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Article

Development of a virtual simulation training platform for physical education teaching posture integrating biomechanics

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Abstract: The development of an immersive virtual simulation training platform designed to enhance physical education by integrating biomechanics for precise posture training. Through the use of biomechanical analysis and virtual reality (VR), the platform offers real-time feedback and assessment, helping students to comprehend and correct their posture while engaging in physical activities. The research introduced an Improved Aquila Optimized Efficient Deep Convolution Neural Network (IAO-EDCNN) model to estimate joint kinematics and strength metrics, which are crucial for posture accuracy and injury prevention. To collect data from VR-compatible sensors to gather motion data continuously while users perform various physical exercises. The data was preprocessed using a Gaussian Filter to smooth data and reduce high-frequency noise in the data. Frequency-domain characteristics were extracted using the Fast Fourier Transform (FFT) as dominant frequency components of motion. IAO model ensures that the joint angles and positions during exercises are optimal and EDCNN can be employed to analyze motion capture data, assess joint kinematics, and predict strength metrics. The results indicate that upper-body kinematics can be accurately estimated with less error for joint angles, allowing for reliable real-time feedback during sessions. In a comparative analysis, the suggested method is assessed with various evaluation measures, such as F1-score (95.60%), recall (95.35%), precision (96.10%), and accuracy (95.85%). The result demonstrated the IAO-EDCNN method to estimate joint kinematics and strength metrics, which are crucial for posture accuracy and injury prevention. This innovative approach demonstrates that VR technology, paired with biomechanics can serve as an effective tool for posture training in physical education. By providing accessible, evidence-based metrics, this platform aims to enhance the quality of physical education through immersive and engaging training experiences.

Keywords: virtual simulation; physical education teaching; posture; biomechanics; improved aquila optimized efficient deep convolution neural network convolution neural network (IAO-EDCNN)

1. Introduction

Physical education instruction has been completely transformed by the use of virtual simulation training platforms in the classroom, which provide creative ways to improve student learning and instructor effectiveness. To enhance the productivity of physical training and understanding the right posture of movement in the virtual simulation training environment the teaching posture on physical training Shan and Sun [1]. Biomechanics was particularly important for the experience of human body actions during various activities. The substance of biomechanics in virtual simulation models also made posture education an essential aspect of preventing injuries, enhancing performance, and promoting the overall health of the subject in the long-term Martay et al., [2]. Teachers of normal physical education classes explain the correct alignment of exercises and sports to their pupils orally. The pupil's instant feedback intricately explains the biomechanical concepts of motion. Furthermore, the organization of classes might be more challenging for educators to address all learners' physical skills, learning preferences, dissimilarities, and levels of prior knowledge Klochko et al., [3]. The virtual reality (VR) platform may provide real-time visuals on biomechanics that enable students to understand the effectiveness of certain movements and how to adjust the movements for effectiveness and efficiency with the prevention of injuries into consideration in sports. Learning is successful, imaginative, and creative to a certain degree, for example, using virtual simulation systems. Moreover, virtual simulation by Xiao et al., [4] was employed to bring/enable scalable training. Instructors should provide individual attention to all students in a physical education context. The incorporation of biomechanics into virtual simulations enables the representation of intricate ideas by using conventional techniques Bores-García et al., [5]. The biomechanical feedback technique of people intends certain exercises or activities such as running, leaping, and stretches. For instance, a VR platform might compare students' body position and posture with motion capture technologies. Students might gradually improve their motions and develop a better awareness of how their posture affects entire physical performance via constant practice with immediate feedback Yevtuch et al., [6].

A virtual simulation training platform offers different interactive ideas on physical education. Students observe and comprehend the biomechanical concepts behind their motions by using the platform to replicate force distribution, joint angles, and muscle activation patterns throughout various workouts Mishra et al., [7]. Students adopt different postures, which helps to lower the risk of injury and enhances their performance by making their motions more effective. The instructors could monitor biomechanical data, analyze individual student development, and provide feedback depending on each student's requirements to ensure individualized training for students Hu and Liu [8]. Every learner might concurrently receive tailored feedback using a virtual simulation platform. The platform could handle several pupils that evaluate each one's motions and offer tailored advice, freeing up the teacher to concentrate on more complex students and other educational activities. It allows all students to obtain high-quality biomechanical input without requiring additional staff or equipment, the scalability was particularly beneficial for educational institutions with limited resources. The capacity of virtual simulation platforms to replicate different kinds of physical activities in secure settings Lin and Song [9]. The virtual platform provides a special chance to practice motions without worrying about physical education since many activities and sports include some degree of physical danger. Students' confidence was increased and they had the opportunity to try out various postures and motions Li et al., [10]. The virtual simulations in physical education classes constitute the current developments of digital learning Boujdi et al., [11]. Students anticipate access to tech-driven, interactive, and fascinating learning experiences as technology becomes more pervasive in the educational system. Students interact with personalized specific requirements, and deliver real-time feedback and the complexity of physical education Ma and Huo [12]. Physical contact and kinesthetic learning take place in conventional physical education that cannot be completely replicated by virtual simulations. The absence of practical experience might impede pupils' growth in physical abilities, coordination, and stamina.

The research intends to develop an immersive virtual simulation training platform designed to enhance physical education by integrating biomechanics for precise posture training. The study aims to develop a novel Improved Aquila Optimized Efficient Deep Convolution Neural Network (IAO-EDCNN) model to estimate joint kinematics and strength metrics, which are crucial for posture accuracy and injury prevention.

