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Article

Humanized physical education teaching plan design: Utilizing biosensors to evaluate students' movement status

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Abstract: Biosensors allow the monitoring of student movement in real-time and enhance the effectiveness of personal workouts through data analysis to enhance performance. Even though there is significant potential, biosensor precision, concern about data privacy, cost, and the need for expert knowledge limit the implementation of such technologies in physical therapy. This research aims to analyze educational systems that make use of biosensors to monitor the movement of students and customize their course of ideas. In addition, it also provides more efficient tools for exercise interventions based on factual information. A Resilient Sailfish Algorithm-tuned Enriched Long Short-Term Memory (RSA-ELSTM) method is proposed to increase prediction accuracy, address data challenges, and improve motion analysis beyond current limitations. Datasets used include motion capture and sensor readings, which capture different student movement patterns. Preprocessing involves image resizing, and normalization, while VGG16-based feature extraction is used to improve model performance and accuracy. The RSA-ELSTM approach uses biosensor data and deep learning (DL) to optimize motion analysis, increasing accuracy, flexibility, and real-time analysis. The RSA-ELSTM the model obtained a 99.1% F1-score, 99.3% accuracy, 98.7% recall, and 99.2% precision. Results revealed improved accuracy in motion prediction and real-time analysis, improving personalized workouts. In conclusion, the RSA-ELSTM approach significantly enhances biosensor-based exercises, provides accurate student movement analysis, and improves individual performance management, thus making educational outcomes good.

Keywords: physical education; teaching plan; evaluate students' movement status; resilient sailfish algorithm-tuned enriched long short-term memory (RSA-ELSTM)

1. Introduction

Importantly, physical education (PE) is a part of the students' total development, as it enhances health and physical fitness and helps persons maintain well-being. Current teaching methods are often characterized by a lack of personalized pointer and real-time monitoring of the individual child's progress. The modern direction of educational practice makes more interest in using technology in PE classes. The integration of Artificial Intelligence (AI), Machine Learning (ML), and biosensors represents a prevailing area for making PE more personalized, data-driven, and responsive to the nuances of each student [1]. Real-time tracking of the physical activities of students during PE classes is currently possible because of using effective biosensors. In contrast with conventional observations, biosensors present highly reliable and objective means of assessing physical activities. This might even renovate the entire aspect of PE instruction by monitoring each student's growth and giving individual feedback based on the progress of learning [2]. **Figure 1** depicts the various human movements to be considered for motion recognition.

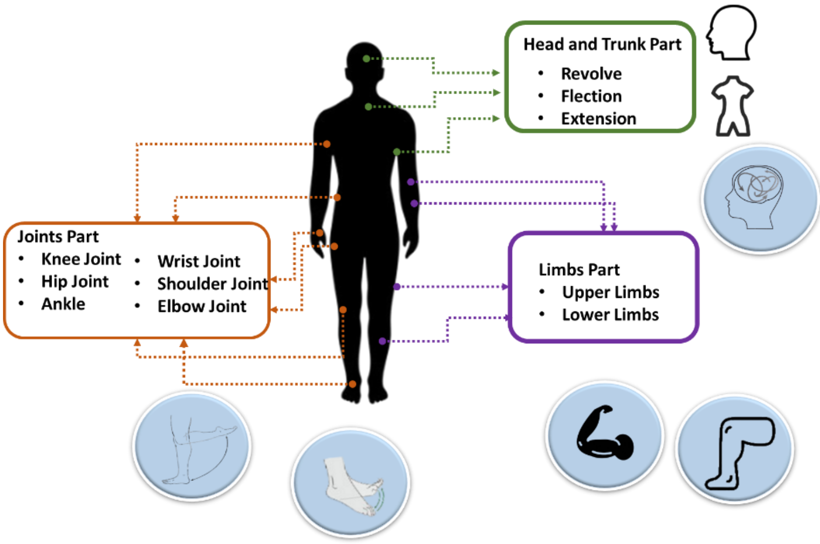

Figure 1. Various human motions for recognition.

Despite the potential benefits, it is difficult that sensor performances may vary in some environments and the human movement complexity cannot be predicted and handled perfectly. The complexity of the dataset demands that AI and ML be used to analyze sensor data, make it more accurate, and extract meaningful insights from such a complex dataset. These technologies remove various restrictions on biosensors' performance and ensure that the data being gathered is meaningful and practical [3]. With these technologies, biosensors combine and link their data to advance their analytical and predictive results toward assessing the physical performance of a student. The training from the past datasets assists ML algorithms in diagnosing patterns in movements, indicating anomalies, and forecasting students' performance. Such capabilities open new prospects for personalized learning. Using AI to analyze movement patterns allows educators to get a deeper understanding of every child's strength and weakness so that the exercise routine for every student can be individually designed to improve student outcomes [4].

Furthermore, AI can facilitate the automated service of student feedback, making it fast and targeted. For PE, real-time feedback plays a significant role in creating immediate corrective measures and enhancing learner engagement. For instance, through AI-enabled systems, students may receive instant feedback on their movement, posture, and technique. Personalized, on-the-spot recommendations enable them to correct things during the exercise, resulting in a faster improvement process and improved learning [5]. The application of biosensors and AI is not limited to using this as an individual performance assessment but also extends to assessing collective group dynamics. Multiple analyses within simultaneous sets of students can give information to the AI system. It indicates different trends, common problems, and a certain number of opportunities, which allows them in advance to adjust lesson plans with PE activities. With the help of AI, educators can develop better group-based activities so that curriculum learning becomes more engaging and inclusive to all students [6].

Even though AI and biosensors will greatly develop PE, data security, and privacy are the significant problems to be concerned. With greater reliance on digital technologies for collecting personal data about students' physical activity, responsible data handling is an ethical issue. Moreover, student data should have a clear policy and guidelines on how to use it to establish trust between educators, students, and their families [7]. Improved biosensors, coupled with support infrastructures to analyze and give feedback, can cost quite a bit. For such systems to become widely adopted, efforts needed toward lowering costs, improving accessibility, and providing affordable solutions to schools should be made. There might be a collaborative partnership between technology developers and institutions of education to make these technologies affordable and scalable [8].

