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Article

Research on the application of biomechanics analysis in optimizing physical education movement techniques

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Abstract: College and university students' general health, fitness, and well-being are greatly enhanced by physical education. As various educational institutions work to improve the efficacy of their physical education programs, more evidence-based techniques are required. Biomechanics, to the movement or structure of student activities, provides insights into the efficiency and effectiveness of physical movements. This study aims to explore how physical activity movement skills can be systematically improved by the use of biomechanics analysis, leading to improved physical results and increased student participation in sports and fitness activities. In this study, a novel synergistic fibroblast-optimized malleable convolutional neural network (SFO-MCNN) is proposed to enhance teaching practices using a biomechanical framework that integrates movement analysis. The data collected from cameras that record students' movements, capturing joint angles and body positions, as well as data from sensors are gathered from the Kaggle. The data was preprocessed using data cleaning and normalization for the obtained data. A system for assessing instruction quality was created using the suggested model and improved SFO. The findings show that the proposed algorithm has the greatest evaluations for average skill performance, physical fitness, student happiness, and physical education teaching efficiency. By comparing the outcomes with those of conventional approaches, the effectiveness of the proposed framework in improving physical education teaching techniques has been established.

Keywords: physical education; biomechanics analysis; movement; synergistic fibroblast optimized malleable convolutional neural network (SFO-MCNN)

1. Background of the study

Modern technical improvements have led to a significant development in the domain of sports biomechanics [1]. The continuous advancement of technology has enabled more effective assessment of the instabilities involved in an individual's motion, thereby improving the accuracy of motion measurement. Physical activity biomechanics is a field of applied biomechanics with the main objectives of lowering the risk of injuries, designing efficient training methods, and improving physical activity operations through investigation and examination of the movements utilized by professional performers [2]. The process that offers quantitative evaluations of sports performance, namely the kinetic and kinematic properties of physical movements is known as sports biomechanics. Measuring and categorizing human movements during physical activity is an essential part of coaching programs to evaluate player performance, enhance technique, and reduce injuries [3]. Physical activities requiring maximum effort over a limited amount of time by employing the utilization of non-sport-specific training techniques to build neuromuscular strength certain to the activity can improve performance in a competitive cognitive activity. Strength training is consequently observed as a crucial component of athletes' physical preparation. Exercise activities that increase the neuromuscular skeletal system's ability to generate strength are known as strength training [4]. Biomechanics is one of the techniques, used in numerous fields, including sports or fitness technology that combines human anatomy and Newton's laws of physics. A required course in biomechanics can be completed by student physical activity movement [5]. The ability to quantify a wide range of movement metrics made available by the latest technological advancements in phones has been utilized by the physical activity and sports-related industries. Many kinds of integrated sensors and functions are included in a large number of mobile phones [6]. To improve sports performance through improved technique, private sports training facilities are investing more in biomechanical stimulation technology [7]. Injuries to the muscular and skeletal system, particularly to the elbow and shoulder, are common in throwing sports, which are established in recreational activity [8]. Kinematics has dominated sports biomechanics research for an extended period. Considering its distinct benefits and fitness values, the running movement engages individuals from numerous corners of society. The knee joint is more infected, and athletes frequently have varying degrees of injury. Running is not possible without both muscle tension and relaxation. There exists no possibility to perform high-speed running without regularly alternating between muscular stress and relaxation exercises [9]. Human movement is introduced in college biomechanics classes through the basics of traditional mechanics, movement control, neural control, and anatomy [10].

Aim and contributions of this study

To improve physical outcomes by increasing student involvement in sports and fitness activities, the objective of this research is to investigate how movement abilities in physical education can be effectively improved through the application of biomechanics analysis. To improve teaching methods, it introduced a unique synergistic fibroblast-optimized malleable convolutional neural network (SFO-MCNN) in this study. It incorporates movement analysis into a biomechanical framework.

- The proposed SFO-MCNN is developed in the research to enhance the teaching practices with the biomechanics to predict the movement analysis.
- The data are gathered from the open source Kaggle and the gathered data are pre-processed by using the *z*-score normalization.
- Feature extraction is performed by employing the Fourier transform (FT) and it performs in the processed data.
- Factors such as average skill performance, physical fitness, student happiness, and physical education teaching efficiency are evaluated in this research.
- The proposed technique is compared with various existing techniques to show the effectiveness of physical activity movement education.

Writing framework: The relevant articles are presented in phase 2. The proposed methodology is explored in phase 3. Phase 4 demonstrated the performance evaluations and discussions. Conclusions and future scopes are provided in phase 5.

