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Evolutionary Algorithm with meta deep learning model for identifying athlete behavior in Sports Analytics

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Abstract:

Research in sports analytics has mostly concentrated on measuring and analyzing performance in three contexts: training, competition, and recovery. Recognizing and analyzing athlete behavior is crucial for enhancing performance, making the most of training, and preventing injuries in sports. The complex and irregular patterns in athletic performance are beyond the capabilities of conventional approaches and mainly depend on subjective observation and oversimplified statistical analysis. This work presents SA-EAMDL, a cutting-edge Sports Analytics (SA) system that combines an Evolutionary Algorithm (EA) with a Meta-Deep Learning (MDL) model to identify the actions of athletes accurately. Its purpose is to address these difficulties. To achieve consistently high accuracy across different datasets, the evolutionary method optimizes the structure and hyperparameters of a deep learning model. Using convolutional neural networks (CNNs) and recurrent neural networks (RNNs), the meta-deep learning model analyzes data on the actions of athletes and can concurrently recognize complex patterns over time and place. The accuracy and efficiency of behavior recognition in sports should be greatly improved by integrating these technologies. This approach is well-suited to modern sports analytics as it reduces the computing load of testing and training models and improves the accuracy of researching player behaviour. Athletes in any activity can benefit from this method's capacity to assist them make quicker, more data-driven decisions on performance evaluations, practice efficacy, and prevention of injuries strategies. The SA-EAMDL framework can greatly improve sports analytics due to its effectiveness and precision.

Keywords: Meta Deep Learning model, Evolutionary Algorithm, Convolutional Neural Network, Recurrent Neural Networks, Sports Analytics, Athletic Behaviour.

1. Introduction

To maximize performance enhancement, training schedule design, and injury risk reduction, sports analytics must thoroughly grasp player behavior. Sports analytics is an exciting new area of study that aims to improve our understanding of the game by analyzing current and previous games. Predicting the match's outcome benefits team members, coaches, and bettors [1]. Feelings significantly influence how well a person performs in a sporting event. Furthermore, it seems that an integral component of athletic success is the ability of athletes to detect, comprehend, and control their emotions to perform at their peak [2]. Leadership traits and greater social integration are fostered by active participation, which promotes tenacity, discipline, and resolve. Participating in regular athletic activities has several health benefits, including easing the symptoms of chronic conditions, promoting heart health, enhancing lung function, and strengthening muscles and bones [3]. The main goal of competitive sports is to provide better sporting performance, which helps in winning tournaments. Evidence from competitive sports is based on the athlete and their actions [4]. There has been a recent proliferation of ML applications in sports, including research surveys on injury prediction, predictive modeling in sports training, and optimum team formations based on forecasts [5]. Since AI has developed into a useful tool for improving competition across many sports, there is a good chance that scientists' interest in AI and its subfields will continue to rise at a healthy rate [6]. Over the last several years, there has been tremendous advancement in deep learning, AI, and ML [7]. Several scientific fields have been profoundly affected by the rise of deep learning in the last several decades. The algorithms outperformed competing state-of-the-art approaches. Compared to earlier efforts, deep learning has produced state-of-the-art results in activities such as autonomous driving [8]. Predicting injuries, incorporating predictive analytics into training, and building ideal teams using forecasts are just a few of the many Machine Learning (ML) applications that have recently exploded in the sports industry [9]. When undertaking method analysis and performance prediction in the field, inertial measurement unit (IMU) sensors are used as inputs to identify and classify complex athletic motions. Noise and signal fluctuations are common in the data produced by inertial measurement unit (IMU) sensors used to track motion in sports, and the data isn't necessarily labelled according to the recognised activities [10]. Throughout training and competition, giving one's is a measure of an athlete's competitive ability. The many manifestations of it, including mental acuity, physical stamina, talent, and sports intelligence, are on full display during the competition and training that make it up [11].

This paper's primary contribution is

- By combining an EA with a meta-deep learning framework, the SA-EAMDL method suggests a new way to analyze complicated athlete behavior for sports analytics.
- To guarantee consistent performance across many datasets, the evolutionary technique optimizes the deep learning model's structure and hyperparameters.
- The meta-deep learning system can detect complex temporal and spatial patterns in data of athletes' actions by combining CNNs with RNNs.
- Ideal for real-time sports analytics, this method reduces the amount of computing resources needed for model training and optimization.

This study introduces a new SA-EAMDL method for detecting player actions in sports analytics, that tackles the problems with previous methods for dealing with complex, non-linear patterns. The state-of-the-art architecture is supported by an evolutionary algorithm and a meta-deep learning framework. The objective is to enhance performance, boost training effectiveness, and reduce accident rates using faster and more precise analysis. This method optimizes the variables of the framework for deep learning using an evolutionary algorithm and employs a meta-model that combines RNNs and CNNs to detect patterns in time and space. The outcomes demonstrate notable enhancements in recall, precision, and accuracy.

