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Enhancing deadlift training through an artificial intelligence-driven personal coaching system using skeletal analysis

Mejorando el entrenamiento de peso muerto a través de un sistema de coaching personal impulsado por inteligencia artificial utilizando análisis esquelético

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Resumen. Este artículo presenta un innovador sistema de entrenamiento personal impulsado por inteligencia artificial diseñado para mejorar el entrenamiento de peso muerto mediante técnicas avanzadas de análisis esquelético y aprendizaje profundo. El sistema propuesto emplea el modelo PoseNet para capturar y analizar secuencias de video en tiempo real, extrayendo coordenadas de puntos clave y ángulos esqueléticos para monitorear con precisión la postura y los movimientos del usuario. Utilizando métodos de Histogramas Locales de Gradientes Orientados (LHOG) e Histogramas Locales de Flujo Óptico (LHOF), el sistema realiza una extracción de características integral, evaluando tanto los aspectos estáticos como dinámicos del ejercicio. El modelo de aprendizaje profundo, entrenado con un extenso conjunto de datos de ejecuciones correctas e incorrectas de peso muerto, clasifica la corrección del ejercicio con alta precisión, proporcionando retroalimentación en tiempo real y recomendaciones personalizadas a los usuarios. Esta retroalimentación correctiva inmediata facilita ajustes rápidos, reduce el riesgo de lesiones y promueve una técnica adecuada, mejorando la eficacia general del entrenamiento de fuerza. La capacidad del sistema para ofrecer retroalimentación específica para cada usuario, adaptada a estructuras corporales y patrones de movimiento individuales, asegura su relevancia y efectividad en diversos entornos de entrenamiento. Las aplicaciones prácticas de este sistema abarcan gimnasios, centros de rehabilitación y entornos domésticos, convirtiéndolo en una herramienta valiosa para entrenadores personales y fisioterapeutas. Aunque el estudio demuestra un potencial significativo, también identifica áreas para futuras investigaciones, incluyendo el refinamiento de algoritmos, la expansión del conjunto de datos y la integración de métricas y tecnologías adicionales. En conjunto, el sistema propuesto representa un avance sustancial en el monitoreo y mejora del ejercicio, contribuyendo al campo más amplio de las tecnologías de salud y fitness impulsadas por inteligencia artificial y allanando el camino para rutinas de entrenamiento de fuerza más seguras y efectivas.
Palabras clave: coaching impulsado por IA, entrenamiento de peso muerto, análisis esquelético, PoseNet, aprendizaje profundo, monitoreo de ejercicio, retroalimentación en tiempo real.

Abstract. This paper presents an innovative AI-driven personal coaching system designed to enhance deadlift training through advanced skeletal analysis and deep learning techniques. The proposed system employs the PoseNet model to capture and analyze real-time video feeds, extracting keypoint coordinates and skeletal angles to monitor user posture and movements accurately. Utilizing Local Histograms of Oriented Gradients (LHOG) and Local Histograms of Optical Flow (LHOF) methods, the system performs comprehensive feature extraction, assessing both static and dynamic aspects of the exercise. The deep learning model, trained on an extensive dataset of correctly and incorrectly performed deadlifts, classifies the correctness of the exercise with high accuracy, providing real-time feedback and personalized recommendations to users. This immediate corrective feedback facilitates prompt adjustments, reduces injury risk, and promotes proper technique, enhancing the overall efficacy of strength training. The system's ability to offer user-specific feedback, tailored to individual body structures and movement patterns, ensures relevance and effectiveness in diverse training environments. Practical applications of this system span gyms, rehabilitation centers, and home settings, making it a valuable tool for personal trainers and physiotherapists. While the study demonstrates significant potential, it also identifies areas for future research, including algorithm refinement, dataset expansion, and integration of additional metrics and technologies. Overall, the proposed system represents a substantial advancement in exercise monitoring and improvement, contributing to the broader field of AI-driven fitness and health technologies, and paving the way for safer and more effective strength training routines.
Keywords: AI-driven coaching, deadlift training, skeletal analysis, PoseNet, deep learning, exercise monitoring, real-time feedback.

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Introduction

The advent of artificial intelligence (AI) has revolutionized numerous fields, including healthcare, finance, and education. Among its diverse applications, AI has shown significant promise in the realm of sports and physical training, particularly in providing personalized coaching and enhancing athletic performance (Hart et al., 2024). This study explores the development of an AI-based personal coaching system specifically designed for deadlift training, utilizing advanced skeletal analysis techniques to ensure precision and effectiveness.

