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Computer aided technology based on graph sample and aggregate attention network optimized for soccer teaching and training

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Abstract

Football is the most popular game in the world and has significant influence on various aspects including politics, economy and culture. The experience of the football developed nation has shown that the steady growth of youth football is crucial for elevating a nation's overall football proficiency. It is essential to develop techniques and create strategies that adapt to their individual physical features to resolve the football players' problem of lacking exercise in various topics. In this manuscript, Computer aided technology depending on the Graph Sample and Aggregate Attention Network Optimized for Soccer Teaching and Training (CAT-GSAAN-STT) is proposed to improve the efficiency of Soccer teaching and training effectively. The proposed method contains four stages, like data collection, data preprocessing, prediction and optimization. Initially the input data are collected by Microsoft Kinect V2 smart camera. Then the collected data are preprocessed by using Improving graph collaborative filtering. After preprocessing the data is given for motion recognition layer here prediction is done using Graph Sample and Aggregate Attention Network (GSAAN) for improving the effectiveness of Soccer Teaching and Training. To enhance the accuracy of the system, the GSAAN are optimized by using Artificial Rabbits Optimization. The proposed CAT-GSAAN-STT method is executed in Python and the efficiency of the proposed technique is examined with different metrics, like accuracy, computation time, learning activity analysis, student performance ratio and teaching evaluation analysis. The simulation outcomes proves that the proposed technique attains provides28.33%, 31.60%, 25.63% higherRecognition accuracy and33.67%, 38.12% and 27.34%lesser evaluation time while compared with existing techniques like computer aided teaching system based upon artificial intelligence in football teaching with training (STT-IOT-CATS), Computer Aided Teaching System for Football Teaching and Training Based on Video Image (CAT-STT-VI) and method for enhancing the football coaching quality using artificial intelligence and meta verse-empowered in mobile internet environment (SI-STQ-AI-MIE) respectively.

Keywords: Graph Sample and Aggregate Attention Network, Improving graph collaborative filtering, Microsoft Kinect V2 camera and Rabbit optimization algorithm

Introduction

The global development of football players is witnessing a growing situation on comprehensive technological advancements [1]. As the game dynamically evolves on the field, players are increasingly expected to exhibit flexibility in their positions [2]. This necessitates excellent physical fitness and adaptability. However, traditional football player training methods often focus on single aspects such as speed, strength training and leading to potential drawbacks [3]. Overemphasizing one specific aspect through repetitive and prolonged training can adversely affect a player's physical function [4]. Moreover, solely concentrating on individual attributes may not yield the most efficient results in enhancing overall performance [5]. Therefore, more holistic and balanced approach to training is required to player. Artificial Intelligence (AI) has made an important influence on various industries, and football teaching is no exception [6]. The integration of AI in football coaching and training has opened up new possibilities for enhancing players' skills and revolutionizing the overall football experience [7]. By leveraging AI technologies, coaches, players, and enthusiasts can access data-driven insights, real-time analysis, and personalized coaching elevating the sport to new heights [8]. AI process more amount of data's from matches, training sessions, and wearable devices to extract valuable performance [9]. This information helps coaches identify players' strengths and weaknesses, enabling targeted improvement strategies [10]. AI-powered systems analyze match footage, opponent data, and historical trends to provide in-depth tactical insights [11–13]. Coaches formulates game plans and make real-time adjustments based on AI-generated recommendations.AI algorithms analyze this data to provide coaches with detailed insights into players' performance, including technical skills, tactical awareness, physical attributes, and even mental aspects of the game. Personalized training plans are tailored to the strength and weakness of each player [14]. Real-time feedback provided by AI-driven training platforms enables players to monitor their progress, identify areas for improvement, and make data-backed decisions to enhance their overall performance [15–17]. AI has revolutionized tactical analysis in football, providing coaches with comprehensive and real-time performance metrics [18–20]. By processing vast amounts of data on player movement, ball possession, passing patterns, and other game-related statistics, AI systems enable coaches to gain deeper insights into team dynamics and opponent strategies [21, 22]. With AI-driven tactical analysis, coaches can make informed decisions about team formations, player positioning, and game strategies. This newfound tactical intelligence has leveled the playing field, enabling teams of all sizes and resources to compete at a higher level [23–25]. AI has also found applications in injury prevention, improving player well-being and reducing the risk of injuries on the field. AI analyzes players' physical data and monitors their movements during training and matches, identifying potential injury risks [26–29]. Coaches and medical staff design targeted training regimes and recovery programs to mitigate these risks, keeping players in optimal condition [30–32]. AI has streamlined the scouting process and talent identification in football. AI algorithms analyze vast databases of player statistics and performance data, helping clubs identify promising talents and potential prospects more efficiently [33, 34]. The advent of Artificial Intelligence in football teaching marks a transformative era in the sport's development and growth. From individual player improvement to team strategies and injury prevention, AI's implementation offers invaluable benefits [35]. This data-driven approach to scouting enables clubs to make informed decisions when recruiting new players, building competitive and sustainable teams for the future. In existing methods the efficiency of soccer teaching and training is low so to get higher efficiency in soccer teaching and training an intelligent and proper way is used.