2. Literature Review

Yang D. et al. [12] presented the ACO real clustering model, substantially enhancing athletic performance assessment. Drawing inspiration from ant colonies' path selection mechanism, this model outperformed previous approaches regarding grouping efficacy and model stability. To optimize athletic preparation and competitive strategies, the ACO model attained a silhouette coefficient 0.72 with a Davies-Bouldin value of 1.05—promising results. However, its reliance on parameter choices makes it difficult to implement. Therefore, more work in this area is needed.

Liu T. et al. [13] took a new approach to examine athletic behaviour. They built a distributed frequency model for behavior classification using the DL-DBN method with probability. This algorithm's potential is enormous given that strength training exhibited the best accuracy (99%) and lowest precision (71%). The necessity for additional study and improvement in this field is highlighted because biased or small datasets may lead to overfitting or incomplete generalization.

In a recent publication, Mou, C. [14] introduced CANet, a novel Class Aware Network (CANet) capable of decoding football players' body movements for performance analysis. We start by discussing the advantages of deep learning methods and the role of the Internet of Things in football matches. Next, attention mechanisms and pyramid pooling modules are presented. To further improve the network's detail perception, the Group-split-bottleneck (GS-bt) module is used, and the CANet is built to extract and use multi-scale feature information. Certain constraints must be considered as the computational complexity of the model has increased due to the use of multiple technical techniques.

Ali-Fakulti, M. F., and Jamil, J. A. [15] suggested the performance optimizing framework for female athletes, POFFA. This framework delves into sports analytics and investigates how pattern mining techniques, specifically the Flexible Fuzzy C-Means (FFCM) algorithm, can aid in predicting female athletes' actions. Coaching methods, training plans, and performance enhancement processes can all benefit from the in-depth insights into behavioural patterns that this study seeks to provide by focusing on female athletes.

Using data from the sports betting market, the anticipated value of the game's state, victory probability, and metrics of team strength are the four main points Baumer S. et al. [16] bring together, which are shared across various sports. We look at the commonalities and peculiarities of analytical methods used in each sport. While we detail the ideas behind each study type, statistical approaches, computer programs, and data sources are essential to any implementation.

García-Aliaga, A. et al. [17] aimed to use machine learning algorithms to classify a team of football players into certain positions on the field according to their technical and tactical abilities. A set of rules found by the machine learning algorithm RIPPER was used to obtain the most discriminatory factors for each group, allowing us to better comprehend the distinctions between the player positions. We were able to draw some helpful findings about how to improve players' performance and how to assign roles on the field by combining the two methods. Positions were created in this study solely based on players' technical-tactical behavior statistics; the study did not consider the players' individual behavior profiles or game patterns.

In their study, Pu, Z. et al. [18] employed soccer match analytics as a comprehensive OODA loop. Various orientation and decision-making models for real-world and virtual soccer matches and event and tracking data are thoroughly examined at the confluence of the OODA loop and the real-virtual domains. At last, we highlight some potential future possibilities for this multidisciplinary field.

Quaid, M. A. K., & Jalal, A. [19] proposed a new approach employing a genetic algorithm to tackle difficult feature selection and classification issues with sensor data. To increase the likelihood of obtaining optimal feature values, the suggested Human Behavior Pattern Recognition (BPR) method has been utilized to identify statistical

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features in addition to acoustic signal features, such as zero crossing rate, based on statistical relationships between behaviors and corresponding signal data.

Zadeh. A. et al. [20] tracked participants across various characteristics. Wearable electronics have the potential to boost athletes' well-being and performance. We collected quantifiable data using the Zephyr BioHarness Wearable technology to learn how to anticipate and avoid injuries caused by the wearer's physical exertion while playing sports. Findings suggest that injury may occur when high mechanical stresses are coupled with a high body mass index (BMI).

Sahebkaran, M. A., & Khazaei, S [21] identified the factors influencing physical education students' perceptions of athletic success. They examined how body image and self-efficacy play a role, with achievement motivation as a mediator. The research was descriptive and correlational, using path analysis as the methodology. According to the results, body image and self-efficacy positively impacted perceived athletic achievement.

