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Article

Comprehensive evaluation of physical education based on personalized training plan generation algorithm and biomechanics

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Abstract: This work builds on advancements in biomechanics and artificial intelligence to develop personalized training plans, enhancing physical education by optimizing movement performance and reducing injury risks. However, limitations include reliance on accurate biomechanical data, potential algorithmic bias in training plan personalization, and challenges in integrating real-time feedback from wearable devices. The aim is to establish a comprehensive evaluation framework for physical education, leveraging personalized training algorithms and biomechanics to enhance performance and create tailored data-driven exercise plans. We propose the Versatile Hunter-Prey Optimizer-tuned Intelligent CNN (VHO-ICNN) to optimize ICNN parameters through VHO algorithms, thereby improving performance analysis, movement optimization, and injury prevention in athletes. The BFP and BMI datasets contain data for various human features and are utilized for biomechanical analysis and optimizing physical activities in sports and education. To preprocess the data, we employ z-score normalization to standardize joint position data, ensuring uniformity across features. Additionally, the Fourier Transform is applied for feature extraction, allowing us to analyze the frequency components of movements and enhance the model's performance. After evaluation, the results demonstrate an F1-score of 92.37%, accuracy of 93.41%, recall of 96.22%, and precision of 92.95%. The results indicate that the VHO-ICNN significantly improves classification accuracy and reduces injury risk, demonstrating its potential as a powerful tool in physical education. At the cell molecular biomechanics level, cells in tissues like muscles and ligaments are affected by mechanical forces during exercise. These forces can change how molecules in cells work. When we design personalized training, understanding these cell changes can help. If we know how cells react to different forces, we can make better training plans. This can make muscles stronger and less likely to get injured. It also ties in with the data we get from biomechanical analysis and the algorithms we use. So, adding cell molecular biomechanics knowledge makes our approach to physical education and athlete training even better.

Keywords: personalized training; injury prevention; biomechanics; muscles and ligaments; versatile hunter-prey optimizer-tuned intelligent CNN (VHO-ICNN)

1. Introduction

Generally, coaches in the sports field train athletes mostly by analyzing their performance and then providing necessary training strategies. In sports, human gestures and movements are regularly studied to help with action interpretation, direction, and evaluation [1]. Sports activities are divided into two categories namely specific and general. Any action that is frequently used in a range of sports is considered an everyday sports activity. The fundamental athletic motions are jogging, walking, leaping, and sprinting. Particular sports activities are dribbling in hockey, smashing in badminton, slicing in tennis, and other sports activities [2]. The computer technology (CT) introduced into the sports field has made it possible to help athletes and coaches develop their plans. Because of the vast amount of information involved in training for competitive sports education, the human motion recognition (HMR) technique is mostly employed in the sports sector [3].

Traditionally, standard technologies for biomechanical data gathering and analysis have been used to evaluate human kinematics and kinetics. An optimal training procedure can ultimately result in more success while lowering the chance of injury and increasing an athlete's performance [4]. For assessing both kinetics and kinematics of motion in humans, the most widely used method is a motion capture system. However, its applicability is severely limited due to the consequent laboratory structure of the devices involved in motion capture [5]. Enhancing the skills of an athlete mostly involves athletic skill assessment and customized training programs. It's essential to comprehend physiological quirks, individual strengths, and shortcomings when creating training plans that can optimize increases in performance while lowering the danger of injury [6]. Some examples of physical education are categorized as shown in **Figure 1**.

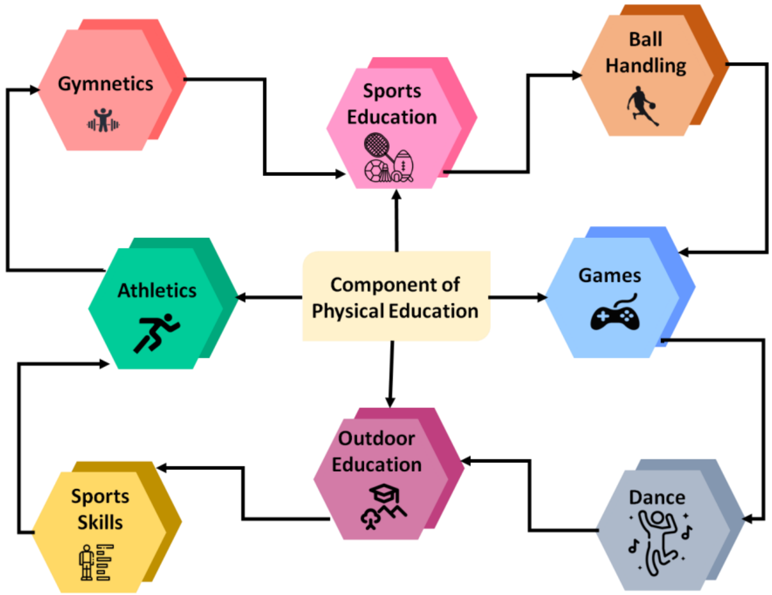

Figure 1. Components of physical education.

Sports video content analysis (VCA) mostly uses the human motion recognition (HMR) approach in conjunction with deep learning (DL) due to the vast quantity of data involved in competitive sports training and the high demands placed on computers' processing power. In many cases, the discovered individuals require additional motion recognition. As a result, in real-world situations, precise and instantaneous HMR in the video picture and motion and location analysis are essential [7]. Motion pose identification needs to be improved in terms of efficacy and accuracy. DL can handle and analyze complex motion pose data by automatically learning and extracting characteristics from a large amount of data through algorithms. The field of intelligent sports is now developing at a steady pace, and numerous examples have demonstrated how intelligent sports may enhance the quality of instruction and foster the growth of sports globally [8].

