IMPECT-POSE: A Complete Front-end and Back-end Architecture for Pose Tracking and Feedback

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ABSTRACT

This paper introduces IMPECT-POSE, an innovative front-end and back-end architecture designed to enhance fitness and sports training through precise body posture tracking. This system integrates advanced computer vision and artificial intelligence in pose estimation to provide real-time feedback on exercise execution, which is crucial for maintaining proper technique, reducing injury risks, and optimizing training outcomes. Our evaluations, conducted at two distinct locations with multiple participants, demonstrate the system's capability to improve exercise performance significantly. The system's flexibility allows sports professionals to monitor and guide clients remotely, enhancing the accessibility and effectiveness of training regimens. This research highlights the potential of augmented intelligence in transforming sports training, offering a scalable and effective alternative to conventional methods, and paving the way for future advancements in AI-driven personalized training programs. The continued development of this technology aims to refine its accuracy, broaden its applicability to diverse user preferences, and extend its use in practical, real-world settings.

CCS CONCEPTS

• **Human-centered computing** → **User studies**; **User models**; **Heuristic evaluations**; *Visualization design and evaluation methods*; *Empirical studies in interaction design.*

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KEYWORDS

Pose Tracking, Keypoint Estimation, Feedback Template, Fitness, Dance.

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1 INTRODUCTION

In recent years, the synergy of augmented intelligence, which combines human cognitive capabilities with artificial intelligence (AI), has brought transformative changes to various sectors, including sports and fitness [10, 12]. This transformation is driven by the confluence of machine learning, sensors, and immersive technologies (e.g., virtual and augmented reality), enabling the creation of immersive learning environments (ILEs) for physical training platforms. These platforms, equipped with capabilities to offer personalized coaching and real-time feedback, significantly improve performance in a range of physical activities [13].

The utility of fitness applications has become particularly evident when personal training is impractical due to logistical or financial constraints. Unlike personal trainers, who are often expensive and difficult to schedule, fitness applications provide expert guidance without costs and scheduling issues [11]. Additionally, these applications address the challenges of self-directed movement activities, such as maintaining proper technique, posture, and motivation without direct supervision. Tailoring activities to individual goals and needs is critical for practical training, and the absence of a coach often complicates this process.

Prevailing research has established the effectiveness of AI in sports, notably in activity recognition within gym settings [14]. Despite their potential, these systems typically demand extensive data collection and substantial computational resources. Moreover, while augmented reality solutions offer promising avenues, they are limited by high costs and potential user discomfort [25]. Additionally, challenges in reliably identifying and replicating complex sports data have underscored the need for more scalable and robust methodologies, as highlighted by research in Multimodal Learning Analytics (MMLA) [7, 17].

We introduce a feedback system that leverages AI and computer vision to address these challenges. This system allows trainers to record demonstrations, which serve as templates for ideal posture and joint angles, adapting to the unique body structures of each individual. This customization eliminates the need for continuous trainer presence and enables participants to adjust activities according to their specific goals and needs. Immediate feedback on posture and technique reduces the risk of injuries. It boosts motivation and adherence to movement goals, enhancing the safety and efficacy of independent practice in various movement-based activities.

2 RELATED BACKGROUND

Augmented intelligence (AuI), blending human and machine intelligence, is increasingly applied to enhance sports and fitness performance and productivity [26]. It offers personalized coaching and feedback. Those AuI systems can track movements, analyze performance data, and provide improvement suggestions for activities like running or weightlifting [13, 14] by leveraging sensors, cameras, and machine learning algorithms. In gym-based activity recognition—a subset of human activity recognition—AuI proves essential. This area thrives in a controlled yet dynamic environment where various exercises are performed, making it ideal for deploying advanced object detection algorithms such as the YOLO (You Only Look Once) framework. The YOLO model recognizes gym activities, including Pushups, Squats, Bench Press, and Shoulder Press with notable accuracy and efficiency [3, 5].