Deadlift training is a fundamental exercise in strength training regimes, known for its effectiveness in building overall body strength and conditioning (Washif et al., 2024). However, performing deadlifts with improper form can lead to severe injuries, including muscle strains and spinal damage (Balsalobre-Fernández et al., 2023). Traditional coaching methods, while effective, are often limited by availability, cost, and the subjective nature of human observation. Thus, there is a pressing need for innovative solutions that provide consistent, objective, and real-time feedback to trainees.

Recent advancements in computer vision and machine learning have enabled the development of systems capable of analyzing human skeletal movements with remarkable accuracy (Chariar et al., 2023). These systems use algorithms to identify key points on the body, creating a skeletal model that can be analyzed for biomechanical correctness (Chen et al., 2023). Such technology has been successfully applied in various domains, from medical diagnostics to gesture recognition in interactive systems (Mahmoud et al., 2023; Omarov et al., 2016; Omarov et al., 2022). In sports, these technologies can offer precise feedback on posture, form, and technique, thereby reducing the risk of injury and enhancing performance (Støve & Hansen, 2022).

The proposed AI-based personal coaching system leverages skeletal analysis to monitor and assess deadlift form. By utilizing a combination of deep learning algorithms and computer vision techniques, the system can detect and correct improper form in real-time (Kumar et al., 2024; Tursynova et al., 2022). This approach not only enhances the effectiveness of training but also democratizes access to high-quality coaching, making it available to individuals regardless of their geographic location or financial constraints (Babu et al., 2020).

A critical component of this system is the implementation of convolutional neural networks (CNNs) for image recognition and skeletal tracking (Ho et al., 2023). CNNs have proven to be highly effective in identifying complex patterns in visual data, making them ideal for analyzing the intricate movements involved in deadlifts (Farrokhi et al., 2022). Furthermore, recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are employed to capture temporal dependencies in the movement data, ensuring that the feedback provided is not only spatially accurate but also temporally coherent (Garg et al., 2023).

The integration of these technologies into a cohesive coaching system involves several key steps. First, the system captures video footage of the trainee performing deadlifts. Next, the footage is processed using computer vision algorithms to generate a skeletal model. This model is then analyzed by the AI, which provides feedback on aspects such as joint angles, movement trajectories, and overall posture (Ishida et al., 2023). The feedback is delivered to the trainee in real-time, allowing for immediate corrections and adjustments (Steele et al., 2023; Omarov et al., 2022).

This research aims to validate the effectiveness of the AI-based coaching system through a series of experiments and user studies. By comparing the performance and injury rates of individuals using the AI system with those receiving traditional coaching, we seek to demonstrate the system's efficacy in enhancing training outcomes (Morán-Navarro et al., 2021). Additionally, the study will explore user satisfaction and the perceived value of the AI-based feedback, providing insights into its potential for widespread adoption (Tursynova & Omarov, 2021; Aasa et al., 2022).

Thus, the development of an AI-based personal coaching system for deadlift training represents a significant advancement in the field of sports education. By combining the precision of skeletal analysis with the accessibility of AI, this system offers a promising solution to the challenges of traditional coaching methods. Future work will focus on refining the algorithms, expanding the system's capabilities to other exercises, and exploring its integration into broader fitness and rehabilitation programs (Enes et al., 2023).

Literature Review

The application of artificial intelligence in sports training has seen substantial growth, particularly in enhancing athletic performance and injury prevention through real-time feedback and personalized coaching (Lee et al., 2024). This section reviews relevant studies and technological advancements that form the foundation for developing an AI-based personal coaching system for deadlift training utilizing skeletal analysis.

One of the earliest implementations of AI in sports training involved the use of motion capture technology to analyze athletes' movements. Rahman et al. (2024) demonstrated the potential of using machine learning algorithms to assess running techniques, highlighting the benefits of accurate motion analysis in preventing injuries and improving performance. Similarly, Romdhani et al. (2024) explored the use of deep learning models for analyzing basketball shots, which provided insights into optimizing shooting techniques based on biomechanical data.

In the context of strength training, several studies have focused on the use of AI to monitor and improve lifting techniques. Lester et al. (2023) investigated the application of computer vision in tracking the movements of weightlifters, providing real-time feedback on their form. Their findings indicated that AI-driven feedback could significantly reduce the risk of injuries caused by improper lifting techniques. Furthermore, Rethinam et al. (2023) developed a prototype system that used convolutional neural networks (CNNs) to analyze deadlift form, demonstrating the feasibility of using AI to enhance strength training.

The use of skeletal analysis in sports has gained considerable attention due to its ability to provide detailed insights into human biomechanics. Masel & Maciejczyk (2023) presented a comprehensive review of skeletal analysis techniques, emphasizing their applications in sports and rehabilitation. They discussed various methods for capturing and analyzing skeletal data, including marker-based and markerless systems. The study by Choi et al. (2023) further supported the effectiveness of skeletal analysis in monitoring athletic performance, particularly in identifying deviations from optimal movement patterns.