1.1. Study purpose

The development of a performance prediction model of athletes in sports and provide movement optimization, and injury prevention is the main motive of the study. Initially, the study gathers data from the body fat percentage (BFP) and body mass index (BMI) dataset that contains data on various human features. Then, the data are pre-processed by employing z-score normalization. Further, feature extraction is performed by implementing the Fourier transform method. Further, the classification of performance is performed by using the Versatile Hunter-prey Optimizer-tuned Intelligent CNN (VHO-ICNN) algorithm. This approach aids in enhancing classification accuracy and performance by reducing injury risks.

1.2. Paper organization

The paper is presented with related works in Section 2 that deliberates the related works to sports performance prediction using different advanced techniques along with research gaps. The proposed methods employed in predicting student performance and classification are discussed in Section 3 elaborately. Results contributed by the model are explained in Section 4 along with appropriate discussion. Section 5 delivers the conclusion.

2. Related works

An intelligent evaluation system based on student actions for physical education to monitor students was implemented by the author [9]. For the classification of risky actions, the model used a deep convolution neural network (DCNN). The methodology applied adjustments and remedial actions after assessing the level of learning, accomplishments, and retention of learners. Lastly, the classification algorithm produced an F1 score of 97.86. A deep neural network (DNN)—based alteration of the teaching approach in physical education was developed, involving the creation of a teaching platform called WeChat [10]. Multiple physical test indicators were compared before and after test scenarios between the control group and the experimental group. It was done to indicate the effectiveness of the instruction following the modification of the physical education method. From the findings, the p-values were all less than 0.05 as a result, and significant differences were observed.

Research [11] developed an index for evaluating the quality of physical education using wearable technology. The wearable gadget recorded electrocardiograms (ECG), determined the level of physical activity engaged, and facilitated a quantitative assessment of the quality of instruction. Then the issues of complicated equipment and poor accuracy were addressed by using a one-dimensional CNN (1D-CNN), to precisely acquire the variability signal of heart rate. The support vector machine (SVM) was applied to detect the intensity of exercise and experiments were conducted to confirm the effectiveness of the strategy and demonstrated improved performance with a classification accuracy of 98%. A recognition model based on human action was deployed by implementing long-short-term memory (LSTM) NN to determine the sports status of the students during sports education lessons and to give teachers feedback on their physical condition [12]. An intelligent wearable system was deployed to identify student's status as well as a feedback system to support instruction.

As a result, the LSTM-based human motion recognition model provided a recognition accuracy exceeding 97.5%.

Using aerobics as the focal point, a hybrid DL-based intelligent system for visual information discovery-based sports action recognition was implemented [13]. In particular, the human-based skeleton graph was signified with the basis of the anatomical configuration of the human body. A selective hyper-graph convolution network was employed to extract the multi-scale data from the skeleton in an adaptable manner. Additionally, a triple loss-based error assessment technique depending on suitable feature extraction was used to design an objective function and a recurrent neural network (RNN) structure to represent dynamic action sequence features. Ultimately, tests showed that the suggested algorithm's efficacy was improved. A DL-based infrared (IR) high-speed motion capture methodology was applied to assess challenging moves [14]. First, variations in ground pressure, joint angle, and movement speed were employed to investigate the biomechanical implications and purposes of motion fluency and completion. To build an unsupervised similarity framework model, the Restricted Boltzmann Machine (RBM) model was also presented. With the use of IR-based technology, motion was more precisely captured and characteristics were extracted from human bone data.

AI position estimation techniques were used, along with a discussion of their principles, potential uses, and limits in table tennis [15]. A real-world table tennis game footage was used to use the OpenPose posture algorithm. The study's findings demonstrated how effectively, in a graphics processing unit (GPU)-accelerated setting, the pose estimation method estimated the stances of table tennis players from the video. Through the collection of inertial measurement unit (IMU) data from human lower limbs, the study [16] aimed to produce the appropriate motion biomechanical factors of joints at different cutting movements (CM). To identify the coordination variability of certain lower extremity couplings at the three different CM orientations, the LSTM model and three inertia sensors were employed. Enhanced prediction accuracy was shown by the motion prediction models under three CM directions. An ensemble of input models for merging data from wearable sensors was implied which supported telemedicine and human performance [17]. Dynamic temporal warping (DTW) and CNNs were two different classifiers that were executed in correlation with four different inputs. Classification of actions for 24 taekwondo kicks and 18 boxing punches showed that the fusion classifiers outperformed. Using a feature-blind approach and minimal computing cost for trained CNNs, the comprehensive expression allowed for movement classification of subject-specific.

A novel personalized fitness recommender system that is privacy-aware and learns key attributes from a large-scale real fitness dataset was implemented by using wearable Internet of Things (IoT) devices [18]. The models and algorithms specifically forecasted the following concepts, personalized recommendations for exercise distance, heart rate, and speed series recommendations. When compared to previous research, the investigation of the real-world Fitbit dataset showed results with improved accuracy in identifying the sequence of exercise speed heart rate, and distance. A method that blends semantic knowledge and DL in the case of physical activity was deployed, to produce personalized and hybrid suggestions was established [19]. A probabilistic interval prediction technique that is naïve in nature was applied.

It utilized the residual standard deviation to give meaningful point predictions for the recommendation presentation. Additionally, the Simple Protocol was implemented to produce individualized recommendations in a comprehensible way. An accuracy of 97% was achieved by the 1D CNN model in the prediction process.

