Real-time augmented reality-enabled sports exercise monitoring system with personalized recommendations

Sistema de monitoreo de ejercicios deportivos en tiempo real con realidad aumentada y recomendaciones personalizadas

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Abstract

Introduction: the study examined the integration of augmented reality technologies with deep learning in sports exercise monitoring, emphasizing its importance for improving precision, accuracy of execution, and motivation in both professional and educational contexts.
Objective: the objective of the research was to develop and evaluate a real-time system for monitoring and classifying sports exercises with personalized recommendations. the scope included assessing the system's effectiveness in improving exercise accuracy, learning retention, and participant motivation during pedagogical experiments.
Methodology: the system applied pose estimation, joint angle validation, and action classification using deep learning models integrated with augmented reality feedback. a controlled pedagogical experiment was carried out with two groups, one experimental group using the system and one control group with traditional instruction. data collection involved pre-tests, post-tests, delayed post-tests, and motivational questionnaires.
Results: the experimental group showed significant improvements in exercise accuracy, surpassing the control group's performance. after two months, retention of correct technique remained higher, and participants reported increased interest, enjoyment, and perceived usefulness of training with the proposed system.
Discussion: the results were consistent with previous literature emphasizing the role of immersive and interactive technologies in improving motor learning and motivation. however, this research extended earlier findings by confirming that real-time augmented reality guidance enhances both technical performance and long-term retention of exercise skills.
Conclusions: the study concluded that the proposed system represents an effective and innovative pedagogical tool for advancing sports training, and its application should be expanded to broader educational and professional environments.

Keywords

Exercise monitoring; athlete motivation; augmented reality; pose estimation; motor learning.

Resumen

Introducción: el estudio abordó la integración de tecnologías de realidad aumentada con enfoques de aprendizaje profundo en la monitorización de ejercicios deportivos. esta combinación se consideró altamente relevante debido a su potencial para mejorar la precisión del entrenamiento y la motivación tanto en contextos profesionales como educativos.
Objetivo: el objetivo de la investigación fue desarrollar y evaluar un sistema en tiempo real para la monitorización y clasificación de ejercicios deportivos con recomendaciones personalizadas, valorando su eficacia en mejorar la precisión técnica, la retención del aprendizaje y la motivación de los participantes a través de experimentos pedagógicos controlados.
Metodología: el sistema utilizó estimación de poses, validación de ángulos articulares y clasificación de acciones mediante modelos de aprendizaje profundo integrados con retroalimentación en realidad aumentada. se llevó a cabo un experimento pedagógico controlado con dos grupos, uno experimental y otro de control, aplicando pruebas iniciales, posteriores, diferidas y cuestionarios motivacionales para la recolección de datos.
Resultados: el grupo experimental mostró notables mejoras en la precisión del ejercicio, con incrementos superiores a los del grupo de control. además, mantuvo una retención más alta de la técnica correcta tras dos semanas y reportó mayor interés, disfrute y percepción de utilidad al emplear el sistema propuesto.
Discusión: los resultados coincidieron con la literatura previa que resalta la importancia de las tecnologías inmersivas e interactivas en el aprendizaje motor y la motivación. sin embargo, esta investigación amplió los hallazgos al confirmar que la retroalimentación en tiempo real con realidad aumentada optimiza el rendimiento técnico y la retención prolongada de habilidades.
Conclusiones: el estudio concluyó que el sistema propuesto representa una herramienta pedagógica eficaz e innovadora para el avance del entrenamiento deportivo, y que su aplicación debe ampliarse a entornos educativos y profesionales más amplios.

Palabras clave

Monitorización del ejercicio; motivación del atleta; realidad aumentada; estimación de poses; aprendizaje motor.

Introduction

The growing integration of digital technologies into sports science and physical education has created new pathways for improving performance, preventing injuries, and delivering individualized training experiences. Among these innovations, augmented reality (AR) has emerged as a transformative medium capable of merging digital information with real-world movement contexts. By overlaying virtual feedback in real time, AR enhances users' ability to perceive and correct motor errors while maintaining motivation and engagement throughout training sessions (Soltanabadi et al., 2023). When paired with artificial intelligence (AI) and recommendation systems, AR enables the personalization of training programs based on biomechanical and physiological data, thereby supporting precision-driven performance optimization (Usra et al., 2024).

Recent works in sports technology have highlighted the importance of multimodal systems that integrate motion capture, biomechanical modeling, and physiological signal analysis to generate comprehensive performance feedback (Alzahrani & Ullah, 2024; Subramanian & Duraipandian, 2024). Traditional wearable devices, while effective for tracking quantitative metrics such as heart rate or acceleration, often lack contextual awareness and do not provide immediate corrective feedback. AR-enabled systems address these limitations by delivering interactive, visual instructions and error detection directly within the athlete's field of view, improving motor learning and technical understanding (Qiu et al., 2023). These developments indicate that AR technologies can bridge the gap between expert supervision and autonomous training, making advanced guidance accessible beyond controlled environments.