Apart from the cost issue, school systems may not have either the financial resources or the technical expertise to effectively implement biosensor-based solutions. Such a problem can be corrected by investing in teacher training and professional development so that these educators can use these technologies in their classrooms. By having the appropriate support and training, teachers can incorporate biosensors and AI tools into their classroom teaching, enhance their ability to monitor student performance and deliver more specific feedback [9]. The integration of AI, ML, and biosensors in PE could make a huge difference in teaching and learning outcomes. The feedback from these technologies would come in real-time, personalized performance tracking. The use of this sort of technological equipment means shifting over to a completely different, transformative way of bringing a more inclusive, responsive, and effective PE experience [10]. The investigation of human body biomechanics and how it relates to athletic performance is known as sports mechanics. Understanding the morphological elements that affect efficiency and risk of injuries, entails the examination of progress, violence, and radiation during sporting events. To assist athletes, maximize their effectiveness and lower their risk of damage, the multidisciplinary area of sports biometrics integrates aspects of science, technology, medical terminology, and metabolism. It is crucial to comprehend sports biomechanics since it can assist the athlete in designing new training regimens and equipment to enhance their performance as well as improve their execution and training approaches [11].

Using handheld devices like tablets and cell phones has become one of the most common applications of information and communication technologies (ICT), and their increasing prevalence in educational settings has demonstrated their potential to be a powerful teaching tool. Students attending colleges frequently use handheld gadgets like tablets and cellphones. notably using social media platforms on them to communicate with one another, remain informed on current events, and find pleasure [12].

1.1. Research objective

The objective of this research is to design a teaching plan in PE in which biosensors track the students' movement in real-time. Thus, the proposed Resilient

Sailfish Algorithm-tuned Enriched Long Short-Term Memory (RSA-ELSTM) system provides feedback to each student for enhanced performance. The RSA-ELSTM method is employed to enhance prediction accuracy and address data challenges. This enables effective and data-driven interventions in PE by optimizing movement analysis.

1.2. Paper organization

The flow of the research paper is arranged initially with Section 2 discussing the detailed related work and research gap. Section 3 provides a detailed methodology section, which contains information about the RSA-ELSTM model data collection process and preprocessing techniques. Section 4 provides experimental outcomes and evaluation of results. Section 5 discusses effectiveness and improvements. Finally, Section 6 presents the conclusion by summarizing the key findings.

2. Related works

A framework was developed [13] incorporating the metaverse and a K-means clustering algorithm with virtual reality (VR) football teaching videos under AI. It was demonstrated to enhance the value of football teaching for mobile internet. The strategy optimized the content delivery by using K-means for video distribution. The simulation experiments using a Content Delivery Network (CDN) simulator demonstrated its superiority over baseline methods. The students analyzed the football actions using the immersion and involvement of the VR experience. Therefore, the results improved the teaching and integration of smart learning into football education. The deployment of AI in PE was explored [14] and it provided how AI is going to influence education and sport by making PE better through assessments of learners, and individualized teaching. Besides facilitating personalization in PE, the application of AI enriched its visualization as well as reproduction. An important finding of the research was that AI application mastery is essential for trainee PE professionals. The findings contributed to the development of research on AI use in education and sport and showed the better improvement of AI in PE.

A self-powered biosensor was introduced [15], which was used to monitor activity during exercise for training and assisting purposes. It comprised a low-cost poly (vinylidene fluoride) (PVDF)/Tetrapod-shaped ZnO (T-ZnO) film, which allowed the sensor to be attached to the skin and operated entirely without the need for a battery. Through piezoelectric surface coupling, it monitored real-time physical data together with physiological changes. Testing was done with a professional speed skater. Better results have been obtained in the evaluation and piezoelectric motion monitoring. By combining convolutional neural networks (CNN) with bidirectional long short-term memory (BiLSTM), a strong classification model for activity recognition was developed [16]. The model required minimal preprocessing to automatically extract feature information from raw sensor data. The model automatically identified both sequential information through long-term dependency as well as local features. The capability of the model to capture different temporal dependencies through varying filter sizes enhanced the feature extraction procedure. The model's accuracy was refined when its performance was assessed.

A structure for action recognition was employed [17], with the incorporation of waterway and spatial attention modules in a typical deep learning (DL) setup. The four primary components were visual skin tone extracted by a pre-trained CNN, relayed through an attention module. Then followed by a BiLSTM network that could capture the sequential dependencies. The output was forwarded to a fully associated layer, where the SoftMax classifier assigned action probabilities. Marginal loss function and cross-entropy loss were added to increase class difference. The model was trained and validated using a tennis dataset and the results demonstrated improved results. LSTM networks were used to design a model that detected the intervals of muscle activation from the electromyography (EMG) signals [18]. The model was then compared to other methods and portrayed its benefits in the detection of muscle activity. It achieved reasonably fair performance in the distinction of muscle activation from the background noise, and its applicability was evaluated on simulated and real EMG signals. The results revealed that the LSTM model performed better in detecting muscle activation.

A framework for the real-time spatiotemporal analysis of tennis on standard hardware was demonstrated [19]. It applied DL above all through enlarged neural networks (NNs). The recognition module integrated the CNN and the dilated recurrent neural network (RNN)for achieving successful spatiotemporal feature modeling. The hard class mining technique was developed to enhance the learning capacities and communication between the prediction and recognition modules. Therefore, action identification and prediction with the use of LSTM architecture along with generative adversarial network (GAN) produced better accuracy, recall, F1-score, and precision. Activity recognition from human beings employing bio signals acquired with a smart knee bandage was examined [20]. A Deep Recurrent Neural Network (DRNN) was developed for biosensor-based activity recognition from human beings using activity recognition. To evaluate its performance, numerous measurements from the given bio-signatures of participants on 22 daily tasks were employed. Several cross-validation techniques were employed in the systems' testing and training. The results showed superior F1-score values and increased accuracy.

For training disabled persons for the Para Olympics, a framework was designed [21] using VR-assisted effectively in augmentative communication. The framework utilized several biosensors that could track the physiological parameters of a body at various simulated conditions using VR technology. It allowed for the presentation of an interactive real-time environment for persons who were disabled. The framework was validated based on optimization parameters. Simulation results demonstrated that the model enhanced players' confidence, sports knowledge, and response time, and reduced error rates. A CNN-based human pose recognition algorithm was employed [22] to overcome technical limitations in sports management systems, in particular in the module for sports recognition classification. Feature extraction, feature selection, choice of support vector machine model functions, and principal component analysis were all considered in the research. The recognition algorithm was used to optimize the parameters and structure of the CNN, and a motion management system was developed. As the results indicated, the method provided preferable theoretical insights and has better practical significance.