To simulate in vivo adaptations to resistance training, [20] examined whether mechanical loading causes tissue-engineered skeletal muscle to undergo an anabolic hypertrophic response. Mechanical loading was applied by lengthening the construct by 15% using a three-dimensional murine C2C12 cell line model that mimics natural muscle tissue. Candidate gene expression, Akt-mTOR (Protein Kinase B- Mechanistic Target of Rapamycin) signaling, myotube development, and contractile function were all analyzed throughout time. Atrophic Muscle Atrophy F-box (MAFbx) gene expression was downregulated at 45 hours, p70S6 kinase and 4EBP-1(Eukaryotic Translation Initiation Factor 4E-Binding Protein 1) phosphorylation were raised immediately after loading, and Insulin-like Growth Factor 1 (IGF-1) and Matrix Metalloproteinase-2 messenger RNA (MMP-2 mRNA) expression was markedly elevated at 21 hours. At 45 hours, there was a 265% increase in maximal contractile force and myotube hypertrophy. With an emphasis on the control of the contractile protein, myosin heavy chain gene, [21] examined the adaptive mechanism of skeletal muscle adaption. A key structural and regulatory element of the contractile apparatus, this protein can express itself in several isoforms, which affects the variety of muscle functions. Numerous factors influence the myosin gene family's regulation, which makes it a biological marker for research on muscle plasticity.

The molecular processes behind skeletal muscle plasticity during acute exercise and long-term training adaptations were investigated [22], which concentrated on resistance and endurance training. Using a multiomic and multi-cellular analytical approach, it synthesizes current studies on the signals, sensors, regulators, and effectors involved in muscle adaptation, emphasizing molecular principles and processes. Key mechanisms in muscle remodeling and adaptation are identified, with a focus on the knowledge gaps regarding signal integration, functional redundancy, and stimulus-specific responses in resistance and endurance training. Sprague-Dawley rats were used in [23] to assess the effects of high-frequency resistance training and conventional-frequency resistance training on signaling pathways. IGF-1-mediated AKT phosphorylation was inhibited by high-frequency training, but Tumor Necrosis Factor-alpha (TNFα) and Inhibitor of κB kinase (IKK) phosphorylation prolonged inflammatory signaling. TNFα had returned to baseline, demonstrating the quick adaptation of conventional frequency training by Day 5. Both procedures led to a comparable rise in p70 S6K phosphorylation, suggesting that kinase activity associated with translation initiation remained unchanged.

Individual differences in training-induced adaptations were revealed by [24], which examined the molecular and cellular processes determining skeletal muscle adaptation to exercise. It reveals the differences in adaptive responses to resistance and endurance training and identifies important signaling proteins and pathways associated with improved performance. The intricate relationship between molecular markers and performance results was also presented. The molecular processes underlying muscle wasting, a significant cause of persistent muscular tiredness, were examined in [25]. It examined research on COVID-19, aging, immobility, insulin resistance, systemic inflammation, and chronic diseases. According to the research, a combination of hereditary triggers, biochemical alterations in muscle cells, and muscle wastage results in chronic muscular fatigue, which impairs quality of life (QoL) by reducing muscle function and causing persistent weariness.

Research gaps

While many studies utilize specific data sources such as ECG or motion capture, there is a lack of research that integrates modalities like physiological, and biomechanical into a unified intelligent evaluation system. Exploring how combining these data types could enhance the accuracy and effectiveness of personalized training plans remains a critical area for investigation. The generalizability of the models remains uncertain, which may limit their applicability across different demographics and educational settings. Current studies primarily focus on performance metrics like classification accuracy and F1 scores without adequately considering the feedback mechanisms for students and trainers. Research exploring effective ways to provide actionable insights from the data, including how feedback can influence coaching strategies and student engagement, would enhance the practical application of these intelligent systems. Thus, investigating how adaptive learning algorithms can enhance the personalization of physical education would provide valuable contributions to the field. To address the issues related to existing studies, the present study implements intelligent evaluation systems in physical education called VHO-ICNN to optimize performance analysis, movement optimization, and injury prevention in athletes.

3. Research methodology

The research methodology involves the combination of a physical activity training with help of VHO-ICNN, and biomechanics to facilitate the improvement of physical education results. The process starts with data extraction from a fitness dataset which includes height, weight, and BMI. To pre-process the data standardization z-score normalization is used. For feature extraction Fourier transform (FT) is used to quantify paradigms of movements by frequency. The ICNN categorizes the data through convolutional activation, pooling layers, full connection layers, and the final output layer. The VHO algorithm fine-tunes the parameters of the model to increase outcome precision as well as students' interest in physical classes in **Figure 2**.

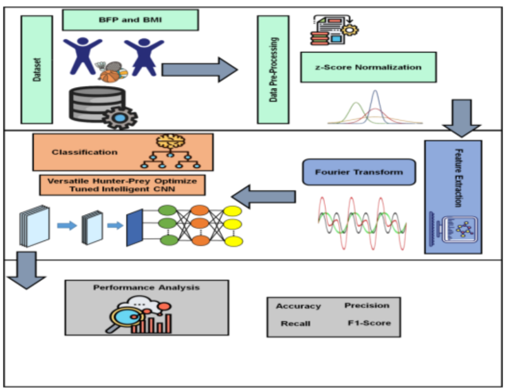

Figure 2. Overall proposed flow diagram.

3.1. Dataset description

The fitness exercise using the BFP and BMI dataset [26] is used in the present study. With the help of this fitness dataset, users can create individualized workout programs based on their gender, activity level, and physical characteristics. Its purpose is to help people reach their fitness objectives by providing personalized exercise plans that maximize efficiency and security.