Furthermore, the effectiveness of machine learning in decoding human actions is underscored by studies utilizing neural networks for interpreting electrocardiograms (ECGs) in aerobic activities and wristband or belt-based accelerometers alongside Artificial Neural Networks (ANNs) for classifying weightlifting activities [15, 16]. These approaches have laid a solid foundation for our Gym Activity Recognition (GAR) research using the YOLO model. Additionally, the importance of real-time feedback in exercise routines is highlighted by research in clustering algorithms to provide immediate performance feedback during weight training [11]. Such real-time feedback is crucial for enhancing exercise outcomes. Aspects in Human-Computer Interaction (HCI) also play a significant role, with various studies emphasizing usability, learnability, and user satisfaction as critical evaluation metrics for activity recognition systems [2, 6]. These insights are integral to our forthcoming user study, which will integrate HCI principles to assess the effectiveness of our YOLO-based model. Moreover, extensive previous research has investigated feedback methods in motor learning, with significant impacts noted from well-integrated visual and auditory cues on movement learning and execution [19, 21, 22]. The use of immersive technologies and sensors enables the creation of ILEs, further enhancing these techniques and providing innovative ways to augment users' movements with training content, exemplified by the augmented mirror approaches [1, 4, 8, 23].

3 SYSTEM ARCHITECTURE OVERVIEW

This document outlines the architecture of the IMPECT-POSE system, which is an advanced training toolkit designed to support ILEs for psychomotor skills training. Leveraging sensors and immersive technologies, the toolkit enhances the capability of trainers to assess and provide feedback in various training scenarios such as fitness and dance [18].

3.1 Server and Client Architecture

Figure 1 illustrates the system architecture and the data transmission flow. The IMPECT server operates as a Python Flask web application, incorporating a socket server and a REST API. An SQLite database is employed to gather and store data. The server-client connection is established through a TCP socket, transmitting information as JSON messages. Upon connection, the server registers the active client application in the database, assigns it a unique ID, and designates 'sports training' or 'dance' as its specific use case (see Figure 2a). The REST API endpoint facilitates the YOLOv7-pose evaluation platform's posting of evaluation results derived from the client's session recordings. Based on the identified mistake, the appropriate feedback card (see Figure 2b) is dispatched to the client's application. Experts from the German Sport University Cologne have been hired to conduct feedback cards for exercises. The system is hosted at a server of RWTH Aachen University[1].

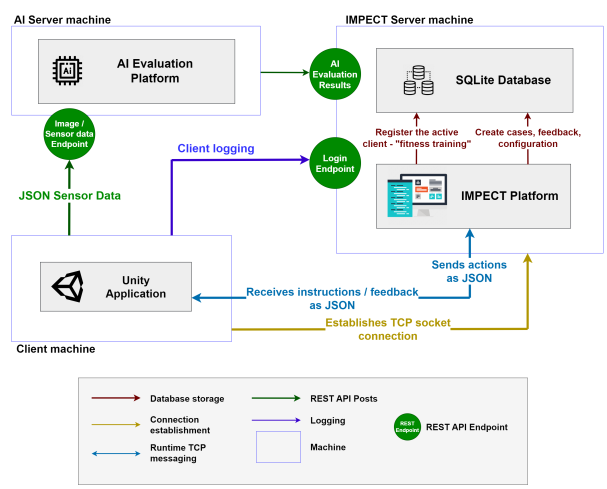
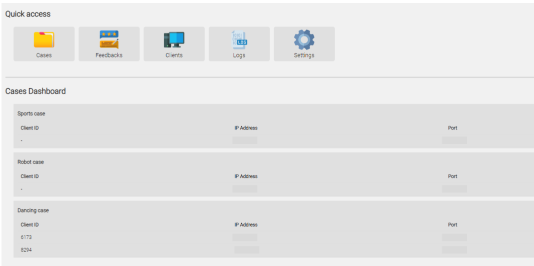


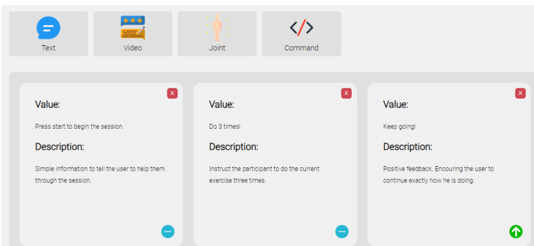
Figure 1: IMPECT-POSE backend architecture.