Major contributions of this work are summarized below:

- Computer Aided Technology Based on Graph Sample and Aggregate Attention Network Optimized for Soccer Teaching and Training (CAT-GSAAN-STT) is proposed.
- The study of the Soccer Teaching and Training using AI is introduced.
- Using Microsoft Kinect V2 smart camera the data is collected and for noise reduction Improving Graph Collaborative Filtering (IGCF) is proposed.
- In motion recognition layer, Graph Sample and Aggregate- Attention Network (GSAAN) based motion prediction is proposed and GSAAN is optimized by Artificial Rabbits Optimization.
- Human Interface for Users Verification based cloud computing system is introduced to store the player data.

Remaining manuscript is organized as: part 2 defines literature review, part 3 designates proposed Methodology, part 4 illustrates the performance metrics, the results,part 5 proves the discussions and finally, part 6 concluding this manuscript.

Literature review

A lot of researches on computer aided teaching in soccer technology have been already suggested in the literature. Amongst these, some of the recent investigations are reviewed here:

Li and Zhang [36] have presented a computer aided teaching scheme under artificial intellect in football teaching with training. The presented research was based on the FTT intelligent integrated scheme and they included the following: the design experiment of the highly intelligent system in use for training; the overall architecture design of the football teaching intelligent integration system; and the specific design of the football teaching intelligent integration scheme. The training empirical, comparative analysis, interview, and support vector machine for action realization were used in the teaching of football. The suggested article test outcomes depicts that 90.70% of players prefer the intelligent FTT teaching mode, and the intelligent FTT system helps to enhance the interest of the players for training and learning. It attains high learning activity and high evaluation time.

Wang, [37] have presented Computer Aided Teaching System for Football Teaching and Training Based on Video Image. The presented paper focuses on the application of artificial intelligence in football teaching and puts forward the related ideas of AI, neural network and computer-aided teaching. The suggested paper embraces the exploration techniques like writing information strategy and numerical measurement strategy, and behaviors as an overview and examination by giving surveys to educators and understudies partaking in open actual instruction classes in a specific college.

The experimental results show that 23.3% of the total students think that CAI has a promoting effect on the mastery of knowledge and skills, while only 12.8% of the total students think that it has no promoting effect. It attains high student performance ratio and low teaching quality.

Li et al., [38] have presented an approach for increasing football instruction quality in a mobile internet context using AI and met averse. The aim of the presented study was enhancing the football education in the mobile Internet environments with 360-degree panoramic virtual reality football instruction videos made possible by the K-means algorithm and Met Averse rely on AI's machine learning capabilities. The authors present a K-means based 360-degree panoramic VR football training video distribution method. Furthermore, simulation studies are carried out using the content delivery network simulator, and the proxy server hit ratio, byte hit ratio, mean response time as well as student experience quality, the simulation results show that the provided solution exceeds the baselines. It provides high Recognition rate and low student performance ratio.

Lin [39] have presented web 2.0 technology application to the construction of football instructional cooperative learning environment setting. The objective of the presented study was to examine at the interactive approach of football training in the information technology era. To learn more about the enjoyment, the coach along players use mobile learning tools. The coach use mobile learning technology to deploy a variety of modes to assist participants in learning the game. Convolutional neural networks were employed in the presented study to evaluate the effectiveness of web 2.0 technology integration in the construction of a cooperative learning environment system for football instruction. The presented method provides high teaching quality and high evaluation time.

Wang [40] have presented computer-aided college English teaching scheme under virtual reality along artificial intellect. The presented method focuses on an immersive context teaching technique for collegiate English which involves computer vision and machine learning. The aim was to enhance the students' proficiency in studying English. In a comparative study involving two university freshman courses, the experimental groups employed virtual reality (VR) as an innovative immersive environment for education, drawing on constructivist theory. The control class utilized standard multimedia equipment and traditional teaching methods. It provides high Recognition accuracy and low Learning activity.

Li et al., [41] have presented network management scheme design for computer-aided instruction in college physical education. Using network technology to carry out auxiliary physical education teaching, the presented technique examines into the auxiliary network structure of physical education teaching and creates a smart physical education teaching system based on dynamic physical education teaching features. The approach makes education more adaptable, as it was not restricted by time or location and fulfils the requirements of students in a variety of scenarios. The physical education teaching module's design and implementation are examined. To allow system login, the Internet application system was used to build system functionalities and a database server as a tool for selecting network training. It provides low evaluation time and low student performance ratio.