Contribution of the study

- The dataset was initially collected from different types of workouts. The virtual simulation training platform was an innovative instrument for enhancing physical performance and posture correction in physical education since it uses real-time biomechanical data.
- The data was preprocessed using a Gaussian Filter to smooth data and reduce high-frequency noise in data. Fast Fourier Transform (FFT) to extract frequency-domain features, such as the dominant frequency components of motion.
- The innovative novel of Improved Aquila Optimized Efficient Deep Convolution Neural Network (IAO-EDCNN) model to estimate joint kinematics and strength metrics, which are crucial for posture accuracy and injury prevention.

The article is comprised of the following sections: In Part 2, the related works are presented along with a summary of the research; Part 3, the study's strategy and methodology are detailed; Part 4, the experimental and assessment results are presented; Part 5, a discussion is contributed; and Part 6, the research is concluded.

2. Related works

Saklani [13] examined VR and artificial intelligence (AI) and how it signifies physical education. AI intends to be a personal trainer in the field of public education. It provided immediate feedback, personalized workouts, and even employed clever arithmetic to improve fitness regimens. It ignites innovative and inventive teaching methods in the field of physical education. The experimental outcome demonstrated the characteristics of both physical health and education. The computer modeling and simulation of physical education intends the teaching by the developments of the digital era. Hou and Ouyang [14] explored how the technologies could improve teaching effectiveness and student learning. The VR and accurate movement modeling were used to constitute the effects of computer-assisted simulations with traditional instruction. The experimental outcome demonstrated the student's proficiency in athletics and physical performance.

The demands of the modern environment constitute the conventional sports education approach to handle by Chen [15]. To incorporate digital media and virtual crowd simulation for practical requirements of physical education. The Distributed Management System's (DMS) approach is model tracking to compute the center points of each grid sequence to produce a center point matrix of physical education.

The result findings show the good performance of DMS. Akanmu et al., [16] examined a cyber-physical posture training environment for pupils to practice the tasks with less ergonomic dangers. Body kinematics and interaction of tangible building materials were tracked by using VR, wearable sensors, and machine learning. An interactive user interface used to deliver the feedback. The experimental outcome demonstrated the practical and workspace disturbance of the user interface.

Fernández-Vázquez et al., [17] investigated how student's physical skills and physical education were affected when VR and gamification combined with practice teaching style (PTS). The participant views constitute the perceived effort of physical skills impacted by the kind of activity, competition-based incentive, and rewards. When combined with VR and gamification tactics, it could increase physical skills and reduce physical education programs. The experimental outcome demonstrated the higher perceived effort achieved by PTS. To improve teaching methods and support students' physical health, Lai [18] explored the integration of knowledge convergence technology in physical education. The field of physical education constitutes the revolutionary transformation of the digital era, as rapid information requires creative ways of teaching practices. The experimental outcome demonstrated the real-time physiological measurements and workout condition monitoring.

Yuan [19] examined how field sports were taught to students and practiced in physical education classes. The fundamental part of sports and physical education curriculum, requires imaginative and efficient teaching strategies, training methods, and physical education classes for students' growth globally. The experimental outcome demonstrated the social and psychological dimensions of experience. The student's physical and mental abilities could be improved during physical education by combining the use of biomechanical assessment and psychological feedback. The integration of psychological feedback with biomechanics offers a novel strategy for enhancing physical education Jiang [20]. The psychological feedback techniques help to teach pupils and develop mental resilience, like self-reflection and stress management techniques. The experimental findings indicated the psychological health and physical abilities of students.

The standard teaching method fails to intrigue students' attention and prime the position of people's physical and mental growth Xie [21]. Physical education requires constant innovation and instructional strategies for students. Inspire kids to engage in physical activity to foster their enthusiasm for learning. The result findings demonstrated the challenges and problems of team sports. The virtual simulation experimental platform utilized an innovative teaching tool on physical education of the environment to comprehend sports education and help students to grasp the technical issues of sports by Xiao [22]. The experimental teaching makes it more difficult to advance a more comprehensive transformation in sports education. The result findings demonstrated the test platform for instruction.

Zhai [23] investigated the innovative technology of online teaching techniques for courses in physical education. The design of instructional materials based on psychology and sports biomechanics constitutes online learning environments and integrates the curriculum framework flexibly. The efficiency of instruction and the learning experience of the students were assessed by the teaching statistics. The result findings demonstrated the dramatic increases in learning performance and engagement of students. During physical education and training, sports biomechanics played an important role. To enhance the impact of sports biomechanics constitutes the importance and necessity of physical education and training by Niu [24]. Recognizing its role to improve teaching methods, and optimizing training outcomes promotes a deeper understanding of the biomechanics involved and improves the students' performance and physical development. The experimental outcome demonstrated how pupils work to obtain physical patriotism.

The VR system addresses the issues of teaching techniques and inadequate long-distance teaching capabilities of physical education by Ding et al., [25]. To improve the efficiency of higher education, the physical education teaching system should be constructed in a modern and scientific manner. The experimental outcome demonstrated how teaching levels were constructed and successfully advanced the educational reform process. The Intelligent Virtual Fitness Trainer (IVFIT) was an AI-based program that was designed and developed to customize the student's learning experience by Mokmin [26]. When feasible, a customized virtual fitness trainer might constitute the role of a physical trainer. Instructors of physical education in schools used to encourage students to work out. The experimental outcome demonstrated the precise computation of the virtual trainers' attributes.

Consuming input from biomechanics, ZhaoriGetu et al., [27] attempted to establish and assessed the efficacy of specific physical training for instructors. For real-time biomechanical feedback and motion tracking, a sophisticated convolutional neural network (RCNN) was employed. 158 people from various universities participated in the study, which discovered a beneficial change in the way biomechanical feedback was used to give individualized instruction. It demonstrates how crucial technology was to enhancing toddlers' educational and athletic experiences.

