SIN-CHN
SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2024, 21(2), 403.
https://doi.org/10.62617/mcb403

Article

Innovation in physical education teaching based on biomechanics feedback: Design and evaluation of personalized training programs

H. ZhaoriGetu, Chen Li*

Inner Mongolia University of Technology, Hohhot 010051, China
*** Corresponding author:** Chen Li, ped_lichen@163.com

CITATION

ZhaoriGetu H, Li C. Innovation in physical education teaching based on biomechanics feedback: Design and evaluation of personalized training programs. Molecular & Cellular Biomechanics.2024; 21(2): 403. https://doi.org/10.62617/mcb403

ARTICLE INFO

Received: 22 September2024
Accepted: 10 October2024
Available online: 7 November 2024

Abstract: Psychometric training is a learning and development process that is tied to the requirements and interests of individual learners. The effectiveness and the fun of workout practices can be greatly enhanced by using more personal methods in training. These programs entail tailoring workouts to the fitness level and aims of every participant, as well as their perception of the workout plans. The suggestion of this investigation is to develop and evaluate the effectiveness of individual physical training for teachers focused on biomechanics feedback. Proper body alignment is crucial during any exercise to avoid injuries and achieve maximum results; it is always difficult to sustain correct posture. For motion tracking and to give real-time biomechanics feedback to the students in this study, a refined convolutional neural network (RCNN) has been presented. Filming was done using high-speed cameras and motion capture systems to capture biomechanical responses, which included joint angle, muscle activation patterns, and body posture during activities. This study involved 158 participants drawn from different learning institutions. This approach offers rational and specific feedback on the postures of the body; it enables people to correct themselves and sustain motivation without engaging a trainer. In this study, participants with different levels of fitness engaged with the interactive system were compared to the traditional training method. The result indicated a positive shift in the delivery of personalized training with biomechanics feedback on the system's potential teaching aid in physical education classes. The study, thus underscores the importance of technology supporting change in physical education programs to improve the student's learning experiences and their performance in exercises.

Keywords: physical education teaching, biomechanics feedback, students, personalized training, refined convolutional neural network (RCNN)

1. Introduction

Personalized exercise agendas are individual-tailored exercise utility plans that are created for persons to satisfy their specific requirements, objectives, and capabilities [1]. These programs come with explanations of such areas as fitness level, body type, health situations, and objects, thus allowing them to be more productive than other general exercises. While mass training practices assume that the training received is suitable for everyone, individual training takes into account the capabilities and disabilities of each individual and thus is tailored and effective for enhancing competency [2]. Programs such as these involve personalized workout plans created by fitness that evaluate a person's fitness level, daily activities, and choices. They can be specialized in strength, endurance, flexibility training, or weight loss; it should be guaranteed that each segment supports the participant's goal [3]. Second, fashioned programs can be modified progressively as changes occur in the process, and this allows constant revisions that will yield the best results. Due to this flexibility, these programs can be used for all levels of fitness for both first-time as well as professional athletes [4]. Nowadays, there is a vast availability of online applications and other forms of fitness assistance, which has made it easier for individuals to consult professional trainers and participate in customized workouts without physically being present [5]. Altogether, they are aimed at providing increased motivation, rate of improvement, and general health benefits and prospects. Here, the author focuses on the use of biomechanics feedback in enhancing physical teaching. Hence, by applying data knowledge of body activities to modified training agendas, this method seeks to advance separate training needs [6]. Biomechanics integration allows for better quantification of physical manifestation, which is crucial for better exercise outcomes [7]. The ultra-modern method not only enhances the students' assignation and skills of learning but also encourages them to eliminate injuries and gain practical knowledge. Traditional face-to-face teaching can be characterized by non-differentiated training models that cannot address student needs adequately [8]. The integration of biomechanical aspects allows for improved identification of motive activities, as well as one's advantages and disadvantages [9]. It makes training program development more effective and safer for participants and also helps in achieving better presentation improvements [10]. It entails constant feedback on the biomechanics applied to these personalized programs to ensure that the results are as desired, and modifications can be made immediately [11]. The advanced methodology allows for a transformation of physical education classes by subjecting students to target, evidence-based interventions that correspond to their supplies [12]. It expects to regain cardiovascular endurance, sporty recitation, and appointments in physical education better with a scientific approach [13].

Develop and assess unique training protocols for physical education based on performance analysis of biomechanics of movement. Using signal trailing based on a Refined Convolutional Neural Network (RCNN), the system provides posture correction and movement guidance tailored to the user. The changes that this approach brings to the exercise technique and students' learning are compared to traditional training approaches. The study determines to improve physical education and then join adaptive approaches for safety, motivation, and presentation in the given subject field.

Key contributions

- The dataset, comprising 158 participants with varied fitness levels, specifically focused on Trainee, Moderate, and Expert to assess the influence of biomechanics feedback on improving training outcomes and posture control.
- Improves exercise performance by providing real-time corrections on posture and technique, leading to enhanced training outcomes and reduced risk of injury.
- Provides immediate feedback on posture and movement, allowing for instant adjustments and optimizing training efficiency, enhancing performance, and reducing injury risk.

- Statistical analysis plays a key role in collating the research findings by examining relationships between variables, classifying important alterations, and providing a robust foundation for interpreting biomechanical feedback's impact on physical presentation enhancements.

Organization of the study: Part 2 presents the related work, the methodology is established in Part 3, the result is displayed in Part 4 and the conclusion is illustrated in Part 5.