3. Proposed Work

a. Dataset Explanation

Compiling the UCF50 dataset aimed to promote computer vision-related activity detection development by providing a carefully chosen set of pertinent data. It expands the existing UCF11 dataset by incorporating more types of activities from real, uncut YouTube videos, making it better. This essential realism is vital for representing real-world situations and presenting difficulties and opportunities for researchers and practitioners. The use of exclusively YouTube footage ensures high authenticity. The dataset has twenty-five clusters in all. Each grouping contains action clips with at least four similar clips, like backgrounds or points of view. Train models and execute layered analysis with ease with this clever grouping.

b. The Proposed SA-EAMDL in the identification of Athletes' behavior

In sports analytics, the phrase "athlete's behavior identification" explains analyzing and making sense of data of athletes' movements, decisions, and activities. This study will enhance athletes' talents through data collection, statistical analysis, and deep learning.

Figure 1 provides a brief description of the SA-EAMDL framework's proposed method. Sports analytics takes a holistic view of player behavior analysis with the proposed SA-EAMDL method. This cutting-edge technology can use a CNN to recognize spatial features from pictures or sensor data. An RNN is employed for temporal analysis after receiving the CNN's output to represent crucial spatial aspects of sporting motions. The RNN can assess if a player's strategies and tactics are changing by analyzing the data in a sequential manner. Adding the EA to the model improves both the CNN and RNN components. The EA builds better structures over many generations using mechanisms including mutation and crossover. Methods for accomplishing this goal include gathering model arrangements, evaluating them, and implementing the best ones. The product of this procedure is a deep learning system capable of recognizing complicated, time-dependent sporting events through the application of spatial and temporal analysis. Its novel use of CNNs, RNNs, and EA can enhance various evaluations, including strategy recognition, injury threat assessments, and efficiency.

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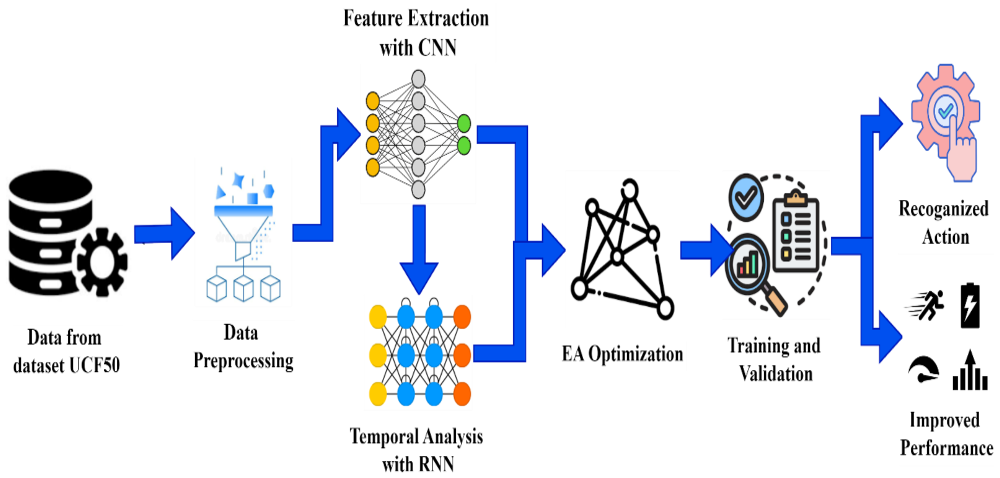

Figure.1 The SA-EAMDL framework's overall operation

c. The general process of the SA-EAMDL approach

i. Data Collection

This system is fed data from the UCF50 dataset. The raw data retrieved from this set includes video segments and still images of athletes engaged in different pursuits. The SA-EAMDL system uses the UCF50 dataset, a gold mine of authentic action footage mined from YouTube. This dataset is ideal for motion job recognition in sports analytics, as it contains four action clips, twenty-five categories, and fifty different sorts of actions. Throughout the data-collecting phase, multiple techniques are employed to record the athletes' motions meticulously. The performance of athletes may be better understood if data collected from monitoring devices and wearable sensors were integrated into the system. To do more accurate and thorough assessments of athlete behavior, the SA-EAMDL framework uses a variety of data collection approaches.

ii. Data Preprocessing

Preparing the raw data is essential for time series analysis as well as feature extraction. The preprocessing process includes several steps: resizing, normalizing, augmenting, and segmenting.

Resizing: Since convolutional neural networks (CNNs) require uniformly sized input images, adjusting their sizes is critical for neural networks in general. To maintain a steady aspect ratio and prevent distortion, pictures should be scaled to a specific size, such as 224 by 224 pixels. This guarantees that every image is handled consistently. Cropping or padding may be required to attain the desired size without distortion. This study made great strides in computer resource management by standardising input size.