Primary school girls' endurance, coordination, and adaptability were evaluated about the effects of integrating a school-based plyometric training program (PMT) into physical education (PE) classes. According to Radwan et al., [28], except for the anterior guidance, the PMT group had more notable gains in extended maximum force, overall work, and SEBT ratings. Based on the research's findings, PMT can greatly improve primary school girls' PE competence.

3. Methodology

The Improved Aquila Optimized Efficient Deep Convolution Neural Network (IAO-EDCNN) model used to estimate joint kinematics and strength metrics, which are essential for posture accuracy and injury prevention. Data pre-processing is used to preprocess the raw data using a Gaussian filter to smooth data and reduce high-frequency noise in data. Frequency-domain characteristics were extracted using the FFT as the dominant frequency component of motion. IAO model ensures that the joint angles and positions during exercises are optimal and EDCNN can be employed to analyze motion capture data, assess joint kinematics, and predict strength metrics. **Figure 1** represents the overall paper flow.

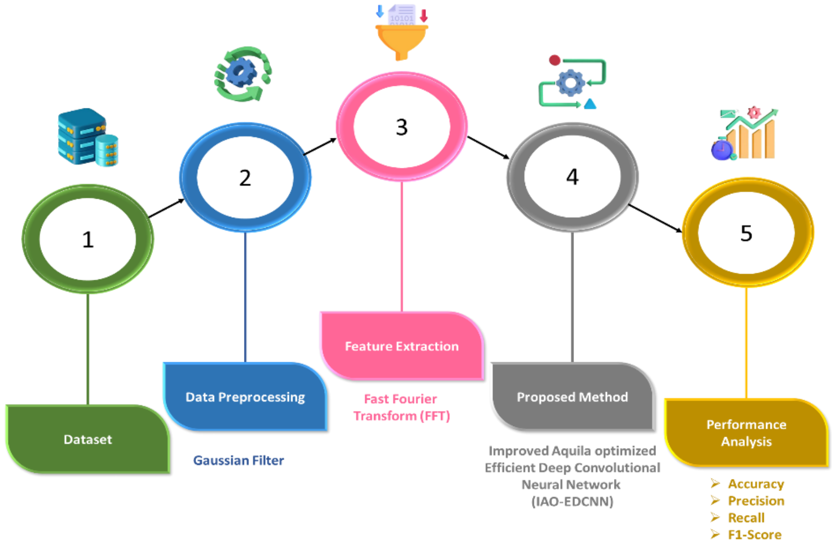

Figure 1. Workflow of the virtual simulation training platform for physical education teaching posture.

3.1. Virtual simulation for physical education

The creation of a biomechanics-integrated virtual simulation training platform for physical education mostly depends on kinematic sensors, especially inertial measurement units (IMUs). The sensors were used for accurate tracking and evaluation of a user's body motions during workouts by capturing real-time motion data, such as joint angles, locations, velocities, and accelerations. IMU was used to track multi-dimensional movement on a variety of body parts, including the head, chest, and limbs. It helps to analyze and estimate the user's joint kinematics, including rotational, flexion, and extension angles. Through real-time analysis of angles, the platform can detect departures from ideal posture. The device gives users instantaneous feedback to help improve their motions. Kinematic sensor integration improves the platform's capacity to provide dynamic, personalized corrections, guaranteeing that users retain appropriate technique and posture when engaged in physical activities. In tracking progress, it helps to avoid injuries from improper motions, which increases the efficiency of training. The virtual simulation training platform was an innovative instrument for enhancing physical performance and posture correction in physical education since it uses real-time biomechanical data.

3.2. Data collection

The data was initially collected from a variety of workout types like squats, lunges, push-ups, planks, jumping jacks, and deadlifts, with a range of kinematic and biomechanical factors, including joint angles, positions, velocity, acceleration, strength metrics, frequency and posture feedback. The data aids in tracking and evaluating the user's workout performance, enabling the platform to offer real-time feedback and adjustments to guarantee good posture and avoid injuries. **Table 1** illustrates the sample data of physical education. This dataset has included other biomechanical factors such as joint torques, muscle activation patterns, and range of motion for every exercise. These parameters are associated with a more profound analysis of posture dynamics and further help in the accuracy and efficiency of the virtual simulation platform in optimizing performance and injury prevention.

Table 1. Kinematics and biomechanical data of common exercises with posture.

Exercise type	Joint angle (degrees)	Joint position $X\ (m)$	Joint position $Y\ (m)$	Joint position $Z\ (m)$	Velocity (m/s)	Acceleration	Strength Metrics (Nm)	Frequency (Hz)	Posture label	Feed back
Squat	−11.29	−0.379	−0.50	−0.97	−2.01	6.94	370.7	05.2	Suboptimal	Adjust posture
Lunge	−43.1	−1.48	1.45	1.13	4.07	9.59	350.5	5.33	Optimal	Correct
Push-up	10.06	−0.725	−1.38	0.249	−3.88	−2.974	42.3	4.24	Optimal	Correct
Plank	9.67	−0.836	−1.015	−0.38	−0.049	2.977	76.81	7.61	Optimal	Correct
Jumping jack	−34.01	−1.43	−0.75	1.172	0.020	3.622	109.3	3.65	Optimal	Correct
Deadlift	24.50	1.42	−0.506	−1.1440	3.811	7.38	160.5	4.83	Suboptimal	Adjust posture

3.3. Data pre-processing

In data preprocessing, a crucial step in data analysis and machine learning transforms unprocessed data into a comprehensible format. Encoding, classifying variables, removing duplicates, scaling or normalizing data, and handling missing values are among the tasks involved. Preprocessing enhances the model's functionality. The data was preprocessed using a Gaussian Filter to smooth data and reduce high-frequency noise in data.