Yang, [42] have presented a research called Teaching optimization of interior design under 3 dimensional computer-aided simulation. The presented study presents the strategic and structural optimization of curriculum architecture in interior design using three dimensional computer-aided simulations. The study suggested an interior design path based on 3 dimensional computer-aided simulation as the basis for the teaching optimization mode and its realization through the practice of teaching interior design optimization using three-dimensional computer-aided simulation., including teaching system optimization and practice system optimization. It offers high Learning activity and low recognition accuracy.

Proposed method

In this research work, a Computer aided technology utilizing GSAAN Optimized for Soccer Teaching and Training (CAT-GSAAN-STT) is proposed for Soccer teaching and training. Proposed method contains four stages, First stage is Data Collection layer here data is collected using Kinest second generation intelligent soma to sensory camera. In second layer the data is preprocessed using Improving graph collaborative filtering, Third layer includes prediction and optimization using Graph Sample and Aggregate-Attention Network (GSAAN) and artificial rabbits optimization algorithm. Then forth layer consists of cloud storage and Human compute Interaction Interface. The suggested approach is put into action, and its efficacy is evaluated using simulated metrics. The overall block diagram of CAT-GSAAN-STT is shown in Fig. 1.

Data collection layer

Initially, the input data is collected real time by Microsoft Kinect V2 smart camera [43]. The Kinect camera employs Microsoft's KinectV2 second-generation intelligent soma

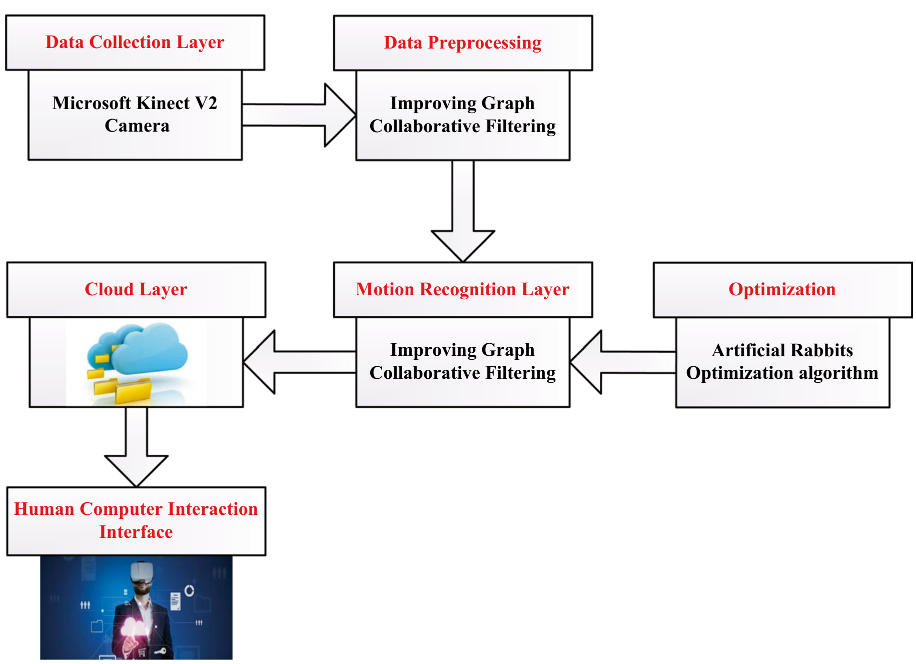

Fig. 1 Proposed CAT-GSAAN-STT method

to sensory camera. It consists of athlete data streams obtained using the Microsoft KinectV2 smart camera. During sports training, it collects three-dimensional data from human bone nodes and transfers it to the application layer for further analysis. The gathered bone data streams are used to identify bone movement. The Intel i7 G-4600 processor, Direct X11 core display, GIGABYTE B85-HD3, 3.6GHZ main frequency, and a 64-bit Windows 10 computer operational scheme are used in PC host CPU; the cost is maintained as low as possible in order to match the usual operation of KinectV2. KinectV2 transmits a colour data, a bone data and depth data streams to the preprocessing layer over the USB3.0 interface for motion detection. This is primarily used to show the user's sports training procedure and the score of performance results, also accomplish real-time feedback from human–computer interaction to increase user involvement and satisfaction. For every position, an alternate display is chosen. Indoors, 15-inch touch displays are incorporated with soma to sensory equipment; while an outside 50-inch vertical touch screen is used. Then, the output is fed to the preprocessing stage.