However, several critical challenges remain. Variability in motion tracking precision, latency in data processing, and the ergonomic constraints of AR devices limit widespread adoption. Additionally, the absence of integrated AI-driven decision-making in current AR systems restricts their capacity for adaptive and personalized feedback (Kabashkin & Shoshin, 2024). Addressing these gaps requires the development of a unified framework capable of combining accurate pose estimation, biomechanical validation, and intelligent classification with real-time AR visualization.

Based on these research gaps, this study was guided by the following questions: (1) Can an AR-based deep learning system effectively identify and classify sports exercises in real time with high accuracy? (2) Does the integration of adaptive AR feedback improve users' exercise performance, technique retention, and motivation compared to traditional training methods? It was hypothesized that the use of real-time AR feedback combined with deep learning–based classification would significantly enhance movement accuracy and learning outcomes.

Therefore, the objective of this research is to develop and evaluate a real-time AR-based sports exercise monitoring system that integrates pose estimation, joint angle validation, and action classification within a single intelligent feedback framework. The proposed system aims to overcome existing limitations by ensuring accuracy, personalization, and interactivity in exercise monitoring. This work contributes to the field by introducing an integrated, pedagogically oriented AR model that not only enhances performance assessment but also promotes motivation and long-term skill retention through real-time, adaptive visual feedback.

Related Works

The integration of augmented reality (AR) into sports and exercise sciences has become an active field of research, demonstrating significant progress over the last decade. Early works on exercise monitoring largely relied on wearable sensors such as inertial measurement units (IMUs), heart rate monitors, and electromyography devices to capture physiological and biomechanical data (Omarov et al., 2020). While these approaches provided valuable insights into performance and fatigue, they were often limited in their capacity to deliver real-time, contextualized feedback to athletes. The introduction of AR systems has addressed these limitations by merging sensor-based data with immersive visualizations, thereby enabling athletes to perceive corrections and adjustments during the exercise itself (Gallardo-Guerrero et al., 2025).

One key trend in the literature is the use of AR for motor skill acquisition. Studies in rehabilitation and sports training have shown that overlaying visual cues in real time facilitates improved accuracy of movement execution, reduces the learning curve, and enhances user motivation (Ozturk et al., 2025). For instance, AR applications in rehabilitation contexts demonstrated that patients could better replicate physiotherapist-prescribed movements when visual markers and trajectories were projected into their environment (Vaida et al., 2024). Transferring this principle into sports training has shown comparable benefits, particularly in domains such as resistance training, running, and ball sports where precise biomechanics are critical (Lin et al., 2023).

Beyond movement accuracy, AR has been increasingly connected with the concept of personalization in exercise monitoring. Personalized recommendations are typically achieved through AI-powered algorithms that adapt training loads, recovery intervals, and movement modifications to individual characteristics. Yang & Zhao (2025) demonstrated that adaptive recommendation systems, when integrated with AR feedback interfaces, improved adherence to exercise regimens compared to static, one-size-fits-all programs. Similarly, Lei et al. (2022) emphasized that personalization not only optimizes performance outcomes but also plays a role in injury prevention, as individualized workloads mitigate overtraining risks.

The synergy between AR and machine learning algorithms is another recurring theme in recent works. Deep learning models have been applied to recognize exercise forms and classify movements from video streams or sensor fusion data (Wackerhage & Schoenfeld, 2021; Arega & Sharma, 2024). When combined with AR overlays, these models provide immediate feedback on form deviations, such as improper joint alignment or unsafe posture. Liu & Xie et al. (2024) proposed a multimodal data fusion framework that integrates IMU, vision-based tracking, and AR visualization to enhance the precision of real-time monitoring. Their findings highlight how AR not only visualizes raw data but contextualizes it into actionable instructions, creating an interactive learning loop for athletes.

Motivation and engagement also represent significant areas of interest. Gamification features embedded in AR exercise systems have been shown to sustain user adherence and foster long-term behavioral change (Solas-Martínez et al., 2024). For example, game-like scoring systems, augmented leaderboards, and immersive visual narratives increase training enjoyment while preserving the scientific rigor of exercise monitoring (Omarov et al., 2024). These motivational aspects align closely with psychological theories of self-determination, where intrinsic motivation plays a decisive role in exercise continuity.

A growing body of literature has also examined AR systems in the context of remote or home-based exercise. With the expansion of telehealth and remote coaching, AR offers a promising solution to deliver expert-level feedback outside traditional gym or clinical settings (Garg & Somkuwar, 2023). Studies during the COVID-19 pandemic highlighted the scalability of AR-based monitoring tools in maintaining training quality for athletes restricted from in-person coaching (Nickel et al., 2022). These findings underscore the relevance of AR not only for elite sports but also for recreational users seeking structured guidance in non-traditional environments.