2. Relevant articles

Zulkifli and Danis [11] determined the evaluation program with the coach's eye movement for operating the combination with a smart device used in physical education. The findings of the research could improve student engagement, educational value, and content value. Zhang et al. [12] performed an interventional study within the artificial intelligence (AI) framework that focused on the exercise and overall strength. To develop a virtual sports simulation teaching mode, it suggested utilizing AI's Kinetic algorithm with virtual simulation technologies. Based on the examination and study of students' overall quality, the findings indicated that the total number of students who were qualified or not qualified is established by the overall quality. The motivation and effects of learning among college students were examined by Chu et al. [13], for the sports education model's application to physical education. Findings demonstrated that the students intended to engage actively in learning and modify their sports behavior positively, resulting in a highly effective sports education framework. Li and Li [14] investigated how sports training and teaching in colleges have grown in combination to create a framework for evaluating sports teaching efficiency. The study findings presented that it could identify different behavior patterns and has an average rate of detection in utilizing standard motion identification of patterns. The benefits of the concept of multiple abilities in physical education were completely reflected by examining the framework and content, Xie and Xu [15] developed the teaching framework by employing established techniques and fuzzy mathematics with the idea of multiple intelligences. Experimental results indicated that the numerous intelligences theory-guided teaching approaches had been modified to the intelligent features of the pupils. The distributed badminton agility training device described by Tan et al. [16] consists of Android software and an embedded system. Free distribution, real-time full reaction time display, and wireless communication and connection were all possible with technology. The trial individuals were split into two groups: one that utilized the technology for agile training and the other that employed agile training methods. Among college students attending physical education programs, Huang et al. [17] established the Lower Quarter *Y*-Balance Test (YBT-LQ) is an effective predictor of sports injury risk. It investigated the relationship between physical activity and athletic achievement. Sports performance and physical activity could have an impact on an individual's capacity to maintain their balance dynamically. To capture motion data using the machine vision principle, Lin and Song [18] developed the model needed for human motion capture. Colleges and institutions' standards for teaching physical education were examined and the algorithm transformed action recorded results in visual data for system accuracy assessment. It enhanced the field of college sports teaching by applying machine vision technology to capture system design in sports education. Tang [19] investigated the mechanics of the physical movements utilized by athletes during competition, taking into consideration fundamental principles of physical activity and relevant research. It could suggest the specific methods of execution for leveraging the regulations of mechanics to improve athletes' skills and make it possible to effectively demonstrate personal abilities and maximize the significance of sporting activities. To attain superior results and the intended outcomes to significantly enhance the total strength of the players. The investigation of the muscle activation during forward bending and its relation to the inactivity of physically active students was described by Zawadka et al. [20]. The results demonstrated that in the task of assessing the lumbar spine's velocity in squats, the lumbar-pelvic ratios in the highest sitting category were significantly stronger compared to the low sitting category. The validation of convergence among functional motions tests and fundamental motion abilities was examined with the huge samples in adolescents examined by O'Brien et al. [21]. The findings suggested in the object management category of basic movement skills, boys probably demonstrate greater real motor competence levels than girls. It discovered a highly probable relationship between the locomotor category with basic movement abilities and the overall scores on the functional movement screen. Two distinct course designs' implementations of AL for biomechanical concept learning were compared and examined by Wallace and Knudson [22]. The study aimed to determine whether the course design had an impact on students' assessments of learning theory and learning factors. The effects of the course format were found to have mixed outcomes and students' assessments of the characteristics of learning biomechanics showed a single major distinction, and the assessments of AL showed a significant variation. These findings need to be established, and any possible relationships with the attitudes and traits of the students could be investigated. Fernández-Vázquez et al. [23] explored how the physical teaching style (PTS) and gamification affected students' perceived effort and movement skills during physical education. Perceptions from participants indicated that the estimated effort and movement skills were influenced by the type of activity, competition, and benefits. It discovered that paired with virtual reality (VR), gaming techniques could improve motor skill development and decrease the effort required in physical education classes. Ochia [24] designed to inform students about the possibilities for developing a hybrid or online upper-level biomechanics classroom that corresponded to the primary goals of the class. Whereas an all-digital presentation cannot troubleshoot mechanical experimentation, numerous biomechanical methodologies and experimental designs were maintained. In physical education, task progression occurs when activities have been developed to provide students with a physical activity curriculum progressively and successively, resulting in increased performance and comprehension with more sophisticated skills. Ward et al. [25] described the research on instructional tasks, subject comprehension, and content development, and then utilized it to investigate the idea of functioning models as a method of instruction in physical education. It concluded the implications for learners, instructors, instructors, and researchers. It offered the propositions to assist in developing effective models.

