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Deep learning in sports skill learning: a case study and performance evaluation

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Abstract

Deep learning in sports uses neural networks to evaluate data from sensors and cameras, providing coaches and players insights to enhance training methods and performance. Sports skill development include issues with data availability, trouble interpreting methods for coaching purposes, possible financial constraints for players and regional sports teams. To overcome this, we proposed an Artificial Hummingbird Optimized XGBoost (AHO-XGB) to provide accurate predictions and analysis of an athlete's performance.In this study, the research consists of 20 faculty members and 250 learners from 3 universities.Many sports talents are currently taught to students in famous colleges and universities, but they truly become proficient in the skills. To evaluate the performance of the proposed method in terms of accuracy (92.6%), precision (90.5%), and recall (94.3%). The outcome of this research in sports skill learning transforms performance and training analysis by examining large amounts of data and offering suggestions for skill development.

Keywords: Deep learning, sports, skill, learning, Artificial Hummingbird optimized XGBoost (AHO-XGB).

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1. Introduction

Sports skill learning is a complex and dynamic process that includes developing physical, mental, and perceptual skills with a vision of improving performance in a variety of athletic contexts. The core of athletic development is the acquisition of sports skills, whether it is playing a soccer ball, delivering a perfect serves in tennis, making a three-point basket in basketball or mastering a gymnastics routine [1].Sports skill acquisition is a combination of mental concentration, sensory feedback, and physical practise. To succeed in their particular sports, athletes need to improve their decision-making skills, improve their tactics, and build muscle memory [2]. This is a fundamental procedure for any age or ability level of sports companions, not just professional players.

The growth and development of physical motions necessary for certain sports is known as motor skills acquisition, and it is a crucial aspect of sports skill learning [3]. In addition to sport-specific motions like golf swings or an ice skating spin, these motor skills encompass basic activities like sprinting, jumping, throwing, and catching. It takes time and repeated practise to become proficient in these abilities. As movement patterns are gradually improved, activities become more fluid and accurate [4].Learning athletic skills also depends on cognitive factors. During sports or competitions, athletes must make rapid choices, under intense pressure. This involves collecting data from the surroundings, evaluating the circumstances, and deciding on the best course of action [5]. Sports skill acquisition involves cognitive components, such as the capacity to predict a soccer ball's direction or read an opponent's movements in a game of chess.Learning a sport is not a standardized activity [6].

It varies according to the sport, the participant's skill level, and personal interests. Some athletes perform well in sports like archery, that require for proficiency, while

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others perform well in contact, fast-paced sports like football [7]. Age, prior experience and inherent abilities are some of the variables that can influence the learning process for athletes.The value of intentional behaviour is one of the core ideas of sports skill development. Training to be methodical, targeted, and intentional with the goal of enhancing particular performance areas is known as deliberate improvement [8]. It involves pushing itself to the limit, making objectives, and getting advice from experts. Deliberate practice is the foundation of skill development, whether a swimmer improves their flip turn ability or an athlete is refining their striking precision [9].Deep learning in sports skill learning aims to use sophisticated neural network models to improve athletic talents by offering predictive information for optimising technique, tactics, and training.

The study components might be classified: We will discuss the related works in Section 2. The approaches are discussed in Section 3. The experiment's findings are presented in Section 4. Discussion is presented in Section 5. The last section of this paper, section 6, is the conclusion.

2. Related works

Study [10] developed a personalised federated learning technique that uses deep learning and an adaptable federated method for learning before offering a way for predicting the achievement of learners.These techniques combine the quantitative approaches to motor skill evaluation with standards for undergraduates, which make them useful for assessing their athletic abilities.The model proposed in their work has an accuracy rate of 91.7% on average for each athletics item in terms of predicting the pupil's athletic success.

Study [11] created a Deep Convolutional Neural Network for sensor-based behaviour categorization to explore the potential of deep learning in their environment. Five popular grouping algorithms are compared to determine their new method performs.Tracking player behaviour could assist in detectingand recognising risk factors to avoid these kinds of injuries.Their deep neural network method outperforms existing approaches by a significant margin, indicating that Deep Learning was capable of improving the capabilities of sensor-based movement identification.

Study [12] described the concept of machine learning in a high-level, non-technical manner, emphasising its potential to improve sports analysis.Among its benefits, artificial intelligence (AI) was having a fast growing impact on both the academic and business worlds in sports by helping with prediction and decision-making.They give out some speculative scenarios in sports could change in the future due to AI and ML.