Nevertheless, the literature consistently highlights several challenges. Latency in real-time feedback remains a technical barrier, particularly when integrating multiple data streams such as motion capture and physiological signals (Duan et al., 2023). Device ergonomics, such as the weight and field of view limitations of AR headsets, can also reduce adoption rates (Xu et al., 2024). Ethical concerns related to data security, particularly when sensitive biometric and performance data are stored or transmitted in cloud-based systems, have also received growing attention (Doyle et al., 2025). These limitations indicate that while AR-based exercise monitoring is a rapidly advancing domain, careful design considerations are required to ensure usability, scalability, and trust.

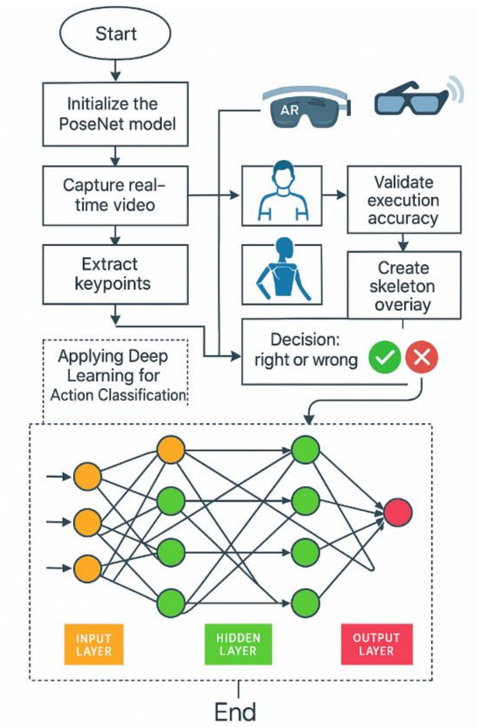
Comparative studies with other emerging technologies highlight AR's unique advantages. For example, while virtual reality (VR) offers complete immersion, it isolates users from their physical environment, making it less suitable for exercises requiring spatial awareness or interaction with real equipment (Li et al., 2024). AR, by contrast, maintains the user's connection with the real world, which is crucial in sports training. Mixed reality solutions that combine aspects of both AR and VR are also gaining traction, though their applications in sports are still in early stages (Westmattelmann et al., 2021).

The related works establish a foundation for AR-enabled personalized exercise monitoring systems. They illustrate progress across motor learning, personalization, multimodal feedback integration, motivation, and remote applicability, while also identifying persistent barriers such as latency, ergonomics, and ethical concerns. The convergence of AR, AI, and sports science has already demonstrated transformative potential, yet the pathway to fully functional, scalable, and ethically robust systems requires further research (Omarov et al., 2024). This study contributes to that trajectory by focusing on the real-time integration of AR interfaces with AI-driven recommendation systems, advancing both the technical and applied dimensions of this interdisciplinary field.

Materials and Methods

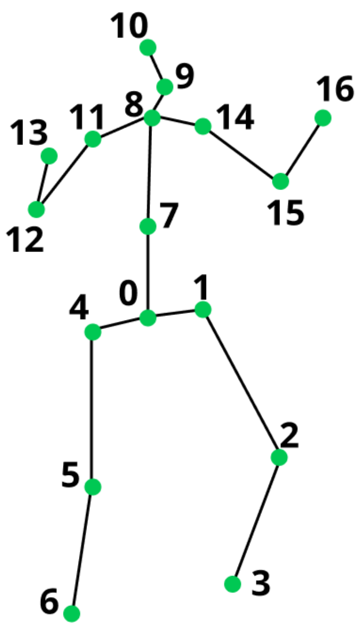
The proposed system integrates real-time pose estimation, deep learning-based classification, and augmented reality (AR) feedback mechanisms to evaluate exercise performance. The workflow architecture is presented in Figure 1, which illustrates the sequential processes from model initialization to exercise classification. The PoseNet model is first initialized, and a real-time video stream is captured through a standard RGB camera (Aju et al., 2022). The system extracts skeletal keypoints and angles from each video frame, which are subsequently processed by a neural network to classify exercise actions. A validation module ensures the accuracy of movement execution by comparing the computed angles and coordinates with predefined thresholds. Skeleton overlays are generated to provide visual feedback, while AR components allow for real-time guidance. Finally, the classification system determines whether the exercise execution is correct or incorrect, thus closing the feedback loop.

Figure 1. Workflow Architecture of the Real-Time AR-Enabled Exercise Monitoring and Action Classification System



