingly. A notification confirming correctness is displayed if "CP" (correct posture) is detected. An example of the mobile-based application interface is illustrated in Fig. 5, demonstrating how the system provides intuitive and accessible feedback to older adults during their exercises.

Fig. 5 demonstrates a user-friendly presentation of the AR posture guidance system for elderly marching exercises. Figs. 5(a-c) illustrate the under, correct, and over postures evaluated by the angle θ, respectively. Fig. 5(d) summarizes the results of the actions at the end of the two-minute step test, allowing older adults to pre-screen whether their body functions correctly or require further improvement. This visualization highlights the system's ability to simplify numerical outcomes and present them in an accessible format, enabling older adults to effectively incorporate the two-minute step test into their daily routines.

However, while the application appears straightforward for conducting the two-minute step test, the proposed system's effectiveness depends on the accuracy and reliability

(a) A UP case (b) A CP case (c) An OP case (d) A report of individual information

Fig. 5: An application AR posture guidance system for the elderly two-minute step test based on marching exercise based on the correct, over, and under posing evaluated by θ.

of the detection process. Therefore, evaluating the performance of the detection process is critical to proving the system's overall effectiveness and determining its suitability for real-world applications.

5. Experiment

The evaluation measures the effectiveness of an AR posture guidance system for elderly marching exercises. It is required to confirm whether the AR application reaches robustness and is fitted with real-world applications.

5.1 The experimental objective

We aim to evaluate the detection process's capability by identifying the angle θ between the shin and thigh during elderly marching exercises. This focus is critical because the effectiveness of the system's guidance relies heavily on the accuracy of θ computation. If the proposed approach is well-designed, the detection performance of the application in real-world scenarios should align closely with the results obtained under controlled laboratory conditions.

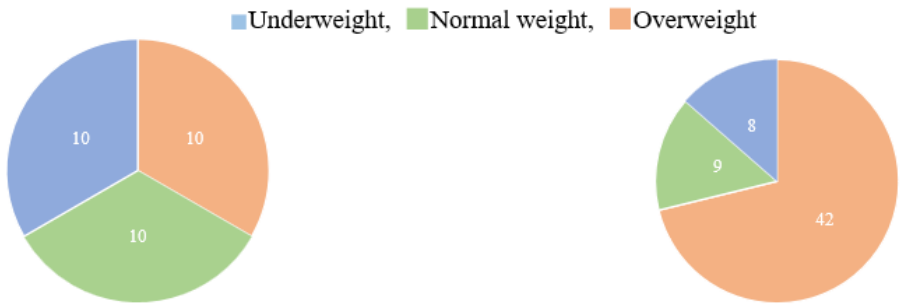
5.2 The description of the dataset

Our experiments were conducted through two distinct case studies: a laboratory-based study and a real-world study. Thirty participants, 15 males and 15 females, were evaluated in the laboratory-based case study. For the real-world case study, sixty participants were recruited through random assignment based on follow-up scheduling at the comprehensive geriatric clinic of Tha Walailak University Hospital, Nakhon Si Thammarat, Thailand, including 23 males and 37 females. The average age and body mass index (BMI, kg/m^2) of female participants were 67.59 ± 4.63 years and 25.28 ± 5.24 kg/m^2, respectively, while those of male participants were 67.35 ± 4.50 years and 25.16 ± 4.59 kg/m^2, respectively. The sample size (N = 90 total) aligns with established AR-based exercise guidance systems for older adult research (Table 1), where 10–60 participants per group are typical for pilot studies. This design balances statistical robustness (accounting for environmental variability in mobility, health status, and exercise patterns) with ambient validity. While larger samples could enhance generalizability, our focus on real-world deployment prioritizes pragmatic applicability, mitigating laboratory bias through comparative analysis of controlled and naturalistic conditions. These studies validate our approach's authenticity and translational potential across idealized and practical scenarios.

The experiments were conducted strictly with ethical standards for human research, as authorized by the Office of the Human Research Ethics Committee of Walailak University (approval number: WU-EC-IN-2-076-67; approval date: 5 June 2024). The study adhered rigorously to the ethical principles outlined in the Declaration of Helsinki and the guidelines established by the Council for International Organizations of Medical Sciences (CIOMS) and the World Health Organization (WHO). These measures protected the participants' rights, safety, and well-being throughout the research process.