Study [13] provided an empirical basis for encouraging the use of deep learning in basketball and serves as a theoretical guide for the wider use of deep learning in athletics.A multitraining target technique can be used in training to gather more precise and multidimensional information, various indicators were identified and feedback was offered. More accurate standards for players and coaches were provided by the sports data analysis system that was created in real time.

Study [14] used artificial intelligence technologies to perform intelligent analysis throughout executing instruction. Artificial intelligence technology was able to assess and estimate the sports training orientation needs.They makes use of the gateway recursive unit (GRU), long and short-term memories (LSTM), recurrent neural networks (RNN), and athletic training information in the form of heart rate captured on aGlobal Positioning System(GPS) intelligent sports watch. These three different kinds of neural network techniques can determine the approach that was most appropriate for a road marathon.

Study [15] proposed an attention based long-short-term memory (AS-LSTM) model for match performance prediction, it integrates the AS-LSTM structure.A sports match forecast allows understanding the team's state before the match and making adjustments to their strategy as needed. Predicting a sporting event was a tough task.They conducted a case study, using the football game as an example, and suggested if their approach would be feasible.

Study [16] used an optimised Convolutional neural network models (OCNN) based on a deep learning framework to ensure precise risk assessment and identification associated with sports-related illnesses. It implements the self-Modification diminishing algorithm, which was enhanced by the convolution's self-coding mechanism (SCM).In order to develop a modern health information network for sports medicine, the CNN makes the processing of complicated athletic health data simpler and completes a cloud-based circuit model.

Study [17] suggested an interactive control approach for sports training that raises the standard for instruction using the deep fusion of data and increases human-machine interaction.The aggregation of wireless sensors and neural networks for deep learning techniques led to a current revolution in sports training methods. Theyallow for the development of more efficient and scientific sports methods.

Study [18] presented a multigenerative aggressive algorithm for image restoration that uses reconstructive sampling with multigranularity.Reconstruction sampling was used to ensure there was a Lebesgue value in the area of the producing samples that overlaps. For distributing weighted attention to various weekly behavioural aspects of students, a temporal attention system was incorporated at the recurrent aggressive deep neural network's interface.

Study [19] integrated support vector machine (SVM) with a machine learning algorithm to create a physical education assessment system. The system algorithm makes use of optimised machine learning. Their investigation employs a framework consisting of three layers to develop a fundamental representation of the system's framework and analyse its functional modules. It also optimises the network material layer approved to boost the system's

efficiency in operation by increasing the rapidity and precision of information analysis.
Study [20] createda system for the instruction and assessment of sports-specific abilities by utilizing pertinent machine learning concepts and techniques. The most crucial aspect was recognizing that the trainer's physical state could change throughout the activity. But the conventional training approach was completely unable to detect and anticipate it, which could result in an excessive amount of training that the athletes were unable to handle and irreversibly damage their bodies.Evaluating the experimental participants' data findings allowed to confirm the viability and efficacy of their instructional assessment system.

3. Methodology

3.1. Datasets

The paper selects 250 students from three universities and 20 athletic instructors from physical education institutions.It retrieves pertinent literature, including reading, reasoning, and summarising skills, physical theory, “Curriculum and Teaching Theory”, “Physical Education Teaching Skills”, and “Physical Education teaching theory”. Additionally, these resources are examined and evaluated in accordance with the specified standards to provide a particular theoretical structure for the ongoing discussion, examination, and solution of current problems.

3.2. Artificial hummingbird optimized XGBoost (AHO-XGB)

Artificial hummingbird optimization

Every hummingbird in the AHO has a designated food source it could use to stay healthy. A hummingbird could recall the location and the speed at which nectar was added at this feeding site. It could recollect the duration of time between visits to each food source. The AHO has extraordinary capability in its search of the best options due to these unique skills. First, g_m numbers were assigned at random to g_m food sources for a hummingbird swarm.

$$Ga_i = (Up - Lo).Q + Mo, \quad \forall i \in g_m \tag{1}$$

WhereGa_i stands for the position of the i^{th} source of food, and it represents a solution vector that includes the power and voltage of the generators, the reactive energy generated by the compensators, and the faucet configuration of the transformers. Within the range of the OPF issue, R is a randomized vector. Up and Lo are the boundaries in their upper and lower limits for the control variables.

$$US_{i,l} = \begin{cases} null & if\ i = l \\ 0 & else \end{cases} \forall i \in g_m, l \in g_m \tag{2}$$

Where $US_{i,l}$ is the interval of time that a hummingbird (i) failed to visit the food resource (l), and null means no value.