Data pre processing using improving graph collaborative filtering

Here, the preprocessing is done using Improving graph collaborative filtering [44] (IGCF) for checking missing values in the data and delete the noises in the data. Improving Graph Collaborative Filtering is a popular recommendation technique that leverages graph-based models to provide personalized recommendations. However, one of the challenges in Improving Graph collaborative filtering is dealing with finding missing values in the user-item interaction matrix, which will affect recommendation accuracy. Additionally, noisy data, such as incorrect or irrelevant interactions, also lead to biased recommendations. By using IGCF is used for Checking Missing Values and Identifying Noisy Data proposes a novel approach by using various step by step procedures. First a graph is constructed from the user interaction matrix. It is denote d by using Eq. (1)

$$G = [R * W] \tag{1}$$

where G is denoted as constructed graph, R is denoted as user interaction and W is denoted as weighted edges. The user and item is represented as a node in the graph, and the interactions between users and items are represented as weighted edges. Next one way to handle missing values is by using graph-based diffusion method. The imputation problem is formulated by using Eq. (2).

$$Diff[G,R] = \sum (I_{ij} - \widehat{MI_{ij})}2 + \lambda_1 * \xi(I) subject\ to \quad ,M \tag{2}$$

where $Diff[G,R]$ is denoted as propagates information between connected nodes in the graph to estimate the missing values,I_{ij} is denoted as the observed interaction amongst the user i and item j,MI_{ij} is denoted as value for the missing interaction amid the user i and item j, λ_1 is denoted as regularization parameter to balance the imputation term with the graph regularization term, $\xi(I)$ is denoted as regularization term that encourages smoothness of the input values based on the graph structure. To find the noisy data, a noise detection term is needed and it is derived using Eq. (3)

$$Noise\,Detection = \sum (I_{ij} - \widehat{MI_{ij})}2 + \lambda_1 \times \xi(I) + \lambda_2 \times \Omega(G) \quad (3)$$

where, λ_1 is denoted as regularization parameter to balance the imputation term with the graph regularization term, λ_2 is denoted as regularization parameter for the noise-detection term,$\xi(I)$ is denoted as regularization term that encourages smoothness of the input values based on the graph structure, I_{ij} is denoted as the observed interaction betwixt the user i and item j,MI_{ij} is denoted as value for the missing interaction amongst the user i and item j and $\Omega(G)$ is denoted as noise detection in the graph deviate significantly from expected patterns. Finally regularization terms are added to the objective function to control the models complexity and over fitting using Eq. (4)

$$\text{Reg}ularization = \sum (I_{ij} - \widehat{MI_{ij})}2 + \lambda_1 * \xi(I) + \lambda_2 * \Omega(G) + \lambda_3 * \varpi(H) \quad (4)$$

where $\sum (I_{ij} - \widehat{MI_{ij})}2 + \lambda_1 * \xi(I) + \lambda_2$ is defined above, λ_3 is denoted as regularization parameter for the additional regularization term and $\varpi(H)$ is defined as additional regularization term that penalizes large eights on edges in the graph. These are potential equations that are used in the context of improving graph collaborative filtering with missing value imputation and noise detection. Then these preprocessed data's are given for classification in motion recognition layer for teaching and training data's.

Motion recognition layer using graph sample and aggregate-attention network (GSAAN)

The motion recognition layer is a key component of the proposed model. It is responsible for identifying the diverse sports in which athletes contribute training by predefined motion data collection. The underlying algorithms used in the motion recognition layer include the GSAAN [45] model for action recognition. In action recognition, GSAAN can be trained on a set of predefined motion data to recognize and classify different actions based on their characteristic features. GSAAN is a deep learning-based framework that can be used for soccer teaching and training using computer aided technology. The GSAAN framework comprises two main stages: the first stage involves generating the graph structure for the soccer training, while the second stage involves teaching for soccer game. In the first stage, the graph structure is generated by sampling points on the surface and connecting them to form a graph. The sampled points are used as nodes in the graph, while the edges represent the connections between the nodes. In the second stage, the GSAAN is used to teach the soccer game. Specifically, the GSAAN aggregates information from the neighbouring nodes on the graph then applies attention mechanisms to the aggregated data to compute the new features for each node. The updated features are then used to compute the optimal values for the soccer teaching and training purpose. The GSAAN framework can be trained using supervised learning, where the training data comprises input–output pairs of soccer game and their corresponding gain values are derived using Eq. (5).

$$O(i) = Sample\;[O(i), l] \quad (5)$$

where $O(i)$ as set of training of neighbours for node i, and l is denoted as feature vectors for the nodes.Next, an attention mechanism to assign weights to the sampled neighbours based on their relevance to the target node. The attention weight for neighbour j with respect to node i can be computed in Eq. (6)

$$a(ij) = soft\max(f(a) * (X(i) + X(j)) \tag{6}$$

where $f(a)$ denotes learnable function that maps the concatenation of the feature vectors for nodes i and j to a scalar value, and softmax is a function which normalizes the attention weights for each node i. The aggregated depiction for node i is derived in Eq. (7)

$$h\_i^{(l+1)} = g\_agg\ [sum\ (j)[a\ (ij)W^{(l)}h\_j^{(l)}]] \tag{7}$$

where g_agg signifies non-linear activation function, $W^{(l)}$ denotes learnable weight matrix for layer l, and $h\_j^{(l)}$ signifies hidden state of neighbour j at layer l.The output of the GSAAN network is typically obtained by passing the final hidden state matrix through a linear layer and a soft max function. A probability distribution over the nodes in the graph in terms on its degrees is labelled in Eq. (8)