Research gaps

Considering the advancements made in biomechanics, AI, and movement analysis, there are an extensive number of issues in physical education. To produce more immersive and customized training indicated the need for more thorough research combining biomechanical analysis with immediate-time AI algorithms. Whereas the applications, such as machine vision models and the broad influence on improving patterns in a variety of sports remain unclear. More empirical support is required for the relationship research findings between biomechanical optimization and long-term physical education outcomes like student motivation, skill retention, and injury prevention. VR, gamification, and other technology-driven teaching techniques have a lot of potential, and it needs more research to determine how they can be effective with various student populations. The inconsistent course design outcomes for biomechanics education indicated the need for improved methods of instruction to provide consistent learning that could significantly improve the physical education optimization based on biomechanics. The combination of real-time biomechanical data with an AI-based algorithm known as SFO-MCNN resolves the existing difficulties by enhancing specific instruction and movement techniques. The proposed SFO-MCNN presents a more effective approach by utilizing extensive movement data and ML to provide useful data for enhancing the overall physical education results, injury prevention, and skill retention.

3. Proposed methodology

In this phase, the dataset description, pre-processing of data, feature extraction, and the proposed methodology were determined and the phases of the proposed methodology are demonstrated as shown in **Figure 1**.

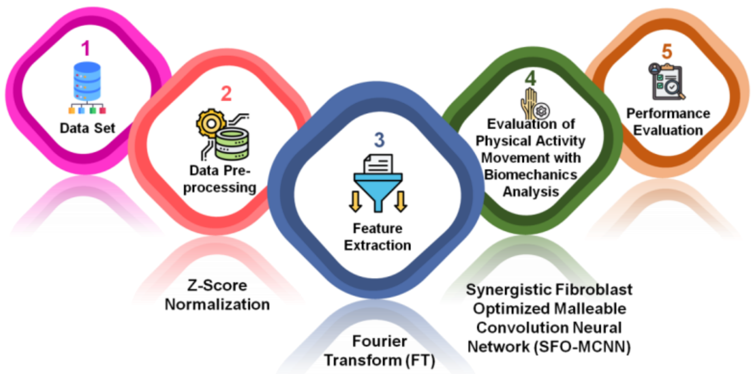

Figure 1. Phases of proposed approach.

3.1. Database description

The data were gathered in the open-source Kaggle [26]. The dataset contains a thorough collection of 10 different bodily postures linked with five common exercises: squat, jumping jack, push-up, pull-up, and sit-up. Each exercise is distinguished by terminal positions including the "up" and "down" states for push-ups allowing for detailed analysis movements dynamics. This extensive dataset was methodically compiled from over 500 recordings of individuals doing these physical activities, laying the groundwork for future research. To compile this dataset, a primary Python script was used to systematically extract relevant video footage from various YouTube links featuring those specific exercises. The extraction mechanism ensures that at least two frames are video are captured, accurately depicting each workout's starting and ending positions. These extracted frames serve as critical reference points for analysing final positions, allowing for a thorough examination of the biomechanics and general performance characteristics associated with each movement. By documenting these exercises through video analysis, the dataset aims to provide useful insights regarding physical activity patterns, informing training strategies and performance optimization techniques.

3.2. Data preprocessing through Z-score normalization

The process of organizing, cleaning, and converting unprocessed data into machines that can read is known as data preprocessing. It occurs prior to evaluating data or neural network modeling and it is a crucial stage in data analysis and data management measures. The data preparation technique of normalization enhances the reliability and effectiveness of the technique using neural networks to convert the information into the collection of data to a common scale. Reducing any biases caused by the different feature scales is the primary objective of normalization.

The process of normalizing data by reducing features that correspond to a conventional normal distribution is called Z-score normalization, or standardization. It is essential to numerous linear models and other techniques to consider normally distributed data. The Z-Score normalization method restructures a dataset in its average is equal to 0 and its standard deviation (SD) is equal to 1. Similarity between various variables or factors is frequently employed in ML and statistics. The Z-Score normalization equation for the data point a is as follows (Equation (1)).

$$U = \frac{a - \mu}{\sigma} \tag{1}$$

The standard value is represented by U. a is the first set of data. μ used to denote the mean, or average, of the dataset. σ is the symbol for the dataset's SD.