Axial, diagonal, and bidirectional movements are the three flying skills that the AHO employed and modelled during feeding. Equations (3) through (5) are used to express solutions.

$$CE^{(i)} = \begin{cases} 1 \\ 0 \end{cases} if\ i = O(j), j \in [1, n], O = randperm\ (w), w \in \left[2, 1 + [q_1.(\dim - 2)]\right] \tag{3}$$

$$CE^{(i)} = \begin{cases} 1 & if\ i = rand_j(1, dim) \\ 0 & else \end{cases} \tag{4}$$

$$CE^{(i)} = 1, \quad \forall i \in dim \tag{5}$$

Where q_1 is a random value that follows a standard distribution between [0, 1],d is a random value that is arbitrary created within the range [0, 1] resulting from the uniform distribution, so no modification of this parameter was necessary. Where$randperm$ and $rand_j$represent the algorithms of integer combinations and randomly assigned number development for integers.

The AHO replicates the three different foraging strategies used by hummingbirds: instructed, territorial, and migratory. One of the flying skills listed in Equations (3) to (5) is the basis for the first two approaches, which are chosen at random. Hummingbirds use the directed method to search for a particular food source, which results in the discovery of a possible food supply that can be characterized as follows:

$$Ganew_i(s+1) = \left(Ga_j(s) - Ga_{j,target}(s)\right).M(0,1).CE + Ga_{i,target}(s) \tag{6}$$

Where the place associated with the expected and current food sources at time s are denoted by $Ga_j(s)$and$Ga_{j,target}(s)$,$M(0,1)$ represents a Gaussian distribution function.

$$Ganew_i(s+1) = (1 + M(0,1).CE).Ga_i(s) \tag{7}$$

$$Ga_i(s+1) = \begin{cases} Ganew_i(s+1) & if\ SE\left(Ganew_i(s+1)\right) < SE\left(Ga_i(s)\right) \\ Ga_i(s) & else \end{cases} \forall j \in g_m \tag{8}$$

A hummingbird typically migrates to a farther-off food source when there is insufficient food in its area. In order to implement this strategy, the hummingbird, as shown in equation (1), goes to a different food source chosen at random from the entire searching space if it is situated at the food resource with the smallest nectar-refill frequency.

$$Ga_{worst} = (Up - Lo).q + Lo \tag{9}$$

In order to confirm that every hummingbird is moving inside the designated search region, a method for verification must be developed. Any control parameter that is violated would be redirected to the searching area boundary as follows:

$$Ga_i^{(c)}(s+1) = \begin{cases} Up^{(c)}, if\ Ga_i^{(c)}(s+1) > Up^{(c)} \\ Lo^{(c)}, if\ Ga_i^{(c)}(s+1) < Lo^{(c)} \quad \forall i \in g_m, \forall\, c \in dim \\ Ga_i^{(c)}(s+1),\ else \end{cases} \tag{10}$$

An essential part of the AHO for maintaining track of excursions to food sources is the visit chart. A hummingbird that investigates its food source each time could discover it'sfavourite. Each bird can have its equation (2) changed in the following ways:

$$US_{i,l} = US_{i,l} + 1,\ \ if\ l\ \neq i\ \&\ l\ \neq target, s \tag{11}$$

$$US_{i,target} = 0 \tag{12}$$

$$US_{i,l} = \max_{K \neq i\ \&\ K \in g_m} (US_{i,k}) + 1,\ \ if\ l\ \neq i, l = 1{:}\,g_m \tag{13}$$

Extreme Gradient Boosting (XGBOOST)

TheXGBoost algorithm, based on the Gradient-Boosted Decision Trees (GBDT) structure. It has received much attention due to its exceptional performance in the ML competitions on Kaggle. The XGBoost objective feature, unlike GBDT, has a phrase for regularization to prevent over fitting. Following is anequation (14) description of the primary objective function:

$$U = \sum_{j=1}^{n} S(y_j, \left(F(x_j)\right) + \sum_{h=1}^{t} G\,(f_h) + D \tag{14}$$

D is a constant that can be selectively eliminated, and $G(f_h)$ denotes the regularization term at iteration h.

