Design and Implementation of Sports Network Teaching Platform Based on Discrete Similarity Method

Jian Cui
University of Perpetual Help System DALTA
Philippines

Lan Shi
Anshan Normal University, China
lanshiphd@gmail.com

Abstract: *Sport is the most important topic in education, which individually shows motor skills in health activities. Athletic training should focus graduates on sports, low-involvement task activities, and physical fitness or exercise. Teaching concepts and methodologies are innovative, coaching methods and procedures, evaluation of coaching sessions in sports-all this is accompanied by development in the sports hall and successful improvement of sports performance. Here, he provides extraordinary assistance to students by predicting early school leaving and improving the potential application of wireless platforms in sports programs and changing the nature of sports, including visualization and repetition, and incorporating it into sports training. A sports network learning platform based on the discrete similarity approach is proposed for design and implementation in this paper. First, data is collected from a real-time data set. After that, the data submitted for preprocessing removes noise and imperfect records, which can be removed using a global constant or a most likely learning method using an Adaptive Savitsky-Golay Filtering (ASGF) method. The preprocessing method is fed into the feature extraction utilizing Multi-Hypothesis Fuzzy-Matching Radon Transform (MHFMRT). MHFMRT extract statistical features such us kurtosis, variance, energy, mean and standard deviation. Then, the Similarity-Based Convolutional Neural Network (SBCNN) method is optimized by the Chaotic Satin Bower Bird Optimization (CSBBO) algorithm, which effectively classifies the visualization and a satisfactory training platform of the sports network. The proposed system is executed in the MATrix LABoratory (MATLAB) platform and the performance of the proposed methods attains 28.5%, 27.9% and 29.5% higher accuracy, 28%, 21% and 26.5% higher precision, 21.2%, 28.75% and 21.3% higher recall compared with the existing methods like Recurrent Neural model to analyze the effect of Physical Training and Treatment in Relation to Sports Injuries (PTT-RSI-RNN), recognizing Sports Activities from Video Frames using Deformable Convolution and Adaptive Multiscale Features (SAVF-DCN) and Sports Match Prediction model for training and Exercise using attention-based LSTM network (SMPE-LSTM) respectively.*

Keywords: *Adaptive savitzky-golay filtering, chaotic satin bower bird optimization, multi-hypothesis fuzzy-matching radon transform and sports network teaching.*

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1. Introduction

The biological foundation for the ongoing development of human functions is training adaptation [3]. Enhancing human functions is a key responsibility of sports training, and it is contingent upon the training adaptation process itself [16]. In order to ensure that the training task is completed, the body adapts its training to muscle activity by consuming the least amount of energy, causing the least harm to the internal environment, and maintaining a good of muscular energy resources [7]. This implies that tasks that once required a lot of effort can now be finished with less effort [26]. The body can now handle a higher workout load and exhibit improved physical capabilities [14]. The biological foundation for the creation of a competitive state is training adaptation; an extremely advanced training adaptation process leads to the construction of a competitive state in sports [11]. For the athletes' training adaptations in form, technology, tactics, quality, function and psychological state of each organ system to produce the competitive condition, they must have typically attained full capacity and harmoniously integrated into the entire [28]. But training anti-adaptive decline causes the competitive condition to momentarily vanish [9]. An athlete can regain their competitive status and improve their athletic performance by experiencing this type of anti-adaptive decline, which in turn enables the athlete's body to heal and create novel training adaptations [21]. Training adaptation serves as the biological basis for the theory of sports training, which is the synthesis and generalization of sports practice [6]. It serves as a guide for sports training practice and is founded on the objective rules of sports training [2, 22]. Theory of sports training cannot be confirmed by actual sports training, it cannot form a scientific theoretical framework, and it cannot serve as a guiding principle if it is founded on training adaptation and other aim principles of sports training [18]. The term "adaptation" describes the equivalent, long-lasting modifications to the structure and function of the human body brought about by sustained environmental change [1]. Applying exercise load is a technique used in sports training that primarily breaks the body's natural relative balance to elevate it to an elevated level of function and then restores it to a level appropriate for the applied exercise load. Training adaptation is the process of continuously adjusting the organism to the external environment that applies pressures as a result of sports training [32]. Training adaptation both raises and lowers the sensory threshold of many tissues and organs, including the nervous system, while also improving the body’s compensation mechanism [17]. The nerve-humoral pathway is primarily responsible for adjusting the training adaption process, and when this pathway functions better, the body produces the aforementioned adaptive modifications [29]. The way extracurricular sports are currently growing in universities is out of step with the needs; facilities and resources are not being used effectively; students lack technology awareness; and the extracurricular sport management model is not meeting expectations [13]. The various movement types of students are accommodated by traditional management strategies [30]. The difference between them will become more noticeable [12, 24]. The management of extracurricular sports in colleges and universities is careless and unscientific. Regular physical activity and extracurricular sports participation help kids assimilate classroom sports knowledge more effectively [19].

A limitation in utilizing Recurrent Neural Networks (RNNs) for sports training is managing long-term dependencies. One potential drawback of using RNNs for assessing complicated sports training data over long time periods is their propensity to have difficulty capturing relationships in very long sequences. Especially when working with limited training data, overfitting is a possible downside of employing Long Short-Term Memory (LSTM) networks for sports training. Complex models with a lot of parameters, LSTM networks are renowned for their capacity to identify long-term dependencies in sequential data. An LSTM can be shown to memorize noise or certain patterns in the training data that don’t translate well to new data when the training dataset is short or not sufficiently varied. Due to its overfitting, it reduced performance and accuracy when the LSTM model is applied to new sports training data or real-world scenarios.