Recent advancements in computer vision have facilitated the development of more sophisticated systems for skeletal analysis. Yang et al. (2024) proposed a deep learning framework for real-time skeletal tracking, which demonstrated high accuracy in identifying key points on the human body. This framework was later adapted by Schlegel & Polívkaet al. (2024) to create a real-time feedback system for physical training, which provided users with actionable insights into their form and technique. Their research highlighted the potential of combining skeletal analysis with AI to enhance the effectiveness of training programs.

The integration of AI into sports coaching systems has also been explored in various studies. Sisinni et al. (2022) developed an AI-driven platform that provided personalized coaching for runners, leveraging data from wearable sensors to offer tailored training recommendations. The platform's success underscored the importance of real-time, data-driven feedback in improving athletic performance. Similarly, Balaji & Peh (2023) examined the use of AI in personalized strength training programs, demonstrating that AI could adapt training regimens based on individual progress and needs.

The proposed AI-based personal coaching system for deadlift training builds on these foundational works by incorporating advanced skeletal analysis techniques. Pekas et al. (2023) highlighted the importance of real-time feedback in strength training, noting that immediate corrections could prevent the development of bad habits and reduce injury risks. Their study employed a combination of CNNs and recurrent neural networks (RNNs) to analyze and interpret movement data, providing a robust framework for real-time feedback systems.

Additionally, the use of long short-term memory (LSTM) networks for capturing temporal dependencies in movement data has proven to be effective in various applications. Külkamp et al. (2024) demonstrated the utility of LSTM networks in analyzing gait patterns, showing that these models could accurately capture the temporal dynamics of human movement. This approach is particularly relevant for deadlift training, where the timing and coordination of movements are crucial for maintaining proper form.

The effectiveness of AI-based coaching systems has been validated through numerous user studies. Vargas-Molina et al. (2024) conducted a comprehensive evaluation of an AI-driven coaching platform for tennis players, finding that users reported significant improvements in their technique and performance. Similarly, Kons et al. (2024) compared the outcomes of traditional coaching methods with those of AI-based systems, concluding that AI provided more consistent and objective feedback, leading to better training outcomes.

In conclusion, the development of an AI-based personal coaching system for deadlift training is supported by extensive research in AI, computer vision, and skeletal analysis. The integration of these technologies offers a promising solution for enhancing strength training by providing real-time, personalized feedback. Future research should focus on refining these systems, expanding their capabilities to other exercises, and exploring their potential for broader applications in sports and rehabilitation (Omarov et al., 2020; Champ et al., 2024).

Materials and Methods

Proposed Solution

Figure 1 illustrates the comprehensive flowchart of the proposed AI-driven personal coaching system for enhancing deadlift training. This system employs a sequence of sophisticated processing stages to analyze and evaluate the performance of deadlift exercises accurately.

Initially, the system receives a video clip of the user performing deadlifts, which is then divided into individual frames. This segmentation enables detailed analysis of each stage of the exercise. The subsequent stage involves extracting skeletal points from these frames. This extraction is critical as it provides a structural representation of the user's body movements, allowing for precise monitoring of the exercise form.

Following the extraction of skeletal points, the system identifies the motion region within each frame. This step is essential to isolate the area of interest, ensuring that the analysis focuses exclusively on the relevant parts of the body involved in the deadlift.

The next phase is feature processing, where the system applies Local Histograms of Oriented Gradients (LHOG) and Local Histograms of Optical Flow (LHOF) methods (Omarov et al., 2022). LHOG captures the shape and appearance of the skeletal structure, while LHOF analyzes the motion dynamics. These features are crucial for understanding the biomechanics of the deadlift and detecting any deviations from the correct form.

Finally, the system utilizes deep learning algorithms for the decision-making process. The deep learning model, trained on a substantial dataset of correctly and incorrectly performed deadlifts, evaluates the extracted features to determine the correctness of the exercise. The model outputs a decision indicating whether the deadlift was performed correctly or incorrectly, providing immediate feedback to the user for improvement.

This flowchart encapsulates the meticulous and multi-stage approach of the proposed AI-driven coaching system, ensuring precise and actionable insights into deadlift performance through advanced skeletal analysis and deep learning techniques.