$G(f_h)$is a regularization term written asequation (15),

$$G(f_h) = \alpha\mathrm{T} + \frac{1}{2}\eta \sum_{\mathrm{i}=1}^{\mathrm{H}} \mathrm{w}_\mathrm{i}^2 \tag{15}$$

Where α is the leaf complexity, H stands for the leaf count, η is the consequence variable, and $w_i$is the end product for each side node. In contrast to the leaf node, this represents a tree node that cannot be separated, leaves representbased on classification criteria, the anticipated categories.

The main function can be expressed as follows equation (16)if mean square error (MSE) is the loss function:

$$U = \sum_{j=1}^{n} \left[p_j \omega_{p(y_j)} + \frac{1}{2}(q_j \omega_{q(y_j)}^2)\right] + \alpha T + \frac{1}{2}\eta \tag{16}$$

Where g_j and T_j stand for 1st and 2nd derivatives of the loss function, respectively, $q(y_j)$is a procedure that changes data points into leaves.

The total of the loss values determines the final loss value. Since the DT samplessummarize the leaf node loss values, they yield the absolute loss value of leaf nodes. Therefore, the primary function can be expressed as equation (17).

$$U = \sum_{i=1}^{H} [p_i \omega_i] + \frac{1}{2}(Q_i + \eta)\omega_i^2 + \alpha T \tag{17}$$

Where $p_i = \sum_{j \in I_i} p_j$, $Q_i = \sum_{j \in I_i} q_j$, and $I_i$are the overall sample count in leaf node i.

The difficulty of maximizing the primary function is simplified to locating a quadratic function's minimum. Regularization phenomena have been added, giving XGBoost a stronger capacity to prevent over fitting.

Algorithm 1: AHO-XGB

```
Initialize algorithm parameters and hyperparameters
Load and preprocess sports data (e.g., player statistics, game outcomes)
function AHO_XGB(data):
split_data(data, train_set, test_set)
fori in range(Num_Hummingbirds):
hummingbird = create_hummingbird()
hummingbird.fly_to_target(train_set)
xgb_model = train_xgboost(train_set, hummingbird.params)
accuracy = evaluate_model(xgb_model, test_set)
hummingbird.set_fitness(accuracy)
save_hummingbird(hummingbird)
best_hummingbird = select_best_hummingbird()
returnbest_hummingbird.xgb_model
functioncreate_hummingbird():
    Initialize random hyperparameters for XGBoost
hummingbird = Hummingbird(hyperparameters)
return hummingbird
functiontrain_xgboost(data, params):
xgb_model = XGBoost.train(data, params)
returnxgb_model
functionevaluate_model(model, test_data):
predictions = model.predict(test_data)
accuracy = calculate_accuracy(predictions, test_data.labels)
return accuracy
functionsave_hummingbird(hummingbird):
functionselect_best_hummingbird():
    Sort hummingbirds by fitness in descending order
return the top hummingbird
Initialize Num_Hummingbirds
best_model = AHO_XGB(data)
```

4. Experimental analysis

Twenty faculty members from physical learning centres and 250 learners from three universities were selected as research subjects for this investigation.The study questionnaire was created based on a review of the literature and consultation with experts and tutors to guarantee the validity and correctness of the content arrangement.Following approval, a formal questionnaire is created, its validity is assessed, and an expert review is conducted. There are four assessment levels "very reasonable, reasonable, general, and unreasonable" are created based on the information in the questionnaire.Table 1 provides the fundamental scenario.

Physical education currently dominates students' teaching skills and capacities.In these five schools, a survey using a questionnaire were given to 226 students and 20 teachers.The overall conditions of every institution, the instructors' evaluation of their learners' current level of knowledge education, and the self-evaluation of each university's students' learning talents and skills are acquired through the statistical analysis of the questionnaire's findings. Fig.1 shows the three universities U1, U2, and U3 performance.