To overcome these limitations, Simplified Needs Test-Simplified Bayesian convolutional Neural Network-Chaotic Satin Bower Bird Optimization (SNT-SBCNN-CSBBO) is proposed. Sports training can be revolutionized by using a Similarity-based Convolutional Neural Network (SBCNN) optimized with Chaotic Satin Bower Bird Optimization (CSBBO). SBCNN is perfect for assessing complex sports training sequences because of its spatial awareness and capacity to identify long-term connections in sequential data. Better generalization to unknown data is ensured by the model’s use of CSBBO, which helps to avoid overfitting problems that are frequent in existing networks. By efficiently optimizing network parameters and extracting statistical features from training data, this cutting-edge method improves performance. Sports training applications can achieve greater accuracy, flexibility, and efficiency in modelling and analysing training data thanks to the synergy between SBCNN and CSBBO.

Contributions can be abbreviated as trials:

- The proposed sports network learning platform introduces a novel integration of real-time data collection, adaptive savitsky-golay filtering, multi-hypothesis fuzzy-matching radon transform for feature extraction, and an optimized similarity-based CNN with CSBBO, achieving unprecedented sensitivity and transforming sports education through enhanced visualization and repetition techniques.
- The input data is initially gathered from a real-time dataset.
- The proposed method integrates multiple advanced techniques, including Adaptive Savitzsky-Golay Filtering (ASGF) for pre-processing. The pre-processed data undergoes feature extraction using Multi-Hypothesis Fuzzy-Matching Radon Transform (MHFMRT).
- MHFMRT extract statistical features such as kurtosis, variance, energy, mean and standard deviation. Extracted features are given to Similarity based Convolutional Neural Network (SBCNN) for classifying the visualization and a satisfactory training platform of the sports network.
- Unlike traditional SBCNN approaches, which lack optimization methods for computing optimal parameters, the proposed method incorporates CSBBO. CSBBO optimizes the weight parameters of SBCNN.

The following is the structure of the paper: the recent study findings and introduction are explained in chapters 1 and 2. Section 3 presents the suggested methodology. Parts 4 and 5 explain the results and recommendations.

2. Recent Research Work: A Brief Review

There was several research studies were presented sports network teaching platform based on discrete similarity method. Some of them were reviewed as here:

Dhanke *et al.* [5] have presented a RNN model to examine the impact of physical therapy and training on sports injuries. Within an Artificial Neural Networks (ANN), RNN was a subclass that makes use of neural nodes linked in a temporal sequence. A fundamental idea in this study was the temporal sequence, which was a data series of events that occur inside a particular time frame. A complex machine learning strategy that makes use of a neural schema similar to that of a person was called the recurrent neural model. This neural schema examines prior injuries to process the data it receives from the athletes or players. Sports injuries need to be studied since, in certain situations, they become so dangerous for the athlete that they could end up permanently disabled and lose their career. Occasionally, it could result in a significant loss for the team or business that employed the athlete. This technique attains high accuracy and low recall.

Zhang *et al*. [31] have presented an attention-based long short-term memory network was used to train and exercise a sports match prediction model. Around the world, sporting events are very popular. A sports match prediction can assist you understand the team's condition ahead of time and modify your approach as the game progresses. It was hard to predict a sporting event. Consequently, a strategy based on teams' past match data was put forth to forecast the outcome of the upcoming game. Established an AS-LSTM model for prediction by fusing the attention mechanism with the LSTM model. Low accuracy and great recall are achieved using this strategy.

Xiao *et al*. [27] have presented an Adaptive multiscale features and deformable convolution were used to identify sporting events from video frames. This research provides a realistic evaluation of intelligent real-time monitoring systems' suitability for use in different sports situations. Because capturing athletic events requires a lot of offline and real-time data, motion and activity detection has evolved. We expand on standard DL models to precisely recognize and assess human behaviour in sports by employing deformable learning techniques. Complex sports recording detection frameworks can benefit much from the system's robustness, statistical analysis, and efficacy. A thorough understanding of action recognition was crucial for sports administration and identification. Using a mixed deep learning approach, human activities and sporting events may be accurately classified. This method attains high accuracy and low F1-score.

Elnour *et al*. [7] have presented a model predictive control system based on neural networks for sports facilities' building automation and management systems optimization. With the help of an optimizer and a prediction element, the recommendation offers an integrated dynamic optimization technique that takes future system behavior into consideration while making decisions. A NN was contrasted with several machine learning models, like k-Nearest Neighbor (k-NN), Support Vector Regression (SVR), and Decision Trees (DT), in order to construct the dynamic prediction portion of the Mobile Passport Control (MPC) system. A part from providing suggestions for occupancy profiles to assist facility managers in monitoring their functioning, two models of the suggested NN-based MPC system are scrutinized for overseeing and refining the Heating, Ventilation and Air Conditioning (HVAC) system of the hall to enhance energy efficiency and indoor air quality. Low accuracy and a high F-score are achieved by this strategy.

Dan and Hu [4] have presented a study on an intelligent internet of things-based sports training model that uses data aggregation and processing. The computer multimedia simulation approach was used to build the mathematical model of body movement and human body sports training. An attitude change space quick exploration control-based design method was proposed for the sports training model. The kinematics and physical training models allowed for the quick extraction of feature information about the human body's position and attitude. The process of human sports training was simulated by multimedia picture analysis and intelligent control, which also analyzes the motion planning constraint factors in attitude change space to achieve the best possible control over physical training and body movement coordination. This method attains high precision and low Receiver Operating Characteristic (ROC).

