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Article

Optimization strategies for physical education teaching movements using biomechanical analysis and deep learning techniques

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Abstract: Accurately evaluating and improving students' motor skills and physical quality are essential to physical education's (PE) efficacy. Biomechanics, which explores the mechanical aspects of movements within biological systems, offers important insights into optimizing PE performance. At the cell molecular level, biomechanics is highly relevant. For example, during physical activities, cells experience mechanical forces. In muscle cells, the interaction between actin and myosin filaments is a fundamental molecular biomechanical process. These molecular events determine muscle contraction and relaxation, which directly affect students' motor performance. DL for optimization and the integration of biomechanical data are lacking from existing methodologies. The suggested technique improves the prediction of movement's optimization and recognition in PE using the DK-LSTM, an optimized DL model. A comprehensive action dataset that included a variety of physical movements related to PE has been used. This dataset includes a wide range of activities and skill levels, ensuring robust model training and validation. The dataset undergoes preprocessing applying normalization to improve model performance. The Discrete Wavelet Transform (DWT) is used to extract the datasets. Using the processed dataset, the optimization method is utilized for training the DK-LSTM model and adjust its parameters for best results. The DK-LSTM model significantly improves movement recognition accuracy when compared to traditional methods. Recall (96.7%), accuracy (98.3%), precision (95.3%), and score (98%) are performance indicators that show how well a model that distinguishes between various activities can lead to PE teaching movements. Understanding cell molecular biomechanics can help refine training. By knowing how molecular forces impact muscle function, educators can design more suitable PE programs. This integration of knowledge and technology can lead to more precise evaluation and improvement of students' physical abilities in physical education.

Keywords: physical education; deep learning; biomechanical analysis; physical movements; recognition; physical quality

1. Introduction

In recent years, the mixing of time into PE has converted traditional teaching techniques, improving each student's engagement and getting to know outcomes [1]. The incorporation of biomechanical analysis and DL techniques offers a unique approach to optimize motion education in PE [2]. By utilizing larger algorithms and statistics-pushed methods, educators can benefit from insights into students' movement patterns, become aware of areas for improvement, and tailor instructions to fulfill male or woman requirements [3]. Biomechanical analysis affords a scientific basis for understanding the mechanics of human moves, permitting educators to break down complicated movements into their essential components [4]. Focused on developing the PE curriculum's fundamental competencies and on converting and educating the PE curriculum [5], the development of the essential excellence of PE among college students is prompted by using numerous elements [6]. First and primary, PE is the primary method of bodily exercise for university students [7]. It is closely associated with the capacity of professional PE teachers as well as the school's extracurricular management structure, sports program, sports environment, and policy for implementing policies [8]. PE learning assessment is becoming a significant hotspot in the field of education nowadays, regardless of the particular utilization and execution of learning assessment or the interaction between learning assessment and curriculum development [9]. To help kids have fun, build their bodies, develop their personalities, and moderate their motivations through PA, it is imperative to establish the pedagogical paradigm of health first and to provide proper PE sessions [10]. These important gatherings have significantly increased the visibility of collegiate athletics and act as essential staff training guides regarding the rising importance of assessment in educational environments [11]. The TCD, assessment, and implementation are significantly impacted by the NPE curriculum perspective, which is centered on ND and YHI [12].

By employing an optimized DL model, DK-LSTM, the proposed method enhances the prediction of movement optimization and recognition in PE.

The key contribution of this paper

- Robust training and validation for model performance are provided by an extensive dataset comprising 751 movies that capture handball motions in seven different categories.
- In this study, data preprocessing is conducted using min-max normalization to improve the physical teaching movements.
- The feature extraction method used in the study is the DWT. Because it computes gradient orientations in specific areas of the image, it is effective at extracting structural and shape information from images.
- When compared to conventional techniques, the DK-LSTM model dramatically increases the accuracy of movement recognition in PE.

The remaining content in this research is organized into five sections. In Section 2, the suggested method for physical teaching movements with existing methods was compared by looking at related studies. In Section 3, the proposed methodology, which entails data gathering and model implementation for data preparation, is explained. The experimental results are reported in Section 4 and correspond to the measures of accuracy, recall, precision, and F1-score that are employed in this evaluation approach to assess physical instructional motions. Section 5 presents the study's conclusion.

2. Related work

To improve the effectiveness of ML and AI in the evaluation of PE [13] and to minimize calibration errors, the approach averages several sample points and constructs system function modules according to real-world requirements. The findings indicate that the suggested model has a useful impact on enhancing the assessment of PE. The updated educational requirements for training prospective PE teachers to teach sports and PA to secondary school students should be empirically validated [14]. Modelling, observations, tests, questionnaires, educational experiments, and a variety of statistical and physical evaluations were some of the techniques used. The experimental group's preparedness for sport and PA significantly improved as a result of the applied pedagogical settings, which was consistent with cutting-edge neuropsychological approaches. Using virtual reality technology powered by artificial intelligence to support college physical education instruction [15], the technique compared the movements of athletes in real time and used spline keyframe interpolation for virtual human animation. As a result, the use of VRT in higher education has advanced, with 35% of the VT experiment group achieving excellence and 10% of the CG. Increase the efficiency of training by better identifying the shooting motions of basketball players [16], feature extraction from images was used to gather action posture data, as well as feature selection and Gaussian hidden variables were used for multi-dimensional motion posture feature extraction and classification. The outcomes showed how effective the suggested basketball shooting motion identification technology was, and they offered a reliable scientific benchmark for the advancement of contemporary basketball training techniques. To use VRT with NBT of movement building to improve PE instructors' competency in maintaining good health [17], the methodology involved two steps: Creating a software program VMINBTMC and carrying out an experimental investigation. The findings show that the virtual model successfully promoted the acquisition of health-preserving competence by enabling a range of techniques for technological and recreational PA. The methodology involved looking at several PE technology domains, such as information delivery, learner assessment, counseling techniques, and personalized learning, where AI might be used to explore concepts and potential applications in PE [18]. The findings highlight the competence needed for future PE teachers and offer larger implications for other educational domains and future research. AI advances could have a substantial impact on PE.