3.3. Extracting features by utilizing Fourier transform (FT)

The Fourier transform (FT) approach is used to achieve the feature extraction. The suggested models for tracking and assessing student behavior can perform significantly improved when feature extraction utilizing the FT is utilized to analyze the frequency elements of motions in physical education. By modifying the time-domain signal, FT generates a frequency-domain representation that allows for the analysis of frequency components found in the data, such as angular velocity or acceleration. This is performed as comprehending the biomechanics of physical activity depends on these circumstances. Equation (2) describes how to represent the constant FT of the time-domain signal $Y(s)$.

$$y(e) = \int_{-\infty}^{\infty} Y(s) f^{-j2\pi ds} ds \tag{2}$$

The $y(e)$ represents the FT of a signal, $Y(s)$ represents a time-domain signal, e represents frequency, and s and j represent time and intermediate units. When examining how students move during physical education, joint angles are represented throughout time using a signal denoted by $Y(s)$. Equation (3) is used to extract the characteristics following the application of the FT.

$$Mean\ Frequency = \frac{1}{n} \sum_{k=0}^{n-1} |y[k]| \tag{3}$$

The model can become more effective in identifying and anticipating student movements by including these acquired frequency features in the proposed component. It can enhance the monitoring and feedback systems in physical education environments.

3.4. Evaluation of biomechanics analysis in optimizing physical education movement techniques by employing synergistic fibroblast-optimized malleable convolutional neural network (SFO-MCNN)

To assess the optimization of physical movement techniques with biomechanics analysis, the deep learning techniques called SFO-MCNN, which incorporates the malleable convolutional neural network (MCNN) and the synergistic fibroblast-optimization (SFO).

3.4.1. Malleable convolutional neural network (MCNN)

Deep neural networks (DNN) include MCNN. It corresponds to the category of supervised DL models. MCNN is initially implemented using the sequential model. A model is produced layer by layer. It generates a prediction network using four separate layers. To verify the output neurons connected to the input, a second layer called a convolution layer is established. The convolutional layer input is $n \times o$. Where o is the matrix's width and n is the height. When a matrix's dimension is smaller than the dataset, the kernel size is employed as a filter. The feature mapping function is provided. In this instance, the kernel size or filter for feature mapping. The network's connected structure is provided by the filter's size. $ReLU$ is computed using Equation (4) and utilized as an activation function. $ReLU$ receives an input data point, a, and returns 0 (the default value) when the input is negative and returns the identical value alternatively.

$$ReLU(a) = max(0, a) \tag{4}$$

The network uses max-pooling as a third layer to provide a small-valued matrix. For instance, maximum pooling selects the greatest values among numerous matrices. Then use the information to create a tiny matrix. Equation (5) provides the formula to determine the convolutional layers output size O with N as input, e filter and padding q, and stride s.

$$O = \frac{N+2q-e}{S} + 1 \tag{5}$$

In the following example, N is the size of the input, e is the number of filters, and q is padding. The dropout layer is used for the last layer to avoid the issue of over-fitting. To create a single, interconnected layer, all of the neurons are smashed. The application of dense layers to carry effective categorization is the next step. Nodes are interconnected with one another. Neuron loss rate value is found with early prevention. A network in an optimal state gets a further examination when the early stopping attempts to determine the loss rate. To prevent an over-fitting issue, it applies the thick layer again and proceeds to the dropout layer. The prediction's outcome is finally displayed in the output layer.

3.4.2. Synergistic fibroblast-optimization (SFO)

A bio-inspired computer program called SFO was created by deriving inspiration from the cognitive actions of the fibroblast cells, which are physical entities involved in the process of sports movement wound healing in the skin. The extracellular matrix (ECM) has discrete units of cells and continuous units of formation of collagen, which makes the SFO algorithm. Body movement and distinct body positions and velocities are constantly needed to find the ideal solution in the n-dimensional solution field. The movements are randomly selected for the iterations of biomechanical analysis, and the fitness is assessed using the physical activity movement evaluation. The results are compared to the optimal $solution\ best_{-1}$ or the prior best. Considering the updated position and velocity equation, the movement with the highest value is considered the best solution (the current optimum) and determines the next movement in the evolving region.

The biomechanical analysis modification is updated by the ECM with each cycle. The movements are continuously developed by a randomly selected student assessment from the movement matrix to produce the global optimum (the minimum or maximum). Fibroblasts are dispersed over the specified physical coordinates, slowly gathering to find the optimal solution and preventing the prediction in movement difficulties from getting stuck in the local optimum. It includes a description of the SFO algorithm. Movements have to maintain join variety in a limited field and gradually converge to the optimal solution by the parameter, which is formed of movement speed (t) and diffusion coefficient (ρ). Fibroblasts could have movement-based techniques that utilize existing sources of information to move the search forward with modifications. The ability of fibroblasts to recover from wounds through interaction and self-adaptation is strongly linked to the use of evolutionary algorithms in the search field to find the wide optimum.