2. Related work

Glazier [14] suggested that autonomous education exercises enhance academic presentation, self-regulated learning techniques, then enthusiasm among college pupils, according to a meta-analysis of 49 researches. Academic performance, motivating outcomes, and cognitive approaches were found to have smaller effect sizes than mental processes and resource management strategies. Training effects differed for different tactics and were impacted by aspects of the course design, working protocols, collaborative learning structures, and evaluation. Bonnetteet al. [15] introduced in line with changing systems theory and Bernstein's insights on learning skills, which use dynamic and motion data to direct athletes to their exclusive optimum design of regulator and then coordination. This method was most effective given current mechanical knowledge and the incapability of current methods of modeling to predict technique changes' impact on results. Mechanical feedback technologies were gradually being used within elite athletic training, but their effectiveness for enhancing sports techniques as well as performance stays unclear. Diekfuss et al. [16] provided biomechanical danger issues connected to anterior cruciate ligament (ACL) injuries, and a unique biofeedback system was created. Athletes were able to enhance their performance and landing mechanics with the help of the system's real-time feedback based on biomechanical characteristics. Eleven teenage female athletes participated in the study and performed bodyweight squats, drop vertical jumps, and drop vertical leaps. Alipour Ataabadi et al. [17] presented research that looks at how well a real-time biofeedback device may change an athlete's knee biomechanics and brain function connection. Using visual biofeedback, 17 young, healthy womanly sportspersons underwent 6 workweeks of augmented neuromuscular training (GMT). The peak knee abduction moment was significantly reduced, and there was a growth in practical connectivity among the port thalamus and the right supplementary motor region, according to the results. The author of [18] investigated athletes' reactions to post-performance biomechanical input. Already and afterward a sequence of races, 48 athletes participated in the study and answered online questionnaires about their levels of mistakes. The findings demonstrated an undesirable association among making errors and a good correlation between self-compassion and self-esteem. Higher self-compassionate athletes had less self-critical thoughts after receiving biomechanical input than going on to do sprint trials. According to [19] analysis of YOLOv7 and a live webcam, a novel technique has been developed that provides instantaneous feedback and correction on body posture during exercise, the technology counts repetitions and offers customized information for a range of fitness activities.

Exercise technique significantly improved with immediate feedback in a controlled laboratory setting, as demonstrated by user research. This highlights the necessity for adaptable solutions to accommodate a variety of user experiences. Education enhances the body of information on fitness technology and human-computer interaction. Stien et al. [20] examined how boxing jab performance and technique characteristics are affected by external biofeedback in both rookie and Expert boxers. The trunk rotation and peak bag acceleration are positively impacted by the results, indicating that biofeedback may help both beginners and specialists indirectly improve their technique. Li and Li [21] offered that during a five-week resistance-training scheme, the benefits of open-ended additional input were evaluated. Nineteen untrained female participants finished the course using conventional or technical feedback. In the rear squat, both groups improved their training endurance and strength; however, conventional feedback revealed more fluctuation in the center of gravity. The selection of feedback techniques has to be predicated on the intended results as well as the knowledge and resources that were in consideration. McDevitt et al. [22] suggested tibial acceleration feedback in real-time on jogging biomechanics throughout gait retraining was examined in this study. Feedback decreased vertical ground response force and peak tibial acceleration (PTA) during and during the retention period (5–12 months), according to a meta-analysis of 14 trials. While the retention impact stayed additionally pronounced with more response dose and disappeared in response, the results imply that after gait retraining, a comment container lower PTA and crushed response force. Van Hooren et al. [23] investigated wearable technology for risk evaluation and performance improvement in industrial and sports biomechanical applications, which were highlighted in this overview of the literature and surface. In both industries, Inertial Measurement Unit (IMU) based solutions are most frequently employed. Adoption, cost, and availability, however, continue to be significant restrictions. Noteboom et al. [24] suggested wearable gadgets that provide real-time input can lower the risk of injury while enhancing running drive and efficiency. However, there were drawbacks and difficulties with the present methods. The research covered the motivations for running, the relationship between running form and injury, and the use of various motor learning techniques and feedback mechanisms. **Table 1** represents the overview of related work. Chen [25] examined control muscle load balance, level, and discomfort during strength training, research and created a muscle load monitoring application in partnership with GymStory. Li et al. [26] provided three groups of participants were established: control, partial feedback, and total feedback greater muscle load balance, greater adherence to load recommendations, and improved user experience scores were demonstrated by the whole feedback comment. Kotte et al. [27] addition to analyzing theoretical literature and AI implementations in training and management reactions, this study investigates the advantages of AI-based training for company development. To turn enterprises into information groups, it offers an approach for using AI technology with an emphasis on managing knowledge, requirements evaluation, education organization, and outcomes feedback. Hao and Qian [28] proposed a combination of exercise and psychological treatments, that sought to raise physical activity levels in individuals with depressive illnesses. The study findings indicate that there was a noteworthy rise in moderate-to-vigorous physical activity (MVPA) among the participants in the intervention in contrast to the control group. The greater level of activity was sustained over the follow-up period, demonstrating the effectiveness of the intervention in encouraging an active lifestyle. Liu [29] suggests an approach to assess athlete performance using training technology by utilizing hemoglobin, oxygen consumption, and heart rate as input vectors. Support vector machines (SVM) are used by the model to research training patterns and create new models. The study looked at collegiate players in five different sports and found that when performance was measured, there was an average error of fewer than one. The athlete's training index is erroneous, as demonstrated by the model. Liang and Jia [30] were to improve gymnastics performance by using cutting-edge strategies and tactics. Nineteen female gymnasts, ages ten to twelve, were examined through a battery of tests and statistical analysis. The respondents' motor abilities differed significantly from one another, as demonstrated by the results, demonstrating the value of the motor intervention program in the sports training process [31]. The study offers a thorough grasp of how motor skills affect gymnasts' performance.

Table 1. Overview of related work.