Basketball technology uses neural network-based motion sensors, and physical fitness evaluation [19]. The technique used motion sensors to gather various human body data, which was then analyzed by sophisticated algorithms to provide an accurate diagnosis. The findings showed that there was potential for growth in athletes' agility and reaction times, allowing for focused training to improve their basketball abilities and physical fitness. By recommending an IoT-DPARS for higher education, collegiate PE could be improved [20]. The process entailed real-time heart rate monitoring, cloud-based communication with a mobile terminal, and the collection of pertinent data via IoT devices. The findings show that the suggested approach successfully promoted better teaching strategies and PE methodologies, creating a healthier learning environment for pupils. To enhance the current teaching mode using AI technologies to encourage personalized and intelligent PE instruction [21], as well as to improve individualized education, the approach entailed creating a voice-interactive artificial intelligence teaching robot using a speech recognition system and assessing its effectiveness through examinations and trials. The findings showed that after introducing the robot, pupils' learning interest (21 points) and learning attitude (9.8 points) significantly increased, with a recognition accuracy reaching 90%. The process involved developing a mobile client, a cloud platform, and an IoT-IVRS for college PE that enables real-time interaction and data gathering. The following occurs to solve the problems of solitary instruction methods and insufficient capacity for distant instruction to improve the efficacy and scientific foundation of PE teaching in colleges and universities [22]. The approach offered a scientific framework for transforming college PE, and the findings showed that it had a positive application and promotion effect.

The impact of the changes made to PE during the COVID-19 epidemic on pre-service Spanish PE instructors [23]. Twelve pre-service teachers who experienced the lockdown during their practicum were interviewed in a semi-structured manner as part of this methodology. The results show that pre-service teachers encountered obstacles in adjusting to the new physical education environment, including feelings of uneasiness, dread, and precocity, as well as difficulties integrating digital tools into their lesson plans.

In the investigation of alterations in the attitudes, cognizance, and readiness of pre-service early childhood educators to coach PE [24], pre-service teachers took elements within the technique's PE course, which included theory and practical applications. Pre-test and post-test questionnaires, cognizance organization interviews, and microteaching reflections were used to collect information. The path appeared to have a positive impact on attitudes towards PE, even though the training did not adequately prepare teachers to teach in a classroom setting. By creating and evaluating a custom PA recommender device for exergames, want to increase user efficacy and engagement [25]. PMRS was used together with participant preference evaluation to customize recommendations. The findings validated that, in contrast to an existing model, the recommended technique produced suggestions that had been more correct in predicting users' alternative preferences for various kinds of PA. Enhanced the utilization of hybrid teaching in PE by proposing a quality assessment method based on mobile edge computing [26]. To analyze quality effectively, the method entailed building a system of quality evaluation indexes, factoring, and clustering index items to make them simpler, leveraging mobile edge computing to calculate weights for the evaluation indexes, and applying a fuzzy comprehensive evaluation model. The findings showed that the approach enhanced teaching quality and evaluation effectiveness while lowering expenses and errors. The effect of gamification on teachers' and students' experiences in PE [27] included 290 students, aged 6 to 14, from four Spanish schools. It included a 15-week intervention program that was themed around the Marvel universe. The findings revealed a student's innate motivation, and themes of enjoyment, camaraderie, and learning emerged in their responses. The processes of result in the characteristics of resistance training (RT) or aerobic training (AT), which are primarily hypertrophied and oxidative, accordingly, are being uncovered [28]. Human muscle tissue displays general "moving around psychological" communication, gene expression, and translations responses when native individuals are exposed to either AT or RT. Nonetheless, distinct adjustment to AT and RT is driven by significant, unidentified, variations in signaling and protein formation modulation. To gain a better understanding of the varied link between physical activity and phenotypic results, investigations are necessary.

New understanding of the intricacy and scope of intracellular messenger systems involved in responding to endurance-based exercising has been made possible by the use of molecular approaches to exercise physiology [29]. These methods are predicated on the idea that increasing the respiratory load and causing drastic disruptions in cell equilibrium enhance acute exercise reactions, replicated over a period of time to increase training adaption. A wide range of human actions are taught by fitness instructors, and biomechanics offers a crucial justification for assessing technique and recommending interventions to help youth get better [30]. It demonstrates how the nine fundamental concepts of biophysics and electromechanical information can be combined with other sport disciplines to qualitatively analyze human motion. The use of biomechanics to practical exercise instruction is demonstrated through real-world athletic capabilities and standard teaching aids. One important diagnostic and assessment tool that can be used to enhance mobility in physical instruction is qualitative evaluation.

Every living thing on the planet, including people, is always impacted by the global force of gravity as well as internal and external influences. Therefore, examining the etiology of illnesses, choosing a course of medication, and assessing the results of that treatment all benefit from knowing of the dynamics and pressure of each component throughout movement utilizing motion analysis [31]. It is proposed that integrating current engineering methods with ongoing technological progress aid future research into human bodily biomechanical and its therapeutic applications. Although biomechanical information is crucial for fitness instructors' professional development, they nonetheless apply it sparingly. The research looked at how well a continuing instruction course grounded in effective instructional theory helped instructors in sports better comprehend biomechanical concepts [32]. Educators who had positive opinions of the course, their interactions with peers, and its applicability to their profession showed notable improvements in their comprehension of mechanical fundamentals as a result of the course's implementation. Lack of educational time and prior biomechanics expertise were cited as challenges.