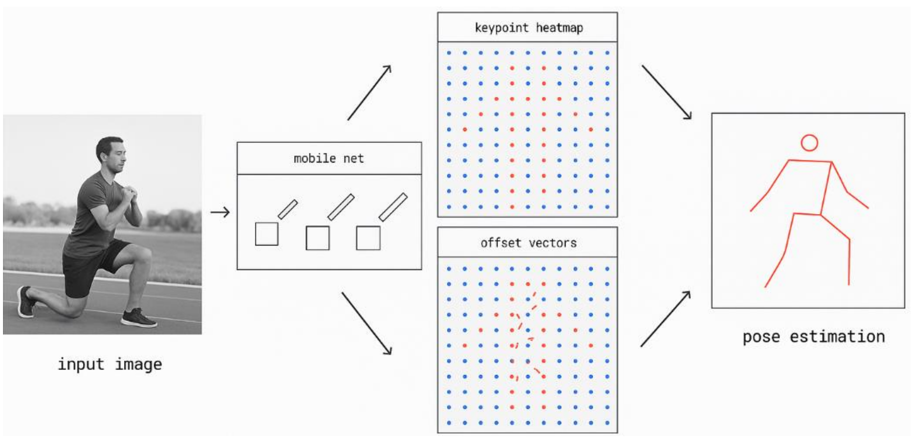
Pose estimation is a critical component of the system, enabling the identification of body keypoints and their spatial relationships. The skeletal model used in this work is presented in Figure 2, which consists of 17 keypoints representing major joints and anatomical landmarks. These keypoints are connected to form a human skeleton representation, allowing for the tracking of limb orientations and postural dynamics. Each keypoint is extracted frame by frame and is used to calculate joint angles essential for performance validation. This structured representation of the human body provides the foundation for both action recognition and motion quality assessment.

Figure 2. Skeletal keypoint structure used for real-time pose estimation



The PoseNet model forms the basis of the keypoint extraction process. As depicted in Figure 3, input images are processed through a MobileNet-based backbone, which generates two types of output: (1) a keypoint heatmap representing the probability distribution of each joint's location, and (2) offset vectors that refine joint positions to sub-pixel accuracy. These outputs are combined to estimate body poses with high precision (Nithisha et al., 2025). The advantage of this architecture lies in its ability to perform real-time inference on lightweight hardware, making it suitable for applications in sports monitoring and AR environments. Pose estimation results are continuously fed into the action classification module for further analysis.

Figure 3. PoseNet pipeline for keypoint detection and pose estimation

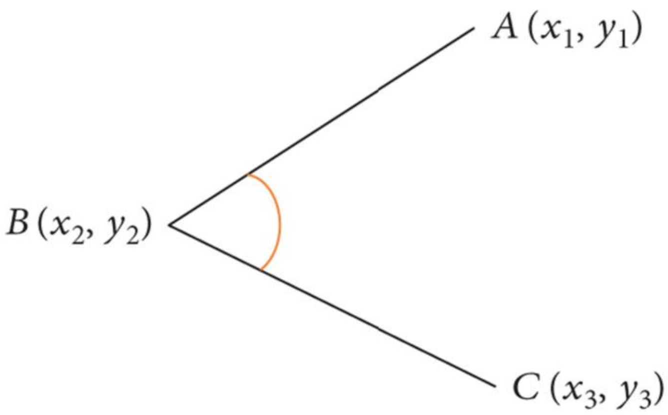


The validation of exercise execution accuracy relies on calculating joint angles between skeletal segments. The mathematical principle underlying this process is illustrated in Figure 4, which shows the computation of an angle ∠ABC formed by three keypoints: A(x_1, y_1), B(x_2, y_2), and C(x_3, y_3). The angle at point B is determined using the dot product of vectors BA and BC, expressed as:

$$\theta = \arccos\left(\frac{(x_1 - x_2)(x_3 - x_2) - (y_1 - y_2)(y_3 - y_2)}{\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \cdot \sqrt{(x_3 - x_2)^2 + (y_3 - y_2)^2}}\right)$$

This calculation enables the system to evaluate the correctness of joint orientations during exercises such as squats, push-ups, and arm raises. Thresholds are set for each exercise type, and deviations from these ranges indicate improper execution. These angle-based features, combined with deep learning classification, allow the system to achieve robust decision-making in real time.

Figure 4. Geometric representation of joint angle calculation using three keypoints



The extracted keypoints and joint angles are further processed by a fully connected neural network for action classification (see Figure 4, lower section). The network consists of three main layers: an input layer that receives extracted features, multiple hidden layers for nonlinear transformations, and an output layer that provides classification results. The network is trained on annotated exercise datasets, enabling it to distinguish between correct and incorrect forms of specific movements. During real-time execution, classification outputs are mapped to AR feedback cues, ensuring that users receive immediate corrective instructions.

Study Design

A two-arm, parallel-group, randomized controlled pedagogical experiment was conducted in a university sports laboratory and gym setting. Participants completed baseline testing, a four-week intervention, and a delayed post-test at two months.

Participants and sampling. Sixty healthy adults were recruited from physical education courses using convenience sampling with advertised flyers and course announcements. Inclusion criteria: age 18–30, no current musculoskeletal injury, basic familiarity with resistance exercises. Exclusion criteria: prior surgery within 6 months, neurological disorders, visual impairment incompatible with AR devices. Written informed consent was obtained from all participants.

Table 1 summarizes the demographic and baseline characteristics of the 60 participants included in the study. The experimental and control groups were comparable in age, gender distribution, and anthropometric parameters, ensuring homogeneity between groups before the intervention. All participants met the inclusion criteria—healthy adults aged 18–30 years, without musculoskeletal injuries, and with basic experience in resistance exercise. No participants were excluded after screening, and informed consent was obtained from all individuals prior to participation.