Gaussian filter

More precise monitoring of body motions was ensured by the Gaussian filter, which lowers noise in motion data recorded by sensors. The simulation platform uses filtered data to evaluate and adjust posture during workouts, giving real-time feedback to enhance performance and training in physical education. The Gaussian filter was one of the most important functions. The most widely used technique for image filtering is termed Gaussian filtering, which uses weights expressed in Equation (1).

$$\overline{w}_{ji}\ \alpha\ \exp\left(||x_j - x_i||\right), j = i \tag{1}$$

The geographical filtering method is known as Gaussian filtering. A common technique for denoising images is the Gaussian filter, which tends to produce smooth images and clearly reduces data, particularly surface clarity. Although it allows the image to stay reasonably steady, Gaussian smoothing, referred to as lower-pass filtering, preserves the image's lower-frequency components by lowering high-frequency characteristics like distortion and borders.

3.4. Feature extraction

Feature extraction is used in machine learning and data analysis to minimize the dimensionality of data. It cracks unprocessed data into a collection of useful characteristics that make analysis easier while preserving details. It improves the efficiency and interpretability of the model, concentrating on important characteristics. Frequency-domain characteristics were extracted using the FFT as the dominant frequency component of motion.

FFT

To find patterns and anomalies, motion data, including joint angles and velocities might be analyzed and transformed into the frequency domain using FFT. The process of breaking down function or signal over time into a component of frequency is known as FFT. The perception of the Fourier transform was essential for image processing, speech and communication, signal processing, and many other fields. Equation (2) describes the FFT mathematical form.

$$W(\zeta) = \int_{-\infty}^{\infty} w(s)\, f^{-2\pi j \zeta s} ds \tag{2}$$

Here, $W(\zeta) \in D$ as Lebesgue integrals, and ζ indicates the frequency. FFT can be used to implement quickly. The discrete Fourier transform (DFT) was calculated by FFT, which yields the same outcome as evaluating the DFT directly. The primary distinction of DFT was significantly quicker and less precise. Equation (3) represents the DFT mathematical form.

$$W_l = \sum_{m=0}^{M-1} w_m f^{-\frac{j\pi m}{M}}, (l = 0, .., M - 1) \tag{3}$$

Here, $w_0, .., \, and \, w_{M-1}$ represent the complicated integers. The FFT was used to translate and evaluate the spinning machine's data into the frequency plane from several experiments.

3.5. Improved aquila optimized efficient deep convolution neural network (IAO-EDCNN)

A hybrid of Improved Aquila Optimizer with Efficient Deep Convolutional Neural Network method integrates biomechanics for improved movement analysis to transform virtual simulation training for physical education (PE) and posture instruction. Inspired by eagles' predatory habits, the Aquila Optimizer has adapted to enhance its global search capabilities while avoiding conventional optimization constraints. The IAO optimization constitutes real-time biomechanical simulations because it converges more quickly and produces more accurate solutions. The EDCNN was a deep learning architecture that optimally processes and stores fine-grained patterns of human motion data. The neural network enhances the position of the body segments, the joints' orientations, and movements to detect PE postures. The EDCNN minimizes errors in practical applications that involve the reality of information because it optimizes the architecture for posture classification. The biological concepts used by the system ensured that every stance was evaluated based on biomechanics, including muscle activation and joint loading, which made for realistic training. The application of biomechanics understands the body mechanics during various physical education activities. The IAO-EDCNN method was suitable for predicting postures in post-physical activities since it is based on real conditions, which enhances performance and reduces vulnerability to accidents.

3.5.1. Efficient deep convolution neural network (EDCNN)

The EDCNN was a designed deep learning architecture that effectively processes and logs human motion data features. To determine the PE postures of neural networks, constitute the changes in body angles and joint motions and alignment. The EDCNN reduces mistakes that could occur in practical applications by improving posture classification accuracy through its effective architecture. The recognition architecture EDCNN is based on inception BN and Faster RCNN. The feature extractor constitutes a layer structure with the use of Inception BN rather than the traditional CNN. The final layer creates feature maps and predicts areas by using RPN with a shared convolutional network. The spatial pooling layer synthesizes the input data from RPN to create the proposed feature maps. Bounding box regression and softmax classifier were utilized to identify optimizations by utilizing the suggested feature maps.

Inception BN:

Inception BN refined by employing 3×3 convolutional layers rather than a single 5×5 convolutional layer, which implies the kernel sizes as 1×1 and 3×3, in contrast to previous convolutional networks. The enhancement could provide more nonlinear transformations in addition to reducing superfluous parameters that intend the network with higher learning capacity. Inception incorporates batch normalization (BN) as an effective regularization technique. By incorporating the current model, the huge convolutional network's training might be significantly increased and the classification accuracy of the following convergence was significantly increased. BN was integrated into a network layer and applied to the internal representation of the testing data, producing an output as a normalized distribution. When the distributions of the input data change, an internal attribute shift occurs. The activations of each hidden layer were updated to constitute the weight across layers during batch gradient descent. In EDCNN attribute shift results from the internal layers' constant adaptation to change the distribution. The normalized input layer was expressed in Equation (4).

$$w = \frac{w - F[w]}{\sqrt{Var[w] + \omega}} \tag{4}$$

Here, w and $\widehat{w}$ represent the input and normalized values of a certain layer, respectively. The input's expectation and variance represent the variables $F[w]$ and $Var[w]$, respectively. Furthermore, ω indicates the internal covariance offset. After normalizing, it might be removed by using BN and each layer will have the same input distribution. The network layer might be less affected were expressed in Equations (5) to (11).