A transient, reversible sensation that manifests as fatigue or low energy [33] and physiological injury, and overload are the main causes of temporary weariness. In serious and lasting condition, if it is connected to medical disorders or occurs after prolonged being exposed to dangerous substances or particular drugs. To assist in comprehending how they can avoid or treat this crippling situation, the present overview only emphasizes and discuss what is currently known about the molecular pathways that lead to the increase of decreased muscle mass. The health and pathology of the musculoskeletal system are significantly influenced by mechanical loads. It has long been recognized that physical strain plays a part in "overuse" injuries like the condition, but it is also becoming more widely recognized as a potential cause of rheumatoid disease and a condition called, two types of chronic joint inflammation [34]. The development and maintenance of hamstring and tissue structure in tissue depend on appropriate levels of forces, which is accomplished at the cellular level by mediated optimizing of the extracellular matrix, which is created by ligament and elastic stromal cells.

3. Methodology

The handball action dataset, which includes a variety of handball-related moves, is utilized in this study. To improve the accuracy of movement recognition, the methodology consists of preprocessing the data, extracting features using the HOG, and optimizing the model parameters using the suggested method DK-LSTM for improving the physical teaching movements. **Figure 1** shows the overall process of the DK-LSTM method.

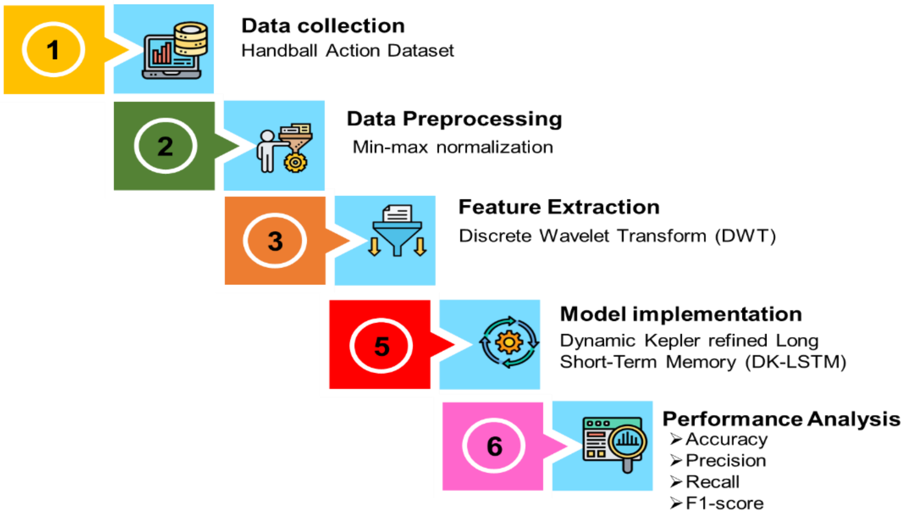

Figure 1. Proposed method flow for optimizing PE movements.

3.1. Data collection

The research experiments involved 28 participants, ranging in age from 19 to 48. Wearing a smartphone around their waist, every individual engaged in 6 different actions such as walking, sitting, walking upstairs and downstairs, lying, and standing. They employed its embedded accelerometer and gyroscope to capture three-axial forces angular speed and 3axial linear accelerations at a continuous amount of fifty Hz. To enable manual labelling of the information, the experiments were documented. A random division of the gathered data was made, using 70% of the information provided by the respondents for training and thirty percent for testing. The information was gathered in windows that slid with predefined widths of 2.56 seconds and 50% overlaps after sensor signals had been processed using noisy filtering technologies. Using a Butterworth low-frequency filtering, the bodies accelerated was separated and elements of the sensor's rapid signal related to gravitation, which also includes components related to gravitational and body motion. A filter with a 0.3 Hz threshold was employed since it is believed that the pull of gravity only consists of low-frequency elements. By computing variables from the temporal and frequency domains, a series with characteristics was derived from every window. This dataset was gathered from open source (https://www.kaggle.com/datasets/mboaglio/simplifiedhuarus)

3.2. Data pre-processing using Min-Max normalization for improving physical education movements

When Min-Max normalization is applied to the data before it is used for physical education teaching movements, DK-LSTM performs better for accurate predictions. Min-max normalization is a process that requires performing linear alterations on the original data to produce an even set of value comparisons between the data before and after the operation. Equation (1) that this method can apply is as follows:

$$W_{\text{new}} = \frac{W - \min(W)}{\max(W) - \min(W)} \tag{1}$$

Where; W is the old value, $\min(W)$ in the datasets is the minimum value, and $\max(W)$in the datasets is the maximum value, W_{new}isobtained from the normalized outcomes.

3.3. Feature extraction using DWT

The characteristics of the wavelet function and the function for scaling are covered. Presumptuous that Haar, Daubechies wavelets, and so on are the wavelet and scaling functions. First, consider that the foundation is established. An equation in $k^2(Y)^1$can be used to approximate a discrete signal, as shown in Equation (2).

$$e[v] = \frac{1}{\sqrt{N}}\left(\sum_{l} X_{\phi}[h_0, a]\phi_{h_0,a}[v] + \sum_{h=h_0}^{\infty}\sum_{a} X_{\psi}[h,a]\,\psi_{h,a}[v]\right) \tag{2}$$

The separate functions are denoted in $e[v], \phi_{h_0,a}[v]\ and\ \psi_{h,a}[v], [0, N-1]$. Considering that the sets of $\{\phi_{h_0,a}[v]\}_{a\in Y}\ and\ \{\psi_{h,a}[v]\}_{(h,a)\in Z^2, h\geq h_0}$ are perpendicular to one another. The wavelet transform coefficients can be obtained by taking the Centre of the product, as shown in Equation (3) and (4).

$$X_{\phi}[h_0, a] = \frac{1}{\sqrt{N}}\sum_{v} e[v]\phi_{h_0,a}[v] \tag{3}$$

$$X_{\psi}[h, a] = \frac{1}{\sqrt{N}}\sum_{v} e[v]\psi_{h,a}[v]\ h \geq h_0 \tag{4}$$