$$p\_i = \deg(i)/sum\_j \deg(j) \tag{8}$$

where p_i denotes distribution over the nodes, $\deg(i)$ is degree of node i, $sum\_j \deg(j)$ is sum of degrees of all nodes in the graph. Teaching in GSAAN network for soccer game consists of skill improvement over the time in the game. To teaching soccer game it is trained using Eq. (9)

$$R(t) = R(O) + \sum [\Delta R(i)] \qquad\qquad i = 1\ to\ t \tag{9}$$

where $R(t)$ denotes player skill level at time t,$R(O)$ denotes skill level of player at the beginning of training, $[\Delta R(i)]$ is denoted as the change in skill level at each discrete time. The cross-entropy loss is expressed by using Eq. (10)

$$L = -Sum(Y * \log(Y))/N \tag{10}$$

where L is denoted as cross entropy loss, N is denoted as number of classes and Y is denoted as total no of players. By minimizing the overall loss by adjusting the network parameters the output is derived using Eq. (11)

$$PC = ArgMax(W_{out} * Context + B_{out}) \tag{11}$$

where PC is denoted as predicted class of output, W_{out} is denoted as weight matrix for the linear transformation, B_{out} is denoted as bias term.Finally the index of the predicted class with the highest score indicating the predicted outcome in GSAAN. During testing, the model does not update its parameters; instead, it uses the learned weights from training to make predictions for new inputs efficiently. The training and testing are done using GSAAN in this layer for getting better accuracy. But GSAAN does not show any optimization adoption method to calculate optimal parameter to give accurate teaching and training. So for optimize the weight parameters $h\_i^{(l+1)}$ and $R(t)$ from the GSAANis done using Artificial Rabbits Optimization.

Optimized GSAAN using artificial rabbits optimization

The Artificial Rabbits Optimisation algorithm [46] was inspired by rabbits' inherent survival strategies. Rabbits use a foraging strategy called diversion to get food away from their nests. They dig burrows around the nests and sporadically conceal inside one of them to evade hunters and predators; this technique is known as the random hiding technique. They hide themselves according to their energy. They search food near the nests, if they have energy and they will hide in nests if they have low energy. Artificial Rabbit's Optimization Algorithm optimizes the weight parameter of GSAAN. The weight parameters of the GSAAN is p $h\_i^{(l+1)}$ and $R(t)$ and they are optimized using following steps:

Step 1: Initialization

The initialization of populace in parameter space is on the basis of Artificial Rabbits Optimization algorithm. A random uniform distribution and individual fitness and is characterized in Eq. (12).

$$G = \begin{bmatrix} G \\ . \\ . \\ . \\ G_j \\ . \\ . \\ . \\ G_o \end{bmatrix}_{o\times n} = \begin{bmatrix} G(z_1) \\ . \\ . \\ . \\ G(z_j) \\ . \\ . \\ . \\ G(z_o) \end{bmatrix}_{O\times 1} \tag{12}$$

The size of female group $_G$ represents mean distribution and standard deviation $G(z_o)$ denotes remaining populace, up to $G(z_1)$ individuals, contains males.

Step 2: Random generation

The weight parameters are produced in random after initialization. The best fitness value is selected depend on clear hyper parameter conditions.

Step 3: Evaluation of fitness function

The random solution is created from initial assessments. The fitness function is evaluated through parameter optimization values to optimize loop parameter $ph\_i^{(l+1)}$ and $R(t)$. It is exhibited in Eq. (13)

$$Fitness\ Function = optimizing\ \left[\mathrm{ph\_i}^{(\mathrm{l}+1)}\ \text{and R(t)}\right] \tag{13}$$

Step 4: Transition from exploration to exploitation using $ph\_i^{(l+1)}$

In the Artificial Rabbits Optimization, rabbits tend to exhibit continual detour foraging in the initial iteration stages. However, as the search progresses, they shift their behavior and start engaging in random hiding more frequently. This adaptation helps the rabbits strike a balance among exploration and exploitation during the optimization process, ensuring they conserve their energy effectively. The energy is computed using Eq. (14)

$$Ey = z_{JJ}\left(l + \beta 1 * \left[z_{best}(l) - z_{bestup}(l)\right]\right) \tag{14}$$

where Ey is denoted as energy for rabbits, z_{JJ} is the population member who is in his or her adolescence, z_{bestup} signifies current best group member position, z_{best} represents current best optimal solution, and $\beta 1$ denotes random integer drawn at random from an uniform distribution in range [0, 1].

Step 5: Random hiding using $R(t)$

In the face of potential threats from predators, rabbits instinctively take measures to ensure their survival. In the Artificial Rabbits Optimization algorithm, each rabbit, during every iteration, creates multiple burrows scattered across the search space dimensions. The rabbit randomly choses among these burrows to use as a hiding spot. This strategic behavior of creating and choosing burrows helps the rabbit reduce the risk of being captured, increasing its chances of survival during the optimization process. For hiding purpose it is done by using Eq. (15)

$$c_{j,s}(u) = \left[y_j(u) + I \times h_s \times y_j(v) \right] \qquad j = 1, ...o \tag{15}$$

where I is the hiding parameter, $c_{j,s}(u)$ is denoted as randomly selected burrow for hiding the o^{th} rabbit.