Table 1 evaluates factors such as height, weight, BMI, BFP, and muscle mass and it covers both genders. It quantifies different types of activities by duration, daily activities, intensity, and frequency of exercising. The exercise choices also involve endurance activities, flexibility, strength training, and generalized fitness objectives in general health and well-being, endurance, muscle building, and weight loss. This multi-faceted approach should additional advantage in the use of individual training programs based on biomechanical evaluation.

Table 1. Key features of dataset.

Features	Detail
Physical Features	Height, Weight, BMI, BFP, and muscle mass
Gender	Male and Female
Activity Levels	Duration, Daily physical activity, Intensity, and exercise frequency.
Exercise Preferences	Endurance activities, flexibility, strength, and training.
Fitness Goals	Overall health and wellness, improved endurance, muscle gain, and weight loss.

3.2. Pre-processing using z-score normalization

Before feeding data into the network, it often requires preprocessing steps, to enhance the model's robustness. Thus, z-score normalization or standardization is applied in the pre-processing technique, which is used to transform data into a uniform scale. This is particularly useful in biomechanical analysis, where joint position data varies significantly across different measurements. By making the mean as well as scaling to the unit variance, it creates standardized features that verify each feature adds the same amount of information. Initially, the average mean (μ) and standard deviation (SD) (σ) values of each feature dataset are computed by using Equations (1) and (2).

$$Mean\ (\mu) = \frac{1}{N}\sum_{i=1}^{N} a_i \tag{1}$$

$$\text{SD}\ (\sigma) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(a_i - \mu)^2} \tag{2}$$

Here, a_i denotes each data point, and N represents the total number of observations. Further, each data points are transformed by applying z-score normalization by using the formula as shown in Equation (3).

$$z_i = \frac{a_i - \mu}{\sigma} \tag{3}$$

For each feature value in the input dataset, the mean is subtracted and then divided by SD values. It results in the formation of a new dataset, in which all the values are altered into z-scores making it suitable for input into the VHO-ICNN model. By verifying, the new mean should be close to 0 while the SD should be close to 1 for each feature.

3.3. Feature extraction fourier transform (FT)

After pre-processing, the feature extraction is implemented by using the Fourier transform (FT) method. It is applied for analyzing the frequency components of movements in physical education, which can significantly improve the performance of the VHO-ICNN models used for monitoring and evaluating student actions. In FT, the frequency-domain representation is produced by altering the time-domain signal and this transformation permits analyzing the frequency components present in the movement data, such as acceleration or angular velocity. This is performed as these data are critical for understanding the biomechanics of physical activities. The continuous FT of a time-domain signal $y(t)$ is denoted as discussed in Equation (4).

$$Y(f) = \int_{-\infty}^{\infty} y(t) e^{-i2\pi f t} dt \tag{4}$$

Here, the FT of a signal is denoted by $Y(f)$, time-domain signal as $y(t)$, frequency as f, time and imaginary unit as t and i.

In the context of analyzing student movements during physical education, a signal $y(t)$ is considered for representing joint angles over time. After applying the FT, the features are extracted by using Equation (5).

$$Mean\ Frequency = \frac{1}{M} \sum_{l=0}^{M-1} |Y[l]| \tag{5}$$

By incorporating these obtained frequency features into the proposed VHO-ICNN module, the model's ability will be enhanced to classify and predict student movements, leading to improved monitoring and feedback mechanisms in physical education settings.

3.4. Proposed improved convolutional neural network (ICNN)

The proposed ICNN comprises several layers in which the raw input data is transformed into meaningful classifications. Following are the descriptions of layers involved in enhancing classification accuracy in intelligent evaluation systems for physical education. The working of ICNN layers is illustrated in **Figure 3**.

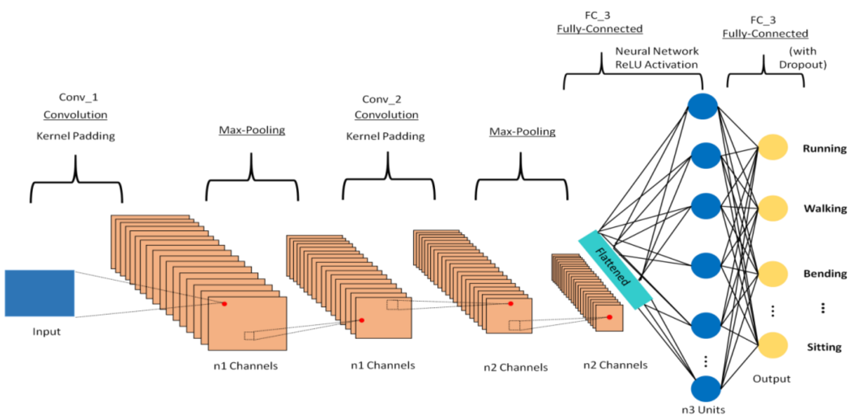

Figure 3. Improved convolutional neural network.