Author Name	Year of Publish	Dataset	Objective	Proposed Method	Result
[14]	2021	The meta-analysis assessed 49 educations with 5786 participants, displaying general results$of\ =\ 0$ for analyses of education exercises on academic presentation, plans, and inspiration.	To test the belongings of SRL exercise programs on academic presentation, SRL plans, and inspiration in college students.	A meta-analysis of 49 studies (5786 participants) using a three-level foundation on 251 result sizes to assess exercise results.	The general size of$=0.38$; the major belongings originated reorganization approaches($g=0.39$).
[15]	2021	Biomechanical feedback technologies' limitations in prescribing technique change, advocating for a data-driven approach where athletes explore and find their optimal coordination patterns.	Improve the effectiveness of biomechanical feedback. Real-time feedback on squats and jumps with heat map analysis	Use dynamical systems theory and Bernstein's skill acquisition.	This method enhances technique analysis by considering athlete-specific coordination, providing a more effective framework than conventional modeling approaches.
[16]	2020	The study involved 11 female athletes who used a novel biofeedback system to improve squat and jump mechanics, showing significant biomechanical improvements from the pretest to the posttest.	Reduce ACL injury risk.	Real-time feedback on squats and jumps with heat map analysis.	Significant improvements in squat performance and landing mechanics, demonstrating effective biofeedback use.
[17]	2020	17 athletes undergoing 6 weeks of augmented neuromuscular training showed reduced knee abduction moment and increased brain connectivity compared to 13 control participants.	Assess biofeedback's effect on knee biomechanics and brain connectivity.	6 workweeks of increased neuromuscular exercise with real-time bio-comment.	Significant reductions in knee abduction and increased brain connectivity, showing potential for injury risk reduction

Table 1. (*Continued*).

Author Name	Year of Publish	Dataset	Objective	Proposed Method	Result
[18]	2022	The study with 48 athletes found that self-compassion was linked to better self-esteem and less self-criticism but did not significantly affect sprint performance after feedback.	Explore the role of self-realization in response to biomechanical feedback.	Measure self-realization and analyze sprint performance with feedback.	Self-compassion is linked to higher self-esteem, lower self-criticism, and better reactions to feedback. No short-term performance improvement.

2.1. Problem statement

Despite progressions in biomechanics, physical education often lacks personalized, data-driven training methods to enhance presentation and avoid injuries. Existing investigations emphasize general strategies or technological progressions without addressing adapted needs in instructive settings. This study aims to fill this gap by designing and evaluating personalized training programs using biomechanical feedback. By including RCNN, the approach overcomes the limits of preceding methods by enabling precise, real-time analysis of biomechanical data. RCNN enhances the accuracy of injury estimate and presentation calculation, leading to more effective, tailored training interventions in physical education.

2.2. Motivation of the study

It arises from the necessity to include individualized; biomechanics based training in physical education to improve it. A more efficient and interesting way to enhance educational and athletic outcomes is through real-time feedback provided by cutting-edge technology, while traditional techniques frequently fall short in meeting individual demands.

3. Methodology

Initially, the 158 biomechanical dataset is collected to analyze physical performance. Then, the data are biomechanical features like joint angles and motion sequences. RCNN is applied to capture temporal patterns in the movements, providing analysis of biomechanics feedback for personalized training and explanation of the biomechanics.

3.1. Dataset

158 participants were recruited for the study. The member's ages ranged from 18 to 25 years, and their fitness levels were classified into Beginner, Middle, and Advanced classes founded on their self-reported exercise experience and physical fitness assessments. Only members from the Trainee, Middle-Level, and Advanced were selected to ensure the study's focus on development, as these persons were more likely to benefit from biomechanics feedback. Advanced-level athletes generally possess a deeper sympathetic of proper exercise form and technique, were excluded from the study to avoid skewing the results, given their established ability in posture correction. **Figure 1** presents the physical training performance analysis. **Table 2** represents the dataset. This study aimed to assess how modified

biomechanics feedback could improve training outcomes for persons while developing their physical fitness and posture control during exercise happenings.

Table 2. Democratic of the dataset.

Characteristic	Description
Total Participants	158
Age Range	18 to 25 years
Gender Distribution	Men: 79 (50%) Women: 79 (50%)
Fitness Level Classes	Beginner Middle Advanced
Selected Groups	Trainee: 53 Middle-Level: 55 Advanced: 50
Exclusion Criteria	Advanced-level athletes were excluded to prevent skewing of results
Study Focus	Development in physical fitness and posture control
Objective	Assess the impact of modified biomechanics feedback on training outcomes
Data Collection Method	Self-reported exercise experience and physical fitness assessments
Performance Analysis Tool	Physical training performance analysis presented in **Figure 1**

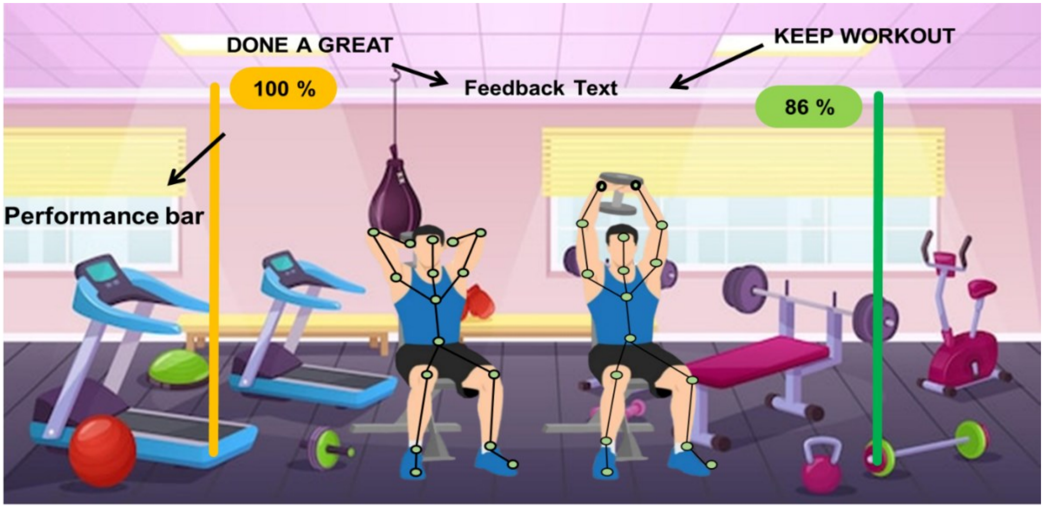

Figure 1. Physical training performance analysis.