3.4. DK-LSTM

Combining the DK-LSTM framework offers a progressive technique for figuring out and optimizing physical training instructional moves. Drawing suggestions from heavenly mechanics, the DKO models planet motion around a sun to efficiently explore and exploit the solution area. It modifies its seek approach in response to candidate answers' proximity to a most required state. In addition, long-term dependencies in sequential data are a strong suit for LSTM networks, which makes them perfect for understanding intricate movement patterns. Real-time feedback on instructional movements is made possible by this dynamic synergy, which also makes it easier to identify the biomechanically best practices for enhancing students' motor skills. The algorithm of DK-LSTM is shown in Algorithm 1. The DK-LSTM approach improves teaching effectiveness and student engagement in PE settings by utilizing the advantages of both the LSTM's temporal analysis and the DKO's adaptive optimization. For higher motion identification and performance evaluation, this novel strategy helps instructors improve their techniques of practice even as additionally making a major contribution to the overall development of students' bodily abilities.

3.5. LSTM

The LSTM model can identify and establish a dependency between components that come before and after those from the examples, and it produces a distinct memory storage device by connecting all three of the memory cells' mutually intricate gates.

To help the neural nodes in the buried layer of the RNN recall previous information, LSTM incorporates a structure known as a Memory Cell. This structure serves to record past data. The LSTM model additionally adds three gate structures shown in **Figure 2**, which are used to govern how the historical data, such as input, forget, and output gates, is used. LSTMs can be used to assess and expect movement patterns concerning PE motor skill optimization. By feeding sequential data from multiple physical activities into the LSTM model, it can learn complicated temporal correlations, leading to greater accuracy in identifying and classifying different movements. This effort intends to greatly improve the optimization of teaching movements in PE by utilizing the capabilities of LSTM networks.

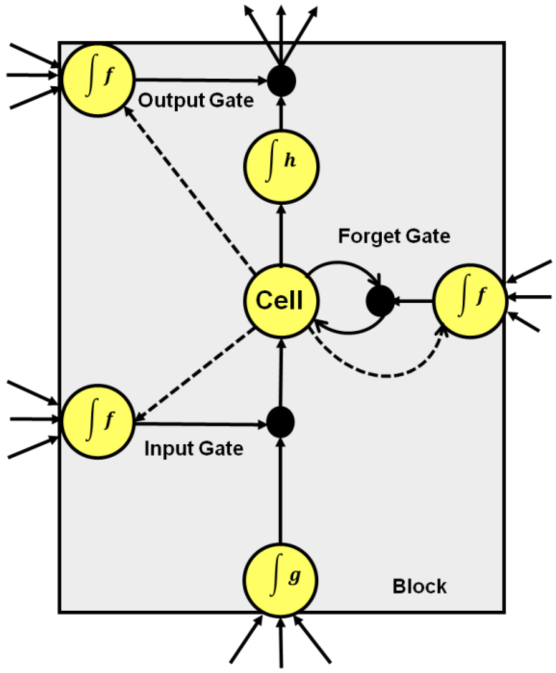

Figure 2. Structure of LSTM model for movement optimization analysis.

The IG, indicated by k, decides whether data from the IL can be added to the hidden layer node. An output from the current node is indicated by ω and is determined by the output gate as to whether it can be sent on to the next layer. Forget Gate, indicated byϕ, decides whether or not to retain the historical data stored inside the node of the current concealed layer. The data that was stored was occasionally represented byt^{es}. The output vectoring from the node in the IL, the output vectoring from the cell in the preceding layer, and the data stored by the preceding cell make up the input value of an IG. It can then calculate the output vectoring that comes from this IG activation function at that moment by using b_k^s to represent the input vectoring of the IG at time s.

$$a_k^s = e(b_k^s) \tag{5}$$

The same three input vectors that make up the input value of the IG also comprise the input value of the FG. It uses b_{φ}^{s} to represent the input vector of the FG at time s. Then, the output vector that results from this FG activation function at time s is calculated using Equation (6).

$$a_{\varphi}^{s} = e(b_{\varphi}^{s}) \tag{6}$$

The input vectoring from the IL and the output from the OG of the preceding buried layer make up the cell unit's input. To represent the input vector of the cell unit of time s, use c_{d}^{s}. FG calculates the worth of the old data and decides whether to keep it in Equation (7).

$$t_{d}^{s} = a_{\varphi}^{s} t_{d}^{s-1} + a_{k}^{s} h(c_{d}^{s}) \tag{7}$$

Three components make up the output value of an OG: (1) The IL output vector; (2) the cell's output vectoring from the preceding buried layer; (3) the data recorded by the current cell unit. The input vectoring of the OG at time s is represented by b_{ω}^{s}, and the output vectoring resulting from the activation function of this OG at time s is computed using Equation (8).

$$a_{\omega}^{s} = e(b_{\omega}^{s}) \tag{8}$$

Consequently, the cell unit's output vector is computed by:

$$a_{d}^{s} = a_{\omega}^{s} g(t_{d}^{s}) \tag{9}$$

g Stands for the activation function in Equation (9).

The cell unit's output vector, sometimes referred to as the OL input vector, is computed by Equation (10).

$$b_{l}^{s} = \sum_{d=1}^{g} \omega_{dl} a_{d}^{s} \tag{10}$$

The OL final output vector is computed by Equation (11).

$$a_{l}^{s} = e(b_{l}^{s}) \tag{11}$$

The BPTT determines the updated weight at time s from node j through to node i.

$$\omega_{ji} = \omega_{ji} - \eta \delta_{i}^{s} a_{i}^{s} \tag{12}$$

The value of the node's residual at time s is represented by δ_{i}^{s} in Equation (12).