Wang and Du [23] have presented an Optimization of sports training and training system based on Machine Learning (ML) and Internet of Things (IoT). In this research, machine learning and IoT technologies were combined to detect sports training features and action prediction, process sports training and training data, and create a machine learning and IoT-based sports training and training system. Through the optimization of the hidden layer mapping and parameter adjustment, this research gradually deals with some of the limitations of the original extreme learning machine in order to further increase prediction accuracy. Furthermore, Internet of Things (IoT) technology was used in this study to continually gather data over a long duration. Utilizing extreme machine learning, the condition of sports training was forecast following some processing. This method attains high ROC and low accuracy.

Meng and Qiao [15] have presented a dual-feature fusion NN analysis and design for a sports injury assessment model. An athlete often trains at a higher intensity level each day. An athlete who engages in this type of prolonged, high-intensity training was subjected to overload and physical and mental stress, which can result in sports injuries. These injuries prevent the athlete from engaging in high-intensity training, which prevents them from performing to their full potential in competition. An intelligent system was required in order to efficiently assess, forecast, and identify sports injuries. Motivated by the significance of NN for target identification, develop a novel dual-feature fusion NN model for estimating athlete injuries. Low accuracy and a high ROC were achieved by this strategy.

3. Proposed Methodology

SNT-SBCNN-CSBBO is proposed for Sports Network

Teaching in this section. Figure 1 displays the Block schematic of the proposed system. Pre-processing, categorization, and data gathering are some of its three steps. The input data is first gathered from a real-time dataset. Next, pre-processing using Adaptive Savitsky-Golay Filtering (ASGF) is applied to the gathered data. The ASGF generates normalized data that is higher quality and has less noise. Then the pre-processed data are given to MHFMRT for feature extraction. MHFMRT extracts statistical features like energy, kurtosis, variance, mean and standard deviation. Extracted features are given to SBCNN for classification. In general, SBCNN does not express adapting optimization strategies to verify optimal factors to classify the visualization and a satisfactory training platform of the sports network. Hence, the CSBBO is used to optimize SBCNN which accurately classifies the sports training. Thus, a thorough explanation of each step is given below.

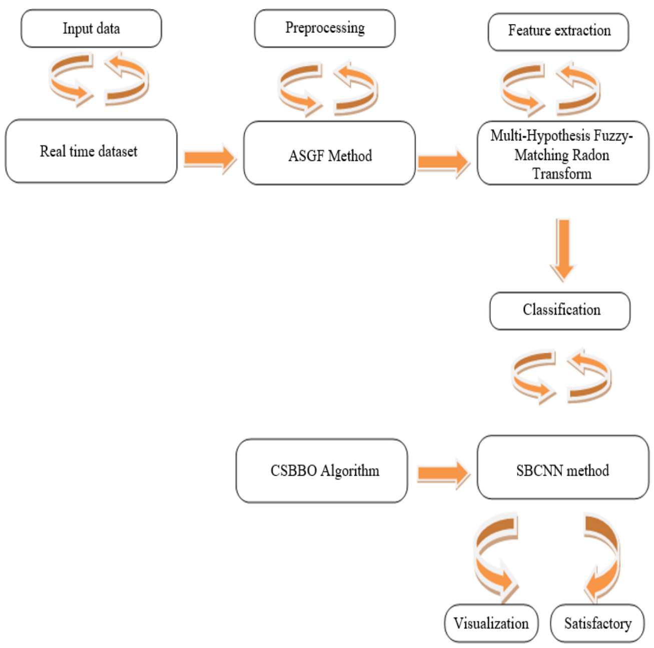

Figure 1. Block schematic of the proposed system.

3.1. Data Acquisition

In this work, a real-time dataset is used. Different sample sizes are included in each dataset for testing and training. The index parameters are the input for each model, and the output is the matched sports network training. After that, the raw data is sent to the preprocessing technique listed below.

3.2. Pre-Processing using Adaptive Savitzky-Golay Filtering

First, using the Adaptive Savitsky-Golay Filtering (ASGF) approach, the input data is pre-processed to provide normalized data with lower noise and higher quality [10]. ASGF is inspired by the methods used to generate additional data: in addition to the biases that can appear, there are also variations. In a similar vein, certain curved structures exhibit a level of curvature that makes them challenging to detect using the original filter, as they are not perfectly straight. An elastic deformation transformation is used to model the curve inside the original filter in order to take this curvature into account.

A digital filter operates using a group of evenly spaced data points, denoted by the $f_i = f(t_i)$ and $\equiv t_0 + i\Delta$, where the sampling interval is constant The index is represented by the integer Δ and i. The filter then modifies all data point, f_i, by combining a specific number of its closest neighbors linearly with the data point itself, g_i was expressed in Equation (1).

$$g_i = \sum_{n=n_L}^{n_R} C_n f_{i+n} \tag{1}$$

Here $^n{}_R$ and n_L indicates the count of data points in the 'right' and 'left' side of the data point. f_i is the data value. For a causal filter $n_R = 0$.

One way to get g_0 may be to explore how to determine the set of filter coefficients c_n to do least square fitting inside the moving window. To fit a degree M polynomial in.