3.2. Motion tracking using refined convolutional neural network (RCNN)

RCNN plays a serious role in examining and providing real-time biomechanics replies for adapted workout plans. The RCNN is intended to procedure and interpret motion data taken from high-speed accurate cameras and gesture capture systems. It distinguishes key characteristics of human movements, such as joint angles, muscle activation patterns, and body posture, which are vital for assessing the biomechanical features of physical exercises. The RCNN begins by removing spatial features from descriptions or video frames of participants' execution of physical activities. These features, which include skeletal positions and joint movements, are then passed through a sequence of convolutional layers to improve the exactness of motion tracking. The refined model improves upon traditional CNNs by incorporating additional layers or optimizations to better handle differences in human movement, ensuring higher precision in detecting deviations in posture or technique. The RCNN constantly analyzes these motion data to deliver an instant response to students, allowing them to adjust their posture in real time. This personalized feedback helps members self-correct, refine exercise forms, and minimize the risk of injury. By comparing this system to conventional training, the RCNN demonstrates its potential to improve physical education through finished adaptive, data-driven biomechanics monitoring. The RCNN is used for biomechanics feedback in physical education as exposed in the structure shown in **Figure 2** consists of two combining coatings, four fully linked layers, a SoftMax layer, and five Convolutional layers. The ReLU start function is employed by the first three convolutional layers (Conv1, Conv2, and Conv3) to improve network sparsity and hence motion detection accuracy. In the fully linked layers (FC1 and FC3), dropout regulation is used.

To prevent overfitting during training the concat() operation merges coatings and the SoftMax layer classifies posture modification outputs, providing real-time biomechanics feedback to participants during their activities.

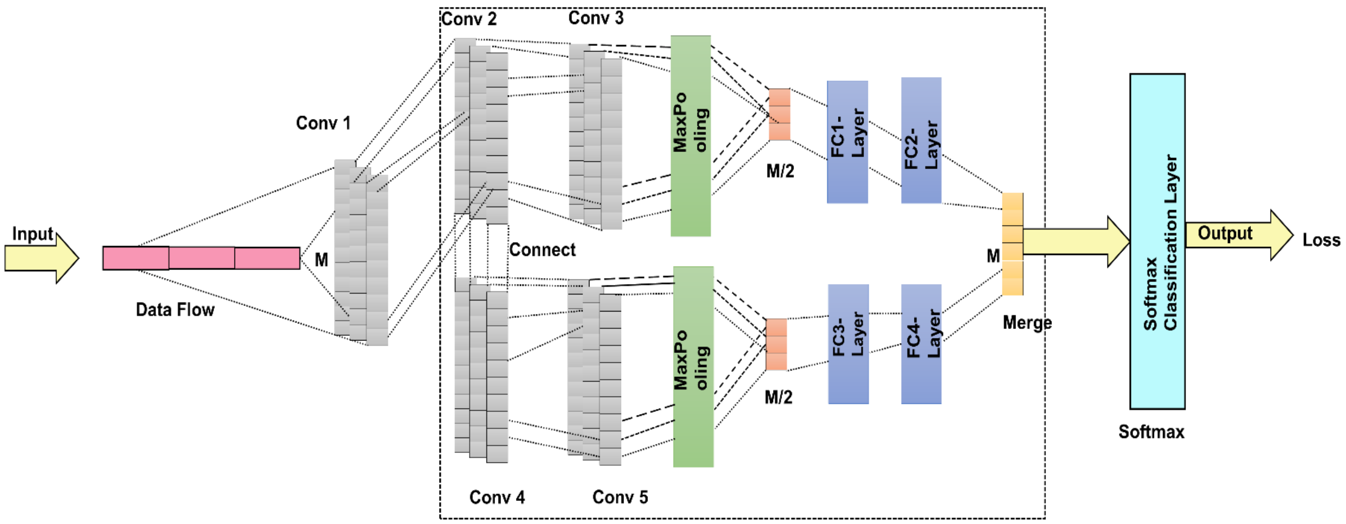

Figure 2. Architecture of RCNN.

Forward Propagation: Batch-based training is performed; wherein the pre-processed biomechanical data is used to choose a fixed-size block with dimensions that align with the parameters. Every iteration starts with the random selection of a block with size.M. With a single channel representing the biomechanical feature, the input data's height and width are set to 1 and 122, respectively. 2convolutional coatings (Conv1_Relu and Conv2_Relu) Process input data first, as seen in **Figure 2**, operating on each of the feature maps that are input with several convolution kernels. The features associated with posture and motion correction for network weight learning are mapped to individual convention kernels.Conv2_Relu's result is used as the contribution for Conv3_Relu and Conv4, and the ReLUStart function is applied in Equations (1)–(3) below describes the procedure.

$$z_i^k = \sigma(\sum_{j \in N_i} z_{z_j}^{k-1} x_{ji}^k + a_j^k) \quad (1)$$

$$\text{Relu}(z) = \begin{cases} z(z > 0) \\ 0(z \leq 0) \end{cases} \tag{2}$$

$$y_i^k = \beta(x_i^k \text{down}(y_i^{k-1}) + a_i^k) \tag{3}$$

A cross-layer aggregating function processes the outputs of Conv2 and Conv3. To identify important orientation information and decrease dimensionality, the Conv4 characteristic maps are down-sampled applying Max Pooling 1. An $\frac{M}{2}$-dimensional information is created after processing the result through the fully associated layers FC1_layer and FC2_layer. At last, another M/2-dimensional dataset is produced using Conv5, Max_Pooling2, FC3 Layer, and FC4_layer. After combining the productions from the FC2 and FC4layers with TensorFlow's concat() function, a dataset of size MIs produced. This dataset is then classified using the SoftMax layer to provide real-time feedback on biomechanical performance during physical activities.