Step 6: Natural repulsion for optimizing $C_p b_2$ using artificial rabbit's optimization

The survival stratagems utilized through rabbits at nature served an inspiration for artificial rabbit's optimization approach. They consist of two steps; to find time integral, absolute error in control loop. It is Energy Shrink and Random Hiding. The loop parameters from the cheetah is optimized here by the Eq. (16)

$$K_{tt} = L_q.D_p \tag{16}$$

Step 7: Energy shrink

Rabbits usually hide themselves. For its energy it comes out from nest like that this optimization also used for energy for the control loop. To calculate energy shrink equations are needed it is denoted in Eq. (17)

$$B(u) = 4(1 - \frac{u}{U})\frac{1}{s} \tag{17}$$

where $B(u)$ is denoted as energy factor.

Step 8: Termination condition

In this step, the weight parameter values $h\_i^{(l+1)}$ and $R(t)$ are optimized with the Artificial Rabbit's Optimization method, repeat the step 4 as well as step 8 until the halting criteria $d = d + 1$ is achieved**.** Artificial Rabbit's Optimization weight parameter of GSAAN is optimized. Then the details are given for cloud section for storing purpose.

Cloud storage section

Cloud computing is the computing service distribution using internet to enable on-demand access to shared pool of computational resources, like servers, storage, databases, networking, and software. Cloud service providers provide cloud services, and consumers access and use these resources remotely over the internet, eliminating the need to maintain or manage physical infrastructure. The cloud section for storing data of a soccer game refers to a cloud-based storage solution designed to store various types of data related to soccer matches, players, teams, and other relevant information. Cloud storage offers several benefits for storing soccer game data due to its scalability, accessibility, and reliability. The cloud storage system accommodate different data types, including player statistics, match events, game videos, team formations, and coach's notes. It also easily scales to handle large volumes of data generated from numerous matches, tournaments, and training sessions. Protecting sensitive players' information is crucial for maintaining privacy and security. In this section data security of several terms such as robust security measures, such as encryption and access control, ensure the protection of sensitive player and team information successfully. For data security, role-based access control is implemented to ensure that only authorized individuals, such as coaches, physical trainers, and team managers, have access to specific player information. User authentication mechanisms will be in place to verify the identity of individuals accessing the system. Here, Logistic Mapping encryption method is utilized to secure player data at rest and in transfer. This comprises encrypting databases, communication channels, and stored data. By using cloud it consists of real-time data updates during live matches, enabling instant access to match statistics and highlights. Regular data backups and redundancy measures confirm data integrity and facilitate quick retrieval in unforeseen incidents by using cloud.

Human computer interaction interface

Human–Computer Interaction Interface (HCII) refers to the point of interaction between a human user and a computer system. It encompasses the design and presentation of visual and interactive elements that allow users to communicate, input data, and receive outputs from the computer. An HCII interface aims as user-friendly, intuitive, and easy to navigate, ensuring that users can interact with the computer system efficiently and effectively. HCII interfaces support various input mechanisms such as keyboard, mouse, touch screens, voice commands, gestures, and even brain-computer interfaces, depending on the system and the intended use case. The visual presentation of the interface includes graphical elements, icons, buttons, menus, and layouts that convey information and enable users to interact with the computer system. The interface provides timely feedback to users, acknowledging their input and showing the system's response to the actions taken. By using HCII by using application installed in operating system they allow users to interact with the computer using icons, windows, and menus. Touch screen interfaces on smart phones and tablets, where users can input commands directly with their fingers. Voice assistants, such as Siri or Alexa, that enable users to interact with computers using natural language voice commands. An effective HCII is crucial for enhancing user experience, productivity, and satisfaction when interacting with computer systems. A well-designed interface will simplify complex tasks, reduce learning curves, and minimize errors, making technology accessible and usable for a broader audience. HCII design is a multidisciplinary field that combines elements of psychology, design, usability, and technology to create interfaces that meet users' needs and preferences while ensuring efficiency and effectiveness in human–computer interactions. The intellectual auxiliary teaching system meets both functional and nonfunctional demands. Initially, the functional requirements are system login, resource management, data collecting, user information management and system administration.

Subsequently, the auxiliary teaching system's performance metrics, operability traits, and security requirements are examined. Backend administrators, players, coaches, physical trainers, and team managers are a few categories that make up the HCII's user roles. Upon accessing the major system interface, every user is presented with unique user interface tailored to the specific operations and features available to them within the system.