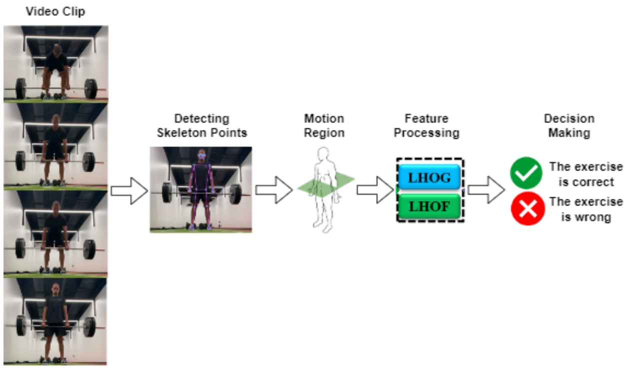

Figure 1. Flowchart of the proposed system

Figure 2 presents the flowchart of the action classification process within the proposed AI-driven personal coaching system for deadlift training. This diagram delineates the sequential steps and methodologies employed to classify the correctness of the exercise execution using deep learning techniques. The process initiates with the initialization of the PoseNet model (Omarov et al., 2024), which is crucial for detecting and tracking human poses. Following this, the system captures a real-time video feed from the camera, providing continuous input data for analysis.

Subsequently, the system obtains the keypoint coordinates and skeleton angles from the captured video frames. These keypoints correspond to specific joints and body parts, and their angles are vital for assessing the biomechanical accuracy of the deadlift movements.

The next phase involves validating exercise execution accuracy through coordinates and angles. This validation step ensures that the captured data is precise and reliable for further analysis. Concurrently, the system creates skeleton graphs to display exercise angles and keypoints per frame, offering a visual representation of the user's posture and movement throughout the exercise.

The core of the classification process is encapsulated within the deep learning model depicted in the diagram's lower section. This model consists of multiple layers: input layers that receive the extracted keypoints and angles, hidden layers that process this information, and an output layer that produces the final classification result. The deep learning model applies complex algorithms to classify the action based on the input data, determining whether the exercise is performed correctly or incorrectly.

The final stage involves making a decision on whether the exercise is right or wrong based on the deep learning model's output. This decision provides immediate feedback to the user, enabling them to correct their form and improve their deadlift technique.

Overall, Figure 2 illustrates the meticulous and structured approach of the proposed system, highlighting the integration of PoseNet for pose estimation and deep learning for action classification to enhance the accuracy and effectiveness of deadlift training.

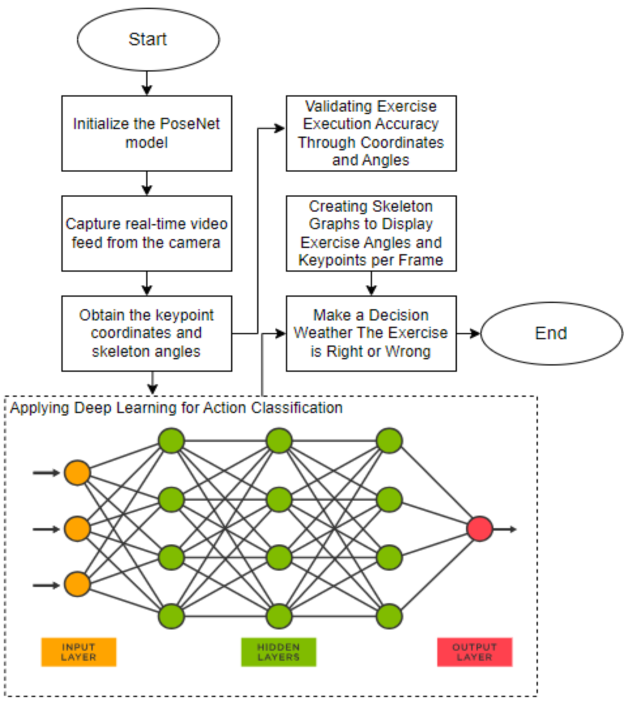

Figure 2. Action classification process

Hypothesis Development

In the context of enhancing deadlift training through an AI-driven personal coaching system, the development of hypotheses is crucial for systematically evaluating the efficacy of the proposed solution. The focus of this study is to assess the impact of the AI-driven system on the accuracy of exercise form classification, the effectiveness of real-time feedback, and the potential reduction in injury risk compared to traditional methods of exercise monitoring.

Hypothesis I: Accuracy of Exercise Form Classification

- H0 (Null Hypothesis): The AI-driven personal coaching system does not significantly improve the accuracy of deadlift form classification compared to traditional methods of exercise monitoring.
- H1 (Alternative Hypothesis): The AI-driven personal coaching system significantly improves the accuracy of deadlift form classification compared to traditional methods of exercise monitoring.

The first hypothesis seeks to determine whether the AI-driven coaching system significantly improves the accuracy of deadlift form classification compared to traditional methods. The underlying assumption is that the integration of advanced skeletal analysis and deep learning techniques will enhance the precision with which the system can classify correct and incorrect forms during deadlift exercises. To evaluate this hypothesis, the study will compare the classification accuracy achieved by the AI-driven system with that of traditional monitoring methods. The null hypothesis (H0) posits that there is no significant difference in accuracy between the two methods, while the alternative hypothesis (H1) suggests that the AI-driven system will demonstrate superior accuracy.