- Input layer: This layer is denoted as the primary layer of the ICNN, which is accountable for acquiring input raw data from the previous stage. This data includes multidimensional data formats and this layer does not perform any computations but serves as a conduit for data to enter the network. The working of each layer present in ICNN is described as follows.
- Convolutional Layer: From the input data, the layer derives features by implementing a convolution procedure using learned kernel filters. A filter slide present over the input image evaluates dot products between the local regions and filter. Thus, the operation helps in detecting features like shapes, edges, and textures. The result produced is a collection of feature maps, each highlighting different aspects of the input data based on the learned filters. The number of filters defines the number of output feature maps. Additionally, the stride (step size of the filter) may affect the output dimensions, while padding (adding zeros around the input) helps control spatial size. It is expressed as depicted in the Equation (6).

$$P(x,y) = \sum_i \sum_j I(i,j) \cdot K(x-i, y-j) \tag{6}$$

- Activation Layer: This layer introduces non-linearity to the proposed module, entitling it to learn other complex patterns efficiently. Here, Rectified linear unit (ReLU) is employed as an activation function that produces zero as output for negative inputs and the input itself for positive inputs. This function aids in minimizing the vanishing gradient issues often encountered with the traditional sigmoid or tanh activation functions.
- Pooling Layer: It aids in mitigating the spatial dimensions such as the height and width of the input feature maps and retains the most important features. This reduces the computational complexity and thus helps in preventing over-fitting issues. Max pooling chooses the maximum value from a defined window and moves it across the feature map, effectively by down-sampling. Further, the number of computations and parameters is reduced in the network, allowing for deeper architectures without a significant increase in training time. This layer is expressed as in Equation (7).

$$S(x,y) = {}_{(i,j)\complement window}^{max} P(x+i, y+j) \tag{7}$$

- Fully Connected Layer (FC): This layer tends to connect every neuron present in one level to each neuron in the subsequent layer. FC also assimilates the input features that are learned in preceding levels to make a final decision. Every neuron in the FC layer computes the sum of weighted inputs after the activation function. Thus, the output from this layer represents the network's prediction scores for each class, which are then passed to the output layer and represented in Equation (8).

$$n = f(W^T m + b) \tag{8}$$

- Output Layer: It produces the final class probabilities or predictions based on the processed information from the preceding layers. In the present multi-class classification of students' movements, the softmax activation function is typically applied to convert the outputs into probability distributions over the classes. The predicted class is the one with the highest probability, providing a clear and interpretable result for classification tasks. It can be signified by using Equation (9).

$$S(n = k|m) = \frac{e^{f_k(m)}}{\sum_{y=1}^{K} e^{f_k(m)}} \tag{9}$$

- Dropout layer: This layer indulges a fraction of input units to 0 by random setting during the training process, to get rid of over-fitting problems. It also encourages the network to learn robust features and prevents reliance on any single feature. When the dropout rate is denoted as α, then the output of this layer is given by Equation (10).

$$Output = \frac{Input}{1-\alpha} \tag{10}$$

- Batch Normalization: The normalization layer normalizes the outputs of the prior layer to stabilize and accelerate training. This tends to reduce the internal covariate shift, allowing for higher learning rates and improving convergence speed. Then the output is given by Equation (11).

$$\hat{y} = \frac{y-\mu}{\sqrt{\sigma^2+\varepsilon}} \tag{11}$$

Here, the variance of the mini-batch is represented by σ^2, with mean μ, ε is the small constant. By employing a structured approach with convolutional, activation, pooling, fully connected, output, and loss layers, the CNN can effectively learn and adapt to complex patterns, significantly enhancing classification accuracy in physical education monitoring and assessment applications.

3.5. Proposed versatile hunter-prey optimization (VHO)

Robust search and fast problem-solving abilities are provided by the hunter-prey optimization (HPO) technique, which imitates the behavior of an animal hunter. HPO is a population-based optimization technique that draws inspiration from nature to solve optimization issues in several domains. It can traverse and utilize the search space efficiently using a limited amount of intuitive principles, which makes it computationally efficient and potentially useful for a wide range of optimization tasks. The behavior of prey species like stags and gazelles as well as predators like wolves, leopards, and lions serves as inspiration for the HPO algorithm.

VHO algorithm has presented the flow of this algorithm as shown in **Figure 4** which also emphasizes the way to balance exploration and exploitation for optimization problems. By focusing on the complicated process of interaction between hunters and prey, the diagram also stresses the general possibilities of making asked improvements in parameter tuning in models. This unique strategy results in better performance-related outcomes and thus VHO is considered to be an optimal tool to manage various systems.

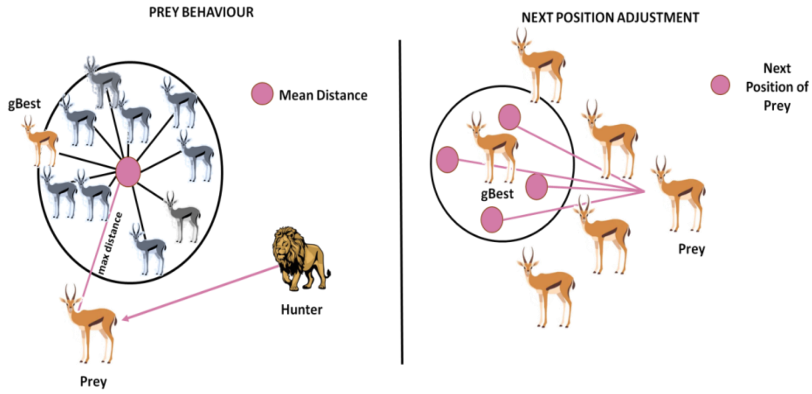

Figure 4. Versatile hunter-prey optimization.