$$z_j = \gamma \widehat{w}_j + \beta \tag{5}$$

$$\frac{\partial k}{\partial \widehat{w}_j} = \frac{\partial k}{\partial z_j} \times \gamma \tag{6}$$

$$\frac{\partial k}{\partial \delta^2 \theta} = \sum_{j=1}^{n} \frac{\partial k}{\partial \widehat{w}_j} \times \left(w_j - \mu_\theta\right) \times \frac{-(\delta_\theta^2 + \omega)^{-3/2}}{2} \tag{7}$$

$$\frac{\partial k}{\partial \mu_\theta} = \left(\sum_{j=1}^{n} \frac{\partial k}{\partial \widehat{w}_j} \times \frac{1}{\sqrt{\delta_\theta^2 + \omega}}\right) + \frac{\partial k}{\partial \delta^2 \theta} \times \frac{-2\sum_{j=1}^{n}(w_j - \mu_\theta)}{n} \tag{8}$$

$$\frac{\partial k}{\partial w_j} = \frac{\partial k}{\partial \widehat{w}_j} \times \frac{1}{\sqrt{\delta_\theta^2 + \omega}} + \frac{\partial k}{\partial \delta^2 \theta} \times \frac{2(w_j - \mu_\theta)}{n} + \frac{\partial k}{\partial \mu_\theta} \times \frac{1}{n} \tag{9}$$

$$\frac{\partial k}{\partial \gamma} = \sum_{j=1}^{n} \frac{\partial k}{\partial z_j} \times \widehat{w}_j \tag{10}$$

$$\frac{\partial k}{\partial \beta} = \sum_{j=1}^{n} \frac{\partial k}{\partial z_j} \tag{11}$$

Here, k represents the gradient loss from backpropagation, and n indicates the size of the mini-batch θ. Where, w_j and z_j represent the input value w within the mini-batch and the output after the BN process, respectively. The minibatch's mean indicates as μ_θ, while its variance represents as δ_θ^2. Equation (12) represents the final output of the BN network.

$$z = \frac{\gamma w}{\sqrt{Var[w] + \omega}} + \beta - \frac{\gamma F[w]}{\sqrt{Var[w] + \omega}} \tag{12}$$

Region proposal network (RPN):

RPN differs significantly from border cases and selective search. The RPN might accept an image of any size as input, allowing it to generate a sequence of rectangular areas. During the procedure, a sliding network adopts a 3×3 window and slides across the feature maps that were created by the last layer.

A fixed-size vector was created at last. A desirable translation-invariant was obtained with different multiscale and aspect ratios of every window position. To estimate offsets and evaluate the foreground, the resultant vector ensures the regression and classification layers. Softmax produces the anchors' foreground scores, whereas box regression yields the anchor's coordinates. Equations (13) and (14) represent the loss function.

$$K(o, o^*, s, s^*) = K_{cls}(o, o^*) + \lambda K_{reg}(s, s^*) \tag{13}$$

$$\begin{cases} s_w^* = \dfrac{(R_w - O_w)}{O_x} \\ s_z^* = \dfrac{(R_z - O_z)}{O_g} \\ s_x^* = \log\left(\dfrac{R_x}{O_x}\right) \\ s_g^* = \log\left(\dfrac{R_g}{O_g}\right) \end{cases} \tag{14}$$

where the softmax loss indicated as K_{cls} and λ represent the balance losses. The anticipated and true labels are expressed as O and O^*. The ground-truth bounding box regression's offset vectors and the predicted offset vectors are illustrated as $s = \{s_w, s_z, s_x, s_g\}$ $s = \{s_w^*, s_z^*, s_x^*, s_g^*\}$, respectively. $O = \{O_w, O_z, O_x, O_g\}$ and $R = \{R_w, R_z, R_x, R_g\}$ indicate the ground-truth boxes.

Spatial pooling:

The spatial pooling layer receives the generated feature maps and adopts the area of recommendations. The spatial pooling was necessary to map the feature map of every proposal to ensure the image features were located in the same location on the feature map. The particular portion of the feature map was reduced in size to a 7×7 image using the max pooling layer. The region is handled by the sub-window during the max pooling procedure. Lastly, fixed-length outputs as 7×7 dimensions achieved the fact size.

Discrimination

Each proposal might be categorized into a particular group using the feature maps, which provide the discrimination probability vector. The softmax stimulation function calculates the probability of class labels originating from the fully connected layer with weighted inputs. Equation (15) illustrates the stimulation function.

$$z_d = \frac{\exp(w_d)}{\sum_{d=1}^{D} \exp(w_d)} \tag{15}$$

The final output layer of the fully linked network, w_d represents the input of the class. Where D represents the total number of courses and z_d indicates the class d softmax activation function's output.

3.5.2. Improved aquila optimizer (IAO)

Inspired by eagles' predatory habits, the Aquila Optimizer has adapted to enhance its global search capabilities. The IAO optimization constitutes real-time biomechanical simulations because it converges more quickly and produces more accurate solutions. The virtual platform offers realistic, interactive activities and real-time feedback, while IAO evaluates and improves students' performance using data-driven insight. Preventing premature convergence, increasing convergence speed, and maintaining the balance between local exploitation capabilities and global search constitute the IAO.