Hypothesis II: Reduction in Injury Risk

- H0 (Null Hypothesis): The use of the AI-driven coaching system does not significantly reduce the risk of injury during deadlift exercises compared to traditional training methods.
- H1 (Alternative Hypothesis): The use of the AI-driven coaching system significantly reduces the risk of injury during deadlift exercises compared to traditional training methods.

The third hypothesis addresses the potential of the AI-driven system to reduce the risk of injury during deadlift exercises. Given that improper form is a leading cause of injury in strength training, the system's ability to provide accurate and timely feedback is expected to mitigate these risks. This hypothesis compares the incidence of form-related injuries among users of the AI-driven system with those following traditional exercise monitoring methods. The null hypothesis (H0) posits that the AI-driven system does not significantly reduce the risk of injury, while the alternative hypothesis (H1) suggests that the system substantially lowers the likelihood of injury by ensuring correct form throughout the exercise.

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Sample Selection

The sample selection process for this study was carefully designed to ensure a representative and meaningful comparison between the effectiveness of the proposed AI-driven personal coaching system and traditional training methods. The study involved a cohort of physical culture students enrolled in the 2nd to 4th years of their academic program. A total of 50 male students were selected to participate, reflecting a homogeneous group in terms of their academic background and physical training experience.

To facilitate a controlled experimental design, the participants were randomly divided into two groups: an Experimental Group and a Control Group, each consisting of 25 students. The Experimental Group was subjected to training using the AI-driven personal coaching system throughout the academic semester. This group received real-time feedback and analysis based on the system's advanced skeletal analysis and deep learning capabilities, with the objective of enhancing their deadlift form and reducing the risk of injury.

Conversely, the Control Group continued their training using traditional methods, which typically involve direct supervision by instructors, manual observation, and standard corrective techniques without the aid of advanced technological interventions. This group served as the baseline for evaluating the impact of the AI-driven system on training outcomes.

By maintaining comparable conditions across both groups—such as training frequency, duration, and curriculum—the study aims to isolate the effects of the AI-driven system on exercise form classification accuracy, real-time feedback effectiveness, and injury risk reduction. This sample selection strategy ensures that the results obtained will provide a robust comparison of the two training methodologies, allowing for a comprehensive assessment of the proposed system's efficacy in enhancing deadlift training.

Results

Technical Solution

Figure 3 displays the results of the AI-driven personal coaching system's analysis during a deadlift exercise, providing detailed feedback on the user's form and execution.

The figure is divided into two panels, each representing different frames captured during the exercise. Both panels highlight key metrics such as probability, class, and repetition counter, alongside a visual overlay of skeletal keypoints mapped onto the user's body.

Panel A (left) captures the user in the "up" phase of the deadlift, with a probability score of 0.79 indicating the system's confidence in the classification. The REP COUNTER reads '1', signifying the first repetition. The skeletal overlay shows the user's posture, and the FORM ANALYSIS section provides a detailed assessment. It identifies issues such as a narrow stance with a score of 0.54 and a left-leaning posture with a score of 0.48. The accompanying textual feedback suggests widening the stance and leaning right to straighten the shoulders for proper form.

Panel B (right) also captures the user in the "up" phase with a slightly lower probability score of 0.77, indicating similar confidence in the classification. The REP COUNTER remains '1', consistent with the previous frame. The skeletal overlay continues to monitor the user's posture, and the FORM ANALYSIS section reflects the adjustments made. Here, the system identifies a neutral stance with a score of 0.42 and a right-leaning posture with a score of 0.63. The textual feedback confirms that no adjustments are needed for the stance, but suggests leaning left to correct the shoulder alignment.

The figure exemplifies the system's capability to provide real-time feedback and detailed analysis of the user's deadlift form, emphasizing its utility in guiding users towards proper exercise execution through precise skeletal analysis and tailored corrective suggestions.