The algorithm initializes the position of the population in solution space and initialization is expressed by using equation (12).

$$a_k = rand(1, c) \times (ub - lb) + lb \quad (12)$$

Here, the position of i-th hunter or prey is denoted by a_k, where $i = 1,2,3, \dots, n$. The population size is represented as n. The upper as well as lower bounds of the search space are signified as ub and lb. $rand(1, c)$ is the random numbers of [0, 1] with $c = 1,2,3, \dots, C$ in which C is the search space dimension. Two primary components of the strategy are covered such as the predator's search mechanism and the prey's position. These are represented in Equations (13) and (14).

$$a_{k,l}(T+1) = a_{k,l}(T) + 0.5[\left(2PCZ_{pos(l)} - a_{k,l}(T)\right) + 2(1-P)C\mu(l) - a_{k,l}(T))] \quad (13)$$

Here, the site of prey is represented as Z_{pos}, the current predator site is $a(T)$, and $a(T)$ is the predator's site in subsequent iterations.

$$a_{k,l}(T+1) = t_{pos(l)} + PC\cos(2\pi S_4) \times [t_{pos(l)} - a_{k,l}(T)] \quad (14)$$

Here, the global best site is denoted by t_{pos}, while the present prey's location in the next iteration is $a(T)$ and $a(T+1)$, adaptive factor, and the random number are C and S_4. The P is signified as the sum of exploration and exploitation and when the process converges it loses value. It can be expressed as in Equation (15).

$$P = 1 - in(\frac{0.98}{In_{max}}) \quad (15)$$

Here, the present iteration number and the large iteration number are represented by in and In_{max}. Thus, the Euclidean distance of each search individual is indicated by Equation (16).

$$F_{euc(k)} = (\sum_{l=1}^{f} \left(a_{k,l} - \mu_{k,l}\right)^2)^{\frac{1}{2}} \quad (16)$$

The prey Z_{pos} is denoted as the search agents with maximum distance from the average position μ and is expressed by Equation (17).

$$Z_{pos} = a_k | k \text{ is index of } Max(end)sort(F_{euc}) \quad (17)$$

The algorithm's convergence is poor if the greatest distance between the search agent and the average position μ is used in each iteration. When the prey is caught in the real hunting scenario, the hunter will go to the next prey position the next time. The prey tries to escape to the global optima, to improve its chances of survival after being attacked. In that case, the hunter will choose a different prey. Consequently, the following Equation (18) is the combination of Equations (13) and (14), which is considered as the updated equation for hunter or prey position.

$$a_{k,l}(T+1) = \begin{cases} a_{k,l}(T) + 0.5\left[\left(2\, PCZ_{pos(l)} - a_{k,l}(T) + 2(1-P).C.\mu(l) - a_{k,l}(T)\right)\right], r_5 < \beta(a) \\ t_{pos(l)} + PC\cos(2\pi.S_4) \times [t_{pos(l)} - a_{k,l}(T), r_5 \geq \beta(b) \end{cases} \tag{18}$$

Here, β is represented as the adjusting parameter, and r_5 is the random number within the range [0, 1]. Therefore, by balancing exploration and exploitation, the proposed VHO efficiently navigates the parameter space, leading to enhanced model performance in intelligent evaluation systems for physical education. The integration of fitness evaluation, effective movement strategies, and a clear termination condition ensures that the algorithm converges to optimal solutions for classification tasks.

3.6. Hybrid VHO-ICNN approach

The hyper-parameters of the ICNN are optimized by the implementation of the proposed VHO model, including learning rate, number of filters, filter size, and dropout rates. By mimicking the predator-prey dynamics, VHPO explores the hyper-parameter space effectively and balances exploration and exploitation to converge on optimal configurations. This typically improves the performance of ICNN and the presence of multiple convolutional layers in the architecture automatically extracts significant features from the input data. These features are essential for understanding student actions and categorizing them into predefined classes, such as successful movements or risky actions. It also incorporates fully connected layers to further refine classification and improve accuracy. The training process begins with the VHPO optimizing the ICNN's hyper-parameters and once the optimal hyper-parameters are identified, the ICNN is trained on the dataset. It leverages its capacity to learn complex spatial and temporal features. The trained ICNN model is evaluated and the VHPO can also be reapplied periodically to fine-tune the hyper-parameters as more data becomes available. This hybrid approach effectively monitors students' physical activities, providing real-time feedback to trainers about student performance and safety. By classifying actions accurately, it enables timely interventions, enhancing the overall effectiveness of physical education programs. Algorithm 1 provides the procedures for the suggested VHO-ICNN approach.

Algorithm 1 Proposed VHO-ICNN method

```
Step 1: Initialization
Define the number of hunters (N_h) and prey (N_p)
Define hyperparameters: Step size (α), Attraction factor (β), Randomness factor (γ), Maximum iterations (G)
Step 2: Initialize the VHPO population
Initialize hunters and prey randomly within the search space
For each hunter h in hunters:
    h.position = Random initialization
For each prey p in prey:
    p.position = Random initialization
Step 3:  Define ICNN structure
```

Algorithm 1 (*Continued*)

```
Define ICNN architecture:
    Input Layer
    Convolutional Layers
    Activation Function (e.g., ReLU)
    FC Layers
    Output Layer (softmax for classification)
Step 4: Training Phase
For each generation g from 1 to G:
    Evaluate the fitness of each prey using ICNN
    For each prey p in prey:
        p.fitness = Evaluate_ICNN(p.position)
    Update hunters based on the best prey position
    best_prey = Get_Best_Prey(prey)
    For each hunter h in hunters:
        Update_Hunter_Position (h, best_prey)
    Update prey positions
    For each prey p in prey:
        Random_Movement (p, α, β, γ)
    If a stopping criterion is met (e.g., convergence or max iterations), the exit loop
Step 5: Generate Personalized Training Plans
For each student in students:
    student_data = Collect_Data(student)
    personalized_plan= Generate_Personalized_Training_Plan (student_data, best_prey)
Step 6: Comprehensive Evaluation
Evaluate student performance based on training plans:
    For each student in students:
        Performance=Evaluate_Student_Performance (student, personalized_plan)
        Log performance metrics (e.g., F1-score, accuracy)
Step 7: Output the results
Output best_prey position as an optimal training plan
Output student performance metrics
```

4. Results and discussion

A brief discussion of the results gathered by implementing the VHO-ICNN method and the relevant discussion of each outcome is provided. In addition, the analysis of comparing proposed along with conventional methods is also deliberated to predict the effectiveness of the present study.