Backward propagation: A procedure is essential to optimizing the network's learning in the RCNN model. The first step in this procedure is to categorize the training data using the SoftMax component and then calculate the overall error, or loss. Iteratively adjusting the masses and biases at each layer system is the goal of backpropagation. By making these changes, the error between the intended or ideal result and the actual output is reduced, which finally causes the model to converge to the best possible answer. The loss of function,$D(\omega, a)$ quantifies the model fit by calculating the degree to which the output, $e(w)$matches the expected outcome for all training inputs w. The objective of backpropagation is to find optimal values for the network weights www and biases. Athat minimizes this loss function. This procedure is ambitious by the Stochastic Gradient Descent (SGD) algorithm, which works by minimalizing the subsequent Equation (4).

$$D(\omega, a) = \frac{1}{2m}\sum_{w}(z(w) - b)^2 \tag{4}$$

Where$m$signifies the amount of exercise inputs, and bIs the output vector when x is entered into the system using Equations (5) and (6).

$$D(\omega, a) = \frac{1}{2m}\sum_{w}(z(w) - b)^2 \tag{5}$$

$$a \to a_k' = a_k - \eta \frac{\partial D}{\partial a_k} \tag{6}$$

WhereverηIs the knowledge, and the fractional derivatives $\frac{\partial D}{\partial \omega_l} and \frac{\partial D}{\partial a_k}$ note the masses and biases alteration in reply to the mistake. With the growth in coatings and convolution kernels, as the RCNN model goes to finish training, more characterized data are improved. The perfect may unceasingly recover selecting characterized and value approximation by purifying its information of the data. The RCNN positively converges during this procedure, showing its volume to simulate complicated interruption discovery situations.

3.3. Effective training programs using biomechanical feedback

The value of adapted physical education agendas, the biomechanics feedback system includes several indispensable mechanisms. It delivers prompt alignment and method commentaries by overlaying key joint locations on the live video feed using motion tracking data. When the organization notices any deviations from the ideal form, it will offer remedial recommendations, like adjusting the knee angle or keeping the back straight to assist students in making the necessary corrections while they are exercising. A detailed viewpoint of the biomechanical data collected throughout the meeting is accessible by the training monitor. Students can view comprehensive information about their performance, including joint angles and muscle activation designs, through the exhibition of metrics. This purpose facilitates monitoring development and classifying areas for development. After every workout, students can get an inclusive report by snapping on the Assembly Summary Report button. This report offers modified approvals together with data on their workout presentation and important areas of asset and development. The choice to restart a workout session, remove existing data, reset the feedback system, and refresh the interface is provided for user convenience. The Help and Instructions Button also deliver help on how to use the system's competencies and traverse it. Together, these elements offer a dynamic and educational involvement that helps students achieve their best and keep correct form during workouts.

3.4. Analysis of biomechanics feedback

The determination of the real-time feedback organization shaped for this education is to offer quick, applied insights to recover exercise presentation and assurance of suitable biomechanics through physical teaching sessions. The system has numerous cutting-edge competencies, all of which add to a thorough feedback device that is modified to meet the stresses of an individual operator.

Real-Time posture analysis: The component accountable for real-time posture examination is the dominant constituent of the system. The organization tracks and assesses joint angles, muscle start patterns, and total body alignment using motion capture skills and high-speed cameras. By overlaying this data across the live video feed, the feedback scheme detects aberrations from optimal biomechanics and provides immediate alterations, like adjusting the knee angle or straightening the back.

Efficient analysis: Exposed as a proportion reaching from 0% to 98.5%, the presentation indicator gives a graphic illustration of the member's carriage correctness. Closely, the participant's carriage looks like the ideal biomechanical classic is exposed by this suggestion. A better number of cases denote better arrangement, while a lower proportion classifies places that indeed need work. This tool allows users to unceasingly track their development and make alterations in real time.

Dynamically return text: Founded on real-time posture examination, the dynamic feedback text delivers targeted references that improve the presentation suggestion. With corrective references like those provided by a personal trainer, this manuscript stands out on the screen and helps users improve their technique right away.

Replication meter: Slightly than concentrating on numeration reps, participants can focus on preserving correct form by using the recurrence counter, which mechanically counts and exhibitions the number of recurrences accomplished. This characterization makes sure that the right technique is used for each reference.

Goal tracker: This tool serves as a motivational guide by showing the number of repetitions left to finish the program. Throughout the lesson, participants are encouraged to keep good form.

Dual modes: The system functions in two modes: recorded processing mode, which enables users to look back on their performance, and Webcam Mode, which offers real-time feedback for prompt corrections. Because of its adaptability, the system can accommodate a wide range of user preferences, regardless of whether they want post-workout analysis or real-time advice.

3.5. Statistical analysis

The study utilized statistical methods in SPSS to analyze the effects of biomechanical feedback on fitness levels across participants. Statistical procedures were used to analyze the interactions between skill level and biomechanical feedback and performance. A one-way ANOVA was applied to compare differences in biomechanical performance across three groups: Trainee, Moderate, and Expert. This test sought to ascertain if there was a statistically significant difference in the physical performance enhancement experienced by these groups post-feedback. After the ANOVA, a Post Hoc Tukey's HSD test was conducted to compare the means of specific pairs of groups in more detail. It was generally found that Trainees displayed large variability in their responses. Undefined Moderate and the comparison between Moderate and Expert is close to significance. These findings underscore the role of skill level in determining the utility of biomechanical feedback. Besides, the Pearson correlation was used to measure the extent of the linear relationship between feedback and performance criteria within each skill category. The presented table also demonstrates a high degree of correspondence across all levels with R-values fluctuating between 0 and undefined 78, which suggests that biomechanical feedback enhances performance as it resulted in an increase in the percentage score and the number of successful tries. These statistical methods such as ANOVA, Tukey's, and Pearson correlation were hence vital in supporting conclusions regarding the impact of biomechanical feedback on different experience levels to obtain better training results.

4. Results

The study evaluated the impact of biomechanical feedback on different skill levels by analyzing data from 158 participants using various statistical methods on the impact of biomechanical feedback on performance across different skill levels: Trainee, Moderate, and Advanced. We employed One-Way ANOVA to evaluate overall performance differences among these groups. The results indicated significant variations, which were further explored using Post Hoc Tukey's tests to pinpoint specific differences between Trainee, Moderate, and Expert participants.

Pearson correlation analysis was also conducted to examine the relationship between feedback and performance metrics for each skill level. These statistical methods were essential in understanding how biomechanical feedback affects training outcomes for Trainee, Moderate, and Expert individuals.