Performance metrics

The performance metrics are assessed to scale the performance of the proposed method. The performance of the proposed method is assessed with the following performance metrics depicted below,

1Recognition accuracy

Recognition accuracy is used to calculate the performance of a categorization technique. It indicates the ratio of properly categorized instances out of total instances in the dataset. This is computed by Eq. (18),

$$\text{Recognition Accuracy} = \left(\frac{\text{Number of Correctly classified Instances}}{\text{Total no of Instances}}\right) \times 100 \tag{18}$$

2Recognition rate

It represents the accuracy or success rate of a system in correctly recognizing or classifying instances. This is calculated by Eq. (19)

$$\text{Recognition Rate} = \left(\frac{\text{Number of Correctly Recognized Instances}}{\text{Total no of Instances}}\right) \times 100 \tag{19}$$

Evaluation Time

It is relate to the time it takes to evaluate the performance of a trained model on a given dataset. This is measured using Eq. (20)

$$\text{Evaluation Time} = \text{Time taken to process} \times \text{No of samples in the evaluation dataset} \tag{20}$$

Learning activity

It is a systematic approach utilized in education to evaluate the efficiency of various learning activities in attaining educational goals. The learning activity analysis is calculated using Eq. (21)

$$\text{Leaning Activity} = \left[\frac{\text{Learning Outcomes Achieved}}{\text{Learning Objectives}}\right] \times 100 \tag{21}$$

where *Learning Outcomes Achieved* is denoted as number of learning outcomes successfully achieved by students after participating in the learning activity and *Learning Objectives* is denoted as total number of learning objectives set for the specific activity.

Student performance ratio

It is a metric to calculate the relative performance of a student compared to a specific benchmark and also reference group. It is often expressed as a ratio or a percentage to indicate how a student's performance compares to the average and also desired level of achievement. Student performance ratio is calculated using Eq. (22)

$$\text{Student Performance Ratio} = \left[\frac{\text{Student}'\text{s Performance}}{\text{Benchmark Performance}}\right] \times 100 \tag{22}$$

where $Student's\ Performance$ is denoted as achievement level of the student and $Benchmark\ Performance$ is denoted as the desired performance level of predefined standard value.

Teaching quality analysis

Teaching quality Analysis involves assessing and analyzing the effectiveness of a teacher's instructional methods, classroom management, and overall impact on student learning. While teaching quality is subjective and encompasses various qualitative and quantitative factors, one common approach to calculate teaching quality is done using Eq. (23)

$$\text{Teaching Quality Score} = \sum \left[\frac{\text{Score i} \times \text{Weight } i}{\text{Weight } i}\right] \tag{23}$$

where $Score\ i$ is denoted as individual evaluation score provided by student and $Weight\ i$ is denoted as weight evaluation score provided by student i.

Result and discussion

Finally, Computer aided technology depending on GSAAN Optimized for Soccer Teaching and Training (CAT-GSAAN-STT) are proposed. PC involves specifications such as, windows10, Intel Core i5, 16 GB random access memory, Central Processing Unit of 2.50 GHz and executed in python. The performance metrics such as accuracy, computation time, learning activity analysis, student Performance ratio and teaching evaluation Analysis are evaluated. The proposed CAT-GSAAN-STT is compared with existing STT-IOT-CATS, CAT-STT-VI and SI-STQ-AI-MIE models.

Results

The simulation outcomes of proposed CAT-GSAAN-STT are analyzed in this section. Here, the metrics, such as Recognition accuracy, Recognition rate, evaluation time, Learning activity, Student Performance ratio and teaching quality Analysis are analyzed with the existing methods, such as STT-IOT-CATS, CAT-STT-VI and SI-STQ-AI-MIE respectively.

Table 1 depicts Recognition accuracy analysis. The proposed CAT-GSAAN-STT method attains 28.33%, 31.60% and 25.63%better recognition accuracy analyzed to

Table 1 Recognition accuracy analysis

Methods	Recognition accuracy (%)
STT-IOT-CATS	88.76
CAT-STT-VI	78.52
SI-STQ-AI-MIE	82.08
CAT-GSAAN-STT (Proposed method)	99.42

Table 2 Recognition rate analysis

Methods	Recognition rate (%)
STT-IOT-CATS	87.32
CAT-STT-VI	79.97
SI-STQ-AI-MIE	91.26
CAT-GSAAN-STT (Proposed method)	99.54

Table 3 Evaluation time analysis

Methods	Evaluation time (s)
STT-IOT-CATS	250
CAT-STT-VI	276
SI-STQ-AI-MIE	233
CAT-GSAAN-STT (Proposed method)	94

Table 4 Learning Activity Analysis

Methods	Number of students				
	10	20	30	40	50
STT-IOT-CATS	70.09	82.65	86.23	90.49	91.32
CAT-STT-VI	72.54	68.95	77.76	86.45	86.36
SI-STQ-AI-MIE	65.82	71.70	84.69	88.61	89.90
CAT-GSAAN-STT (Proposed method)	98.34	98.48	99.56	99.23	99.35

the existing methods, such as STT-IOT-CATS, CAT-STT-VI and SI-STQ-AI-MIE respectively.