An epidemic prevention and control model was designed using a wristband system combined with CNN [23]. The system collected and processed users' physiological data, especially in PE, and used human action recognition (HAR) to give immediate feedback and personalized training suggestions. To monitor variations in joint action, a dynamic recurrence plot was adopted. One-dimensional acceleration data is transformed into two-dimensional pictures of acceleration for feature extraction purposes. For recognition, the model showed improved precision and algorithm speed by integrating streamlines in feature extraction along with remote physical instructions. The multi-attribute fuzzy evaluation model (MAFEM) was designed for monitoring students' health and physical activity using sensor data [24]. The model used the theories of fuzzy sets and fuzzy logic to establish relationships among various features. It applied preprocessing, fuzzification, defuzzification, and evaluation of rules that can be adjusted based on threshold values to enhance personalization and efficiency. With the MM-Fit dataset, the system showed low computation complexity and latencies, with even better accuracy metrics in terms of precision and decent mean squared error (MSE) values.

More participants per study improve statistical power, enables the use of various data analyses, with sports mechanics, and enables the identification of more complex and subtle variables. Additionally, the total quantity of studies has skyrocketed [25]. Even the more difficult ones, like player-on-player consequences, have some emerging research, but the majority of sports actions are eligible to be examined to some degree. They have a deeper comprehension of the biomechanics of sporting approaches in a variety of sports.

Sports strategies and tactics are evaluated as part of biomechanical assessment. Quality is described by the qualitative way of analysis despite the use of numerical data. Numbers are used in the gathering, measuring, and assessment of data in the qualitative analytical approach [26]. Players and trainers can only accurately of performances on average. Informing participants and instructors about sport skill practices that will enable them to achieve optimal athletic success is the aim of sport biomechanics.

Research gaps

The existing research on biosensor-based movement analysis and personalized physical education reveals several gaps. A lot of research focuses on how to integrate biosensors and AI for movement tracking, but most of them face limitations of inadequate real-time feedback, the inability to adapt to students' needs, and higher costs of implementation. Further, while numerous ML models have appeared promising, limited work has been done on developing advanced optimization algorithms to boost the model's accuracy. And there is very minimal effort to make it work on diverse and noisy sensor data in a dynamic educational environment. The proposed RSA-ELSTM model aims at improving prediction accuracy with real-time movement analysis, and personalized feedback, ultimately overcoming existing limitations in optimizing biosensor-based physical education systems.

3. Methodology

The proposed RSA-ELSTM model is designed to develop the plan of teaching in charge of a biosensor for the area of PE. This approach combines data collection, preprocessing, feature extraction, and RSA-ELSTM model construction to improve movement analysis and generate timely feedback. The general workflow for the RSA-ELSTM model is presented in **Figure 2**.

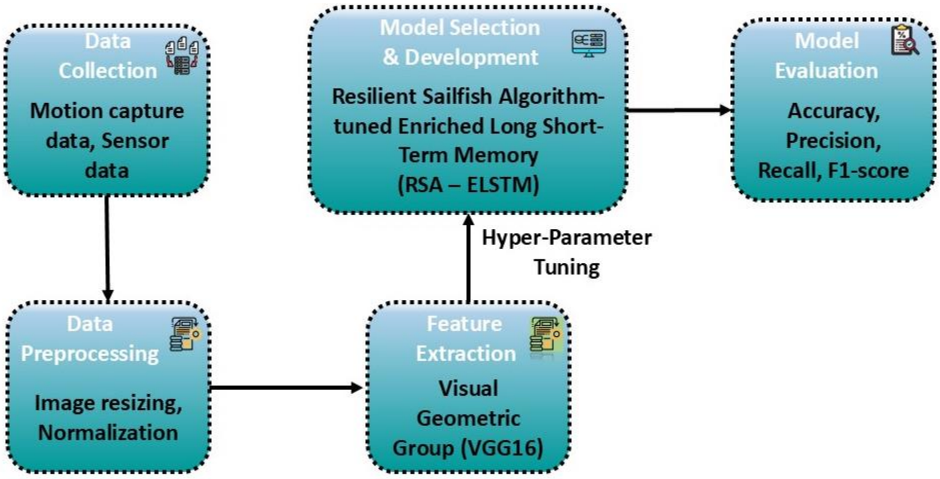

Figure 2. Proposed system architecture.

3.1. Data collection

Two distinct datasets were utilized to develop the education plan and movement analysis using biosensor technology in PE.

- Motion Capture Dataset

The motion capture dataset includes high-definition video footage of students performing various physical activities. High-resolution photographs of students engaging in a variety of sporting events make up the motion capture collection. Real-time tracking of joint locations and body motions by particular cameras yields comprehensive information on movement and stance effectiveness. This information is essential for assessing students' biomechanics and determining how well they execute particular actions. It can be utilized to pinpoint problem areas and maximize the effectiveness of movement by providing insights into the functioning of the body. This information is essential for delivering tailored feedback to learners, boosting their athletic results, and encouraging their growth in sporting activities and other relevant subjects.

- eSports Sensor Dataset

The publicly accessible Kaggle platform is the source of the eSports sensor dataset, which includes information gathered from 10 players over 22 League of Legends games. It contains a variety of sensor readings that provide a thorough picture of the players' mental and physical states while they are playing, including heart rate, muscular activity, eye gazing, and electroencephalography (EEG). The dataset is intended to evaluate the relationship between players' cognitive competence, as demonstrated by EEG and eye gaze data, and their outward physical engagement, as measured by heart rate and the contraction of muscles. Players' tactics, training, and general well-being can be improved with the help of this data, which is useful for comprehending how physical and psychological conditions affect the performance of eSports. The results of this dataset can be used to tailor training programs and feedback in PE settings, enhancing students' physical and mental preparedness participation in competitive settings. This presents fresh chances to improve efficiency in eSports and other fields. The dataset link is as follows: https://www.kaggle.com/datasets/mexwell/esports-sensors-dataset.