That polynomial at i=0, namely a_0, will have a value of g_0, or i, specifically a_{0+} $a_1 i+ \ldots\ldots\ldots + a_M i^M$ to the values $f_{-nL} \ldots\ldots\ldots, f_{nR}$. The design matrix will be

$$A_{ij} = i^j \quad i = -n_L, \ldots, n_R, \; j = 0, \ldots, M \tag{2}$$

Furthermore, the normal equations for the vector of $a'_j s$ in terms of the vector f_i's in matrix notation was shown in Equation (3).

$$(A^T.A).a = A^T.f \quad or \quad a = (A^T.A)^{-1}.(A^T.f) \tag{3}$$

The exact forms can be shown in equation (4)

$$\{A^T.A\}_{ij} = \sum_{k=n_L}^{n_R} A_{ki} A_{kj} = \sum_{k=n_L}^{n_R} k^{i+j} \tag{4}$$

Equation (5) illustrates the unit vector replaces f, the coefficient c_n is the component a_0. en, $-n_L \le n \le n_R$

$$c_n = \{(A^T.A)^{-1}.(A^T.e_n)\}_0 = \sum_{m=O}^{M} \{A^T.A)^{-1}\}_{0M} \; n^m \tag{5}$$

Consequently, the Savitzky-Golay (SG) filter preserves the signal waveform's peak breadth and height, especially when it is designed to handle an oversampled waveform that is impacted by noise. Oversampling occurs when the signal is sufficiently soft to be indicated by a high-degree polynomial. According to this theory, the signal is low-pass.

In order to enhance the sports network's teaching capacity, the ASGF approach employs approximate equations repeatedly for every data point. After the issues are successfully resolved by the proposed ASGF filter, the pre-processed data is finally sent to MHFMRT for further extraction.

3.3. Feature Extraction Using Multi-Hypothesis Fuzzy-Matching Radon Transform

In this section, Feature Extraction Using MHFMRT [25] is discussed. MHFMRT is used to extract statistical features like kurtosis, standard deviation variance, energy, and mean. By managing numerous hypotheses and fuzzy matching, the MHFMRT improves accuracy and is beneficial for sports training. It is appropriate for real-world sports applications due to its resilience to uncertainties and changes in data. Faster study of training patterns and performance measures is made possible by MHFMRT's efficient data processing. Personalized training plans are made possible by MHFMRT's flexibility in accommodating various training situations and athlete profiles. Its fuzzy-matching capabilities also facilitate performance evaluation, helping athletes and coaches gauge their progress and pinpoint areas for development.

The extracted features are given below:

3.3.1. Kurtosis

It compares the distribution to the normal distribution and measures the stability of the latter.

$$Kurtosis = \sum_{j=1}^{M} \sum_{i=1}^{N} \frac{\left(q(j,i) - m\right)^4}{(MN)\sigma^4} \tag{6}$$

Where σ represents the standard deviation, M and N represents the mean and number of observations.

3.3.2. Variance

After the mean value is subtracted, the variance is defined as the mean square and is computed using Equation (7).

$$\theta^2 = \frac{1}{q} \sum_{i=1}^{q} \left(Y_j - M\right)^2 \tag{7}$$

Where Θ represent the variance. q represents the no. of samples. Y_j represents the input.

3.3.3. Energy

As an operation is performed within a probability framework, it is utilized to characterize an information measurement. In conjunction with the markov random domain, this is referred to as the maximal a priori evaluation. Depending on the situation, energy can be used to minimize or maximize positively or negatively was illustrated in Equation (8).

$$F = \sum_{j} \sum_{i} q(j,i)^2 \tag{8}$$

where $q(j,i)$ represent the intensity value of the data at the point (j,i).

3.3.4. Mean

Calculate the average value in the data in Equation (9),

$$Mean = \sum_{i=1}^{r} \sum_{j=1}^{t} \frac{q(i,j)}{rt} \tag{9}$$

Where $q(i, j)$ represent the intensity value of the data at the point (i, j).

3.3.5. Standard Deviation

Finds the mean distance between the data value and the mean; a low standard deviation number suggests that the data deviate from the mean less, while a bigger value implies a high contrast was represented in Equation (10),

$$\sigma = \sqrt{\sum_{i=1}^{r} \sum_{j=1}^{t} \frac{\left(q(i,j) - m\right)^2}{rt}} \tag{10}$$

Where σ represent the intensity value of the data at the point. Finally, MHFMRT extracted the statistical features like kurtosis, variance, energy, standard deviation and mean. Following the completion of feature extraction, SBCNN is given the features for classification.

3.4. Classification of Similarity based Convolutional Neural Network (SBCNN)

Similarity-Based-CNNs (SBCNNs) are a kind of Convolutional Neural Network (CNN) design that aims to reduce the computational complexity and number of parameters of traditional CNNs while maintaining efficient feature extraction capabilities. Similarity-based convolutions are the fundamental building block of SBNNs. A traditional CNN's convolutional layer analyzes the input data by applying many filters, often known as kernels, each of which is responsible for recognizing a distinct feature in the input data. This process involves the convolution of filters with the entire input volume, which can be computationally expensive [20].

Multi-layer neural networks, or CNNs, function best when analyzing scenes with plenty of pictures. Three layers make up the fundamental architecture of a conventional CNN: a fully linked layer a pooling layer, and a convolutional layer as denoted in Equation (11)

$$\overline{O}_{k,l,m} = \sum_{i,i,m} K_{i,j,m,n} . I_{k+i-1,l+j-1,m} \tag{11}$$

The output and input feature maps are denoted by O and I and the convolutional kernels by k.