Table 2 depicts Recognition rate analysis. The proposed CAT-GSAAN-STT method attains 13.35%, 21.84%, 11.72% higher recognition rate analyzed to the existing methods, such as STT-IOT-CATS, CAT-STT-VI and SI-STQ-AI-MIE respectively.

Table 3 shows Evaluation Time Analysis. The CAT-GSAAN-STT attains 33.67%, 38.12% and 27.34%, low evaluation Time while compared with existing STT-IOT-CATS, CAT-STT-VI and SI-STQ-AI-MIE methods.

Table 5 Student performance ratio analysis

Methods	Number of students				
	10	20	30	40	50
STT-IOT-CATS	81.65	87.36	90.74	85.84	79.18
CAT-STT-VI	78.95	82.71	78.10	82.08	86.24
SI-STQ-AI-MIE	87.34	89.87	83.24	90.62	88.07
CAT-GSAAN-STT (Proposed method)	99.14	99.43	98.79	99.08	99.24

Table 6 Teaching quality analysis

Methods	Number of students				
	10	20	30	40	50
STT-IOT-CATS	85.36	79.45	91.63	92.13	79.84
CAT-STT-VI	77.94	90.77	80.34	87.58	92.81
SI-STQ-AI-MIE	82.67	89.01	92.37	87.28	83.97
CAT-GSAAN-STT (Proposed method)	99.21	98.92	99.29	99.43	99.32

Table 4 depicts Learning activity analysis. The proposed CAT-GSAAN-STT method attains 28.35%, 31.25% and 36.33%, higher Learning activity at number of students 10; 30.22%, 34.22% and 34.67%, higher Learning activity at number of students 30; 36.45%, 39.45% and 43.23%, higher Learning activity at number of students 50 while compared with existing methods such as STT-IOT-CATS, CAT-STT-VI and SI-STQ-AI-MIE respectively.

Table 5 tabulatesthe Student Performance Ratio analysis. The proposed CAT-GSAAN-STT method attains 20.45%, 24.45% and 27.34%, higher Student Performance at number of students 10; 27.45%, 30.34% and 35.34%, higher Student Performance at number of students 30; 34.89%, 36.45% and 38.34%, higher Student Performance at number of students 50 while compared with existing methods such as STT-IOT-CATS, CAT-STT-VI and SI-STQ-AI-MIE respectively.

Table 6 tabulatesthe teaching quality analysis. The proposed CAT-GSAAN-STT method attains 26.22%, 28.45% and 30.33%, higher teaching quality at number of students 10; 26.45%, 31.44% and 37.56%, higher teaching quality at number of students 30; 35.56%, 38.44% and 43.44%, higher teaching quality at number of students 50 while compared with existing methods such as STT-IOT-CATS, CAT-STT-VI and SI-STQ-AI-MIE respectively.

Discussion

The teaching methods and means are relatively simple due to the limitations of teaching situations. The utilization of traditional teaching techniques in teaching is not conducive to students' organic connection with abstract concepts, specific technical movements, and tactical awareness. By the development of computer and network technologies, the information method dissemination will continue to be electronic. The entire field of teaching is undergoing large and radical changes. This change is reflected in the teaching concept, teaching content, teaching technology, teaching means, teaching mode, and teaching interaction. There are total 46 number of samples are used to train the proposed method. The cloud server utilized an Alibaba Cloud server through a 2-core CPU, memory4 GB, storage capacity64G, and 1.5 Mbps network bandwidth due to less traffic as well as simple business logic processing at present phase. The proposed CAT-GSAAN-STT model utilized GSAAN method for recognition layer optimized with Artificial Rabbits Optimization algorithm. Then the proposed method is compare with existing STT-IOT-CATS, CAT-STT-VI and SI-STQ-AI-MIE methods. The experimental results show the proposed method attains 99.36% accuracy and 99.43% Student Performance Ratio. It will clearly shows the proposed method is effective at computer based Soccer Teaching and Training.

Conclusion

This paper proposes a computer aided technology based on GSAAN Optimized for Soccer Teaching and Training (CAT-GSAAN-STT). This proposed method accurately teaches and train soccer game for all users. The proposed CAT-GSAAN-STT is activated in Python with the help of rabbits optimizing algorithm. The proposed technique attains 20.45%, 24.45% and 27.34%, higher Student Performance ratio and 26.22%, 28.45% and 30.33%, higher teaching quality while compared with existing methods such as STT-IOT-CATS, CAT-STT-VI and SI-STQ-AI-MIE respectively. However, the proposed method has some limitations. The implementation of the proposed method might be complex, which requiring significant computational resources, technical expertise, and integration with existing systems. In future study, the following components of the approach must be improved and updated: further optimizing the system code and improving interoperability between the online teaching auxiliary scheme and client browser conducted the depth user's operating behavior examination in order to perform humanized structure and evade user annoyance.

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