3.2. Data preprocessing

In this methodology, key preprocessing steps, such as image resizing and normalization, are used. It improves model performance by minimizing computational complexity and providing uniform input for advanced feature extraction and analysis. It reduces the computational complexity and preserves essential features of the data for movement analysis.

- Image Resizing

Image resizing is an essential preprocessing technique Images are resized to a certain dimension used to ensure input images are in a consistent size. The motion capture data used in this work consists of video footage, which is hard to process. By resizing the images to 100 × 100 pixels, it provides a good tradeoff between computation power and important motion details. Bicubic interpolation for the resizing process is used so that the distortion can be minimized. Such techniques are designed to decrease the amount of computation to maintain adequate resolution quality for feature extraction, which is critical for real-time analysis of movement.

- Normalization

Normalization using Z-score normalization (ZSN) is performed to standardize the inputs and enhance the efficiency of the learning process on both the image and sensor data. For image data, normalization adjusts the pixel values to have zero mean and unit variance. And it helps to mitigate variations caused by lighting or inaccuracies in the sensor. Similarly, the sensor data is normalized to ensure that the values are scaled in a uniform range; hence the features can be compared across the entire dataset. It improves convergence during model training, making it easier for deep-learning models to learn patterns effectively. Equation (1) for ZSN is given below:

$$x_{i,j}^{'} = \frac{x_{i,j} - \mu_{i,j}}{\sigma_j} \quad (1)$$

where μ is the mean, $x_{i,j}^{'}$ is the original pixel value,σ is the standard deviation, and $x_{i,j}^{'}$ normalized pixel value of the j^{th} attribute. This step enhances the ability of the model to accurately analyze movement toward potentially improving individualized PE interventions.

3.3. Feature extraction

A well-established CNN architecture called visual geometric group-16 (VGG16) is employed on both image and sensor data in this methodology for feature extraction. It is very effective in extracting meaningful patterns from input data, especially suited for analyzing complex movements by students in physical education. Then, the features extracted from the VGG16 are further analyzed by the RSA-ELSTM model to make a prediction analysis. This step was significant because it reduced the dimensionality of data and kept important movement information needed to make accurate predictions as well as give real-time feedback in educational contexts.

- Convolutional Layers

The VGG16 architecture takes images as inputs and applies numerous convolution layers. Every convolution layer takes an input where a 3 × 3 filter is applied, having a stride of 1 and padding of 1 to retain spatial resolution. Equation (2), is used to calculate convolution.

$$N_{out} = \left\lfloor \frac{W_{in} - F + 2P}{S} \right\rfloor + 1 \tag{2}$$

where W_{in} is the input size, F is the filter size, P denotes padding, and S denotes stride.

- Max Pooling Layers

After every convolution block, 2 × 2 max pooling is used with a stride of 2 to decrease the spatial dimensions of the feature maps. The size after pooling is determined using Equation (3).

$$W_{pool} = \frac{W_{in}}{2} \tag{3}$$

where W_{in} is the input size and W_{pool} is the size after pooling.

- Batch Normalization

Batch normalization is used to stabilize the learning process after each convolutional block and it avoids overfitting. The normalization is done through Equation (4).

$$\hat{z}^{(k)} = \frac{z^{(k)} - \mu_{z^{(k)}}}{\sqrt{\sigma^2{}_{z^{(k)}} + \varepsilon}} \tag{4}$$

where $z^{(k)}$ is the activation values, $\mu_{z^{(k)}}$ denotes the mean of activations, $\sigma^2{}_{z^{(k)}}$ is the variance of activations, and ε represents the small constant for numerical stability.

- Output Feature Map

The size of the output feature map is 5 × 5 × 512 and is further analyzed after passing through multiple convolution and pooling layers.

- Pre-trained Weights

The pre-trained weights of the VGG16 and image-net pre-trained on all data are used for optimization in feature extraction and also reduce the training data. The extracted feature becomes input to the RSA-ELSTM model to make predictions and analyses about students' movements.

3.4. Prediction model development

The hybrid RSA-ELSTM model is developed using the RSA with an ELSTM network for parameter optimization to obtain improved accuracy in movement prediction.

3.4.1. Resilient sailfish algorithm-tuned enriched long short-term memory (RSA-ELSTM) hybrid model

In RSA-ELSTM, real-time feedback is provided in the PE field through this model by incorporating data captured from the motion capture process and also using the sensor dataset. An RSA optimizes the parameters of the ELSTM model by correcting the noise and variability encountered in data. The enhanced feature fusion layer combines sensor data to better represent complex patterns of movement. This hybrid model can process historical data as well as real-time data to predict future movement. The integration of the data with DL enables personalized feedback and adaptive interventions. Continuous monitoring of performance is portrayed as a result of biosensors and the RSA-ELSTM method ensures high accuracy even for varying types of movements. This hybrid approach eradicates some of the biosensor technologies' current constraints while optimizing personalized education.

3.4.2. ELSTM

ELSTM is applied to inspect movement data monitored through biosensors in PE environments. ELSTM is an extension of a traditional LSTM model, which enlists rich features from multimodal sensor inputs and improves the more accurate real-time movement analysis.

- Model Structure

The ELSTM architecture processes real-time data to make accurate forecasts and evaluate patterns in movement. The integration, through ELSTM, of data from several sensor inputs provides deeper insights regarding the dynamics by which students move through any session of PE. This model employs a set of gates and memory units in the learning process to memorize movement sequences over time for effective prediction of movements and providing actionable feedback. **Figure 3** provides the architecture of ELSTM.