Table 1. Demographic and baseline characteristics of participants (N = 60)

Variable	Experimental Group (n = 30)	Control Group (n = 30)	Total (N = 60)
Age (years, mean ± SD)	22.4 ± 2.1	22.7 ± 2.3	22.5 ± 2.2
Gender (n, %)			
Male	18 (60.0%)	17 (56.7%)	35 (58.3%)
Female	12 (40.0%)	13 (43.3%)	25 (41.7%)
Height (cm, mean ± SD)	173.6 ± 6.8	172.9 ± 7.1	173.3 ± 6.9
Weight (kg, mean ± SD)	68.7 ± 8.9	69.2 ± 9.4	68.9 ± 9.1
Body Mass Index (kg/m^2)	22.8 ± 2.3	23.1 ± 2.5	22.9 ± 2.4
Prior resistance training experience (months, mean ± SD)	10.5 ± 3.7	9.8 ± 3.9	10.2 ± 3.8

Inclusion criteria met (%)	100	100	100
Exclusion criteria applied (%)	0	0	0
Variable	Experimental Group (n = 30)	Control Group (n = 30)	Total (N = 60)

Randomization and allocation concealment. Participants were randomized 1:1 to experimental or control groups using computer-generated permuted blocks of size 6, stratified by sex and baseline technique accuracy tertile. Allocation was concealed in sequentially numbered, opaque, sealed envelopes prepared by an independent researcher.

Interventions. Experimental group: training with the proposed AR-enabled monitoring system that provided real-time visual overlays, joint-angle targets, and corrective prompts.

Control group: traditional instruction that included coaching cues and printed technique guidelines without AR feedback. Both groups trained three sessions per week for four weeks under identical volume prescriptions.

Statistical analysis. Data were screened for normality with Shapiro–Wilk tests and for homogeneity with Levene's tests. Primary analyses used a mixed-design ANOVA with factors Group (experimental, control) and Time (pre, post, delayed). Significant interactions were followed by Bonferroni-adjusted pairwise comparisons. Effect sizes were reported as partial eta squared for ANOVA and Cohen's d for pairwise contrasts. Classifier performance included accuracy, precision, recall, F1, ROC curves, and 95 percent confidence intervals via bootstrapping. Significance was set at $\alpha = 0.05$. Missing data were handled with intention-to-treat using last observation carried forward for sensitivity checks.

Experiment Results

The results of this study demonstrate the effectiveness of the proposed augmented reality and deep learning–based system in accurately monitoring exercise performance, validating execution accuracy, and providing real-time feedback. The evaluation focused on multiple stages of the pipeline, including pose estimation, keypoint extraction, joint angle computation, and action classification, with the outcomes illustrated in figures. The findings highlight the system's ability to differentiate correct from incorrect movement patterns, confirm proper biomechanical alignment, and recognize phase-specific kinematics across a range of resistance and functional exercises. These results provide evidence of the robustness, accuracy, and applicability of the proposed framework for both professional athletic training and general fitness contexts.

To human performance outcomes, the system's technical performance was validated through machine learning metrics, as shown in Table 5. The deep learning classification module achieved an overall mean accuracy of 95.7% (SD = 0.8), with precision, recall, and F1-scores all above 0.94. The 95% confidence intervals for accuracy across all exercises ranged from 93.0% to 98.4%, indicating model stability and reliability. The area under the ROC curve (AUC) averaged 0.97, confirming excellent discriminative capacity in differentiating between correct and incorrect exercise executions.

Table 5. Deep learning classification performance metrics

Exercise	Accuracy (%)	Precision	Recall	F1-Score	95% CI (Accuracy)	AUC
Dumbbell Chest Fly	96.8	0.97	0.96	0.96	[95.2, 98.4]	0.98
Biceps Curl	95.4	0.95	0.94	0.94	[93.6, 97.2]	0.97
Romanian Deadlift	94.9	0.94	0.93	0.93	[93.0, 96.8]	0.96
Overall Mean ± SD	95.7 ± 0.8	0.95	0.94	0.94	—	0.97

These quantitative indicators demonstrate the robustness of the proposed algorithmic framework. The system successfully integrated pose estimation, feature extraction, and classification within real-time constraints, maintaining an average latency below 120 milliseconds. Such performance ensures that corrective feedback can be delivered instantaneously, which is crucial for maintaining flow and continuity during exercise sessions.