3.6. Kepler Optimization (KO)

KO is a unique application of meta-heuristic in the field of physics-based innovation. Using Kepler's formulae to forecast the planetary location and motion at a specific moment, each planetary position functions as a candidate solution in KO, and its position about the sunlight, which stands for the optimum alternative solution, is arbitrarily altered during the optimization process.

By applying DL and biomechanical analysis to the optimization of physical education instructional movements, this approach can successfully improve motor skills and performance.

Therefore, the underlying equation states that during initialization, the choice factors of an optimisation solution in Equation (13) will be reflected in the stochastic distribution of a populations number of M_o Planetary in Dim levels.

$$\overrightarrow{W}_{ji}(0) = \overrightarrow{W}_{i,low} + q_1 \times \left(\overrightarrow{W}_{i,up} - \overrightarrow{W}_{i.low}\right), j = 1{:}\, m_o;\, i = 1{:}\, Dim \tag{13}$$

where $W_{j,i}$is a solving vector that represents each planetary and has the variable controls of dimensionDim, and q is an arbitrarily generated number with an interval of 0 to 1. Like other metaheuristics, the KO has a random initialization. The variables $W_{i,}$, low, and $W_{i,up}$ indicate the $lower\ and\ upper$ limits for every controlled parameter (i), which determine the optimization process's restrictions, respectively. Through accurate variable control adjustments and well-informed decision-making, this optimization framework uses biomechanical data to fine-tune teaching actions, boosting the effectiveness of PE.

Next, the position of each object concerning the sun is used to estimate its velocity. The motion patterns can be mathematically expressed using Equation (14).

$$U_j(s) = \begin{cases} q_4 \times G \times \left(\overrightarrow{W}_b - \overrightarrow{W}_j\right) + \left(1 - Q_{j-norm}(s)\right) \times E \times \vec{V}_2 \times \vec{q}_5\left(q_3 \overrightarrow{W}_{j,up} - \overrightarrow{W}_{j,low}\right) & if\ Q_{j-norm}(s) > 0.5 \\ \rho\left(2q_4 \overrightarrow{W}_j - \overrightarrow{W}_a\right) - \rho^*\left(\overrightarrow{W}_a - \overrightarrow{W}_b\right) + \left(1 - Q_{j-norm}(s)\right) \times E \times \vec{V}_1 \times \vec{q}_5\left(\overrightarrow{W}_{j,up} - \overrightarrow{W}_{j,low}\right) & Else \end{cases} \tag{14}$$

$$G = \left[\mu(s) \times (N_t + n_j)\left|\frac{2}{Q_j(s) + \varepsilon} - \frac{1}{b_j(s) + \varepsilon}\right|\right]^{0.5} \tag{15}$$

$$\rho = \vec{V} \times (q_3 \times (1 - q_4) + q_4) \times G \tag{16}$$

$$\rho^* = \left(1 - \vec{V}\right) \times (q_3 \times (1 - q_5) + q_5) \times G \tag{17}$$

where $W_j$represents the jth object position; $V, V_1, and\ V_2$ are random values selected from the given ranges $\{0, 1\}$; $E$is a value from the range that is selected at random $\{-1,1\}$; $q_1, q_2, q_3, q_4\ and\ q_5$ are random uniformly distributed values within the bounds of$[0,1]$; and$U_j(s)$ describes the speed of the jth particle at time$s$. A small number called ε is used to guard against divide-by-zero mistakes. $\mu(s)$ is the universal gravitational constant; W_b *and* W_a are randomly selected options from the full population; the masses of$W_b\ and\ W_a$ are represented by$W_t\ and\ W_j$, respectively; Equation (18) describes Kepler's third rule, which determines the semi-major pole of the particle$j$elliptical orbit at time s.$Q_j(s)$reflects the distance at any moment s between each objectW_j and the sunW_t.

$$b_j(s) = q_3 \times \left[S_j^2 \times \frac{\mu(s) \times \left(N_t + n_j\right)}{4\pi^2}\right]^{\frac{1}{3}} \tag{18}$$

here S_j is an absolute value that represents the orbital interval of each*jth*object. The term$Q_{j-norm}(s)$ refers to the normalization of the ED between$W_t$andW_j, and it can be explained as follows in Equation (19).

$$Q_{j-norm}(s) = \frac{Q_j(s) - Q_{min}(s)}{Q_{max}(s) - Q_{min}(s)} \tag{19}$$

An object moves momentarily closer to the sun before spreading out throughout its revolution around the sun. There are two main stages in which KO models this behavior: Exploration and exploitation. While KO uses alternatives nearer to the sunlight more precisely to find new sites near the best solutions, it also explores items farther from the light in search of innovative solutions. Following the previous steps, any object that is far from the sun is altered in the following ways in Equation (20).

$$\vec{W}_j(s+1) = \vec{W}_j(s) + E \times \vec{U}_j(s) + \left(Eh_j(s) + |q|\right) \times \vec{V} \times \left(\vec{W}_s(s) - \vec{W}_j(s)\right) \quad (20)$$

where $W_t(s)$ gives the location of the sun in relation to the selected ideal solutions, E acts as an indicator that allows the searching parameters to be changed, and$W_j(s+1)$is the recently discovered site at the time $s+1$The gravitational pull that all planets are attracted to is $j\,.W_j$ towards the sun W_t is represented by the symbolEh_j. Through the analysis of these dynamics, it can gain insights into the optimization of movement methods that improve students' learning outcomes by enhancing coordination and performance in PE in Equation (21).

$$Eh_j(s) = f_j \times \mu(s) \times \frac{\left(\overrightarrow{Nm_t} \times \overrightarrow{nm_j}\right)}{\overrightarrow{Qm_j^2} + \varepsilon} + q_4 \quad (21)$$

where μ and ε stand for the forces of gravity constant and a very small value, respectively; $f_j$is a number between$0\ and\ 1$ that denotes the asymmetry of an orbiting planetary, which was added to give KOT a stochastic quality; and$Nm_t\ and\ nm_j$are the normalized values of$Ms\ and\ n_j$, which are provided by Equations (22) and (23), respectively, and which describe the masses of W_t and W_j. Comprehending the influence of these variables can facilitate the creation of biomechanically optimal movement patterns, hence augmenting the overall efficacy of PE programs in Equation (20).