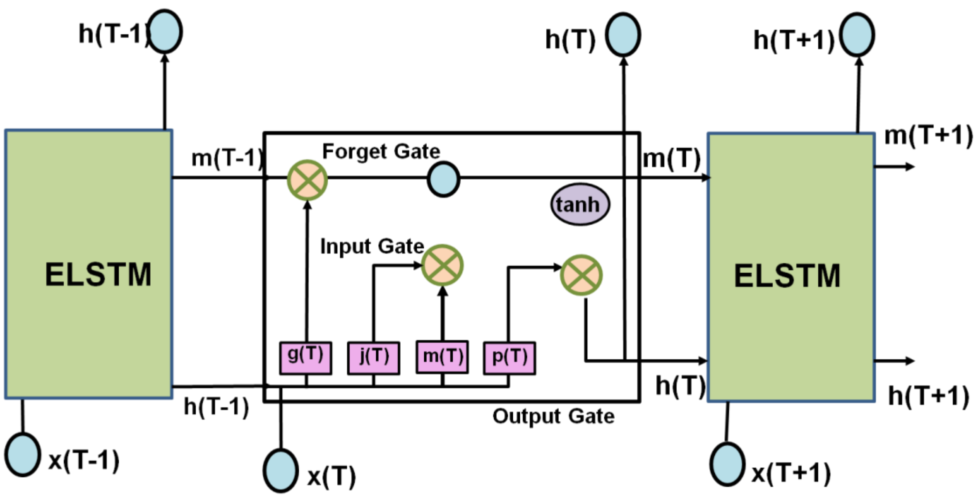

Figure 3. Architecture of ELSTM.

The core components of the ELSTM model are derived from the standard LSTM equations, but with additional data fusion layers to handle enriched sensor inputs. The following equations define the operations of the ELSTM unit.

1) Forget Gate (g_T)

The forget gate controls the amount of the previous memory that should be reserved.

$$g_T = \sigma(V_f \times x_T[h_{T-1} \times Q_f] + B_f) \tag{5}$$

wherex_T is the current sensor input,$B_f$is the bias term, $h_{T-1}$is the hidden state from the previous time step, and V_f and$Q_f$are the weights for the forget gate.

2) Input Gate (j_T)

The input gate governs how much of the candidate memory should be added to the memory cell.

$$j_T = \sigma(V_I \times x_T[H_{T-1} \times Q_I] + B_I) \tag{6}$$

3) Candidate Memory Cell ($\widehat{m}_T$)

The candidate memory cell is computed using the tanh activation function.

$$\widehat{m}_T = \tanh(V_m \times x_T[H_{T-1}, Q_m] + B_m) \tag{7}$$

4) Memory Cell Update (m_T)

The memory cell is updated by combining the forget and input gates with the candidate memory.

$$m_T = g_T \times m_{T-1} + j_T \times \widehat{m}_T \tag{8}$$

5) Output Gate (p_T)

The output gate calculates the hidden state output from the updated cell state.

$$p_T = \sigma(V_o \times x_T[H_{T-1} \times Q_o] + B_o) \tag{9}$$

6) Hidden State (H_T)

In the final step, applying the output gate to the cell state yields the hidden state H_T.

$$H_T = p_T \times \tanh(m_T) \tag{10}$$

- Enhanced Feature Fusion Layer

The multi-dimensional input from sensors can better be handled through an enhanced feature fusion layer that combines such inputs prior to feeding them into ELSTM. This aggregation layer combines multiple sensors for data aggregation with the idea of providing more enriching and inclusive input representation. The aggregation is expressed in Equation (11).

$$x_t^{fusion} = concat(x_t^{sen}, x_t^{motion}) \tag{11}$$

where$x_t^{sen}$and $x_t^{motion}$are the data from the biosensor and motion capture systems. It also ensures that all information sensed by the sensors falls in as a single vector that increases the model's chances to learn complex movement patterns.

- Model Output

The final output from the ELSTM model is to predict the state of a student's movement, thus allowing for instant evaluation. The output most likely forms a probability distribution of several categories of movement, or perhaps a performance score. It denotes how perfectly a student is performing certain physically oriented tasks and it is calculated by using Equation (12).

$$\hat{y}_T = softmax(W_y \times H_T + B_y) \tag{12}$$

$\hat{y}_T$ Represents the predicted output, W_y is the output layer weight matrix, and B_y is the output bias term.

3.4.3. Resilient sailfish algorithm (RSA)

The RSA represents an advanced version of the Sailfish Optimizer (SFO), developed to potentially enhance prediction accuracy and performance. The RSA features a dynamic exploration-exploitation balance of the SFO with resilience mechanisms for more robustness. Inspired by the cooperative hunting strategies of sailfish, the algorithm uses a population of sailfish(M) to explore and exploit the search space for movement prediction solutions. For every iteration, the sailfish generates updated positions using a fitness evaluation of both the sailfish and sardines as follows in Equation (13).

$$P_i(t+1) = P_i(t) + \alpha \times \left(P_{elite} - P_i(t)\right) + \beta \times \left(P_{sardine} - P_i(t)\right) \tag{13}$$

where $P_i(t)$denotes the position of the i^{th}sailfish at time t $(i = 1,2,\ldots,M)$, $P_{elite}$is the best sailfish position identified so far. $P_{sardine}$ denotes the position of one randomly selected sardine, α and β are the coefficients that regulate exploration and exploitation influence.

The adaptive strategy updates the sailfish's movement dynamically with a balance between exploration (searching for new regions) and exploitation (refining its current region), by using Equation (14).

$$P_i(t+1) = P_{elite}\lambda(t) \times (P_i(t) - P_{elite}) \tag{14}$$

where $\lambda(t)$ is a decreasing coefficient that improves the solution progressively at each iteration due to the shrinking of the search space.

The mechanism of resiliency in RSA works on the real-time computation of fitness values and adaptability of attack power (AP). When a sailfish's AP is less than a threshold value, then it will select a sardine for updating the position using the Equation (15).

$$AP = A_{max} \times (1 - 2 \times \text{Iteration Factor}) \tag{15}$$

where A is a constant parameter controlling the aggressiveness of the attack,A_{max} is the maximum attack power parameter. The iteration factor adjusts according to the number of iterations, progressively refining the solution. The final update rule for sardines is as follows:

Here, A is an aggressive attack control parameter,$A_{max}$is the parameter for maximum attack power. The iteration factor is the adjusting value depending on the number of iterations and it refines the solution successively. Finally, the update rule for sardines is provided in Equation (16).

$$P_{sardine}(t+1) = rand \times (P_{elite} + P_{sardine}(t) + AP) \tag{16}$$

where $r\ and$ is a random factor between 0 and 1. This adaptive mechanism allows the sailfish to gradually converge to the optimal solution in cooperation with sardines. Also, it averts early convergence, which means RSA works particularly well with real-time data for movement prediction. The steps involved in RSA are represented in **Figure 4**.