Table 1. Data on the validity assessment

Indexes	Reasonable	Very Reasonable	Unreasonable	Generally
P value	0.064	0.027	0.053	0.042
Frequency	9	4	0	1
Percentage	68	26	0	9

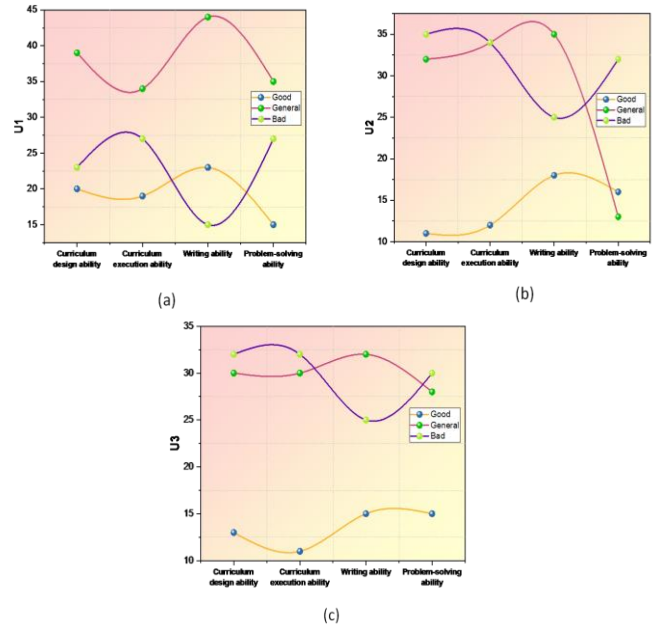

Figure 1. (a) U1 university performance (b) U2 university performance and (c) U3 university performance

Except for schools U1 and U3 in Fig.1, the data indicates that the overall condition in three schools is extremely poor.The contributor has examined this phenomenon in isolation, and the primary reasons are listed below. From the perspective of the students, these two schools are part of university systems that are private. The young people's general standards for quality are slightly higher than the other institutes'. The fact that they outperform some other institutions is hardly surprising, considering the administration and the pupils' self-assurance.A teacher's degree of education is another significant component impacting the education of pupils' academic abilities. Various schools have different pedagogical skills and technological conditions.Based on the traditional teaching approach, teacher training programs and instructional principles have been significantly updated in the two institutions. Encourages students' independent learning and changes the position of the instructor according to the pupils' primary learner.

Students have more opportunity to acquire teaching abilities because to the superior technological environment. When it comes to regulations, policies, and administration in schools have a big impact on learners grow as teachers.In terms of comparison, these two institutions have a stricter management structure than the other one, and they also apply defined educational measures at a higher rate. The survey satisfaction is shown in Fig.2.

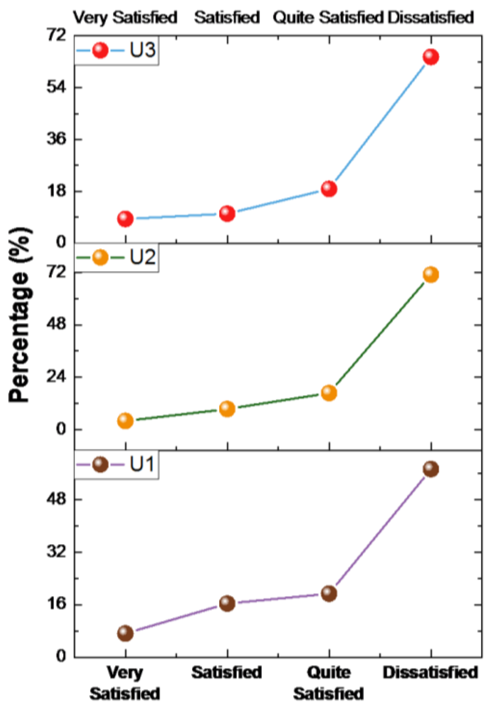

Figure 2. Survey findings on satisfaction

The proposed method is AHO-XGB and compared to the existing methods are SVM, Naive Bayes [21], the performance of these methods are analysed by accuracy, precision, and recall.

4.1. Accuracy

Accuracy in sports skill acquisition refers to an athlete's capacity to predictably and accurately carry out particular motions or activities necessary for their sport.

$$Accuracy = \frac{TP+FP}{(TN+TP+FN+FP)} \quad (18)$$

Fig.3 and Table 2 shows the accuracy performance, the existing methods are SVM, and Naive Bayes, their accuracy are (66.92% and 70.32%). The proposed method AHO-XGB has accuracy of 92.6%. As a result, the proposed system has greater accuracy as compared to the existing systems in sports skill learning.