Conversely, the front-end (e.g., Unity) client application bridges the IMPECT server and the (You Only Look Once) YOLO vision-based pose tracking framework. Initiating an active play session

[1]https://impect.milki-psy.dbis.rwth-aachen.de



(a) The dashboard for managing various use cases.



(b) The creation of feedback cards.

Figure 2: IMPECT backend interface.

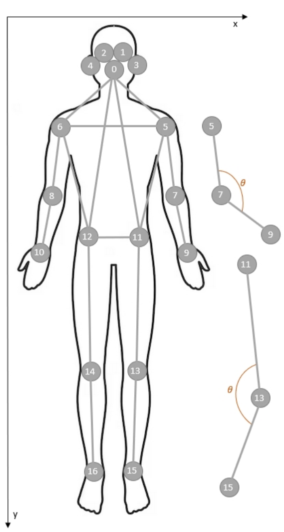


Figure 3: Human keypoints detection by YOLOv7-pose.

within the client application triggers the recording process from the camera. It transmits the image frame data, identified with a session ID, to the evaluation platform. After completing the evaluation process, the client receives information from the IMPECT server and visualizes the feedback according to the selected feedback card.

3.2 Interactive and Responsive System Design

The software architecture is designed to ensure smooth interaction and computational processing. A front-end developed using HTML and JavaScript provides a dynamic user interface. This interface features live video streaming, real-time activity feedback, and interactive elements that allow users to control the system's functionality effectively. The back-end, powered by Python, utilizes the capabilities of machine learning libraries such as YOLO to perform real-time video processing, data interpretation, and analysis. It efficiently handles activity detection and tracking, transforming raw video data into actionable insights for performance improvement.

Integrating the front-end and back-end components ensures that the system captures and processes visual data efficiently and provides immediate, understandable feedback to the user. This cohesive workflow significantly enhances the user experience, promoting effective interaction and real-time feedback essential for improving training outcomes in ILEs. Overall, this architecture supports rigorous activity recognition and enriches user interaction, making it a powerful tool for psychomotor skill development in immersive settings.

3.3 YOLO Framework

YOLO is a renowned object detection system recognized for its precision and high-speed processing. Developed initially for object detection, the YOLO framework has been extended to include applications in human pose estimation, critical for domains such as fitness technology and dance [20, 24, 27]. We have integrated the latest version of YOLOv7-pose in our system to detect 17 critical keypoints of human anatomy, enhancing our tutoring and feedback mechanisms [12]. Figure 3 illustrates the keypoints recognized by the YOLOv7-pose in our implementations. Given three key points $u(x_u, y_u), v(x_v, y_v), p(x_p, y_p)$, the joint angle $\theta(u, v, p)$ (in degree) between two rays formed by three mentioned points is calculated as follows:

$$\theta(u, v, p) = \frac{180(\phi(y_p - y_v, x_p - x_v) - \phi(y_u - y_v, x_u - x_v))}{\pi} \quad (1)$$

where the angle: $\phi(y, x)$ (in radian) between the ray from the origin to the point (x, y)

and the positive x-axis in the Cartesian plane is calculated as follows:

$$\phi(y, x) = \begin{cases} arctan(\frac{y}{x}), & \text{if } x > 0 \\ \frac{\pi}{2} - \arctan(\frac{x}{y}), & \text{if } y > 0 \\ \arctan(\frac{y}{x}) \pm \pi, & \text{if } x < 0 \\ -\frac{\pi}{2} - \arctan(\frac{x}{y}), & \text{if } y < 0 \end{cases} \quad (2)$$

For mistake ID 1.1, we consider the movement of the participant's arms with respect to the ground-truth sequence by comparing the angles. The feedback is provided corresponding to that, as we can see in Fig.4(a).

For the mistake ID 1.2, we compute the vectors between a pair of generated keypoints [Example-(7,11) or (8,12)] which highlight the distance of the elbow to the body. To establish invariances concerning the distance with the camera, we normalize the each vector by the vertical extent of the keypoints (the height of the person).