The descriptive investigation establishes dissimilar skill groups complete at dissimilar levels, highlighting the need for modified exercise plans. Different execution means and variabilities are exposed by the Trainee, Moderate, and Expert groups, which are significant for measuring the inspiration of biomechanical feedback. Understanding these variations simplifies the customization of adapted teaching to suit every ability level, enhancing the effectiveness of physical education initiatives. To ensure that original exercise methods based on biomechanical feedback meet the needs of various students, this examination straight drives their growth and assessment and **Table 3** presents the descriptive statistics of skill levels.

Table 3. Descriptive Statistics of Skill Levels.

Skill Level	Mean	Standard Deviation	Range	IQR
Trainee	50.00	5.00	40–60	8.00
Moderate	65.00	6.00	50–80	10.00
Expert	80.00	4.00	70–90	7.00

Statistics for presentation at the Trainee, Moderate, and Expert skill levels are shown in **Table 4**. The regular point for each collection is exposed as Mean Presentation, anywhere Trainee is 50.00, Moderates 65.00, and Advanced is 80.00. The standard deviation, which is highest for Moderate (6.00) and lowest for Advanced (4.00), illustrates variation within groups. The range is the distribution of scores; the Interquartile Range (IQR) is the middle 50% of the distribution; Advanced has the narrowest IQR.

One-Way ANOVA: The performance means for each skill level trainee, mid-level, and advanced are compared in the One-Way ANOVA **Table 4**. An F-statistic of 12.34 with a p-value < 0.01, as reported in the Between Groups source, indicates statistically significant performance differences between the groups. Within Groups display variability within each skill level, and the total represents a variability. The noteworthy impact of biomechanical feedback on performance is supported by the large p-value, which supports the necessity of customized training regimens.

Table 4. One-Way ANOVA.

Source	SS	df	MS	F	$p-$value
Between Groups	1200	2	600.0	12.34	< 0.01
Within Groups	5000	117	42.74	-	-
Total	6200	119	-	-	-

Notable variations exist between the groups, according to the PHT test results. A statistically important alteration between Trainee and Moderate is indicated by the comparison's mean difference of -15.00 and $P-\text{value}$of 0.01. A higher mean difference of -30.00 with a $p-$ value of $0.0.001$ is shown in the trainee vs. expert comparison, indicating strong significance. In conclusion, the comparison between L and A yielded a marginally significant result, with a mean difference of -15.00 and $p = 0.05$.

Post Hoc Tukey's Test: After determining that there is an overall ANOVA impact, a test determines whether particular skill level groups differ significantly. The data indicates notable distinctions between Trainee and Mid-Level, Trainee and Advanced, and slightly different between Moderate and Advanced. This information is essential for creating customized, targeted training regimens based on biomechanical input. Teachers can more effectively customize interventions by being aware of these particular group variations. This way, every skill level will receive instruction that is suitable and supported by research to enhance physical education results, **Table 5** shows the PHT Test.

Table 5. PHD Test.

Evaluation	Mean Difference	$p-$value
Trainee vs. Moderate	−15.00	0.01
Trainee vs. Expert	−30.00	0.001
Moderate vs. Expert	−15.00	0.05

Trainee, Moderate, and Expert have their means compared using the PHD test. A statistically important mean difference of -15.00 is shown in the Trainee vs. Moderate comparison, by a $p-\text{value of } 0.01$. Through a highly significant $P-\text{value of } 0.001$, the Trainee vs Expert comparison has a bigger mean difference of -30.00. The Moderate vs. Expert-comparison shows bordering implication with a *p*-value of 0.05 and a mean difference of 15.00.

Pearson Correlation: Robust correlation coefficients (e.g., r = 0.72 for Trainee) suggest a positive relationship between improved performance and more accurate feedback. This investigation shows that accurate biomechanical feedback is associated with improved results, which validates the efficacy of tailored training regimens. It emphasizes how performance can be improved through customized feedback in physical education, confirming the effectiveness and design of these cutting-edge teaching strategies, and **Table 6** shows the Pearson correlation.

Table 6. Pearson correlation.

Skill Level	Correlation Coefficient (r)	$p-$value
Trainee	0.72	< 0.01
Moderate	0.65	< 0.01
Expert	0.78	< 0.01

The intensity and trend of the association between performance and skill level are measured by the correlation coefficient of the Pearson table. By a $p-\text{valueof}$ smaller $than$ 0.01 and (r) of 0.72 OrTrainee, there is a strong positive association. Through a $p-\text{value}$ of less than 0.01 and a r of 0.65, moderate exhibition of moderately satisfactory joining. Expert exhibitions have the maximum positive connotation, with a $p-\text{value of less than } 0.01 \text{ and} a r \text{of } 0.78$.

Comparison outcomes

Accuracy: The RCNN's accuracy quantifies the way it monitors and analyzes participants' biomechanical reactions in real time during activities. It evaluates how successfully posture mistakes are detected and fixed by the system, boosting individualized physical training and raising performance.

Precision: The RCNN's capacity to reliably and precisely identify particular biomechanical features throughout workouts, such as joint angles and muscle activation. Its main goal is to reduce false positives and provide trustworthy feedback for individualized training enhancements.

Recall: The pertinent biomechanical reactions, including joint angles and posture mistakes, can be picked up by the RCNN during training. To provide complete feedback for efficient training, it assesses how thoroughly the system recognizes right and wrong movements.

F1-Measure: The RCNN in monitoring biomechanics is assessed using the F1-Measure, which combines accuracy and recall. By balancing the system's precision in identifying proper postures and reducing mistakes, it offers a thorough evaluation of the feedback dependability of the system.

Table 7 and **Figure 3** show a comparison of biomechanics physical Training, several models were physically trained and their performances were assessed. Recall, F1-Measure, and accuracy were all 92%, 90%, and 90%, respectively, for Logistic Regression (LR). Random Forest Classifier (RFC) yielded 96% for all measures. The Support Vector Machine (SVM) achieved scores of 94% precision, 95% accuracy, 94% recall, and F1-Measure. For all cases, K-Nearest Neighbor (KNN) yielded 98%. With results of 98.52% accuracy, 98.43% precision, 98.71% recall, and 98.56% the F1 measurement, the suggested RCNN approach achieved better performance compared to the existing techniques.