Table 2. Values of accuracy

Methods	Accuracy
SVM	66.92
Naive Bayes	70.32
AHO-XGB (proposed)	92.6

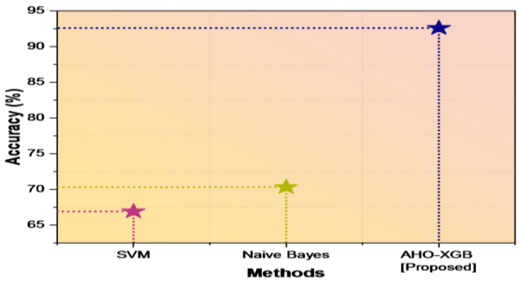

Figure 3. Accuracy performance

4.2. Precision

Precision in sports skill acquisition refers to an athlete's precise movement control and execution, which ensures the regular accomplishment of particular objectives with minimal fluctuation.

$$\text{Precision} = \frac{\text{TP}}{TP+FP} \quad (19)$$

Fig.4 and Table 3 shows the precision performance. In comparison to the existing systems SVM and Naive Bayes, which have corresponding reliable rates of (64.31%, 64.41%), the proposed system AHO-XGB obtained 90.5%. The suggested system is more reliable than the present methods in sports skill learning.

Table 3. Values of precision

Methods	Precision
SVM	61.31
Naive Bayes	64.41
AHO-XGB (proposed)	90.5

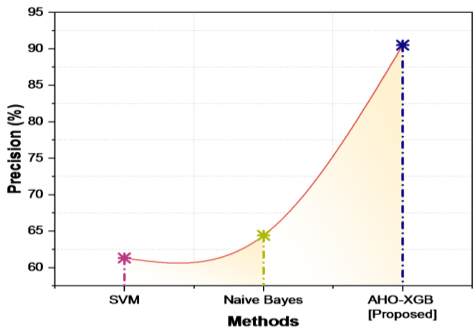

Figure 4. Precision performance

4.3. Recall

Recall is the ability of an athlete to use new tactics and plans in the moment, which is crucial for making fast decisions and adjusting to various game conditions during practice or competition.

$$Recall = \frac{TP}{TP+FN} \quad (20)$$

Fig.5 and Table 4 shows the recall performance. The suggested system AHO-XGB has a performance rate of 94.3%, which is higher than the existing systems such as SVM, and Naive Bayes, which have comparable performance, rates of (92.15%, 90.86%). Therefore, the proposed system is more trustworthy than the current approaches in sports skill learning.

Table 4. Values of recall

Methods	Recall
SVM	92.15
Naive Bayes	90.86
AHO-XGB (proposed)	94.3

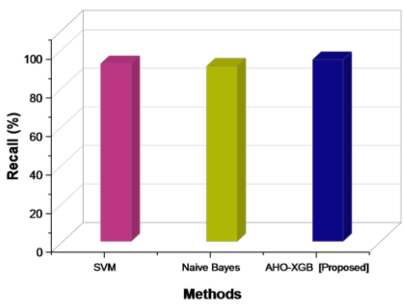

Figure 5. Recall performance

4.4. Discussion

The existing methods are SVM [22], Naive Bayes [22].The sensitivity of Support Vector Machines (SVM) to kernel and hyperparameter selections limits their applicability in sports skill acquisition and makes it difficult to optimize for different sports. Large datasets are challenging to handle and can cause over fitting. Additionally, SVMs require a significant amount of individual tuning and design of features, which limits their adaptability to adaptive sports skill acquisition environments.The assumption of component isolation made by Naive Bayes, which could not be true in complicated sports settings and potentially lower predictive accuracy, is an issue when it comes to sports skill acquisition. High-dimensional data, which is frequently encountered in sports analytics, presents additional difficulties for it and has an impact on performance.XGBoost and AI are used in AHO-XGB to provide incredibly precise performance insights. Considering its superior feature selection, understanding, real-time analytic capabilities, and adaptability to a variety of sports, it is an invaluable tool for maximizing athletic performance and training.

5. Conclusion

Deep learning in sports uses neural networks to assess sensor and video information, providing athletes and trainers with insights to enhance performance and practise. Problems with data quality and availability, difficulties interpreting techniques for teaching purposes, and potential spending limits for athletes and local sports teams were related to sports skill development. In this study, we proposed Artificial Hummingbird Optimized XGBOOST (AHB-XGB) to offer exceptionally accurate predictions and evaluations of the performance of an athlete. The proposed method has an accuracy (92.6%), Precision (90.5%) and recall (94.3%). Sports skill learning using deep learning was limited by issues with data quality and interpretability, also having high computing costs. With improvements in AI and data quality, deep learning become more accessible in the future, offering a promising range. Potential applications include virtual athlete performance and training analysis through connection with VR and AR.

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