For example, $ratio = \frac{dist(7,11)}{dist(0,15)}$. We compare $ratio$ concerning a hyperparameter $threshold$ to check the distance of the elbows to the body for each frame. The feedback is triggered accordingly.

4 RESULTS

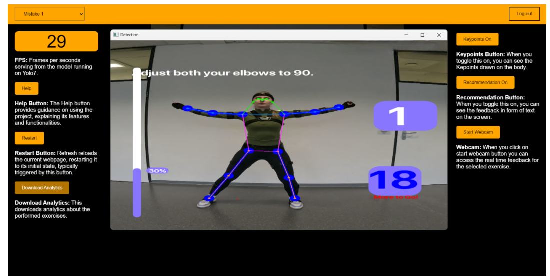
In an initial assessment, we conducted a pilot study to evaluate the effectiveness of our IMPECT-POSE framework in enhancing exercise outcomes at two different locations, each focusing on distinct types of exercises. At one evaluation site in Saarbrücken, we invited four participants. These participants were categorized into two groups to investigate which fitness level derived greater benefits from our system. The primary objective of the pilot study was in evaluating the system's performance and determining whether the feedback given to participants was adequate for posture adjustment. The study found that to facilitate user comprehension, feedback should be provided with a focus on specific joints. Figure 5 displays the setup used for this part of the study. A similar study, involving a larger sample population, demonstrated positive outcomes in the context of gym exercises [9]. Another evaluation site was set up in Cologne where a sports expert conducted a modern dance hip-hop session, as shown in Figure 4. The setup included a webcam positioned in front of the participant, facing a projector screen to simulate a mirror-like feedback mechanism commonly used in sports training environments.

At both locations, we monitored joint angles during various body movements. Some observations are listed in Table 1. These angles are considered hyperparameters in our model and can be adjusted by fitness professionals for each participant according to their specific needs. Performance tracking is an integral part of our system, enabling trainees to monitor their progress or review feedback from their trainer later. Based on this data, sports experts can select appropriate feedback messages for incorrect poses and create feedback cards using the IMPECT dashboard, as depicted in Figure 2b. Table 2 presents examples of feedback cards and the corresponding texts, which are then displayed on the client side.

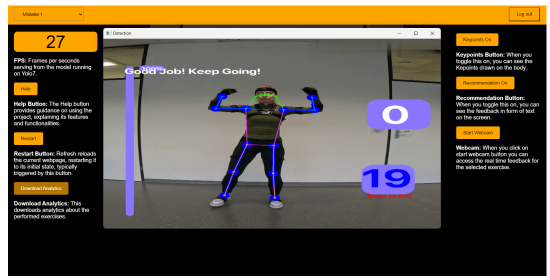
Figure 4 illustrates a use case where our system captured a participant's dance movements. These screenshots were taken from our front-end website. The feedback provided was analyzed and delivered through the IMPECT platform, tailored to each participant's performance, demonstrating our system's capability to provide precise and actionable guidance.

Exercises	Left Side Keypoints (°)	Right Side Keypoints (°)
	5, 7, 9	**6, 8, 10**
Pushups	[210, 280]	[210, 280]
Pullups	[142, 321]	[142, 321]
Lateral Pulls	[191, 327]	[191, 327]
Squats	[220, 280]	[220, 280]

Table 1: Keypoint combination for different human movements.



(a) Posture and real-time feedback: Not correct pose.



(b) Posture and real-time feedback: Correct pose.

Figure 4: Participant's modern dance hip-hop with feedback.