Participants were categorized according to weight status using BMI, with classifications of underweight (BMI < 18.5), normal weight (BMI 18.5–25), and overweight (BMI > 25). This categorization was essential because the movement of leg anatomy (shin and thigh) is influenced by weight status, which may affect the ability to control the angle θ accurately. The proportions of participants in each weight category for the laboratory-based and real-world case studies are illustrated in Fig. 6.

Fig. 6 illustrates the distribution of participants across BMI categories for the two case studies. Fig. 6(a) depicts the laboratory-based study, where the proportions of underweight, normal weight, and overweight participants were equal due to the controlled participant selection process conducted in collaboration with Walailak University Hospital, Nakhon Si Thammarat, Thailand. In contrast, Fig. 6(b) presents the real-world participant distribution, with the highest proportion of overweight individuals. This discrepancy determines the importance of designing the proposed approach to ensure its



(a) The distinctive group with several participants in the laboratory setup

(b) The distinctive group with several participants in the real-world setup

Fig. 6: The colored pie chart-based graphical representation of distinctive groups with several participants in laboratory and real-world setups based on the classification of weight status and gender.

effectiveness, robustness, and applicability across diverse populations from controlled laboratory settings and real-world scenarios.

5.3 Evaluation metrics

This study evaluates the effectiveness of marching exercise detection by comparing the application's performance against physiotherapist-validated measurements, which serve as the ground truth. These measurements are obtained using medical-grade goniometers, and the system's outcomes must align within a gold standard tolerance (α) set to ±5 degrees (as detailed in Section 4.3). The effectiveness of marching detection is determined when participants perform the exercise within the specified range of $\theta = 45° \pm 5°$ between the chins and thighs.

The evaluation employs three retrieval effectiveness metrics: precision, recall, and F-measure. Precision quantifies the proportion of correctly detected marching exercise postures relative to the total number of detected postures. Recall measures the proportion of correctly detected postures among all actual correct postures. The F-measure, calculated as the harmonic mean of precision and recall, provides an overall accuracy assessment. These metrics are formally defined as follows in Eqs. (4)-(6):

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{4}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{5}$$

$$\text{F-measure} = \frac{2 \times (\text{Precision+Recall})}{\text{Precision+Recall}} \tag{6}$$

True positive (TP) is defined as the correct detection of a marching exercise posture action, where the measured angle θ falls within the acceptable range of $45° \pm 5°$. False positive (FP) refers to incorrectly detecting a marching exercise posture action where the measured angle θ deviates outside the range of $45° \pm 5°$. False negative (FN) occurs when the system fails to identify a relevant marching exercise posture action, such as when the system does not detect an angle, but the participant did perform the action. TP, FP, and FN metrics are employed to evaluate and compare marching posture action detection performance across two distinct case studies: a controlled laboratory-based study and a real-world study.

5.4 Results and discussions

The experiment evaluated the effectiveness of the proposed detection approach within the AR posture guidance system across varying bodyweight categories, including underweight, normal weight, and overweight individuals. This assessment was conducted through laboratory-based and real-world case studies. The marching actions of participants from the three body weight categories were analyzed. The detection performance was compared using key metrics such as precision, recall, and F-measure, as detailed in Table 2, to demonstrate the system's capability to accurately detect and guide posture across diverse body weight statuses, highlighting its potential for practical applications in real-world scenarios.

Table 2: The effectiveness of the detection approach for underweight, normal weight, and overweight participants.