$$Nm_t = q_2 \times \frac{fit_t(s) - worst(s)}{\sum_{l=1}^{M_o}(fit_l(s) - worst(s))} \quad (22)$$

$$nm_j = \frac{fit_j(s) - worst(s)}{\sum_{l=1}^{M_o}\left(fit_l(s) - worst(s)\right)} \quad (23)$$

Additionally, as follows, Qm_j denotes the normalized value ofQ_j that represents the ED:

$$Qm_j(s) = \left\|W_t(s) - W_j(s)\right\|_2 \quad (24)$$

The option with the highest fitness score is indicated by the symbol (.) worst. The value ofq_2, which is a random number between $0\ and\ 1$is used to divide the weights of many planetary bodies. The$function\ \mu(s)$ is defined as follows: It is a function that exponentially decreases with time (s) to control the precision of searches in Equation (25).

$$\mu(s) = \mu_0 \times f^{-\gamma\frac{1}{s_{max}}} \quad (25)$$

where s is the current iteration number, γ is a constant, μ_0 is the starting value, and S_{max} is the total number of iterations.

KO will provide utilization activities when planets are close to the sun, and it will enhance the exploration operators when the sun is distant. To further improve both operators, the concept can be formally represented as follows. This adaptable technique allows for customized approaches that maximize student engagement and learning results by reflecting the dynamic nature of movement patterns in physical education in Equation (26).

$$\vec{W}_j(s+1) = \vec{V}_1 \times \vec{W}_j(s) + \left(\frac{\vec{W}_b(s) + \vec{W}_t + \vec{W}_j(s)}{3} + \frac{1}{f^{(q\times(1+(b_2-1)\times q_4))}} \times \left(\frac{\vec{W}_j(s) + \vec{W}_t + \vec{W}_b(s)}{3} - \vec{W}_a(s)\right)\right) \times \left(1 - \vec{V}_1\right) \quad (26)$$

where b_2 is a periodic controlling variable that gradually drops from one to two for S cycles during the optimization process and$q$ is a random number generated using the normal distribution, as stated below. These specific types of factors aid in simulating realistic movement events, which makes it possible to identify the best teaching practices that can greatly improve physical education outcomes for students from a variety of backgrounds in Equation (27).

$$b_2 = -1 - 1 \times \left(\frac{s}{S_{max}}\right) \quad (27)$$

By employing an elitist strategy, the final stage of elitism guarantees the sun's and planets' ideal positions. Equation (26) offers a synopsis of this procedure. By prioritizing the most successful physical education methods, this strategy improves the selection of the best movement strategies and raises student engagement and performance in Equation (28).

$$\vec{W}_{j,new}(s+1) = \begin{cases} \vec{W}_j(s+1) & if\ e\left(\vec{W}_j(s+1)\right) \leq e\left(\vec{W}_j(s)\right) \\ \vec{W}_j(s) & else \end{cases} \quad (28)$$

3.7. Dynamic Kepler

This barrier was lessened by adding a LEO to the standard KOT to create an Improved KOT (IKOT), It results in an improved search strategy that avoids local optima. Local optima in the program are avoided with the help of the LEO. The KOT method modifies the outcomes following each iteration by using the related mathematical model:

An Improved DK (KO) was created by adding a LEO to the conventional KO to improve the search procedure and prevent local optima in movement optimization. This innovation makes it easier to explore biomechanical strategies in physical education more efficiently. After every repetition, the DKO dynamically modifies the results by using a mathematical model to improve movement strategies and increase student performance and engagement.

$$\vec{W}_{j,new}(s+1) = \begin{cases} \phi_1\left(\beta_1 \vec{W}_t - \beta_2 \vec{W}_{vu}\right) + \dfrac{\sigma_1 \phi_2 \beta_2}{2}\left(\vec{W}_{Q1} - \vec{W}_{Q2}\right) + \vec{W}_j(s+1) \ \ if\ q_3 < 0.5 \\ \phi_1\left(\beta_1 \vec{W}_t - \beta_2 \vec{W}_{vu}\right) + \dfrac{\sigma_1 \phi_2 \beta_2}{2}\left(\vec{W}_{Q1} - \vec{W}_{Q2}\right) + \vec{W}_t \qquad Else \end{cases} \quad if\ q_4 < R_x \tag{29}$$

The deployment of the LEO will be regulated by the probability ratio R_x.

W_{Q1} and W_{Q2} are two responses chosen at random from the group; q_3 and $q_4$represent the range's randomized integers[0,1); ϕ_1 and $\phi_2$represent two randomly selected values from the set's equal distributing model $[-1;\ 1]$.

To create the two randomized values, β_1 and $\beta_2$use Equations (30) and (31).

The best movement patterns to improve physical education results are found by using this probabilistic approach. These variables are essential to the optimization process because they allow movement techniques to be improved for better results in physical education in Equation (31).

$$\beta_1 = 2 \times q_5 \times U_0 - (U_0 - 1) \tag{30}$$

$$\beta_2 = q_5 \times U_0 - (U_0 - 1) \tag{31}$$

$$U_0 = \begin{cases} 0 & U_1 < 0.5 \\ 1 & Else \end{cases} \tag{32}$$

where U_1 is a randomly generated integer from the interval $[0, 1]$ this number adds variability to the optimization framework, which is necessary to find movement techniques that work and improve students' performance in physical education.