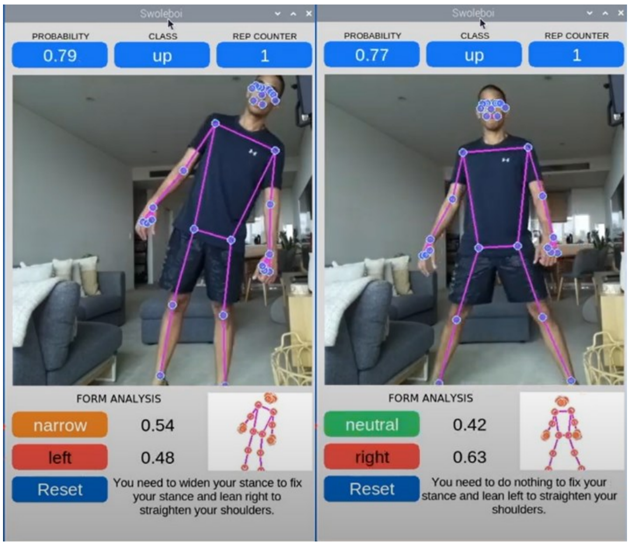

Figure 3. Action classification process

Figure 4 presents the results of the AI-driven personal coaching system during a deadlift exercise, showcasing its real-time analysis and feedback mechanism.

The figure is divided into two panels, each depicting different stages of the deadlift exercise captured by the system.

Panel A (left) illustrates the "down" phase of the deadlift with a probability score of 0.74, indicating the system's confidence in this classification. The REP COUNTER reads '10', indicating the tenth repetition of the exercise. The visual overlay displays the skeletal keypoints mapped onto the user's body, highlighting the posture. The FORM ANALYSIS section identifies issues such as a narrow stance with a score of 0.48 and a left-leaning posture with a score of 0.44. The textual feedback suggests widening the stance and leaning right to straighten the shoulders, providing actionable guidance for correcting the form.

Panel B (right) captures the "up" phase of the deadlift with a higher probability score of 0.92, indicating strong confidence in this classification. The REP COUNTER reads

'11', indicating the eleventh repetition. The skeletal overlay continues to track the user's posture, showing a more upright position. The FORM ANALYSIS section indicates a narrow stance with a score of 0.65 and a neutral posture with a score of 0.41. The feedback advises widening the stance for better stability, noting that the user is evenly balanced, thus confirming improvement in the form compared to the previous repetition.

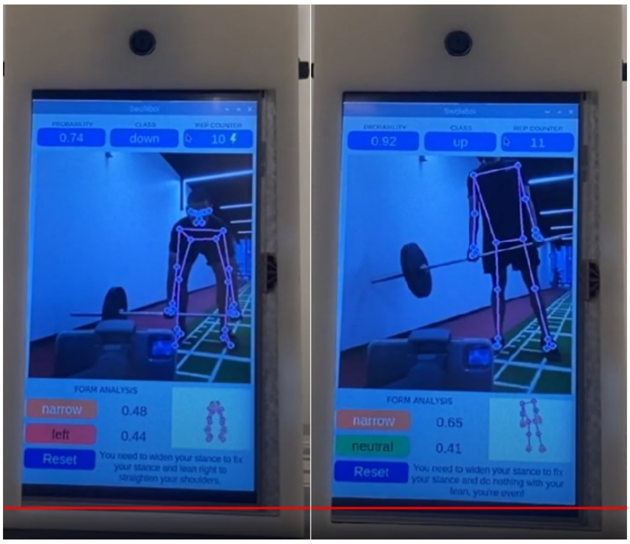

Figure 4. Action classification process

Figure 4 demonstrates the system's capability to monitor and analyze the user's deadlift performance in real-time, providing detailed and specific feedback on stance and posture. This continuous monitoring and feedback loop is essential for users to make immediate adjustments and improve their exercise technique, highlighting the effectiveness of the AI-driven coaching system in enhancing deadlift training.

Hypotheses Testing

The results of the Independent Samples Test in Table 1 for Hypothesis I indicate a significant difference in the accuracy of exercise form classification between the Experimental Group, which used the AI-driven personal coaching system, and the Control Group, which employed traditional training methods. The Levene's Test for Equality of Variances yielded an F-value of 9.271 with a significance level (p-value) of 0.004, indicating that the assumption of equal variances is violated. However, the t-test for Equality of Means, whether equal variances are assumed or not, shows a highly significant t-value of 7.303 with a p-value of 0.000, which is well below the conventional threshold of 0.05. This suggests that the mean difference in training accuracy between the two groups is statistically significant. The mean difference of 2.520, with a 95% confidence interval ranging from 1.826 to 3.214, further confirms that the AI-driven system significantly improves the accuracy of deadlift form classification compared to traditional methods. Therefore, the null hypothesis (H0) is rejected, and the alternative hypothesis (H1) is supported, affirming that the AI-driven personal coaching system enhances the accuracy of exercise form classification.