Weight Status	Precision (%)		Recall (%)		F-measure (%)	
	Real-world	Lab-based	Real-world	Lab-based	Real-world	Lab-based
Underweight	100.00	99.73	98.01	98.56	99.00	99.14
Normal weight	98.86	98.72	99.74	99.17	99.30	98.95
Overweight	99.78	98.54	96.86	95.83	98.30	97.17

According to Table 2, the proposed approach achieves an overall average precision, recall, and F-measure exceeding 95% across two distinct case studies—a controlled laboratory-based setting and a real-world scenario—demonstrating robust performance. Notably, the approach yields superior results for underweight participants compared to other groups. In the laboratory-based case study, precision, recall, and F-measure values for underweight participants reached 99.73%, 98.56%, and 99.14%, respectively, while in the real-world case study, these metrics were 100.00%, 98.01%, and 99.14%, respectively. This exceptional performance can be associated with the methodology's reliance on posture matching, which involves detecting the knee lift based on the angle θ between the shins and thighs. Underweight participants likely outperformed their overweight counterparts due to their greater flexibility and agility, enabling more precise and efficient execution of the required anatomical movements. For normal-weight participants, the proposed approach detected the marching action with slightly lower precision, recall, and F-measure values (approximately 2% lower) than underweight participants. However, the difference was not statistically significant, as the anatomical movements of normal-weight participants are nearly identical to those of underweight participants, allowing them to perform the knee lift correctly and effectively.

In contrast, the proposed approach demonstrated lower detection accuracy for overweight participants' marching actions than others. For overweight participants, precision, recall, and F-measure values in the laboratory-based case study were 98.54%, 95.83%, and 97.17%, respectively, while in the real-world case study, these metrics were 99.78%, 96.86%, and 98.30%, respectively. This reduced performance can be linked to overweight participants' challenges in executing marching exercises, particularly in lifting the knee correctly due to anatomical constraints. Additionally, the proposed approach encountered difficulties in accurately determining whether overweight participants performed the actions, as the increased volume of fat around the shins and thighs complicated the algorithm's ability to compute the angle θ between these body parts. Consequently, overweight participants exhibited the highest FN rates, resulting in the lowest recall among all groups. Fig. 7 summarizes the comparative F-measures of the proposed approach for detecting marching actions across different bodyweight categories, providing a comprehensive overview of these findings.

Fig. 7 presents a comparative analysis of precision, recall, and F-measure as a histogram, evaluating the effectiveness of the detection approach across underweight, normal-weight, and overweight participants in laboratory-based and real-world case studies. The proposed approach demonstrates high performance for underweight and normal-weight participants but exhibits lower performance for overweight participants, except for precision in the real-world case study, where normal-weight participants scored slightly lower than overweight participants. This discrepancy can be attributed to the relatively lower proportion of normal-weight participants in the real-world study, reflecting the natural tendency of older adults to gain weight as they age. Consequently, the underrepresentation of normal-weight participants may introduce bias into the evaluation. Future studies should aim to recruit a more balanced sample to address this limitation, including a more significant number of normal-weight participants, to ensure a more comprehensive and unbiased assessment of the detection approach.

Fig. 8 presents a comparative analysis of the detection approach's effectiveness in laboratory-based and real-world case studies stratified by body weight categories and genders.