Quasi-opposition learning technique:

The opposition-based learning (OBL) technique served as the foundation for quasi-opposition learning (QOL), which could increase population variety, improve solution quality, and ultimately boost algorithm performance. To determine the contrasting resolution of the search dimension, the OBL technique broadens the search space were expressed in equation (16).

$$W_j' = KA + VA - W_j \tag{16}$$

Here, KA and VA indicate the lower and upper limits of search space and W_j represents the present solution. The QOL technique yielded a solution that constituted the disapproval resolution of the midway boundaries. The QOL solution was near the ideal solution. The QOL technique is mathematically expressed in Equation (17).

$$W_j^r = \begin{cases} n + (n - W_j) \times q_1, if\ W_j < n \\ n - (W_j - n) \times q_2, else \end{cases} \tag{17}$$

The search space's midway represented as $n = \frac{KA+VA}{2}$, and q_1, $and\ q_2$ were random values ranging from 0 and 1. Using the QOL technique, additional M individuals were created after the locations were initialized. The initial M people with higher fitness were chosen as the new population after the $2M$ people were arranged in ascending order based on the fitness scores. The IAO algorithm's exploration and exploitation procedures were carried out.

Strategies of wavelet mutations:

The QOL approach could increase population variety and improve solution quality, but it does not address the issue of the algorithm's easy premature convergence and local optimum. An essential technique for assisting the algorithm on local optimum is termed mutation. The mutation of the wavelet technique intends to enhance IAO functionality. Following the exploitation and exploration phase of every individual constitutes the opportunity to use the wavelet mutation technique by setting the mutation probability. The individual executes wavelet mutation as $rand < O$. The mutation formula was expressed in Equation (18).

$$W_j^{new}(s) = \begin{cases} W_j(s) + \sigma\left(VA - W_j(s)\right), rand < 0.5 \\ W_j(s) + \sigma\left(W_j(s) - KA\right),\ \ rand \geq 0.5 \end{cases} \tag{18}$$

Here, VA and KA represent the lower and the upper boundaries of the present search dimension. Where $W_j(s)$ $(j = 1,2, \ldots, M)$ represents the location of the jth person generation. The coefficient of wavelet mutation represented as σ was expressed in Equation (19).

$$\sigma = \frac{1}{\sqrt{\alpha}} \psi\left(\frac{\varphi}{\alpha}\right) \tag{19}$$

The wavelet function indicated as $\psi\left(\frac{\varphi}{\alpha}\right) = e^{-\left(\frac{\varphi}{\alpha}\right)^2/2} \cos\left(\frac{5\varphi}{\alpha}\right)$ and its energy was constituted. The compression factor was expressed in equation (20) as follows:

$$\alpha = t \times \left(\frac{1}{t}\right)^{\left(1 - \frac{1}{s_{max}}\right)} \tag{20}$$

Wavelet mutation possesses the IAO method to enhance solution stability by dynamically adjusting the mutation space through the scale parameter of the wavelet function. Following the wavelet mutation procedure, the original person indicated as W_j and the mutant individual represented as W_j^{new} were chosen by desire expressed in Equation (21).

$$W_j(s+1) = \begin{cases} W_j^{new}(s), e\left(W_j^{new}(s)\right) \leq e\left(W_j(s)\right) \\ W_j(s), e(W_j^{new}(s) > e\left(W_j(s)\right) \end{cases} \tag{21}$$

The procedure guarantees the higher fitness values to advance the following iteration and enhance the algorithm's capacity for optimization through the rate of convergence. The wavelet mutation and QOL strategies were added to obtain the IAO. Wavelet mutation could increase the algorithm's capacity to depart from the local optimum, while the QOL approach boosts the diversity of populations and global exploration capabilities. Algorithm 1 shows the IAO-EDCNN pseudocode.

Algorithm 1 Process of IAO-EDCNN

```
def preprocess_data(raw_data):
    preprocessed_data = normalize(raw_data)
    denoised_data = noise_reduction(preprocessed_data)
    return denoised_data
def biomechanics_analysis(posture_data):
    joint_angles = calculate_joint_angles(posture_data)
    body_movement = analyze_body_movement(posture_data)
    return joint_angles, body_movement
def build_cnn_model(input_shape):
    model = Sequential()
    model.add(Conv2D(64, (3, 3), activation = 'relu', input_shape = input_shape))
    model.add(MaxPooling2D((2, 2)))
    model.add(Conv2D(128, (3, 3), activation = 'relu'))
    model.add(MaxPooling2D((2, 2)))
    model.add(Flatten())
    model.add(Dense(128, activation = 'relu'))
    model.add(Dense(10, activation = 'softmax'))
    return model
def improved_aquila_optimizer(model, data, labels, max_iterations = 100):
    best_solution = initialize_ia_solution()
    best_score = float('inf')
    for iteration in range(max_iterations):
        new_solution = ia_explore_exploit(best_solution)
        model.set_weights(new_solution)
        score = evaluate_model(model, data, labels)
        if score < best_score:
            best_solution = new_solution
            best_score = score
    return best_solution
def virtual_simulation(training_data, model):
    posture_data = get_posture_data(training_data)
    recognized_posture = model.predict(posture_data)
    joint_angles, body_movement = biomechanics_analysis(posture_data)
    posture_error = calculate_posture_error(recognized_posture, ideal_posture)
    feedback = generate_feedback(posture_error)
    return feedback
def generate_feedback(posture_error):
    if posture_error > threshold:
        return "Adjust your back angle and knee position"
    else:
        return "Posture is correct!"
def main():
        train_data, test_data, train_labels, test_labels = split_data(preprocessed_data)
    cnn_model = build_cnn_model(input_shape = (64, 64, 3))
    optimized_weights = improved_aquila_optimizer(cnn_model, train_data, train_labels)
    cnn_model.set_weights(optimized_weights)
    feedback = virtual_simulation(test_data, cnn_model)
    print(feedback)
main()
```

4. Experimental results

The virtual simulation training platform was designed in Python 3.8 using a system with an Intel Core i7 CPU, 32 GB of RAM, and Windows 11. Data is acquired from motion sensors during physical education exercises to test the accuracy of posture and validate the prevention of injuries. The analyzed joint movements and body alignment are based on biomechanical principles.