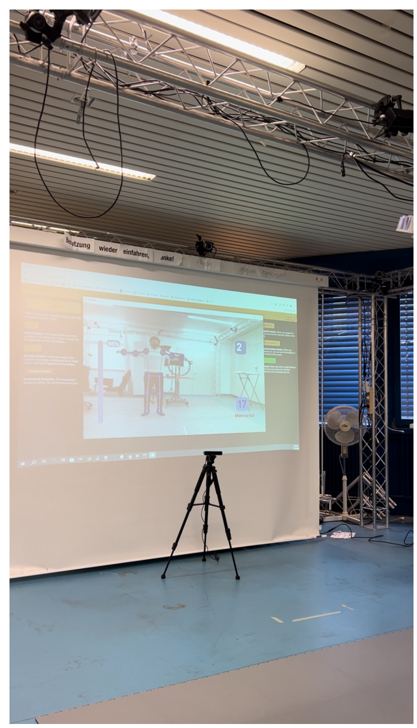


Figure 5: Apparatus of the pilot study.

5 FUTURE WORK AND LIMITATIONS

Our system has shown considerable promise in enhancing training by accurately estimating body postures. It utilizes the YOLOv7-pose model as a front-end client and IMPECT-POSE as the back-end feedback engine. We intend to build on this success to explore wider

Mistake ID	1.1	1.2
Mistake	Arms not 90°	Elbows close to body
Left Hand	Arm not 90°	Elbow too close
Feedback	Move left arm to 90°	Keep LE at shoulder level
Right Hand	Arm not at 90°	Elbow too close
Feedback	Move right arm to 90°	Keep RE at shoulder level

Table 2: An example of a feedback card to be displayed on the client side. It highlights mistake descriptions corresponding to the Mistake ID. LE and RE stand for left and right elbow, respectively.

applications in tracking postures for fitness and dance. Currently, our system effectively tracks postures in standard exercise and dance routines. We plan to evolve into a comprehensive platform that monitors postures in various physical activities, including free weight exercises and complex dance moves. These activities require precise body alignment for effectiveness and safety. Although IMPECT-POSE includes a Unity component, we have yet to deploy it due to the significant cost of acquiring Microsoft Hololens for numerous participants.

Another limitation of our system is related to the YOLO model's ability to recognize human keypoints. It can accurately identify keypoints from front or back angles, but it fails when limbs are occluded, which is a notable challenge as the camera is currently positioned at the front angle. This issue is particularly relevant for dance, which often involves turning movements. Addressing this limitation is essential for accurately capturing the full range of dance motions and will be a focus of our future research efforts.

Nevertheless, the objective is to develop a platform that allows users to monitor and adjust their posture during these activities and integrates smoothly with their fitness goals and routines. We aim to enhance our AI algorithms to encompass a wider array of human movements and postures, thereby delivering more personalized and precise feedback. The personalized feedback will be tailored to the dance learners' understanding, ensuring greater relevance and effectiveness. This feedback will be meticulously fine-tuned, with comprehensive research conducted by the sports department to provide specific guidance for maintaining and executing the proper form in dance scenarios.

Our future research will also explore additional applications of YOLOv7-pose in tracking complex postures, expanding the scope of AI-assisted fitness training. These advancements will improve the scalability and efficiency of our approach, opening new avenues for research and development in AI-powered personalized sports training.

6 CONCLUSION

This research marks a significant advancement in the field of fitness and sports training through the development of a new system named IMPECT-POSE, which offers precise body posture tracking and feedback by integrating a comprehensive front-end and back-end architecture. The evaluation, conducted with participants from two different locations, demonstrates that the system significantly enhances exercise performance. A key feature of our system is the implementation of real-time feedback, which is critical for maintaining correct exercise posture, reducing injury risks, and optimizing the effectiveness of workouts. Additionally, our system enables sports professionals to provide remote guidance and create feedback cards based on client exercises. On the client side, our system utilizes computer vision and AI to display feedback and improve exercise execution.

Looking ahead, we aim to refine the system's accuracy further and enhance its adaptability to accommodate a wider variety of user preferences, thus increasing its versatility. We plan more field tests to obtain deeper insights into its practical application and user engagement in realistic scenarios. Furthermore, subsequent studies focused on the long-term effects of this technology on user motivation and sports performance will be crucial for understanding and enhancing user engagement and sustained usage. Overall, this technology's integration of augmented intelligence into sports training represents a transformative leap forward. It provides a scalable and effective alternative to traditional training methods and paves the way for new research and development opportunities in AI-driven personalized training.

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