Standard convolution's parameters are calculated in Equation (12).

$$\alpha = M \times N \times D_k^2 \tag{12}$$

Standard convolution's parameters are calculated in Equation (13),

$$\beta = M \times N \times D_i^2 \times D_k^2 \tag{13}$$

here, D_i^2 indicates the object map's spatial width and height squared input features, here N represents the output feature map's channel number, F indicates the computational cost, M indicates the input feature map's count of channels, G indicates the entire count of the model's parameters and D_k indicates the convolution's height and width. SBC splits the traditional convolution into 2 consecutive steps to reduce the repetition of the conventional convolution caused by misunderstandings of information types: point wise convolution (1×1) after Similarity based convolution kernels for convolution. The conventional Convolutional layer is divided into two layers by SBC; one layer is used for filtering, and the second layer is used to extract features using multiple 11 convolution kernels. A channel of the picture is first given the convolution kernel by Similarity based convolution, and the channel convolution output is then integrated by point-wise convolution. The SBC uses a 1×1 convolution kernel to handle the incoming picture data rather than a 3×3 convolution kernel. The experimental findings will be thoroughly examined. It was found that, in comparison to normal convolution, the SBC greatly reduced both the computational complexity and the model parameters in such a design. Similarity-based convolution applies one filter with zero padding and a stride of one to each input channel. The similarity-based convolution result is then mixed linearly with a convolution kernel of size 1×1 and point-wise convolution. Point wise convolution simulates the effects of down sampling by varying the stride. The result of the Similarity-based convolution's feature map is stated as follows:

$$\overline{O}_{k,l,m} = \sum_{i,j} K_{i,j,m} . I_{k+i-1,l+j-1,m,} \tag{14}$$

here, $\overline{O}$ for the feature maps that are output, I stand for the feature maps that are input, and K for the convolution kernels. The convolution kernel's element position is determined by the values of i and j. K and 1 are the values that determine the input feature map channel's position, which is represented by m.

The Similarity based convolution parameter calculation and cost function are represented by Equations (15) and (16),

$$\alpha_2 = M \times D_k^2 \tag{15}$$

And,

$$\beta_2 = M \times D_i^2 \times D_k^2 \tag{16}$$

Only the amount of convolution kernels and feature mapping input channels affect the count of parameters. However, the processing cost is dependent on the convolution kernel, the number of resources used for input feature mapping, and the feature mapping function with quadratic input. The output feature mapping N need not be considered while assessing the similarity-based convolution parameters and processing cost. The simplicity of similarity-based convolution is clearly illustrated by formulas (15) and (16) provided above SBC, on the other hand, does not combine input channels into new features like the traditional convolution layer does. In order to create new features, this study tries to combine the Similarity based convolution layer's performance features with the point wise convolution.

The formula for SBCNN parameters α and β is computed in Equation (17).

$$\alpha_3 = M \times D_k^2 + M \times N \tag{17}$$

The following is the SBCNN calculation method is expressed in Equation (18)

$$\beta_3 = M \times D_i^2 \times D_k^2 + M \times N \times D_i^2 \tag{18}$$

Using SBC based on a 3×3 convolution kernel, this study achieves a comparable accuracy while computing 8 to 9 times faster than standard convolution.

The parameter reduction is described in Equation (19):

$$\alpha_4 = \alpha_3 - \alpha = M \times D_k^2 + M \times N - M \times N \times D_k^2 \tag{19}$$

The decrease in cost computation is provided by in Equation (20).

$$\beta_4 = \beta_3 - \beta = M \times D_i^k \times D_k^2 + M \times N \times D_i^2 - M \times N \times D_i^2 \times D_k^2 \tag{20}$$

The input feature map is subjected to a size 2×2 down sampling operation by the pooling module of a standard convolutional layer. The SBCNN classifier considers the interactivity and efficiency of the automated accompaniment system optimization technique while teaching piano.

Finally, the proposed technique is used to recommend the appropriate Sports Network Teaching. The implementation of parametric design in two areas of sports network teaching was summed up by the development direction and strategy of the design. To improve the convergence, rate the SBCNN parameter is enhanced by the CSBBO algorithm. The step wise procedure CSBBO algorithm is given below:

3.5. Chaotic Satin Bower Bird Optimization (CSBBO) Algorithm

In this section, sports network teaching based on a CSBBO Algorithm is presented [8]. This component is another part of the hybrid algorithm being considered, which also functions as a population search method. Initially, the population consists solely of a set that provides information about the location of the dark as. The objective here is to maximize the gazebo's parameters. As a result, each individual is indicated as a "n-dimensional" vector, constrained by the number of parameters that need to be further optimized. Considering that population transfer is not a true biological algorithm, the term may be deceptive. Instead, it simulates and emulates biological reproductive processes such as reproduction. In this case, the gazebo's attractiveness is determined by combinations of the characteristics that need to be optimized, which operate as a benchmark.

Step 1. Initialization

To improve sports network teaching, the $[\alpha]$ weight factor is initialized.

Step 2. Random generation

The input factors are generated at arbitrary after the initial stage. The optimal fitness value may be obtained by taking the weight parameter into consideration.

Step 3. Fitness calculation

For each initialized parameter, the fitness function produces a random solution. To ascertain the function of fitness, apply Equation (21).

$$Fitness\ Function = optimize\ [\alpha] \tag{21}$$

Step 4. Evolution.

Evaluate any alterations in the arbors to accommodate the new populace. To that end, the following are some actions to take: The roulette wheel method, which is a random selection process as its name implies, can be used to choose the gazebo as expressed in Equation (22).

Using the following equation, determine the step size:

$$\lambda_k = \frac{\alpha}{1 + p_j} \tag{22}$$

Step 5. Mutation

In this stage of the procedure, random but specified adjustments are made with a given probability.

Step 6. Re-evaluation of error

Using specific macro-blocks, the error is recalculated by adjusting the SBCNN's ideal weights. Figure 2 shows that Flowchart of CSBBO Algorithm.