A positive error rate indicates the percentage of cases in which a negative instance was incorrectly classified as positive by the model. The false positive rate is determined by dividing the number of false positives by the total number of genuine negatives. **Figure 2a** represents the positive error rate. The feedback success rate measures how well a user's posture and performance were improved by the platform's remedial recommendations. A success rate suggests that the user's ability to maintain ideal form throughout workouts was being improved by the feedback, causing more precise modifications. **Figure 2b** illustrates the feedback success rate.

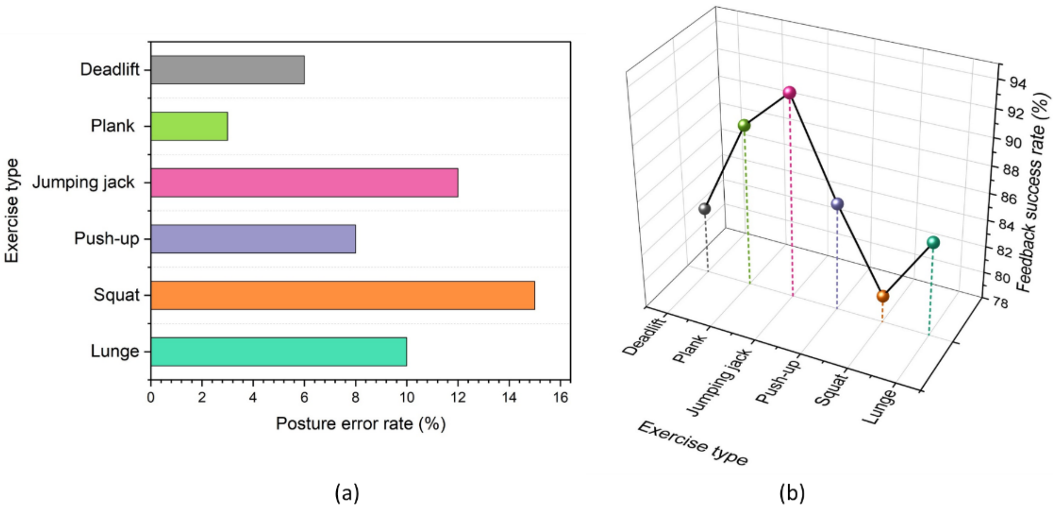

Figure 2. Result of **(a)** posture error rate; **(b)** Feedback success rate.

The proposed strategy was assessed and its effectiveness was calculated using the following indicators: Recall (%), accuracy (%), F1-score (%), and precision (%). Furthermore, a comparison investigation will be conducted with other existing approaches, including the Random Forest (RF) and Artificial Neural Network (ANN) Hu et al. [29] and Attention-based Long Short-Term Memory-Long Short-Term Memory (ALSTM-LSTM) Liang [30].

Evaluating the model's accuracy by calculating the ratio of successfully expected to total occurrences, accuracy offers a robust assessment of the system's efficiency. **Figure 3** and **Table 2** illustrate an evaluation of accuracy in comparison between suggested and existing methods. The proposed IAO-EDCNN achieves an accuracy level of 95.85% in comparison to existing techniques, which have accuracy levels of RF (90.74%), ANN (91.74%), and ALSTM-LSTM (95%), respectively. For accurate posture and injury prevention, the suggested approach produced better results when estimating joint kinematics and strength measures.

Table 2. Performance evaluation of various model for posture detection in virtual training.

Methods	Accuracy (%)	Recall (%)	F1-score (%)	Precision (%)
RF	90.74	92.23	93.85	92.32
ANN	91.74	94.35	94.83	95.42
ALSTM-LSTM	95	94	94.9	95.3
IAO-EDCNN [Proposed]	95.85	95.35	95.60	96.10

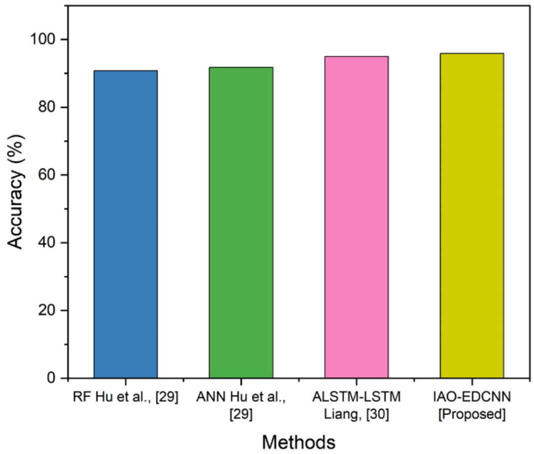

Figure 3. Outcome of accuracy comparison for injury prevention and posture estimation.

A model's precision level indicates how accurately it anticipated results. The assessment is the proportion of precisely predicted positive results to the total expected benefits. **Figure 4** and **Table 2** illustrate an evaluation of precision in comparison between suggested and existing methods. The precision level of the proposed IAO-EDCNN is 96.10%, whereas the precisions of existing methods such as ANN (95.42%), ALSTM-LSTM (92.32%), and RF (95.3%), respectively. The recommended method yielded better findings for the examination of joint kinematics and strength metrics, which are critical for proper posture and injury prevention.