4.1. Experimental setup

Table 2. System specifications.

Components	Details
Operating system	Windows 10
CPU	Intel Core i7-7500U
RAM	16GB RAM
Programming Language	Python
Basic Clock speed	2.70 GHz

Table 2 shows the system specifications utilized in this study with the subsystems required to implement the proposed algorithms. It gives the operating system, CPU, RAM, and programming language, of the technological setting. The system

specifications are helpful during the model's implementation and evaluation for achieving the best performance and dependability.

4.2. Performance metrics

Certain performance metrics are employed to validate the efficacy of the VHO-ICNN model. The present study uses precision, F1-score, recall, and accuracy in classifying actions in physical education.

- Accuracy: It is defined by representing the overall suitability in making predictions by the model. It assesses the model on how often the detection matches the actual class labels in the dataset and is given by Equation (19).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{19}$$

Here, the true negative and positive are denoted by $TP\ and\ TN$, while false positive and false negative are given by $FP\ and\ FN$.

- Precision: It computes the quality of the positive forecasts completed by the VHO-ICNN model, which enumerates the number of instances classified as positive that are positive. This can be expressed by Equation (20).

$$Precision = \frac{TP}{TP+FP} \tag{20}$$

Improved precision denotes that the model possesses false positives with a low rate, and ensures that falsely identifying a student as engaging in risky behavior could result in unwarranted interventions.

- Recall: It evaluates the model's measurements to find all pertinent occurrences and determines the proportion of definite positive situations that were correctly predicted. Recall is signified by Equation (21).

$$Recall = \frac{TP}{TP+FN} \tag{21}$$

Missing a potentially dangerous action could have serious consequences. So, it is significant to produce high recall to effectively capture most of the actual positive instances.

- F1-Score: It is exposed as a composite metric that balances precision as well as recall, delivering a single score. Specifically, it is useful when handling imbalanced datasets, in which one class is more widespread than the other class. It is denoted by Equation (22).

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{22}$$

For instance, in the case of assessing physical activities, prioritizing the correct identification of risky behaviors (high recall) while maintaining a reasonable level of false alarms (high precision) is crucial.

4.3. Performance analysis

Figure 5 shows the comparative evaluation of VHO-ICNN. This **Figure 5** shows the significant difference of significant the proposed model. This analysis strongly suggests that the VHO-ICNN is optimally suited for movement analysis and training outcome improvement, based on the indices of accuracy, recall, precision and F1-score improvements.

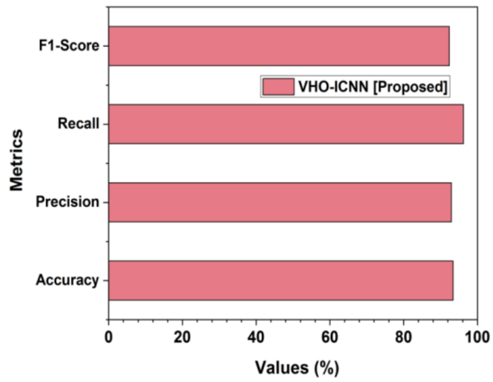

Figure 5. Performance analysis of proposed VHO-ICNN.

The effectiveness of the proposed VHO-ICNN method is evaluated by using the above-mentioned metrics outcomes are shown in **Table 3**.

Table 3. Outcomes of proposed VHO-ICNN.

Metrics	VHO-ICNN [Proposed]
Accuracy (%)	93.41
Precision (%)	92.95
Recall (%)	96.22
F1-Score (%)	92.37

4.4. Comparison phases

The comparison analysis compares the proposed VHO-ICNN model with FDPN [27] and RFC-Net [28] as standards for the proposed model. The VHO-ICNN determines higher performance across four key metrics accuracy, recall, precision and F1-score. However, FDPN [27] and RFC-Net [28] exhibit relatively lower performance levels suggesting that the two models possess defects in identification capacities. In general, the proposed VHO-ICNN has provided better performances and is expected to be an acceptable model for calculated training programs and better safety for users across the board.

Figure 6 presents the performance comparison of the models based on accuracy and precision-based results. The result can express the efficiency of each developed model in providing precise prediction. The FDPN is not efficient, while the RFC-Net is represented as slightly efficient, which has the better-predicting ability. The proposed VHO-ICNN has better accuracy (93.41%), and precision (92.95%) due to advanced optimization procedures. It augments the improvement of the proposed VHO-ICNN, re-endorsing its applicability in generating effective training strategies and boosting performance in physical education.

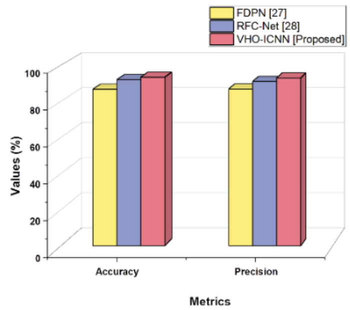

Figure 6. Performance analysis based on accuracy and Precision.

Table 3 presents a comparative analysis of the performance metrics for three models: FDPN, RFC-Net, and the proposed VHO-ICNN. The FDPN model has performances with reasonable accuracy and precision that can be improved. Associated to the performance of the predictive model, RFC-Net performs better than FDPN and there are distinct improvements of the previous. In **Table 4,** however, the proposed VHO-ICNN is the better model and subsequently has the highest accuracy (93.41%), and precision (92.95 %) and uses efficient optimization and classification techniques as compared to the two previous models. This also proves that the VHO-ICNN holds the prospect of being used in real-life applications of the field.