Step 7. Evaluation

New members are added to the group. As with the last set of guidelines, the procedure ends if one of the termination conditions is satisfied. If not, repeat step 2 from the beginning. The last step is to stop when the iteration counter exceeds the highest count of iterations. Table 1shows the Parameters of CSBO.

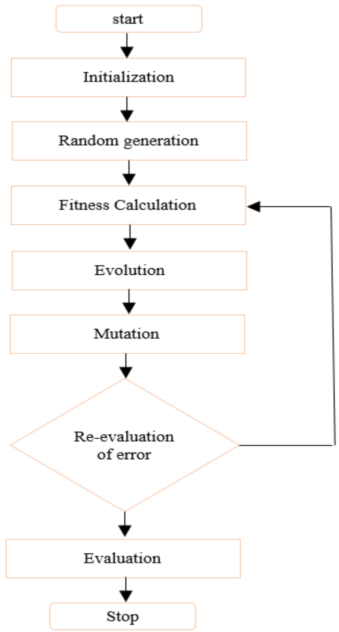

Figure 2. Flowchart of CSBBO algorithm.

Table 1. Parameters of CSBO.

Parameter	Typical range
Population size (NB)	10-100
Greatest step size (a)	[0,1]
Probability of mutation (p)	0-1
Selection pressure (Z)	Small positive value (0.1)

4. Result and Discussion

The proposed SNT-SBCNN-CSBBO method's experimental results are examined. MATLAB is utilized in conjunction with the recommended approach. The model is implemented on a Windows 10 PC with two Intel® Xeon® Silver 4114 CPUs, each with 40 cores and a clock speed of 2.20GHz. Several performance measures are used to examine the proposed technique. The obtained findings of the proposed SNT-SBCNN-CSBBO approach are examined using the PTT-RSI-RNN, SMPE-LSTM and SAVF-DCN methods, in that order, as well as other current approaches.

The proposed approach's performance is investigated using performance matrices like F-score, accuracy, recall, precision, specificity Root Mean Square Error (RMSE) and ROC.

- True Negative (TN): accurately classifies the training platform of the sports network as satisfactory.
- False Positive (FP): inaccurately classifies the training platform of the sports network as visualization.
- False Negative (FN): inaccurately classifies the training platform of the sports network as satisfactory.

4.1. Accuracy

Equation (23) indicates the accuracy value, which is computed as the ratio of the entire count of samples to the count of samples that the scheme is able to effectively classify.

$$accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{23}$$

4.2. F-Score

An F-score composite metric benefits strategies with higher sensitivity and presents challenges to strategies with higher specificity, which is represented in Equation (24),

$$F - score = \frac{TP}{TN + \frac{1}{2}[FN + FP]} \tag{24}$$

4.3. Precision

It calculates a sample's positive or negative predictive value based on the class for which it is computed, or it analyzes the samples' predictive power which is represented as Equation (25),

$$precision = \frac{TP}{TP + FN} \tag{25}$$

4.4. Recall

The ratio of true positive predictions to all real positive samples (both those that were accurately and mistakenly forecasted as positive) is known as recall. The recall formula is stated in Equation (26)

$$\mathrm{Re}\,call = \frac{TP}{TP + FN} \tag{26}$$

4.5. ROC

A ROC is an integrated measurement of a phenomena or effect that is measurable. It is measured by Equation (27),

$$ROC = 0.5 \times \frac{TN}{FP + TN} + \frac{TP}{FN + TP} \tag{27}$$

4.6. Root Mean Square Error (RMSE)

The two main performance metrics of a regression model are accuracy and RMSE. The mean difference between actual values and values predicted by a model is calculated. It estimates how well the model is in predicting the target value was expressed in Equation (28).

$$RMSE = \sqrt{\frac{(Actual\ Value - Predicted\ Value)^2}{Number\ of\ observation}} \tag{28}$$

Figure 3 displays Analyses of Accuracy Performance. To assess the efficacy of various classification strategies, the accuracy performance analysis in the sports training teaching system is essential. A comparison of different categorization algorithms was conducted using accuracy metrics in the proposed SNT-SBCNN-CSBBO. It was discovered that the accuracy levels of the currently used methods, including PTT-RSI-RNN, SMPE-LSTM, and SAVF-DCN, were less than 96%. But compared to the current techniques, the suggested strategy, SNT-SBCNN-CSBBO, showed a noticeably greater accuracy of 99%. The proposed SNT-SBCNN-CSBBO method attains 24.9%, 25.5% and 22.8% higher accuracy for visualization and 28.5%, 27.9% and 29.5% higher accuracy for satisfactory estimated to the existing PTT-RSI-RNN, SMPE-LSTM and SAVF-DCN models respectively.

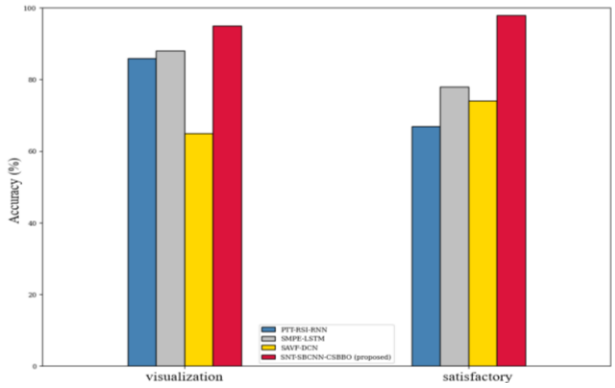

Figure 3. Analyses of accuracy performance.