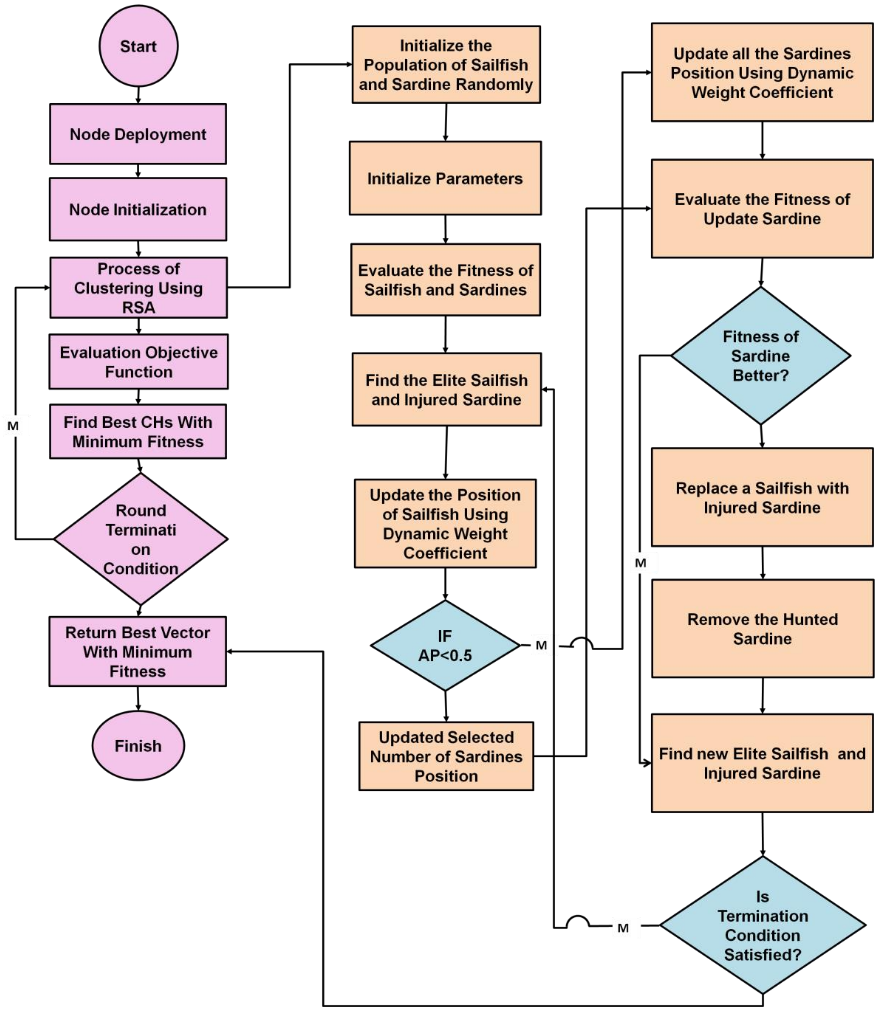

Figure 4. Flow diagrams for resilient sailfish algorithm.

3.4.4. RSA-ELSTM integration for movement prediction

The hybrid approach of RSA with ELSTM is considered optimal for the analysis of motion capture and biosensor time-series data because RSA incorporates the optimization power along with the sequential learning capacity of LSTM. The LSTM network will be the one targeted to predict the next movement using the past movement records. This hybrid combination with RSA fine-tunes the parameters of the ELSTM for optimal predictive accuracy. The RSA hyperparameters used for enhancing the ELSTM performance are population size (N), exploration coefficient (α), exploitation coefficient (β), AP, and iteration factor. The loss function of the RSA-ELSTM network depends on MSE between the actual and predicted positions and is provided in Equation (17).

$$L_{RSA-ELSTM} = \frac{1}{M}\sum_{i=1}^{M}(y_i - \hat{y}_i)^2 \tag{17}$$

Where y_i is the actual position of the student at the time i, M is the total number of predictions, and $\hat{y}_i$ is the predicted position at the time i. Using the RSA-ELSTM hybrid model, this methodology enhances the real-time analysis of the student's movement in the PE intervention to a more accurate and adaptable framework. Integrating RSA optimizes the ELSTM network toward improved performance and towards real-time prediction for movement patterns observed during PE activities. **Table 1** depicts the hyperparameters for RSA-ELSTM.

Table 1. RSA-ELSTM hyperparameters.

Hyperparameter	Value
Population Size (M)	50
Exploration Coefficient (α)	0.9
Exploitation Coefficient (β)	0.8
Attack Power (AP)	0.7
Iteration Factor	Gradually adjusted, starting at 0.05

The model improvement algorithm's parameters are listed in this table. The number of potential solutions taken into account during refinement is indicated by the (M), which is set at 50. By setting the (α) and (β) to 0.9 and 0.8, accordingly, the search is balanced between finding novel solutions and taking advantage of ones that already exist. The AP is set at 0.7, which probably regulates how strongly solutions are adjusted. Finally, as the optimization method advances, dynamical tuning is made possible by the Iteration Factor, which is gradually modified from its initial value of 0.05. The RSA and ELSTM networks are combined in the RSA-ELSTM-based Movement Prediction algorithm to forecast human movement patterns in physical education were shown in Algorithm 1. To increase the precision and effectiveness of movement prediction in dynamic learning environments, it uses RSA to optimize the model's hyperparameters.