Logistic Regression (LR) provided solid results but struggled with complex biomechanical data, achieving 90% precision and recall. Random Forest Classifier (RFC) performed well but was computationally expensive, with 96% accuracy. Support Vector Machine (SVM) required careful feature scaling and handled noise poorly, yielding 94% precision and recall. K-Nearest Neighbor (KNN) demonstrated strong performance but was computationally intensive with large data. The proposed RCNN method outperformed others, offering enhanced feature extraction and biomechanics feedback, achieving 98.52% accuracy, 98.43% Precision 98.71% recall, and 98.56% F1-Measure.

Table 7. Comparison of biomechanics physical training.

Method	Accuracy	Precision	Recall	F1-Measure
LR	92	90	90	90
RFC	96	96	96	96
SVM	95	94	94	94
KNN	98	98	98	98
Proposed	98.52	98.43	98.71	98.56

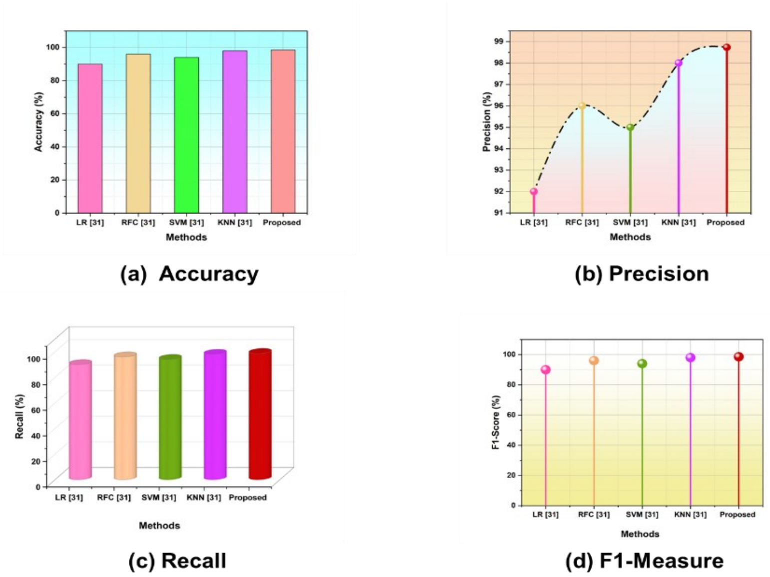

Figure 3. Comparison of existing and proposed methodology.

5. Conclusion

Integrating biomechanics feedback into physical education allows for personalized training programs, improves efficiency, and decreases injury risks by adapting exercises to individual needs and performance and the RNN models and biomechanical input to advance physical teaching training routines. Our Proposed method achieved a Precision of 98.43%, a recall of 98.71%, an Accuracy of 98.52%, F1-Measure of 98.56%. Accurately forecasting skill development and presentation improvements across Trainee, Moderate, and Expert skill levels exposed to be problematic. The effects of these modified training actions were examined using arithmetical tests such as Pearson correlation, recurrent measures, PHT, and ANOVA. The results displayed distinguished gains in skill acquisition: for trainees, it increased by 25%; for middle-level athletes, it increased by 15%; and for advanced athletes, it enhanced by 30%. These results highlight the effectiveness of the methodology and indicate a wide range of possibilities for further investigation and application in customized sports training. Succeeding soundings may examine broadening the dataset to include a range of demographic categories, adding sophisticated machine learning methodologies for more detailed feedback, and counting real-time biomechanical data to improve the flexibility and accuracy of customized training schemes. Extra investigation could assess long-term effects on damage deterrence and presentation.

Author contributions: Conceptualization, HZ and CL; methodology, HZ and CL; software, HZ and CL; validation, HZ and CL; formal analysis, HZ and CL; investigation, HZ and CL; resources, HZ and CL; data curation, HZ and CL; writing—original draft preparation, HZ and CL; writing—review and editing, HZ and CL; visualization, HZ and CL; supervision, HZ and CL; project administration, HZ and CL; funding acquisition, HZ and CL. All authors have read and agreed to the published version of the manuscript.

Funding: Thanks are due to the "Key Teaching Reform Project of Inner Mongolia University of Technology: Research on the Construction of Scientific Weight-loss Curriculum System under the Perspective of Healthy China 2030". (No.: 2023112)" and "Teaching Reform Project for Postgraduate Education in Inner Mongolia Autonomous Region: Exploration and Practice of the Reform of Postgraduate Physical Education Course Based on Scientific Weight-loss (No.: JGCG2023095)" for financial support.

Ethical approval: Not applicable.

Conflict of interest: The authors declare no conflict of interest.