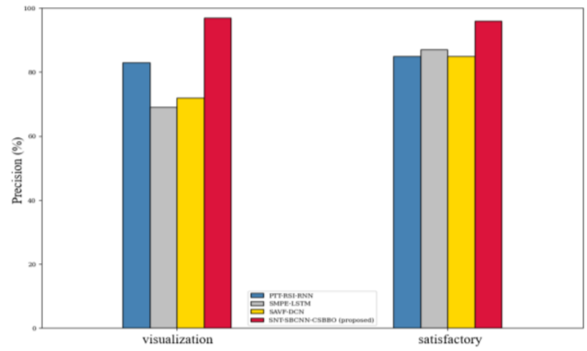

Figure 4. Analyses of precision performance.

Figure 4 displays Analyses of Precision Performance. Accurate categorization methods are essential for determining students' learning styles, areas of strength, and deficiencies in sports training so that teachers can adjust their lessons and interventions. The enhanced precision attained by the SNT-SBCNN-CSBBO highlights its capacity to enhance instructional approaches and elevate the general caliber of sports training curriculums. By comparing the proposed SNT-SBCNN-CSBBO approach to the current PTT-RSI-RNN, SMPE-LSTM, and SAVF-DCN models, it achieves, respectively, 28%, 21%, and 26.5% higher visualization precision and 25.2%, 25.7%, and 18.5% higher acceptable estimation precision.

Figure 5 displays Analyses of Recall Performance. To reduce false negatives and make sure that all pertinent data is taken into account when making decisions on sports training methods, a high recall rate is essential. The SNT-SBCNN-CSBBO's superior recall underscores its potential to improve the inclusivity and comprehensiveness of instructional methodologies in sports training curricula. The proposed SNT-SBCNN-CSBBO method attains 21.2%, 28.75% and 21.3% higher recall for visualization and 28.2%, 25.6% and 27.7% higher recalls for satisfactory estimated to the existing PTT-RSI-RNN, SMPE-LSTM and SAVF-DCN models respectively.

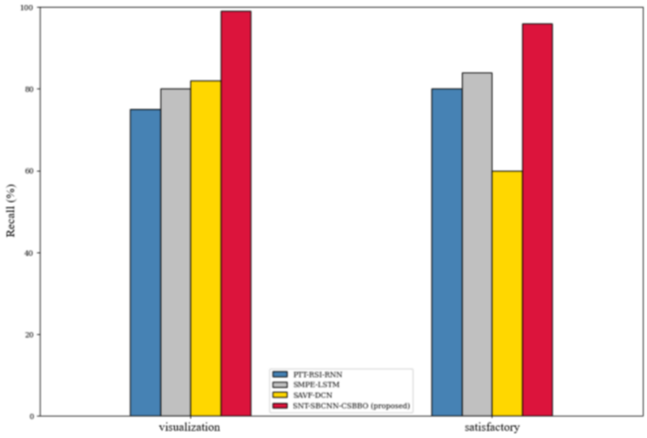

Figure 5. Analyses of recall performance.

Figure 6 illustrates the analyses of F1-score Performance. In sports training activities, a high F1-score is crucial for evaluating the overall efficacy and dependability of classification models. The higher-than-average F1-score attained by the SNT-SBCNN-CSBBO underscores its capacity to maximize instructional strategies and raise the general standard of sports training curriculums. Here, proposed SNT-SBCNN-CSBBO technique attains 27.46%, 21.68% and 20.79% higher F1-score for visualization and 23.79%, 23.51% and 20.81% higher F1-Score for satisfactory estimated to the existing PTT-RSI-RNN, SMPE-LSTM and SAVF-DCN models respectively.

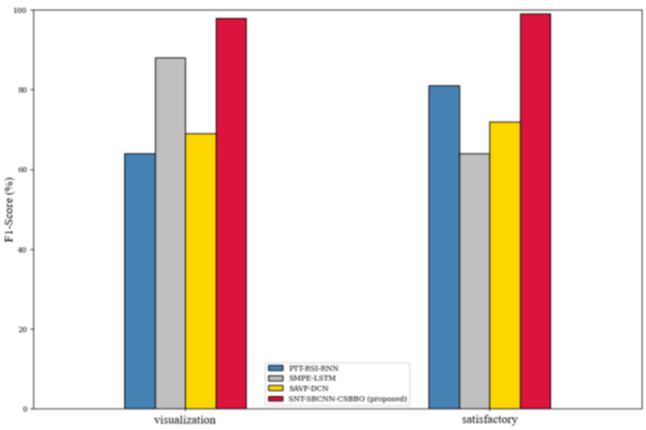

Figure 6. Analyses of F1-score performance.

Figure 7 illustrates the Analyses of RMSE Performance. Regression model accuracy is frequently assessed using the RMSE, which calculates the deviations between expected and actual values. Lower RMSE improves the higher classification performance. Here, proposed SNT-SBCNN-CSBBO technique attains 16.46%, 21.68% and 10.79% lower RMSE for visualization and 23.79%, 10.51% and 20.81% lower RMSE for satisfactory estimated to the existing PTT-RSI-RNN, SMPE-LSTM and SAVF-DCN models respectively.