Algorithm 1 RSA-ELSTM-based Movement Prediction in Physical Education

Step 1 Initialize parameters for RSA and ELSTM
Initialize RSA population (sailfish positions)
Initialize the LSTM model with random weights
Step 2 Data Preprocessing
for each image in the dataset:
Resize(image, 100x100)
$normalized_{image} = x'_{i,j} = \frac{x_{i,j} - \mu_{i,j}}{\sigma_j}$
Step 3 Feature Extraction using VGG16
For each image:
    Apply VGG16 convolution layers to extract features
    Apply max pooling to reduce spatial dimensions
    Normalize features $\hat{z}^{(k)} = \frac{z^{(k)} - \mu_{z(k)}}{\sqrt{\sigma^2_{z(k)} + \varepsilon}}$
    Extract the final feature map of size 5x5x512
For each time step:
$x_t^{fusion} = concat(x_t^{acc}, x_t^{gyro}, x_t^{motion})$
Step 4 Train the ELSTM model

Algorithm 1 (*Continued*)

for each epoch:
    For each time step t:
$g_T = \sigma(V_f \times x_T[h_{T-1} \times Q_f] + B_f)$
$j_T = \sigma(V_I \times x_T[H_{T-1} \times Q_I] + B_I)$
$\widehat{m}_T = \tanh(V_m \times x_T[H_{T-1}, Q_m] + B_m)$
$m_T = g_T \times m_{T-1} + j_T \times \widehat{m}_T$
$p_T = \sigma(V_o \times x_T[H_{T-1} \times Q_o] + B_o)$
$H_T = p_T \times \tanh(m_T)$
$\hat{y}_T = softmax(W_y \times H_T + B_y)$
Step 5 Integrate RSA with ELSTM for optimization
for each iteration of RSA:
$P_i(t+1) = P_i(t) + \alpha \times (P_{elite} - P_i(t)) + \beta \times (P_{sardine} - P_i(t))$
$P_i(t+1) = P_{elite}\lambda(t) \times (P_i(t) - P_{elite})$
    if AP < threshold:
$AP = A_{max} \times (1 - 2 \times \text{Iteration Factor})$
$P_{sardine}(t+1) = rand \times (P_{elite} + P_{sardine}(t) + AP)$
Step 6 Hybrid RSA-ELSTM model training
For each epoch:
$\text{predicted}_{\text{positions}} = \text{ELSTM}_{\text{predict}}(x_t^{fusion})$
$L_{RSA-ELSTM} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$
    Update model parameters using RSA to minimize loss
Step 7 Final Output
Output the predicted student movement categories or performance score direct indicator of its influence and dissemination within the technological field.”

4. Results and analysis

This section provides a detailed analysis of the performance of the RSA-ELSTM model. The performance measures of predicting student movements are measured in terms of several important metrics, and giving feedback tailored to students.

4.1. Experimental setup

The computer with the Intel Core i5 processor with 16 GB of RAM and 512 GB of SSD is part of the setup for the experiments. Python 3.8 is used for this entails using biosensors to gather data on learners’ athletic abilities in real-time, and then evaluating the data to tailor and improve instructional methods. The objective is to improve overall learning results, fitness, and each student’s participation in sporting activities. The experimental setup for RSA-ELSTM would be allowed by using high-definition cameras and the motion capture system for students’ movement recognition. Biosensors capture physiological signals. These were preprocessed in the language Python by making use of libraries like NumPy, OpenCV, and TensorFlow during resizing, normalization, and training. High performance in computing is employed in a computational process since a large quantity is involved.

4.2. Performance analysis

The RSA-ELSTM models’ performance was evaluated using standard metrics. Below are the results for recall, accuracy (Acc), F1-score, and precision (Prec). Accuracy is the correctness of the movement prediction done by the RSA-ELSTM model in personalized PE. Precision measures how well the model can identify specific movements without false positives. Recall measures how well the model detects all instances of a specific movement type. F1-score is the harmonic mean of precision and recall that provides an even level of evaluation over the performance of the model. Each metric is expressed in Equations (18)–(21).

$$Acc = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \tag{18}$$

$$Prec = \frac{T_p}{T_p + F_p} \tag{19}$$

$$Recall = \frac{T_p}{T_p + F_n} \tag{20}$$

$$F1 - Score = 2 \times \frac{Prec}{Rec} \tag{21}$$

Here, T_p is true positive, F_p is false positive, T_n is true negative, and F_n is false negative. The RSA-ELSTM model demonstrated exceptional performance in these metrics and **Table 2** summarizes the resultant values.

Table 2. Performance of RSA-ELSTM.

Metrics	RSA-ELSTM [Proposed]
F1-score	99.1%
Accuracy	99.3%
Recall	98.7%
Precision	99.2%

The effectiveness metrics for the suggested RSA-ELSTM model are shown in this table. Outstanding overall capacity for forecasting is indicated which shows a solid combination of precision and recall. The model's that it can produce precise projections with few errors. The model's great capacity to accurately identify affirmative cases is demonstrated. The further validates the model's accuracy and dependability by demonstrating how well it reduces inaccurate results. The proposed RSA-ELSTM shows promising performance with 99.1% F1-score, 99.3% accuracy, 98.7% recall, and 99.2% precision. These results indicate that the RSA-ELSTM model performs highly accurately, it also has an effective balance between precision and recall, thus ensuring reliable movement prediction and personalized feedback in the course of physical education.

4.3. Comparative analysis

The proposed RSA-ELSTM model is compared with the Internet of Things physical activity monitoring device (IOT-PAMD) [27], CNN-LSTM [28], and LSTM [29], popular models that were used for equivalent tasks. The comparison is done on the accuracy and F1-score level. The results are presented in **Table 3** and visualized in **Figure 5**. The accuracy and F1-score of multiple models are compared in this table. The usefulness of the suggested model is demonstrated by its exceptional performance, which yields superior outcomes across both measures. A different model that performs well but falls just short of the suggested strategy yields the second-best outcome. Lower accuracy and F1 scores are displayed by other models, suggesting less dependable or consistent recommendations. Overall, the table highlights how the suggested model outperforms current techniques.

Table 3. Numerical outcomes of F1-score and accuracy values

Model	F1-score (%)	Accuracy (%)
IOT-PAMD [27]	92.2	98.3
CNN-LSTM [28]	98.8	98.7
LSTM [29]	94	97.5
RSA-ELSTM [Proposed]	99.1	99.3

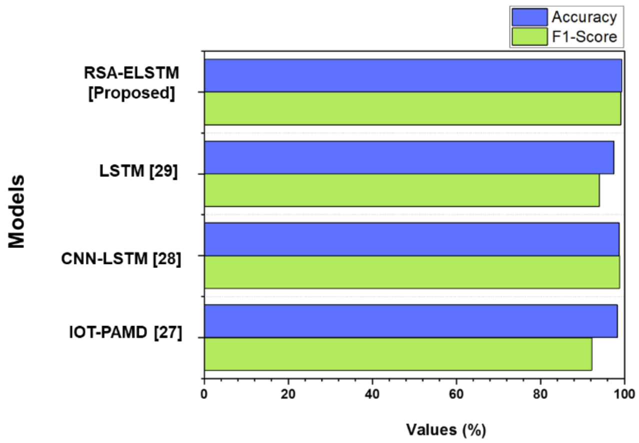

Figure 5. Comparison of accuracy and F1-score values.