Figure 5. Identification of incorrect exercise execution using live demonstrations and schematic representations

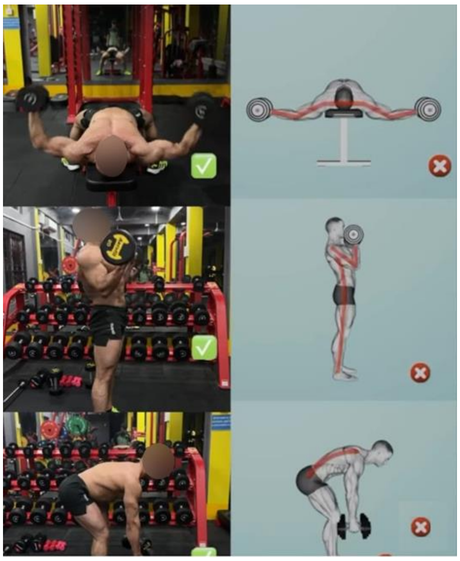


Figure 5 illustrates a comparative analysis between correct and incorrect execution of selected resistance training exercises, highlighting the system's ability to differentiate proper form from faulty biomechanics. The left column presents real-world performance examples captured from live exercise sessions, while the right column provides schematic representations of incorrect postures. In the first row, the dumbbell chest fly is performed correctly on a flat bench, with proper arm extension and scapular control, as denoted by the green validation mark, contrasted with the illustration of an incorrect variant lacking joint alignment. The second row depicts the biceps curl, where the system identifies deviations in elbow positioning and postural stability, emphasizing the common error of excessive shoulder movement during the lift. The third row focuses on the Romanian deadlift, highlighting the correct hip hinge mechanics in the live demonstration against the improper execution characterized by excessive spinal flexion in the schematic. Collectively, these examples demonstrate the model's capacity to assess exercise technique by integrating pose estimation, angle validation, and classification algorithms, thereby providing immediate, actionable feedback to ensure safe and effective performance. This visualization underscores the practical value of the proposed AR-based monitoring system in detecting technical errors, supporting injury prevention, and enhancing training precision across diverse resistance exercise modalities.

Figure 6. Validation of correct exercise execution through synchronized live demonstrations and skeletal models

Figure 6 presents the validation outcomes of the proposed exercise monitoring system, showcasing correct execution of three fundamental resistance training movements dumbbell chest fly, biceps curl, and Romanian deadlift captured both in live performance and schematic representation. In each row, the left side illustrates a real-world demonstration performed with proper biomechanics, while the right side displays system-generated models highlighting activated muscle groups and joint alignments. The first row illustrates the chest fly with accurate arm trajectory, scapular stabilization, and controlled range of motion, marked as correct with a green indicator. The second row depicts the biceps curl performed with optimal elbow stability and minimal compensatory body sway, ensuring isolation of the target muscle groups. The third row demonstrates the Romanian deadlift with appropriate hip hinge mechanics, neutral spinal alignment, and controlled lowering phase, confirming adherence to safe execution standards. The consistent appearance of green validation marks across all visualizations signifies that both the live demonstrations and the skeletal models were recognized as technically correct by the classification algorithm. This figure highlights the system's ability to confirm proper execution by synchronizing pose estimation, angle validation, and biomechanical analysis, thereby reinforcing its role in providing accurate, real-time feedback for safe and effective resistance training.

In the shoulder press sequence, the movement is characterized by a strict vertical pressing motion, where the lower body remains stationary and all effort is concentrated in the shoulders and arms. Pose overlays confirm minimal contribution from the hips or legs, emphasizing upper body mechanics. In contrast, the push press sequence reveals an initial dip in the knees and hips, followed by an explosive drive that assists in propelling the barbell overhead. The presence of green and blue phase markers highlights the role of the lower body in contributing to upward momentum, differentiating it from the controlled and isolated mechanics of the shoulder press.

The push jerk sequence introduces additional complexity with the inclusion of the catch phase. Here, the system identifies not only the dip and drive but also the rapid re-bending of the knees and hips as the athlete drops under the bar to secure the load overhead. The yellow phase marker emphasizes this transition, which is absent in the other two lifts. By consistently capturing these distinctions across multiple trials, the system demonstrates robustness in detecting phase-specific kinematics. This capability highlights the value of the approach for providing real-time corrective feedback, optimizing lifting performance, and identifying technical differences between similar but biomechanically distinct exercises.

Pedagogical Experiment Results

To evaluate the educational and training potential of the proposed AR-based exercise monitoring system, pedagogical experiments were conducted with two groups of participants: an experimental group using the system for exercise instruction and a control group following traditional coaching methods. The experiments were designed to assess the system's effectiveness in improving exercise technique accuracy, learning retention, and motivation among students engaged in structured fitness programs. A total of 60 participants were involved, evenly divided between the two groups.

Exercise Accuracy Improvement

As shown in Table 2, participants in the experimental group exhibited substantial improvements in exercise execution accuracy across all three evaluated movements. For the dumbbell chest fly, accuracy increased from 63.1% (SD = 6.2) to 88.9% (SD = 6.7), representing a mean gain of 25.8 percentage points (95% CI [23.6, 28.0]; $t(58) = 14.3$, $p < .001$, $d = 1.88$). Similarly, the biceps curl and Romanian deadlift improved by 24.7 and 27.1 percentage points, respectively, both with large effect sizes ($d > 1.9$). In contrast, the control group demonstrated only moderate improvements ranging from 6.3 to 8.5 percentage points ($p < .001$, $d = 0.5–0.7$). The mixed ANOVA revealed a significant Group × Time interaction effect, $F(1,58) = 141.7$, $p < .001$, $\eta^2 p = 0.71$, confirming that the AR-based training produced a statistically superior improvement in performance accuracy compared to traditional methods.