- Initialization: In the $N-\text{dimensional}$ solution space, initialize the number of physical activity movements $e_j, j = 1, 2, \dots, N$, with a random position (a_j), velocity (u_j), and biomechanical application. Factors like diffusion coefficient (ρ) values and movement speed (t) are established.
- Fitness function: Apply the fitness function $f(e_j)$ in n variables for n iterations, to assess each physical activity movement of students. To identify the ideal (maxima or minima) solution in the evolution area, a cell can be modified. Equations (6) and (7) can be used to update a movement's position (a_j) and velocity (u_j).

$$u_j^{(s+1)} = u_j^{(s)} + (1-\rho)d\left(e_j^{(s)}, s\right) + \rho * \frac{e_j(s-\tau)}{\left\|e_j(s-\tau)\right\|} \quad (6)$$

where s is the current interval, τ represents the time lag and $\rho = 0.5$.

$$a_j^{(s+1)} = a_j^{(s)} + t * \frac{u_j^{(s+1)}}{\left\|u_j^{(s+1)}\right\|} \quad (7)$$

where, $t = \frac{t}{l_{or}K}$, $l_{or} = 10^3\ \mu/min$, and K indicates the movement length.

Modification of biomechanical analysis is improved in the physical activity movement, once the maximum numbers of iterations or predefined conditions are satisfied. To improve teaching methods using a biomechanical approach that incorporates movement analysis, with the SFO-MCNN technique. By collecting the biomechanical data, the proposed SFO-MCNN allows for immediate input and improves the reliability of movement analysis. Through effective movement modification and customized training, it assists in optimizing the physical techniques, enhancing the performance of students, and lowering the risk of injuries in the students. Algorithm 1 depicts the SFO-MCNN.

Algorithm 1 SFO-MCNN

Import numpy as np
Import math
ReLU Activation Function $ReLU(a) = max(0, a)$
Def $ReLU(a)$:
Return np. maximum $(0, a)$
Convolution Layer Output Size $(N + 2qe + 1)^2$
Defconv_output_size(N, e, q):
Return $(N + 2 * q - e + 1) ** 2$
Max Pooling
DefMax_pooling (matrix, pool_size):
pooled_matrix = np. Zeros $((matrix.shape[0]//pool\_size, matrix.shape[1]//pool\_size))$
For j *in range (*$0, matrix.shape[0], pool\_size$*):*
For i *in range (*$0, matrix.shape\ [1], pool\_size$*):*
pooled_matrix [i//pool_size, j//pool_size] = np.max $(matrix\ [i: i + pool\_size, j: j + pool\_size])$
Return pooled_matrix
DefSFO_algorithm($N, max\_iterations, diffusion\_coefficient, movement\_speed$*):*
Initialize random positions and velocities for the fibroblast cells
Positions = np. random. rand (N)
Velocities = np.random. rand (N)
For iteration in range ($max\_iterations$*):*
For i *in range (N):*
Update velocities and positions
$u_j^{(s+1)} = u_j^{(s)} + (1 - \rho) d\left(e_j^{(s)}, s\right) + \rho * \frac{e_j(s-\tau)}{\|e_j(s-\tau)\|}$
$a_j^{(s+1)} = a_j^{(s)} + t * \frac{u_j^{(s+1)}}{\|u_j^{(s+1)}\|}$
Apply fitness function to assess movement quality
Fitness = np. add (positions)
Check termination condition
If iteration =$max\_iterations - 1$*:*
Break
Return positions, fitness
output_size = conv_output_size(N, e, q*)*
Print (f "Convolutional Layer Output Size: {output_size}")
Generate a random input matrix and apply $ReLU$ *and* $Max\ Pooling$
input_matrix = np. random. randn(N, N*)*
$ReLU$ *_output =* $ReLU$ *(input_matrix)*
pooled_output = max_pooling (relu_output, pool_size)
Print (f "Max Pooled Output: {pooled_output}")
optimal_positions, fitness = SFO_algorithm
$(N\_fibroblasts, max\_iterations, diffusion\_coefficient, movement\_speed)$
Print (f "Optimal Positions: {$optimal\_positions$*}")*
Print (f "Final Fitness Value: {$fitness$*}")*

4. Experimental results

In this section, the implementation details, evaluation criteria, performance evaluation of factors related to teaching physical activity movements among students, and comparison phase are explored.

4.1. Implementation details

The system configurations with Python simulation setups are employed to perform the prediction of physical activity movement with the application of biomechanics. **Table 1** explores the system configuration.

Table 1. System configuration.

Components	Descriptions
Programming Language	Python 3.8
RAM	32 GB
OS	Windows 11
Processor	Intel Core i7
Development Environment	Jupyter Notebook

4.2. Hyper parameters

The hyperparameters utilized in the research are demonstrated in **Table 2**.

Table 2. Hyper parameters.