When compared to alternative approaches, the Proposed Framework performs better, achieving the highest possible values for both metrics. The framework's appropriate ability to anticipate is demonstrated by an even relationship between accuracy and F1-score. Overall, the graph demonstrates the benefit of using the Proposed Framework to complete the assignment efficiently. The RSA-ELSTM model outperforms all compared models; achieving the highest accuracy (99.3) and F1 score (99.1%). This demonstrates RSA-ELSTM's greater ability to forecast student movements accurately. **Table 4** describes the RSA-ELSTM with IOT-PAMD [27], CNN-LSTM [28], and LSTM [29] models and the results are depicted in **Figure 6**.

Table 4. Numerical outcomes of recall and precision values

Model	Recall (%)	Precision (%)
CNN-LSTM [28]	97.5	99
LSTM [29]	94.4	94.6
RSA-ELSTM [Proposed]	98.7	99.2

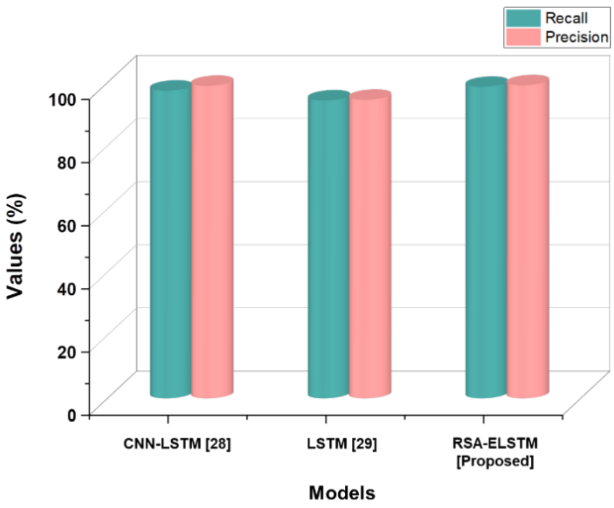

Figure 6. Comparison of recall and precision values.

Recall and precision measurements are used in this table to compare the efficiency of various models. In terms of recall and precision, the suggested RSA-ELSTM algorithm performs well, proving that it can efficiently detect positive outcomes while reducing error rates. Second place goes to the CNN-LSTM approach, which performs well but marginally worse than the suggested model. Predictions from the LSTM model are less dependable due to its relatively lower recall and precision. All things considered; the table shows how well the RSA-ELSTM model performs in comparison to the alternatives. The RSA-ELSTM model also shows the best recall (98.7%) and precision (99.2%) compared to the CNN-LSTM and LSTM models. This indicates that RSA-ELSTM not only identifies movements with high sensitivity but also with minimal false positives. The performance of all models is comparable, the Proposed Framework obtains somewhat better results in both criteria. This suggests that the Provided Framework performs better in precisely forecasting and obtaining pertinent results. The steady development demonstrates the foundation's superior accuracy and dependability over traditional techniques.

5. Discussion

The performance of RSA-ELSTM is compared with several existing established models, such as IOT-PAMD [27], CNN-LSTM [28], and LSTM [29]. The existing models have some disadvantages, which affect their performance in motion recognition. IOT-PAMD is a trustworthy model for movement prediction; however, it cannot track complex movement patterns as this model is mainly proposed to analyze sensor data. It cannot handle spatial-temporal dependencies in dynamic environments. CNN-LSTM performs well but fails to generalize across different movement types, especially in noisy or inconsistent data. LSTM is usually sensitive to the amount and quality of training data, making it less reliable in real-time applications where data can vary significantly in size and format. These problems are addressed by the RSA of the RSA-ELSTM model, which improves the robustness and optimization capabilities of the model in handling high-dimensional movement data. The improved results are achieved by effective tuning of the ELSTM network.

The RSA-ELSTM model efficiently handles complicated movements and data with multiple dimensions, providing notable benefits in motion identification. Under live applications, it performs better than current models, exhibiting more resilience and flexibility under changing conditions. Because of this, RSA-ELSTM is more dependable in identifying different kinds of mobility and producing precise findings in a range of situations. Compared to other models, such as IOT-PAMD, CNN-LSTM, and LSTM, the RSA-ELSTM model has several advantages. RSA-ELSTM efficiently manages high-dimensional information, which makes it more resilient in dynamic contexts than IOT-PAMD, which has trouble with intricate patterns of motion and spatial-temporal interdependence. When it comes to handling noisy or incomplete information, RSA-ELSTM performs better than CNN-LSTM, which can have trouble generalizing across various movement patterns. Furthermore, RSA-ELSTM's utilization of the RSA method improves its optimization skills, enabling it to function dependably in instantaneous applications with changeable data quantities and designs, in contrast to LSTM, which depends on both the amount and quality of the training information. Because of these enhancements, RSA-ELSTM is a more versatile and effective motion recognition model.

6. Conclusion

The RSA-ELSTM model is developed for the analysis and instantaneous feedback providing for student group through real-time feedback in personalized PE. Originally, the data were collected and preprocessed by using image resizing and normalization. Further, VGG-16 was used to extract features effectively and the RSA-ELSTM model is implemented to precisely detect the arrangements. The incorporation of RSA into RSA-ELSTM provides a more efficient way to apply it to PE by resolving complex movement patterns and noisy data. It depicted improved performance on the tasks, indicating movement prediction, 99.1% for the F1-score, 99.3% for accuracy, 98.7% for recall, and 99.2% for precision, in contrast with baseline and state-of-the-art models, including IOT-PAMD, CNN-LSTM, and LSTM models. The results prove that RSA-ELSTM strongly provides accurate feedback in motion recognition. Although this model excels in multiple performance metrics, its applicability in real-time would likely be influenced by hardware and environmental constraints in the implementation process. The model balances accuracy, precision, and recall to a very high degree and is ideal for providing personalized feedback in movement-based learning environments. Future work can be done to make it scalable and applicable in real-time in more diverse educational settings.

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