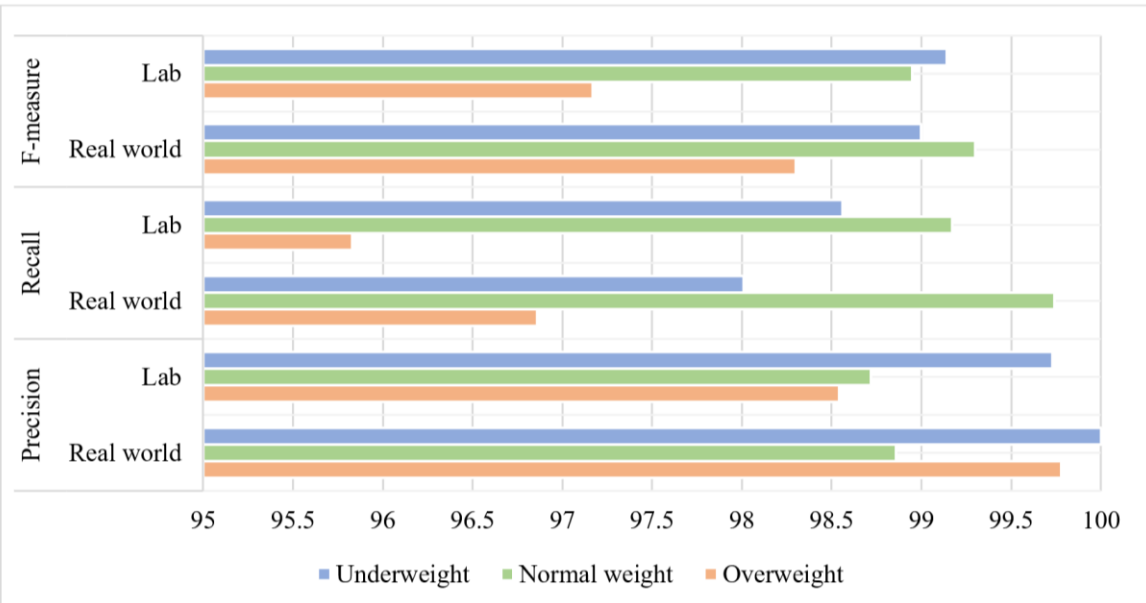


Fig. 7: The comparative effectiveness of the detection approach between underweight, normal weight, and overweight participants based on laboratory-based and real-world case studies.

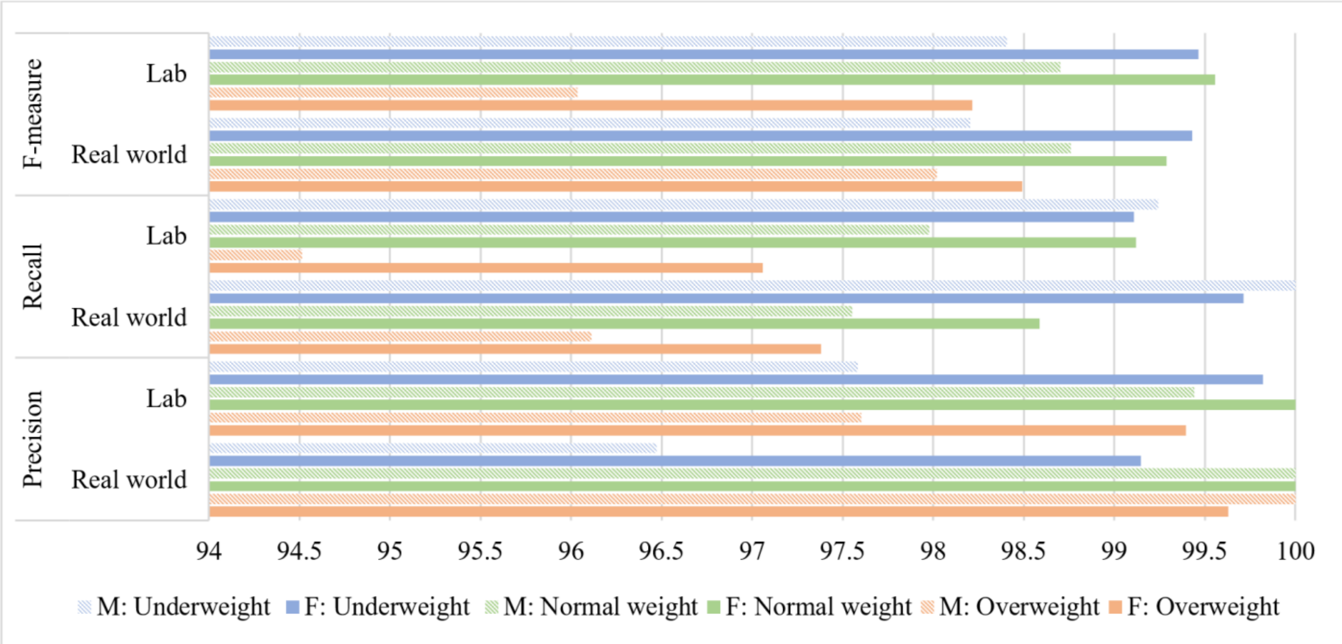


Fig. 8: The comparative effectiveness of the detection approach based on laboratory-based and real-world case studies conditioning on bodyweight categories and genders.

The findings reveal significant gender-based differences in the effectiveness of marching exercises, with females demonstrating superior performance compared to males. Notably, the recall scores were consistently lower for males in both case studies, indicating a higher rate of false detections during marching exercises. Through observations and interviews with male participants, it was identified that their lower performance was attributed to poor execution of actions, influenced by personal behaviors and cultural constraints. Specifically, male participants tended to discontinue efforts after initial failures, whereas female participants persisted until the correct action was achieved. This behavioral discrepancy contributed to the lower recall scores for males across most scenarios. Consequently, it is suggested that male participants require closer monitoring and immediate feedback to address inaccuracies in their exercise execution.