Hyper Parameters	Description	Range
Input size (N)	Size of the input data matrix of the convolutional layer.	Dataset dependent
Kernel size (e)	Size of the filter applied in the convolutional layer for feature extraction.	Variable (based on the data)
Padding (q)	Padding is applied to input data before convolution to the main dimension.	Dataset dependent
Active function	It is applicable in the hidden layers to introduce non-linearity.	$Relu$
Dropout rate	The rate at which neurons are dropped out during training to over-fitting.	Variable (0.2 to 0.5)
A mount of layers	The total amount of layers in the MCNN	Four layers
Pooling technique	It is utilized to minimize the spatial dimensions of the feature maps.	Max pooling
Learning rate (k)	The speed at which the model learns during the training.	Dataset dependent (between 0.001 to 0.1)
Filter count	A mount of filter applied in the convolutional layers.	Variable (based on task)
Fitness function (f)	The objective function is applied to measure the movement fitness (maximum or minimum).	Task-dependent
Movement speed (t)	Speed parameter for optimization in the biomechanical model.	Variable
Diffusion coefficient (ρ)	Coefficient controlling the diffusion of the fibroblast movement across the solution space.	0.5
Time lag (τ)	The time interval between the current movement and the previous movement.	Variable
Iteration limit	Maximum intervals of iterations for the optimization process.	Predefined or dataset-dependent
Loss function	Function to evaluate the model loss and optimize the movement.	Cross-entropy
Optimizer	Optimization algorithm for training (employed with the SFO for biomechanical analysis).	-
Batch size	A mount of samples processed at once during the training.	Variable (commonly 32 to 128)
Epochs	A mount of complete passes through the training dataset.	Variable (frequently with 10 to 100)

4.3. Evaluation criteria

The evaluation criteria assess the performance of physical activity movement teaching with the factors and the comparison phase is examined in the following.

4.3.1. Performance evaluation

This section demonstrates the evaluation of physical activity movement teaching with average skill performance, physical fitness, participation rate, student happiness, and physical education teaching efficiency (**Table 3** and **Figure 2**). Physical fitness had a score of 96.8%, suggesting that it is highly effective in improving students' fitness levels. Student Happiness, at 95.7%, demonstrates the beneficial effect of instructional approaches on students' enjoyment of activities. The average skill performance score of 97.5% shows significant advances in students' physical competencies, while physical education teaching efficiency scored an astounding 98.5%, indicating exceptional productivity and effectiveness in teaching methods. Overall, the table illustrates beneficial ways for promoting health, well-being, skill development, and teaching efficiency in physical education.

Table 3. Performance of the physical activity movement teaching.

Factors	Percentage (%)
Physical Fitness	96.8
Student Happiness	95.7
Average Skill Performance	97.5
Physical Education Teaching Efficiency	98.5

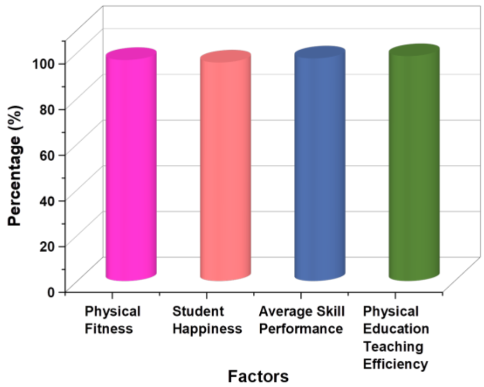

Figure 2. Factors in physical activity movement teaching.

4.3.2. Comparison phase

The comparison between the proposed SFO-MCNN technique and existing techniques like attention-based long short-term memory and LSTM (ALSTM-LSTM) [27] and residual network (ResNet34) and attention mechanism [28] is evaluated by utilizing various matrices like recall, accuracy, $F1$-score, and precision. SFO-MCNN had a recall of 95%, suggesting robust detection capabilities, and a remarkable $F1$-score of 96.2%, indicating a good combination of precision and recall. It also achieved a high precision of 97% while minimizing false positives, and a total accuracy of 98.5%. In comparison, ALSTM-LSTM showed a 94% recall, 94.9% $F1$-score, 95.3% precision, and 95% accuracy. ResNet34 had a lower recall of 85.9%, 84.1% precision, and 90.8% accuracy. Overall, SFO-MCNN outperforms the existing approaches across all criteria, demonstrating its effectiveness in the proposed application. The outcomes of proposed and existing techniques which are examined in **Table 4**.

Table 4. Outcomes of proposed and existing techniques.