Algorithm 1

```
class DK_LSTM:
def __init__(self, input_dim, hidden_dim):
self.W_ih, self.W_hh, self.W_ho = initialize_weights(input_dim, hidden_dim)
def forward(self, inputs):
h_t = initialize_hidden_state()
for x in inputs:
f_t, i_t, o_t, c_t = self.compute_gates(x, h_t)
h_t = o_t * tanh(c_t)
return h_t
def kepler_optimization(population, iterations):
best_solution = None
for _ in range(iterations):
for planet in population:
fitness = evaluate_fitness(planet)
if best_solution is None or fitness < evaluate_fitness(best_solution):
best_solution = planet
planet = update_position(planet, best_solution)
return best_solution
def main():
dk_lstm = DK_LSTM(input_dim = 10, hidden_dim = 20)
training_data = generate_training_data()
dk_lstm.forward(training_data)
optimal_solution = kepler_optimization(population = [random_position() for _ in range(50)],
iterations = 100)
print("Optimal Solution:", optimal_solution)
if __name__ == "__main__":
main()
```

4. Results

The results section demonstrates how the recommended approach to physical education teaching movements outperforms using the DK-LSTM techniques. Several performance criteria were developed to quantify the effectiveness and robustness of the method for detecting physical education teaching movement analysis utilizing a DK-LSTM. Several factors are considered, including F1-score, recall, precision, and accuracy, to determine the best course of action. To demonstrate how the proposed methodology varies from the existing approaches SVM [35], and LSTM-GAN [36]. **Table 1** displays the experimental configuration.

Table 1. Detailed overview of experimental setup and configuration.

Feature	Description
Model	Dell Inspiron 3535
Display	15.6FHD (39.62 cm)
RAM	8GB
Storage	512GB SSD
Operating System	Windows 11
Security Software	15 Month McAfee
Processor	AMD Ryzen 3 7320U

The percentages of the several handball activities that the DK-LSTM model was able to identify are shown in **Table 2**, which also highlights the evaluation of the method in terms of walking, sitting, walking upstairs, laying, walking downstairs, and standing as shown in **Figure 3**.

Table 2. Recognition Rate evaluation for DK-LSTM Model across Physical Activities in handball.

Handball actions	Recognition rate (%)
Walking	92
Walking upstairs	87
Walking downstairs	90
Sitting	88
Standing	94
Laying	82

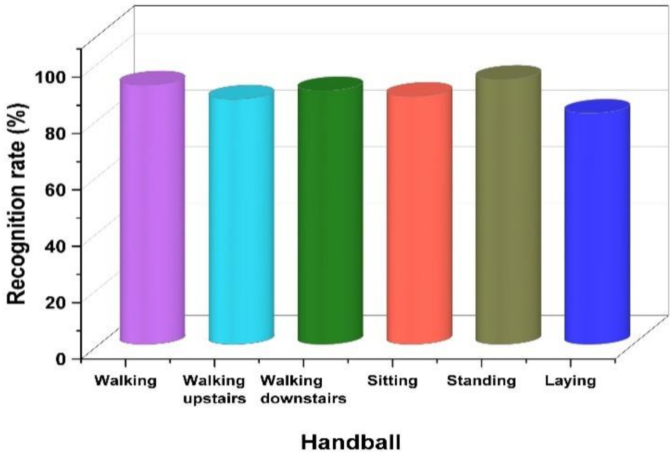

Figure 3. Recognition rate (%) for various handball actions.

4.1. Precision

Precision is the capacity of a model to accurately identify the physical education teaching beneficial events that follow occurrences that its framework anticipates would be beneficial. The total number of true positives in the computation is calculated by dividing it by the entire amount of actual positives. **Figure 4** compares the precision of novel approach to the current approaches and assesses its performance. SVM and LSTM-GAN achieved precision rates of 94.20%, and 92.1%, respectively.

The suggested method's precision, which utilizes DL and biomechanical research, was 95.3% when compared to other approaches. These findings show that the proposed methodology greatly improves the physical education teaching movement when compared to previous methods.

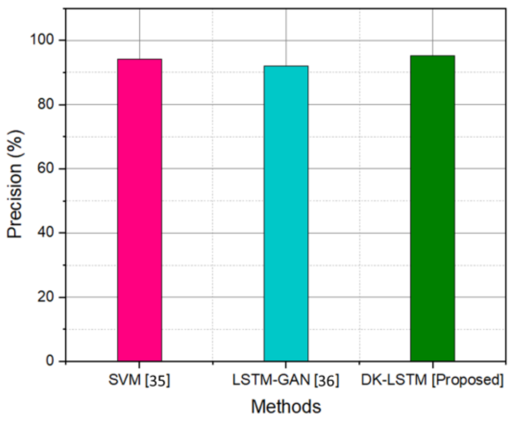

Figure 4. Comparison of precision (%) between the proposed method and different models.

4.2. Recall

A model's recall is a measure of how well it predicts physical education improvements in teaching movements. It is also known as the rate of true positives or the sensitivity rate. **Figure 5** compares the recall rates of the proposed strategy with the existing approaches. For SVM, and LSTM-GAN, the corresponding recall rates achieved were 91.80%, and 94.5%, respectively. When comparing other methods to the suggested methodology, DK-LSTM, the recall rate is 96.7%. The outcomes demonstrate that the proposed approach performs better than the current ones.

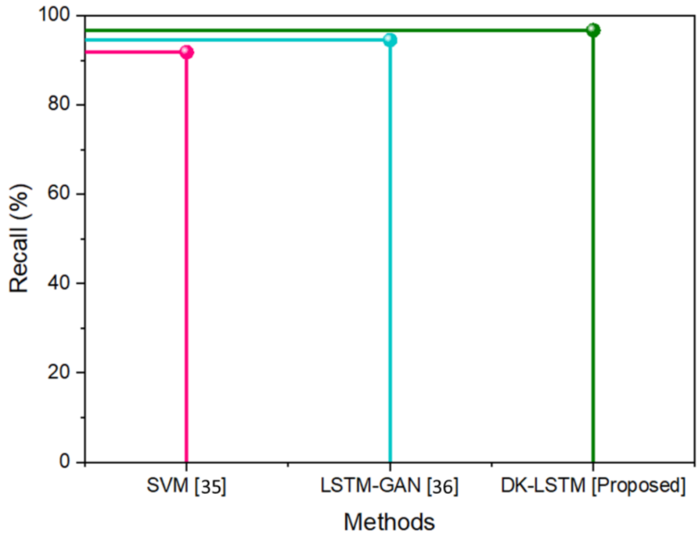

Figure 5. Comparison of recall for DK-LSTM with existing methodologies in PE.