Additionally, the experimental setup at the comprehensive geriatric clinic of Tha Walailak University Hospital, which involved mixed-gender exercise sessions in shared spaces, may have further impacted male performance. Cultural norms in Southeast Asia, which often segregate genders in social activities, likely influenced male participants' reluctance to perform exercises in the presence of unfamiliar females. In contrast, males appeared indifferent to the presence of other males. These findings underscore the need for gender-segregated testing environments to mitigate cultural and social influences on exercise performance in future studies.

The experimental results demonstrate that the proposed AR posture guidance system for elderly marching exercises performs well in laboratory and real-world case studies. The findings suggest that the AR-based system assists older adults during marching exercises by accurately tracking and monitoring their movements, enhancing exercise efficacy, and providing real-time feedback on proper posture. The system's measurements align closely with expert-based standards, indicating its reliability in helping older adults achieve correct posture. These outcomes indicate the potential of the proposed architecture to support older adults in maintaining proper exercise form, thereby contributing to improved physical health and overall well-being.

The current work intentionally focused on establishing proof-of-concept and ambient validity of the core algorithmic approach. However, to strengthen the reliability and generalizability of findings in future studies, we will implement three key statistical improvements: (1) employment of mixed-effects models to properly account for repeated measures and covariates (BMI, gender, age); (2) reporting of Bayesian credible intervals alongside traditional frequentist p-values to better quantify uncertainty, particularly in smaller subgroups such as overweight participants where detection challenges were observed; and (3) a priori power calculations to determine optimal sample sizes for each bodyweight and gender stratum, addressing the current underrepresentation of normal-weight participants identified in our analysis (Fig. 7). These enhancements will provide more precise quantification of effect sizes and confidence in our results while maintaining the environmental validity central to this initial investigation.

6. Conclusion

This study proposes a pilot implementation-based design and evaluation framework for assessing elderly marching exercises, incorporating real-time guidance. This research's primary contribution lies in applying a CNN-based pre-trained model as an automated technology to extract anatomical movement data during marching exercises, specifically focusing on the hip, knee, and ankle joints. It then detects posture by identifying joint angles θ using a cosine-based formula derived from the dot product, thereby replicating the assessment capabilities of exercise specialists. Additionally, AR visualization was integrated to enhance the accessibility and interpretability of the results for non-expert users. This approach enables older adults to perform self-assessments without requiring continuous professional supervision, effectively addressing the challenge of limited access to exercise specialists among the elderly population.

Experimental validation demonstrated the system's effectiveness across diverse weight statuses and genders through comprehensive testing involving 90 participants (30 in a controlled laboratory setting and 60 in a real-world environment). The proposed approach achieved high detection performance, with the majority of participants attaining F-measure scores exceeding 98% in both laboratory and real-world setups. These results indicate the system's capability to address challenges in assessing elderly marching exercises. Furthermore, the findings suggest significant potential for the widespread adoption of the proposed system in home-based exercise programs and rehabilitation settings, thereby enhancing accessibility to professional-level exercise guidance for the aging population.

Building on this pilot study, several critical research directions emerge to enhance the system's robustness and clinical applicability. First, we will refine the deep learning architecture through targeted retraining to improve detection accuracy for overweight participants and expand validation to include individuals aged >70 years, requiring novel adaptive mechanisms in feature engineering and visualization. Second, longitudinal studies (6-12 months) will evaluate the system's efficacy in sustaining exercise adherence and improving measurable health outcomes (e.g., balance, mobility) in real-world settings. Third, comprehensive benchmarking against established technologies (wearable IMUs, Microsoft Kinect) will be conducted using standardized performance metrics and clinical validation against gold-standard motion capture systems. Finally, we will investigate adaptive computer vision techniques to maintain detection accuracy across variable lighting conditions typical of home environments. These advancements will address current limitations while evaluating critical trade-offs between precision, usability, and scalability for geriatric applications.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

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