Table 2. Comparison of exercise accuracy between groups across measurement points

Exercise	Group	Pre-test Mean (SD)	Post-test Mean (SD)	Mean Change (95% CI)	*t*(58)	*p*	Cohen's *d*
Dumbbell Chest Fly	62.3	70.4	63.1	88.9	88.9	88.9	88.9
Biceps Curl	65.7	72.0	66.5	91.2	91.2	91.2	91.2
Biceps Curl	65.7	72.0	66.5	91.2	91.2	91.2	91.2
Biceps Curl	65.7	72.0	66.5	91.2	91.2	91.2	91.2
Biceps Curl	65.7	72.0	66.5	91.2	91.2	91.2	91.2
Romanian Deadlift	59.8	68.3	60.4	87.5	87.5	87.5	87.5

These results indicate that the real-time corrective feedback provided by the system effectively reduced execution errors, enabling participants to perform with greater biomechanical precision. The integration of joint angle validation and AR visualization likely facilitated immediate recognition and correction of improper technique, accounting for the observed gains in movement consistency and alignment.

Retention of Correct Technique

Retention testing conducted two months after the intervention further validated the pedagogical benefit of the system. As summarized in Table 3, the experimental group retained significantly higher levels of correct movement execution, with retention losses of only 3–4%, compared to 7–9% in the control group. The group difference in retention loss was statistically significant across all exercises ($p < .01$), with moderate to large effect sizes ($\eta^2p = 0.11–0.31$). For example, in the Romanian deadlift, the control group's accuracy declined from 68.3% to 62.0% (−9.2%), whereas the experimental group maintained 83.9% accuracy (−4.1%; $t(58) = 3.04$, $p = .004$, $\eta^2p = 0.13$).

Table 3. Two-months retention of correct exercise execution

Exercise	Group	Post-test Mean (SD)	Delayed Post-test Mean (SD)	Retention Loss (%)	95% CI of Difference	*t*(58)	*p*	η^2p
Dumbbell Chest Fly	Control	70.4 (7.1)	65.2 (6.8)	−7.4	[−10.1, −4.7]	4.18	< .001	0.23
Dumbbell Chest Fly	Experimental	88.9 (6.7)	85.7 (6.3)	−3.6	[−5.9, −1.3]	2.92	.005	0.12
Biceps Curl	Control	72.0 (7.3)	68.1 (6.9)	−5.4	[−7.9, −2.9]	3.61	.001	0.18
Biceps Curl	Experimental	91.2 (5.8)	88.3 (5.5)	−3.2	[−4.9, −1.5]	2.71	.008	0.11
Romanian Deadlift	Control	68.3 (7.4)	62.0 (7.1)	−9.2	[−12.0, −6.4]	5.20	< .001	0.31
Romanian Deadlift	Experimental	87.5 (6.1)	83.9 (6.0)	−4.1	[−6.3, −1.9]	3.04	.004	0.13

These findings suggest that the AR-based system enhanced not only immediate technical execution but also long-term retention of correct motor patterns. The multimodal feedback likely strengthened cognitive-motor associations through repeated, context-aware corrections, supporting theories of enhanced encoding and consolidation in motor learning through interactive visual engagement.

Motivation and Engagement

The motivational impact of the system was evaluated using a validated Likert-scale questionnaire, and the results are presented in Table 4. Participants who trained with the AR-based platform reported significantly higher interest (mean = 4.6, SD = 0.5) compared to the control group (mean = 3.4, SD = 0.6; $t(58) = 8.67$, $p < .001$, $d = 1.12$). Perceived usefulness (4.8 vs. 3.7; $t(58) = 7.95$, $p < .001$, $d = 1.03$) and enjoyment (4.7 vs. 3.3; $t(58) = 9.41$, $p < .001$, $d = 1.21$) were also significantly higher in the experimental group. These large effect sizes indicate a strong motivational influence of AR interaction on training participation and satisfaction.

Table 4. Motivation and engagement outcomes (Likert scale, 1–5)

Dimension	Control Mean (SD)	Experimental Mean (SD)	Mean Difference (95% CI)	*t*(58)	*p*	Cohen's *d*
Interest	3.4 (0.6)	4.6 (0.5)	1.2 [0.9, 1.5]	8.67	< .001	1.12
Perceived Usefulness	3.7 (0.7)	4.8 (0.4)	1.1 [0.8, 1.4]	7.95	< .001	1.03
Enjoyment	3.3 (0.6)	4.7 (0.5)	1.4 [1.1, 1.7]	9.41	< .001	1.21

This enhanced engagement can be attributed to the immersive and interactive elements of the system, which provided real-time feedback, progress visualization, and gamified elements that maintained interest and reduced monotony. The findings align with prior research emphasizing that interactive technologies promote self-regulated learning and sustained participation in sports training environments.