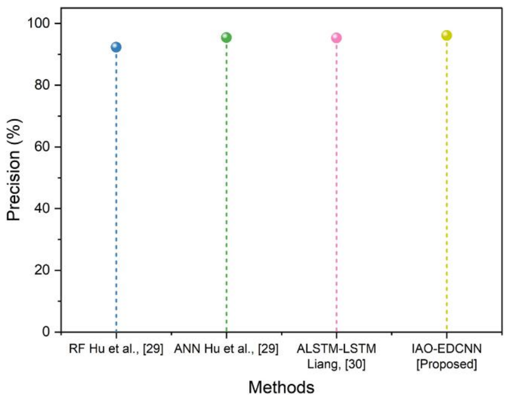

Figure 4. Outcome of precision evaluation for posture estimation and injury prevention.

Recall is a statistic that assesses a model's capacity to locate all pertinent instances of a class. It assesses the model's accuracy in identifying every pertinent among the total number of real positives. **Figure 5** and **Table 2** present an evaluation of recall in comparison between the suggested and existing methods. With a recall level of 95.35%, the suggested IAO-EDCNN outperformed other techniques such as RF (92.33%), ANN (94.35%), and ALSTM-LSTM (94%), respectively. Joint kinematics and strength measures, which are critical for accurate posture and injury prevention, were better estimated using the proposed approach.

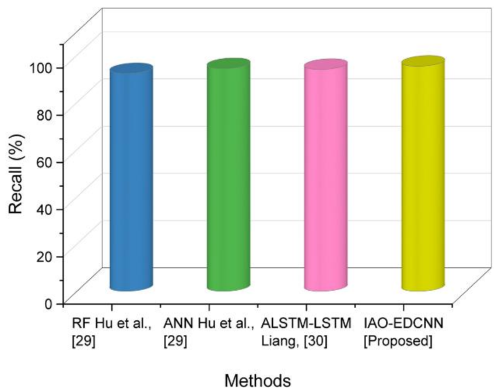

Figure 5. Outcome of Recall assessment for posture estimation and injury prevention.

The F1-score is a statistic that was used to assess how well a classification model is performing. Recall and precision are its harmonic means. **Figure 6** and **Table 2** present an evaluation of the F1-score in comparison between suggested and existing methods. In comparison to existing techniques with F1-scores such as ANN (93.85%), RF (94.83%), and ALSTM-LSTM (94.9%), respectively, the proposed IAO-EDCNN achieved an F1-score level of 95.60%. The suggested approach yielded better results for estimating joint kinematics and strength measures, which are critical for accurate posture and injury prevention.

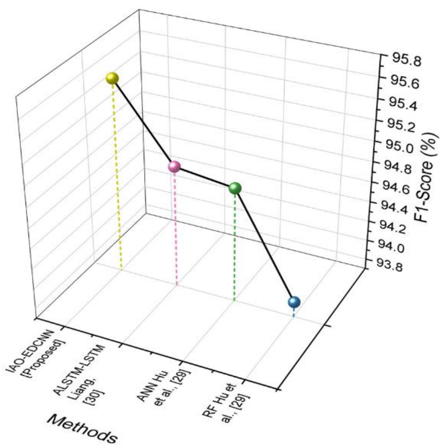

Figure 6. Outcome of F1score evaluation for posture estimation and injury prevention.

5. Discussion

Biomechanics was essential for physical education because it clarifies the actions of human body experiences throughout different physical activities. The RF has the possibility of overfitting the model if it was not adjusted appropriately, which might result in wrong predictions. The model's dependence on high-quality data for training might not accurately reflect real-world situations. The quality and variety of training data have a significant impact on the ANN, it might represent the variety of body actions or situations that occur in actual instruction. Furthermore, it was challenging to reproduce real-time feedback and engagement during physical activities in virtual settings, which might compromise the training's efficiency. The ALSTM-LSTM model might need a lot of computing power for processing, particularly when dealing with real-time interactions. The dynamic aspects of physical exercises might not be completely replicated by virtual simulation platforms, which reduces the training's realism and efficiency. Furthermore, input data quality might have an impact on the system's efficacy, which affects learning outcomes and performance.

To overcome this, the proposed method of Improved Aquila Optimized Efficient Deep Convolution Neural Network (IAO-EDCNN) used to estimate the joint kinematics and strength metrics, which are essential for posture accuracy and injury prevention.

6. Conclusions

The Improved Aquila Optimized Efficient Deep Convolution Neural Network (IAO-EDCNN) model joint kinematics and strength metrics, which are crucial for posture accuracy and injury prevention. The research intends to develop an immersive virtual simulation training platform designed to enhance physical education by integrating biomechanics for precise posture training. The data was preprocessed using a Gaussian filter to smooth data and reduce high-frequency noise in data. Frequency-domain characteristics were extracted using FFT as dominant frequency components of motion. IAO model ensures that the joint angles and positions during exercises are optimal and EDCNN can be employed to analyze motion capture data, assess joint kinematics, and predict strength metrics. The proposed method is implemented using Python software. The results indicate that upper-body kinematics can be accurately estimated with less error for joint angles, allowing for reliable real-time feedback during sessions. In a comparative analysis, the suggested method is assessed with various evaluation measures such as F1-score (95.60%), recall (95.35%), precision (96.10%), and accuracy (95.85%). The result demonstrated the IAO-EDCNN method to estimate joint kinematics and strength metrics, which are crucial for posture accuracy and injury prevention. This innovative approach demonstrates that VR technology, paired with biomechanics can serve as an effective tool for posture training in physical education.

Limitations and future scope

Physical contact and kinesthetic learning take place in conventional physical education that cannot be completely replicated by virtual simulations. The absence of practical experience might impede pupils' growth in physical abilities, coordination, and stamina. Students' passion and dedication to physical exercise might be impacted by the absence of personal interactions. Future scope moving towards the incorporation of technology like VR and AR, which constitute students more engaging and interactive experiences. These platforms should have the potential to replicate the physical settings and enhance the dynamic and fascinating nature of training.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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