Techniques	Recall (%)	*F*1-score (%)	Precision (%)	Accuracy (%)
ALSTM-LSTM [27]	94	94.9	95.3	95
ResNet34 and attention mechanism [28]	85.9	-	84.1	90.8
SFO-MCNN [Proposed]	95	96.2	97	98.5

Accuracy is the term used to describe how biomechanical analysis optimizes movement strategies during physical exercise. Accuracy refers to the model's ability to correctly anticipate the most effective physical movements and approaches for improving performance levels in physical exercise. In "physical education movement techniques", accuracy parameters refer to measurements used to evaluate the accuracy and correctness of movement techniques. Kinematic correctness analyses movement alignment and execution, while kinetic accuracy examines the forces involved. Accurate biomechanical analysis is crucial for improving performance and lowering injury risk in physical education. Equation (8) shows the accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

The proposed SFO-MCNN technique outperformed the existing techniques by providing 98.5% accuracy. Whereas ResNet34 provides 90.8% and ALSTM-LSTM determines 95% of accuracy. The outcomes of the accuracy are demonstrated in **Figure 3**.

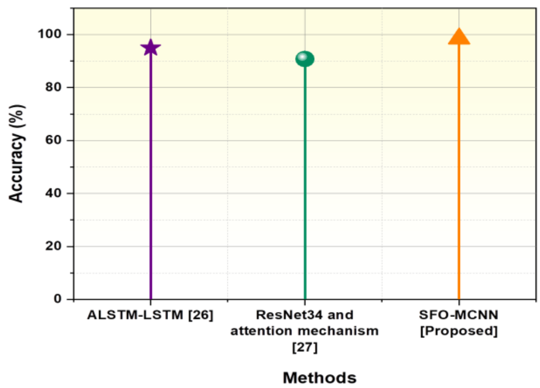

Figure 3. Graphical representation of accuracy.

Recall is defined as the system's ability to detect every true optimal movement strategy inside the dataset. **Figure 4** shows the recall analysis findings, demonstrating the model's effectiveness in recognizing all positive motions made by pupils during physical activities. The recall findings are detailed in Equation (9). Recall parameters assess a biomechanical analysis' capacity to successfully identify and recall important movement data. This statistic measures how well the analysis catches successful executions of movement approaches, ensuring that all instances of optimal performance are recognized. High memory is required for effectively assessing and improving physical education methods with specific biomechanical insights.

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

Results of recall provided ALSTM-LSTM has 94%, ResNet34 has 85.9% and the proposed SFO-MCNN has 95%. Thus, the results showed that the proposed SFO-MCNN improved more than the existing techniques. The results of the recall are shown in **Figure 4**.

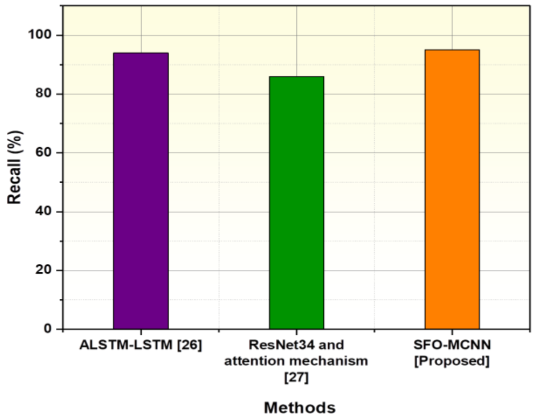

Figure 4. Visual depiction of recall.

Precision is defined as the proportion of true positive forecasts to all positive predictions. In the context of improving student performance in physical activity movement teaching, precision assesses the proportion of ideal movements that are both useful and correct. Precision parameters measure the accuracy of detecting successful movement executions. This metric computes the ratio of successfully identified optimal movement instances to the total number of detected instances. High precision shows that biomechanical analysis efficiently distinguishes between successful and failed strategies, allowing for focused adjustments and improving the overall quality of movement performance in physical education environments. The formula to calculate the precision is determined in Equation (10).

$$Precision = \frac{TP}{TP + FN} \tag{10}$$

In physical activity movement teaching performance, the precision of the proposed SFO-MCNN provided efficient results with 97% and it is superior to all other existing methods like ResNet34 (84.1%) and ALSTM-LSTM (95.3%). **Figure 5** illustrates the visualization of precision outcomes.