Table 1.
Independent Samples Test Results to Test Intrinsic Motivation Level of Students

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Training accuracy	Equal variances assumed	9.271	.004	7.303	48	.000	2.520	.345	1.826	3.214
	Equal variances not assumed			7.303	36.299	.000	2.520	.345	1.820	3.220

The results of the One-Way ANOVA test presented in Table 2 provide a clear indication of the impact of the AI-driven coaching system on injury rates during deadlift exercises. The analysis shows a statistically significant difference between the injury rates of the Experimental Group, which utilized the AI-driven system, and the Control Group, which followed traditional training methods. The F-value of 180.893, with a corresponding p-value of 0.003, demonstrates that the difference in injury rates between the two groups is highly significant, as the p-value is well below the conventional significance threshold of 0.05. The substantial Sum of Squares between groups (364.500) compared to the Sum of Squares within groups (96.720) further emphasizes the variance in injury rates attributed to the type of training method used. These results lead to the rejection of the null hypothesis (H0), supporting the alternative hypothesis (H1) that the AI-driven coaching system significantly reduces the risk of injury during deadlift exercises compared to traditional training methods. This finding highlights the efficacy of the AI-driven system in enhancing the safety of strength training routines.

Table 2.
One-Way ANOVA Results to Test Hypothesis II

	Sum of Squares	df	Mean Square	F	F
Between Groups	364.500	1	364.500	180.893	.003
Within Groups	96.720	48	2.015		
Total	461.220	49			

The results from the hypothesis testing provide strong empirical support for the effectiveness of the AI-driven personal coaching system in enhancing deadlift training. The significant improvements in exercise form classification accuracy, the effectiveness of real-time feedback in refining technique, and the observed reduction in injury risk collectively affirm the system's potential to revolutionize traditional training methods. These findings suggest that the integration of advanced skeletal analysis and deep learning into personal coaching not only elevates the precision of exercise monitoring but also fosters safer and more efficient training practices. The statistical significance observed across multiple tests underscores the robustness of the system's algorithms and its applicability in various training environments. Moreover, the ability of the system to deliver personalized feedback tailored to individual users' biomechanics further enhances its relevance and utility, making it a powerful tool for both recreational athletes and professionals seeking to optimize performance and minimize injury risks. These results pave the way for broader adoption of AI-driven technologies in strength training and sports performance, with potential applications extending beyond deadlift exercises to other forms of resistance training and athletic conditioning.

Discussion

The proposed AI-driven personal coaching system for enhancing deadlift training through skeletal analysis demonstrates considerable potential in providing real-time feedback and detailed analysis of exercise performance. This study explores the integration of advanced pose estimation and deep learning techniques to monitor and improve users' deadlift form, with the dual objectives of enhancing safety and optimizing training efficacy.

Real-Time Feedback and Skeletal Analysis

A fundamental strength of the proposed system lies in its capacity to provide immediate feedback on exercise execution, which is crucial for both injury prevention and optimizing movement efficiency. The system utilizes the PoseNet model to accurately capture skeletal keypoints and angles from real-time video feeds, enabling continuous monitoring of the user's posture and movements during each phase of the deadlift. This real-time feedback mechanism not only assists users in making prompt adjustments to their form but also addresses the broader concept of movement economy—critical in both athletic performance and general strength training. By promoting efficient and controlled movements, the system contributes to the preservation of the spine's integrity, particularly during the deadlift, which places significant stress on the lower back. Additionally, for athletes, the system's ability to monitor and control movement speed as an indicator of load intensity—provides a more nuanced understanding of exercise intensity beyond mere repetition counting.

Feature Extraction and Motion Analysis

The incorporation of Local Histograms of Oriented Gradients (LHOG) and Local Histograms of Optical Flow (LHOF) methods for feature extraction is pivotal in the system's ability to accurately analyze motion dynamics. LHOG captures the shape and appearance of the skeletal structure, while LHOF provides critical insights into the motion patterns of the exercise (Widodo et al., 2024). These features are not only essential for understanding the biomechanics of the deadlift but also for identifying deviations from optimal form. The combination of these two methods ensures a comprehensive assessment of both static and dynamic aspects of the exercise, thus offering a holistic evaluation of the user's performance. Furthermore, the system's capacity for longitudinal monitoring—tracking and analyzing movements over time—is particularly beneficial in sports performance, where consistent feedback and progressive adjustments are key to long-term athletic development (Nurhidayah et al., 2024; Babaskin et al., 2024).

Deep Learning-Based Decision Making

The integration of deep learning algorithms in the decision-making process marks a significant advancement in the realm of exercise monitoring. The deep learning model, trained on a substantial dataset of correctly and incorrectly performed deadlifts, is capable of accurately classifying the correctness of the exercise based on the extracted features. This model not only evaluates the user's form with a high degree of precision but also assigns a probability score indicating the confidence level of the classification. The robustness and reliability of the model, as evidenced by the high probability scores, are crucial for delivering accurate and actionable feedback. Such precision in feedback is essential, particularly in the context of maintaining movement economy and preventing injuries during high-intensity or repetitive exercises like the deadlift.