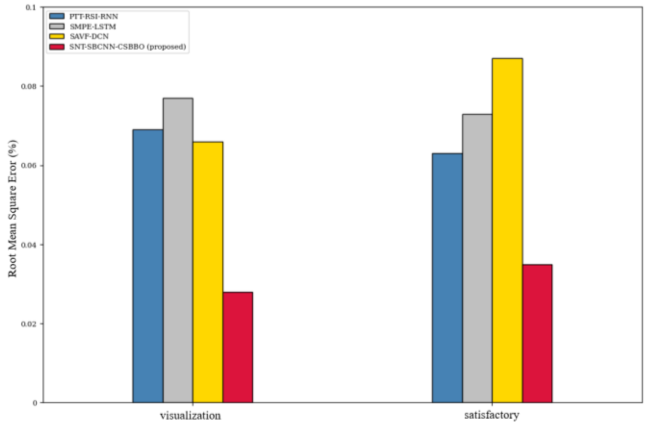

Figure 7. Analyses of RMSE performance.

Analyses of ROC performance is displayed in Figure 8. Selecting the best algorithm to increase the success of sports training programs can be facilitated by integrating ROC analysis into the performance evaluation of classification techniques in sports training teaching practices. This can provide a thorough assessment of the models' predictive capabilities. The proposed SNT-SBCNN-CSBBO method attains 21.2%, 21.75% and 21.3% higher ROC estimated to the existing PTT-RSI-RNN, SMPE-LSTM and SAVF-DCN models respectively.

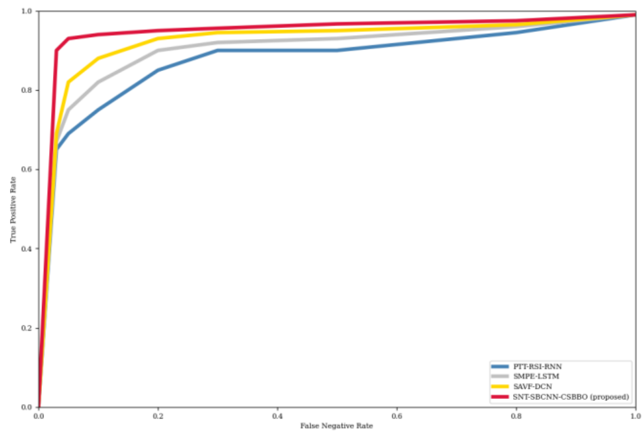

Figure 8. Analyses of ROC performance.

4.7. Discussion

Design and implementation of sports network teaching platform based on discrete similarity method SNT-SBCNN-CSBBO is proposed in this research. The SNT-SBCNN-CSBBO technique makes use of real-time datasets with a variety of parameters connected to sports. Subsets of the datasets are separated for testing and training, with different sample sizes to allow for comprehensive model building and evaluation. The SBCNN-CSBBO model uses index parameters that are obtained from statistical characteristics extracted by

MHFMRT post ASGF pre-processing to learn from the training subset during the training phase. Kurtosis, variance, energy, mean, standard deviation, and other characteristics are essential for connecting inputs to particular sports training results. The testing subset evaluates the model's predictive power and generalization beyond the training set, guaranteeing the model's effectiveness in practical settings. The proposed SNT-SBCNN-CSBBO framework for training platform of the sports network recognition demonstrates a thorough method that combines SBCNN with CSBBO for training platform of the sports. The platform uses SBCNN to handle complicated data efficiently, and CSBBO improves decision-making algorithms to fine-tune coaching techniques based on the needs of specific athletes. This integration helps athletes who are trying to get better by supporting performance monitoring and individualized feedback in addition to increasing training efficiency. Platforms such as this ultimately represent a revolutionary change in sports training, connecting the dots between conventional coaching techniques and state-of-the-art technological innovations for the best possible athletic development. The proposed approach attains higher accuracy and Sensitivity comparing with existing PTT-RSI-RNN, SMPE-LSTM and SAVF-DCN.

5. Conclusions

This section describes the development and deployment of a similarity-based sports network education platform. The proposed system is developed using the MATLAB platform and utilizes a sports network teaching dataset. The proposed strategies efficacy is evaluated using the sensitivity level visualization. The results of the proposed methods are 28.5%, 27.9% and 29.5% higher accuracy, 28%, 21% and 26.5% higher precision, 21.2%, 28.75% and 21.3% higher recall. The accuracy value for SNT-SBCNN-CSBBO remains high. The suggested system shows higher efficiency when compared to current approaches, such as the creation and application of an artificial intelligence-based college sports training system and a machine learning-based approach for recommending physical teaching network course resources. Additionally, for comparison, advancements in the wireless network-based, energy-efficient scalable routing algorithm for sports training instruction are also taken into account. As a valuable resource for enhancing sports performance, the sports teaching network platform's outcomes have the ability to improve students' strength, speed, and characteristics. The suggested approach could improve student engagement to 90% and boost actual attention to sports instruction by 90%. Though useful for classification applications, the SBCNN approach has computational drawbacks, needing significant resources for both training and inference. SBCNNs are also non-interpretable, which makes it difficult to comprehend the decision-making process-a critical aspect for applications that demand transparency. Furthermore, SBCNN performance is contingent upon the caliber and variety of training data, therefore for a robust use in sports network learning systems, careful evaluation of dataset features is required. Future research paths involve broadening the scope of the sports network teaching dataset to cover a wider range of sports and environments, as well as verifying the scalability of algorithms on larger datasets. Optimized sensitivity analysis would investigate how parameters affect the stability of the system. Integrating real-time data and employing sensors to provide sports stats in real-time could enhance system responsiveness. Enhancing user interaction through features like gamification and individualized feedback is the goal of design enhancements. Studies with a longitudinal design could evaluate long-term effects on academic achievement and fitness. Ongoing assessments against AI-driven systems would serve as benchmarks for advancements. Block chain technology and advanced tech integration could produce safe data management and realistic simulations.

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