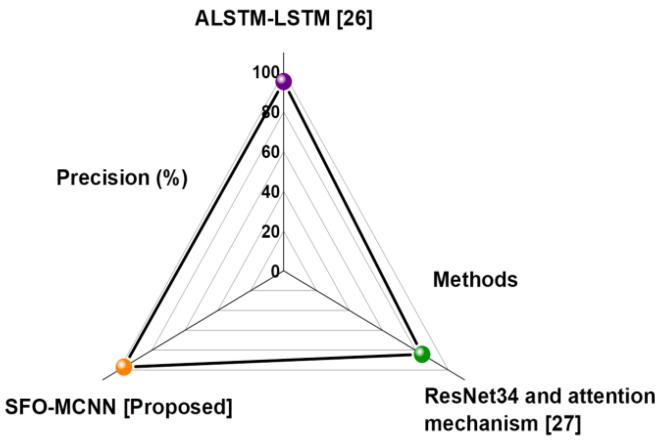

Figure 5. Outcomes of precision.

The $F1$ score shows a balance between recall and precision. This metric is most useful when the two metrics are equally significant or when the class distribution is unequal because it creates a balance between them. The $F1$ score combines precision and recall to give a complete picture of model performance. It is the balanced level of precision and recall, emphasizing the analysis's ability to discover optimal movement strategies. A high $F1$ score implies a great ability to detect successful motions while reducing false positives and negatives, which is critical for effective optimization. $F1$-score is measured by the Equation (11).

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{11}$$

The comparison between the proposed and existing methods is performed in the evaluation of the $F1$-score. The existing technique ALSTM-LSTM provides 94.9% and the proposed SFO-MCNN presents 96.2% of $F1$-score. From the comparison results, the proposed method shows improved performance in the field of teaching physical activity movements among college students. The comparison of proposed and existing methods in evaluating the $F1$-score is represented in **Figure 6**.

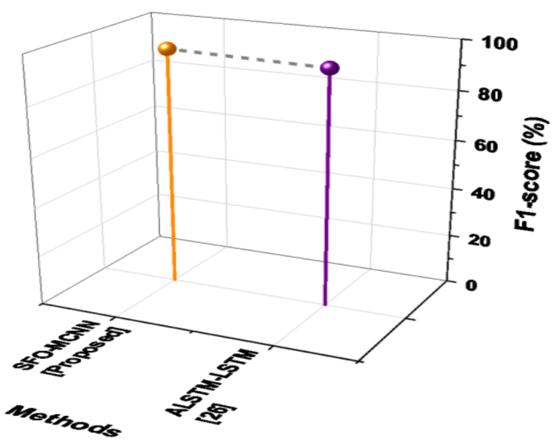

Figure 6. Results of $F1$-score.

4.4. Discussion

The excessive dependence on online video information and DL algorithms, which could not properly represent all the biomechanical complexities of physical education activities, are among the limitations of the ALSTM-LSTM technique. Its wider applicability is limited by the reality, that the results are based on the established educational environment. An important drawback of ResNet34 is its predominant emphasis on virtual learning could not incorporate the intricate details of biomechanics evaluation in enhancing the standard physical activity teaching techniques. When the system is flexible, constant evaluation may face challenges in assessing the minimal biomechanical movements during various physical activities. These limitations are resolved using the proposed SFO-MCNN technique by its versatility in managing various physical activities, it provides thorough movement estimation, eliminating issues with the least amounts of biomechanical movements, and presenting a more extended applicable solution for a range of educational environment and student information.

5. Conclusion

Physical education improves the overall health, fitness, and well-being of college and university students significantly. Colleges and universities are developing more methods based on research to improve the efficacy of physical education applications. Biomechanics offered observations about the efficacy and efficiency of movement in the body, which could be applied to the students, move or organize their activities. It examined how the use of biomechanics analysis in physical education could sequentially develop movement skills, resulting in better physical outcomes and higher student participation in sports and fitness activities. To improve teaching methods utilizing a biomechanical framework that incorporates movement analysis, the research suggested an innovative SFO-MCNN technique. The dataset from open source was employed in the research. Data normalization for the acquired data and data cleaning by employing Z-score normalization were used in the preprocessing stage. Essential features are extracted through the FT technique. Improved SFO and the proposed model were used to develop a system for evaluating the quality of education. Based on average skill performance, physical wellness, student happiness, and physical education efficiency, results showed that the proposed approach received the highest evaluations. The effectiveness of the technique for enhancing physical demonstrated by the comparison of traditional methods with various matrices like recall (95%), accuracy (98.5%), precision (97%), and $F1$-score (96.2%). The conclusion of the research examined that the proposed system is more effective in the field of teaching physical activity with biomechanics analysis to students. The limitations of this study include its reliance on certain datasets that may not fully represent the breadth of physical activities in various educational settings, as well as its emphasis on specific movement techniques. The efficiency of the proposed model may vary based on each learner’s specific talents. Further studies should include a broader spectrum of demographics. Examine additional biomechanical components and the long-term effects of improved movement techniques on students’ overall well-being and athletic performance. The incorporation of teacher assessment may improve the way biomechanics is used in the practical application of physical education.

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