Table 4. Outcomes obtained by proposed and existing approaches.

Metrics	**Accuracy (%)**	**Precision (%)**
FDPN [27]	86.68	86.80
RFC-Net [28]	92	91
VHO-ICNN [Proposed]	93.41	92.95

Performance analysis of the VHO-ICNN proposed and the existing models FDPN and RFC-Net in terms of recall and F1 Score is depicted in the following **Figure 7**. Through the results obtained from the experimental settings, it is that VHO-ICNN has achieved a higher recall value (96.22%) than FDPN and RFC-Net proving its efficiency in categorizing the relevant samples. Furthermore, the F1-score (92.37%) analysis also highlights a properly balanced accuracy of the VHO-ICNN model. This figure supports the superior performance of the proposed model and hence implies that it is well suited for practical use in training and performance improvement.

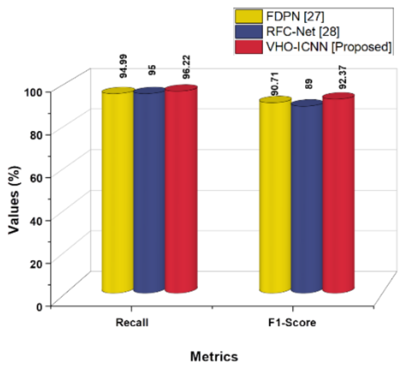

Figure 7. Performance analysis based on recall and F1-Score.

A comparison of the proposed VHO-ICNN, and existing models FDPN, and RFC-Net's F1-score and recall results can be seen in **Table 5** below. The recall shows the models' capability of finding true positives among them, VHO-ICNN has the highest recall (96.22 %), which proves that it is suitable for obtaining relevant information. The F1-score (92.37 %) indicates that the VHO-ICNN has better overall classification performance. Such comparison highlights the lesser complexity of the proposed model, and thus, its reliability in the real-world training and performance improvement domains.

Table 5. Results procured by proposed and existing methods.

Metrics	Recall (%)	F1-Score (%)
FDPN [27]	94.99	90.71
RFC-Net [28]	95	89
VHO-ICNN [Proposed]	96.22	92.37

4.5. Discussion

The proposed VHO-ICNN method significantly enhances performance metrics in physical education training plan optimization, demonstrating a robust capability for movement analysis and injury prevention. The performance metrics represents that effective identification and classification of physical activities is performed by the model, providing optimized training plans that enhance student safety and performance. In comparison, existing methods like the FDPN and RFC-Net fall short in various aspects. Despite their reasonable performance levels, these methods exhibit substantial limitations that the VHO-ICNN overcomes. A significant drawback of the FDPN is its reliance on shallow feature extraction, which may hinder its ability to capture complex patterns in motion data. This architecture leads to reduced predictive accuracy, especially in dynamic environments such as physical education. While RFC-Net leverages recurrent connections, it still lacks the optimization efficiency exhibited by the VHO algorithm, which fine-tunes the ICNN parameters for improved performance. Further analysis based on recall and F1-score values demonstrates that the VHO-ICNN outperforms existing FDPN and RFC-Net models, addressing their drawbacks through advanced optimization techniques and an ICNN structure. This positions the VHO-ICNN as an enhanced approach for personalized training plan generation, highlighting the need for ongoing research to further refine and validate its applications in various student's physical education contexts. The novel VHO-ICNN model which is proposed has the improvement in the capacity to classify and predict student movements in physical education. In the experimental model, an accuracy of 93.41%, precision of 92.95%, and recall of 96.22% confirms the effectiveness of the model in terms of finding an F1-score of 92.37% in practical applications. The results indicate that the VHO-ICNN has a higher precise classification accuracy in comparison with FDPN and RFC-Net, which relates to the model's potential for specific student action detection. It also helps in the development of custom training processes in addition to increasing the safety of students in Physical Education settings and making it effective in dealing with complex classification challenges.

5. Conclusion

The present study denotes a major development in the integration of biomechanics and intelligent systems, to develop personalized training plans that enhance physical education. By focusing on optimizing movement performance and reducing injury risks, the proposed VHO-ICNN showcases a robust approach to training personalization. Using BFP and BMI datasets, a study has demonstrated the efficacy of employing biomechanical analysis in tailoring exercise plans that cater to individual needs. The methodology involves critical preprocessing steps, including z-score normalization for joint position data. Further, FT is implied for feature extraction, which enhances the model's performance by ensuring consistency and providing insights into the frequency components of movements. Further, the analysis and classification of movements are performed by VHO-ICNN. The VHO algorithm fine-tunes the ICNN parameters for improved performance. After evaluation, the results demonstrate an F1-score of 92.37%, accuracy of 93.41%, recall of 96.22%, and precision of 92.95%. The promising results, indicating significant improvements in classification accuracy and a reduction in injury risks, highlight the VHO-ICNN's potential as a transformative tool in physical education.

Limitations and future scope

The limitations include the choice of accurate biomechanical data which is hard to secure in some scenarios. Several issues arise with real-time feedback from wearable devices, which seem to be the stimulating fragment of the model, although they oppose the principles of dynamic environments. The future scope should compare the VHO-ICNN with other methods and datasets to make VHO-ICNN more effective and apply other effective algorithms in it to give more personalized predictions. Moreover, the implementation of actual-time feedback from wearables would improve the responsiveness of the model. Exploring the usage of the VHO-ICNN in other sports disciplines can also add functional use in physical education.

Ethical approval: Not applicable.

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

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