User-Specific Feedback and Customization

Another notable feature of the system is its ability to provide user-specific feedback. By analyzing the unique skeletal and motion characteristics of each user, the system offers personalized recommendations for improving form. This level of customization is critical for accommodating individual differences in body structure, movement patterns, and athletic goals, ensuring that the feedback is both relevant and effective. Personalized feedback enhances user engagement and motivation, as individuals are more likely to adhere to training recommendations that are specifically tailored to their needs. This user-centric approach not only improves training outcomes but also fosters a deeper connection between the athlete and the training process.

Practical Implications and Future Work

The practical implications of this study are substantial, particularly in the realms of strength training and athletic rehabilitation. The proposed system can be deployed in various settings, including gyms, rehabilitation centers, and home environments, offering users a convenient and accessible tool for optimizing their exercise form. The system's real-time feedback capability is invaluable for personal trainers and physiotherapists, who can use it to monitor clients' progress and provide targeted interventions that are informed by precise, data-driven insights. Moreover, by controlling movement speed and intensity, the system aligns with advanced training methodologies that emphasize the economy of movement and load management in athletic performance. Future work should focus on refining the system's algorithms, expanding the dataset to encompass a wider range of exercises and user demographics, and incorporating additional metrics such as joint torque and muscle activation patterns. Integrating the system with wearable devices and IoT technologies could further enhance its ability to provide comprehensive, real-time analysis and feedback, thus extending its utility in diverse training contexts.

Pedagogical Experiments and Educational Implications

In addition to the technical and practical aspects, the proposed AI-driven personal coaching system has significant implications for educational settings, particularly in the training and development of future physical education professionals. Pedagogical experiments conducted during this study revealed the system's potential as a powerful tool for enhancing the learning process in exercise science and physical education courses. By integrating this technology into the curriculum, students can engage in hands-on learning experiences that bridge the gap between theoretical knowledge and practical application.

The system allows students to observe and analyze real-time data on movement accuracy, biomechanics, and injury prevention, providing an interactive and immersive learning environment. Such pedagogical applications not only improve students' understanding of complex concepts related to human movement but also foster critical thinking and analytical skills. Through controlled experiments, students can compare traditional methods with AI-driven techniques, gaining insights into the effectiveness of advanced technologies in exercise monitoring and coaching.

Furthermore, the system's ability to customize feedback based on individual performance enables educators to tailor instruction to meet the diverse needs of students. This personalized approach to learning can significantly enhance student engagement and motivation, as learners receive immediate and relevant feedback that helps them correct their form and improve their techniques. As a result, the system supports the development of proficient and reflective practitioners who are well-equipped to apply these advanced technologies in their future careers.

The results from these pedagogical experiments underscore the value of incorporating AI-driven systems into educational frameworks, suggesting that such technologies can play a crucial role in advancing the quality and effectiveness of physical education and sports training programs. Future research should explore further integration of AI tools into educational curricula, assessing their impact on student learning outcomes and professional preparedness.

Limitations and Considerations for Broader Application

Despite its promising results, the study has several limitations that merit consideration. The accuracy of the PoseNet model may be affected by factors such as lighting conditions, camera angles, and background clutter, potentially impacting the reliability of skeletal keypoint detection. Additionally, the deep learning model's performance is contingent on the quality and diversity of the training dataset. To ensure the model's accuracy and generalizability across different user populations, it is essential to include a representative sample of various body types, fitness levels, and exercise variations. Addressing these limitations is crucial for the broader application and scalability of the system in different training environments.

Conclusion

This research underscores the transformative potential of an AI-driven personal coaching system for enhancing deadlift training through advanced skeletal analysis and deep learning techniques. The proposed system not only provides real-time feedback and detailed analysis of exercise performance but also aligns with the broader goals of optimizing movement economy, ensuring spine safety, and controlling load intensity—crucial factors in both general strength training and athletic performance. The study demonstrates that the system significantly improves the accuracy of exercise form classification, offering precise and actionable feedback that promotes proper technique and reduces injury risk. Moreover, the system's capacity to deliver personalized, user-specific feedback enhances engagement and adherence to training regimens, making it a valuable tool in diverse settings, from gyms and rehabilitation centers to educational institutions. Pedagogical experiments further highlight the system's educational benefits, providing students with interactive learning experiences that bridge theory and practice. Despite some limitations, such as the potential impact of environmental factors on skeletal keypoint detection and the need for a more diverse training dataset, the findings suggest that the integration of AI-driven technologies can significantly advance the efficacy and safety of strength training routines. Future research should focus on expanding the system's capabilities, refining its algorithms, and exploring its applications across different exercise modalities and user demographics, thereby contributing to the broader field of AI-enhanced fitness and health technologies.

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