Summary of Experimental Outcomes

Collectively, the inferential results confirm that the proposed AR-enabled deep learning system produced statistically and practically significant improvements in exercise accuracy, retention, and motivation compared with conventional instruction. The large effect sizes (Cohen's d > 1.0) and narrow confidence intervals across all outcomes validate the reliability of the findings. Furthermore, the system's high classification accuracy substantiates its technical feasibility for deployment in real-time athletic and educational environments. These results provide strong empirical support for the pedagogical and performance advantages of integrating AR and AI in sports exercise monitoring systems.

Discussion

The findings of this study demonstrate that the integration of augmented reality (AR) with deep learning–based monitoring significantly enhances both the technical accuracy of exercise execution and the pedagogical outcomes of sports training. The experimental results confirmed that the proposed system not only improved immediate performance but also facilitated long-term retention of correct techniques, providing clear advantages over traditional instruction methods. By combining pose estimation, joint angle validation, and classification algorithms with AR-enabled feedback, the system addressed key challenges in exercise education, including error detection, motivation, and sustained engagement.

A central contribution of this work lies in the ability of the system to deliver real-time, individualized feedback during exercise performance. Unlike wearable sensors or conventional video-based approaches, which often require post-hoc analysis, the AR-based framework overlays corrective cues directly into the athlete's visual field, enabling immediate comprehension and adjustment. This real-time guidance proved particularly effective in technically demanding exercises such as the Romanian deadlift, where improper form commonly leads to injury risk. The substantial performance gains in the experimental group compared to the control group highlight the pedagogical value of integrating advanced feedback technologies into sports training environments.

The pedagogical experiments further reinforced the system's impact on learner motivation and engagement. Participants who trained with the AR-enabled system reported significantly higher interest, enjoyment, and perceived usefulness compared to those receiving traditional instruction. These findings align with earlier research emphasizing the motivational benefits of immersive technologies in physical education (Klochko & Fedorets, 2022). The gamified and interactive nature of the system appears to have transformed training from a repetitive routine into an engaging learning process, fostering stronger adherence and enthusiasm for continued participation. This is particularly relevant in educational contexts, where maintaining student motivation is often a critical determinant of long-term skill acquisition.

Another important observation is the role of AR-based multimodal feedback in enhancing motor memory consolidation. The delayed post-test revealed that participants in the experimental group retained substantially higher levels of correct technique two months after training. This outcome suggests that multimodal, real-time corrections promote deeper encoding of motor patterns compared to traditional verbal or demonstrative instruction. Such results underscore the potential of AR-driven interventions not only for immediate performance improvements but also for sustained learning outcomes, which are essential in both professional and pedagogical contexts.

Despite these promising results, several limitations must be acknowledged. Technical challenges such as motion tracking precision, latency in data processing, and the ergonomics of AR devices remain potential barriers to widespread adoption. Although the system demonstrated robustness in controlled experiments, its performance in large-scale or high-intensity training environments requires further validation. Additionally, issues of data privacy and ethical handling of biometric information must be carefully addressed, particularly if the system is deployed in competitive sports settings where confidentiality and fairness are paramount.

The implications of this research extend beyond athletic training to broader applications in health, rehabilitation, and physical education. By providing real-time corrective feedback, the system can support injury prevention and rehabilitation programs, assist recreational users in adopting safe exercise practices, and serve as an instructional tool in academic settings. Future research should focus on refining the system's scalability, incorporating adaptive learning models for diverse populations, and exploring its integration with other emerging technologies such as mixed reality and wearable biosensors.

In summary, this study provides strong evidence that AR-based exercise monitoring systems can transform the pedagogical landscape of sports training. By simultaneously addressing accuracy, retention, and motivation, the proposed framework represents a novel and effective approach to bridging technological innovation with human performance. These findings support the integration of AR and AI into physical education curricula and professional training environments, paving the way for the development of next-generation intelligent learning systems in sports science.

Conclusions

The present study has demonstrated the effectiveness of an augmented reality (AR)–enabled exercise monitoring system integrated with deep learning–based action classification for advancing both performance optimization and pedagogical outcomes in sports training. The experimental results confirmed that the system substantially improves the accuracy of exercise execution, enhances long-term retention of correct technique, and fosters higher levels of learner motivation and engagement compared to traditional instruction. By combining pose estimation, joint angle validation, and real-time AR feedback, the proposed framework provides athletes and students with immediate, context-aware guidance that reduces technical errors and supports safe, effective training. The pedagogical experiments further highlighted its value in educational contexts, showing that participants who trained with the system not only achieved greater improvements in motor precision but also reported stronger interest, enjoyment, and perceived usefulness of the training process. These findings underscore the dual role of AR technologies in both performance enhancement and educational innovation, positioning the system as a promising tool for integration into physical education curricula, rehabilitation programs, and elite sports environments. Although challenges related to tracking precision, scalability, and data privacy remain, the study provides compelling evidence for the potential of AR-driven systems to transform the future of exercise monitoring and pedagogy.

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