4.3. Accuracy

The total accuracy of a model's predictions is determined by DK-LSTM. **Figure 6** evaluates and compares the suggested methodology's accuracy to the approaches that are currently in use. The accuracy rates for SVM, and LSTM-GAN were 92.50%, and 95.0%, in that order. By utilizing biomechanical analysis and deep learning approaches, the suggested method, DK-LSTM, maximizes physical movement and effectively improves physical education outcomes with a 98.3% accuracy rate.

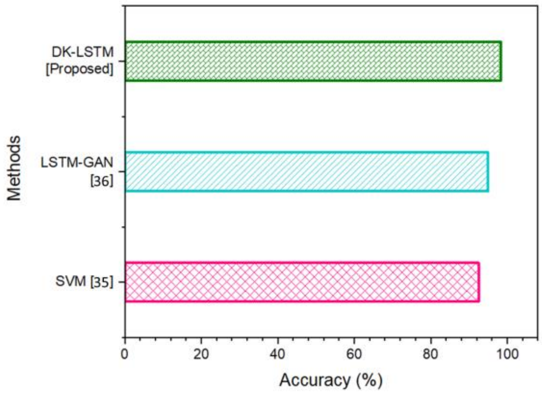

Figure 6. Performance evaluation of accuracy rates for various models, with DK-LSTM.

4.4. F1-score

A single score that achieves a balance between recall and accuracy captures the model's ability to accurately detect motions in physical teaching movements while lowering false positives and negatives. To ensure consistent performance and feedback while assessing instructional actions in physical education, a high F1 score is necessary. **Figure 7** displays the F1-score rates for the traditional approaches, which are SVM (92.90%), and LSTM-GAN (94.5%). In contrast, the F1-score obtained by the proposed DK-LSTM method is 98%. These results show that the proposed solution improves the optimization of instructional motions in physical education by outperforming current methods. **Table 3** provides a detailed display of the F1-score, recall, accuracy, and precision measurements.

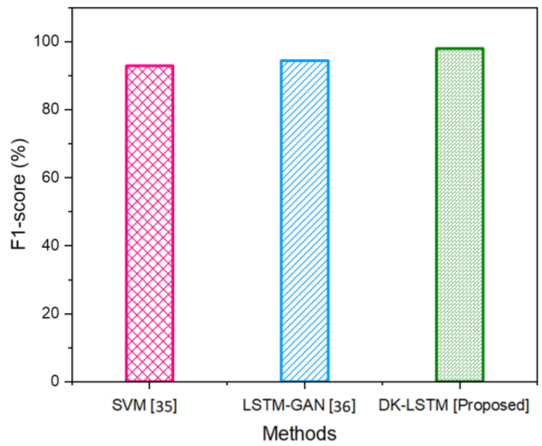

Figure 7. F1-score's performance evaluation for DK-LSTM compared with existing methods.

Table 3. Performance metrics illustrating the effectiveness of the DK-LSTM model with existing techniques.

Methods	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
SVM [35]	94.2	91.8	92.9	92.5
LSTM-GAN [36]	92.1	94.5	94.5	95
DK-LSTM [Proposed]	95.3	96.7	98	98.3

5. Conclusion

The research demonstrated the use of a DK-LSTM model to enhance handball-specific movement identification and optimization in PE. Six action categories were successfully distinguished datasets utilizing advanced detection and tracking techniques. The approach yielded impressive outcomes that showed significant improvements over traditional methods in the identification of movement. Measures such as accuracy (98.3%), precision (95.3%), recall (96.7%), and F1-score (98%) demonstrated the model's dependability in identifying PE movements. The outcomes show how PE techniques can be enhanced by combining DL and biomechanics. The suggested DK-LSTM model exhibited notable advancements in movement identification, yet it has limitations as well, such as its reliance on a particular dataset that might not accurately reflect the wide variety of PE and ability levels found in PE. The generalizability of the model may also be impacted by changes in the dataset's potential biases and environmental variables. Future studies ought to concentrate on broadening the dataset to incorporate a greater range of motions and situations, investigating the incorporation of real-time data from wearable sensors, and evaluating the model's suitability for use in other sports and educational settings.

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Abbreviations

Full form	Abbreviation
Physical education's	PE
Histogram of Orientated Gradients	HOG
Deep learning	DL
New Physical Education	NPE
Long Short-Term Memory	LSTM
Dynamic Kepler refined Long Short-Term Memory	DK-LSTM
Traditional curriculum design	TCD
National development	ND
Youth health issues	YHI
Dynamic Kepler	DK
Machine learning	ML
Artificial intelligence	AI
Internet of Things-driven Physical Activity Recognition System	IoT-DPARS
Internet of Things-integrated virtual reality system	IoT-IVRS
Recurrent neural network	RNN
Input gate	IG
Output Gate	OG
Forget gate	FG
Input layer	IL
Output layer	OL
Back Propagation Algorithm of Time	BPTT
Local Escaping Operator	LEO
Euclidian distance	ED
Virtual teaching	VT
Control group	CG
Nikolai Bernstein's theory	NBT
Virtual reality technology	VRT
Virtual Model Illustrating Nikolai Bernstein's Theory of Movement Construction	VMINBTMC
Physical activity	PA
Player modeling and recommender systems	PMRS
Support vector machine	SVM

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