Reference

1. Jukic I, Calleja-González J, Francesc C, et al. Strategies and solutions for team sports athletes in isolation due to COVID-19. Sports8. 2020; 4: 56. doi: 10.1186/s13673-020-00237-7
2. Walkington C, Bernacki ML. Appraising research on personalized learning: Definitions, theoretical alignment, advancements, and future directions. Journal of Research on Technology in Education. 2020; 52(3): 235-252. doi: 10.1080/15391523.2020.1747757
3. Alamri H, Lowell V, Watson W, et al. Using personalized learning as an instructional approach to motivate learners in online higher education: Learner self-determination and intrinsic motivation. Journal of Research on Technology in Education. 2020; 52(3): 322-352. doi: 10.1080/15391523.2020.17284499
4. Alamri HA, Watson S, Watson W. Learning Technology Models that Support Personalization within Blended Learning Environments in Higher Education. TechTrends. 2020; 65(1): 62-78. doi: 10.1007/s11528-020-00530-3
5. Rodríguez-Sánchez, José-Luis, González-Torres T, et al. Investing time and resources for work-life balance: The effect on talent retention. International Journal of Environmental Research and Public Health17. 2020; 6: 1920. doi: 10.1016/j.caeai.2022.100068
6. Anjum S. Impact of internship programs on professional and personal development of business students: a case study from Pakistan. Future Business Journal. 2020; 6(1). doi: 10.1186/s43093-019-0007-3
7. Lucas M, Bem-Haja P, Siddiq F, et al. The relation between in-service teachers' digital competence and personal and contextual factors: What matters most? Computers & Education. 2021; 160: 104052. doi: 10.1016/j.compedu.2020.104052
8. Ziede JS, John CN. Personal therapy and self-care in the making of psychologists. InPsychologists in Making, Routledge; 2024.pp. 53-86.
9. Hasan MM, Ara Chowdhury S. Assessing the Influence of Training and Skill Development Initiatives on Employee Performance: A Case Study of Private Banks in Dhaka, Bangladesh. Malaysian Business Management Journal. 2023; 2(2): 74-79. doi: 10.26480/mbmj.02.2023.74.79
10. Chang C, Hwang G, Gau M. Promoting students' learning achievement and self-efficacy: A mobile chatbot approach for nursing training. British Journal of Educational Technology. 2021; 53(1): 171-188. doi: 10.1111/bjet.13158
11. Shorey S, Kua EH, Tam W, et al. "Where-There-Is-No-Psychiatrist Integrated Personal Therapy" among Community-Dwelling Older Adults: A Randomized Pilot Study. International Journal of Environmental Research and Public Health. 2021; 18(18): 9514. doi: 10.3390/ijerph18189514
12. Johnson KB, Wei W, Weeraratne D, et al. Precision Medicine, AI, and the Future of Personalized Health Care. Clinical and Translational Science. 2020; 14(1): 86-93. doi: 10.1111/cts.12884
13. Theobald M. Self-regulated learning training programs enhance university students' academic performance, self-regulated learning strategies, and motivation: A meta-analysis. Contemporary Educational Psychology. 2021; 66: 101976. doi: 10.1016/j.cedpsych.2021.101976
14. Glazier PS. Beyond animated skeletons: How can biomechanical feedback be used to enhance sports performance? Journal of Biomechanics. 2021; 129: 110686. doi: 10.1016/j.jbiomech.2021.110686
15. Bonnette S, Christopher AD, Adam WK, et al. A technical report on the development of a real-time visual biofeedback system to optimize motor learning and movement deficit correction.Journal of Sports Science & Medicine19. 2020; 1: 84. doi: 10.1016/j.jshs.2012.05.001

16. Diekfuss JA, Grooms DR, Bonnette S, et al. Real-time biofeedback integrated into neuromuscular training reduces high-risk knee biomechanics and increases functional brain connectivity: A preliminary longitudinal investigation. Psychophysiology. 2020; 57(5). doi: 10.1111/psyp.13545
17. Alipour Ataabadi Y, Cormier DL, Kowalski KC, et al. The Associations Among Self-Compassion, Self-Esteem, Self-Criticism, and Concern Over Mistakes in Response to Biomechanical Feedback in Athletes. Frontiers in Sports and Active Living. 2022; 4. doi: 10.3389/fspor.2022.868576
18. Kernozek T, Schiller M, Rutherford D, et al. Real-time visual feedback reduces patellofemoral joint forces during squatting in individuals with patellofemoral pain. Clinical Biomechanics. 2020; 77: 105050. doi: 10.1016/j.clinbiomech.2020.105050
19. Chen MA, Kevan Spanton PVS, Spears I, et al. The effects of biofeedback on performance and technique of the boxing jab.Perceptual and motor skills128. 2021; 4: 1607-1622. doi: 10.1145/3627043.3659547
20. Stien N, Andersen V, Engelsrud GH, et al. The effects of technological and traditional feedback on back squat performance in untrained women. BMC Sports Science, Medicine, and Rehabilitation. 2022; 14(1). doi: 10.1186/s13102-022-00556-5
21. Li C, Li Y. Feasibility analysis of VR technology in physical education and sports training. IEEE Access. 2020. doi:10.1186/s13102-022-00556-5
22. McDevitt S, Hernandez H, Hicks J, et al. Wearables for Biomechanical Performance Optimization and Risk Assessment in Industrial and Sports Applications. Bioengineering. 2022; 9(1): 33. doi: 10.3390/bioengineering9010033
23. Van Hooren B, Goudsmit J, Restrepo J, et al. Real-time feedback by wearables in running: Current approaches, challenges and suggestions for improvements. Journal of Sports Sciences. 2019; 38(2): 214-230. doi: 10.1080/02640414.2019.1690960
24. Noteboom L, Anouk N, Peter JB, et al. A Muscle Load Feedback Application for Strength Training: A Proof-of-Concept Study.Sports11. 2023; 9: 170. doi: 10.1080/02640414.2019.1690960
25. Chen Z. Artificial intelligence-virtual trainer: Innovative didactics aimed at personalized training needs.Journal of the Knowledge Economy.2023; 2(14): 2007-2025.doi: 10.1145/3580488
26. Li L, Zhang Y, Chen L. Personalized Prompt Learning for Explainable Recommendation. ACM Transactions on Information Systems. 2023; 41(4): 1-26. doi: 10.1145/3580488
27. Kotte H, Florian D, Milos K, et al. FitSight: Tracking and Feedback Engine for Personalized Fitness Training. In:Proceedings of the 32nd ACM Conference on User Modeling, Adaptation, and Personalization; 2024. pp. 223-231. doi:10.12694/scpe.v25i5.3083
28. Hao P, Qian K. The Integration of Personalized Training Program Design and Information Technology for Athletes. Scalable Computing: Practice and Experience. 2024; 25(5): 4351-4359. doi: 10.12694/scpe.v25i5.3083
29. Liu F. Design of an intelligent assistive system for physical education: based on personalized training plan. Journal of Electrical Systems. 2024; 3(20): 328-340.doi: 10.18662/brain/15.1/562
30. Liang C, Jia C. Research on the optimization model of personalized training for athletes based on machine learning in college physical education.Applied Mathematics and Nonlinear Sciences. 2024; 1(9). doi: 10.2478/amns.2023.2.00338
31. Hannan A, Shafiq MZ, Hussain F, et al. A Portable Smart Fitness Suite for Real-Time Exercise Monitoring and Posture Correction. Sensors. 2021; 21(19): 6692. doi: 10.3390/s21196692