Normalization: Resetting pixel to a standard range, usually 0-1 or -1-1, is normalisation and an essential component of any preprocessing effort. This approach works wonders for machine learning models, especially those used for picture analysis. By bringing all attributes to a consistent size, normalization allows for more effective learning and dramatically increases the convergence rate during model training. Global normalization is applied to the entire dataset to shed more light on the data distributions for the model. On the other hand, per-image normalization works well for processing photographs with different lighting conditions. These normalisation factors

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greatly improve the model training's efficiency and resilience when testing athletes' actions in environments with widely varying imaging and illumination conditions.

Data Augmentation: Data augmentation is essential for improved model performance and generalizability. The training dataset's diversity is artificially enhanced. By manipulating the input photos with tools like rotation, flipping, color jittering, magnification, and noise, augmentation trains the model to disregard image quality, lighting, perspective, and size variations. Color jittering represents various lighting situations, and rotating and reversing the screen's orientation simulates changing camera angles. The model can withstand variations in image quality with noise, and activities may be detected from different distances with the help of an improved zoom capability. Overfitting is minimized, and the model's capacity to generalize to new, unknown data in real-world contexts, including athlete behaviour analysis, is substantially enhanced by these augmentation procedures, which expose the model to a wider variety of potential input modifications.

Segmentation: Segmentation is a crucial preprocessing step in athlete behavior analysis. It helps the model focus on the most significant information by separating the athlete or important parts of the frame.

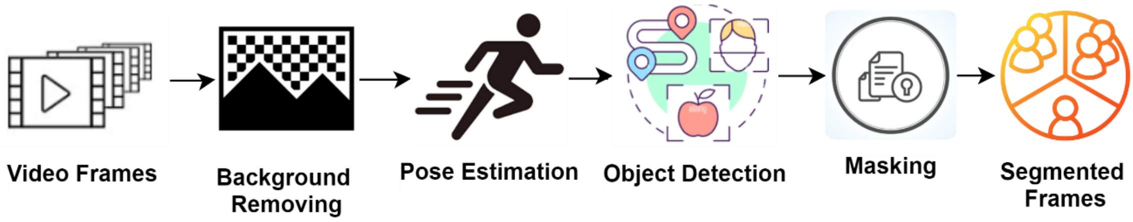

Figure.2 Segmentation Process

Figure 2 shows the segmentation process of the raw data obtained from the dataset. This process involves multiple important techniques: first, removing the background so the model can focus on the athlete's behaviors; second, estimating their poses so they can be analyzed more precisely; third, detecting objects so the model can be focused on the athlete and not other components in the scene; and finally, masking, which creates binary masks that emphasize specific areas of demand. The segmentation algorithms used in the preprocessing pipeline help to remove irrelevant data and guide the model to the most important parts of the picture or video. This targeted method greatly improves the SA-EAMDL framework's performance in sports analytics by increasing the model's accuracy in analyzing and interpreting athlete behavior.

d. Feature Extraction with CNN

A CNN is a picture recognition system miming how the brain processes visual information. This approach uses a convolution computation instead of a regular neural network. Pooling and convolutional layers can react to the translation invariance of the input characteristics, efficiently detecting similar aspects of images because the neurons between the CNN's convolutional layers are only coupled with a few neurons across the adjacent levels.

With CNNs, feature extraction is a way to take raw input data like video or picture frames and turn it into useful representations or features for detection, classification, or regression. CNNs often use a multi-layered architecture to handle and extract information from visual input information effectively. The process starts with an input phase that takes in raw video or picture frames denoted by X_t. Convolutional layers filter the input data to identify specific patterns and features as in equation (1).

$$F_t^l = \sigma(W^l * F_t^{l-1} + b^l) \quad \text{(Eq.1)}$$

where F_t^l is the future map at the layer l, W^l, b^l are the weight and biases at the layer l, σ is the activation function and $*$ is the convolution operation.

Networks may learn complicated patterns with the help of activation layers such as ReLU, introducing non-linearity. After that, the feature maps are downsampled using pooling layers as in equation (2), reducing the dimensionality and computational cost without losing any crucial spatial information.

$$F_t^l = pool(F_t^{l-1}) \quad \text{(Eq.2)}$$

Some architectures incorporate fully connected layers at the end to merge the retrieved characteristics into a final features vector. These architectures are commonly employed for classification tasks. CNNs excel at image and video analysis because their series of layers transform visual input into feature representations that are both abstract and task-relevant.

e. Temporal Analysis with RNNs

Recurrent neural networks (RNNs) process data in sequences to analyze patterns and dependencies over time. This is quite helpful, particularly in time-series estimation, language simulation, and sequential decision-making, where the sequence and timing of data points are critical. Specialized neural network topologies, RNNs, are made to process and interpret sequential input in equation (3).

$$X = [X_1, X_2, X_3, \ldots\ldots, X_t] \quad \text{(Eq.3)}$$

where $X_1, X_2, X_3, \ldots\ldots, X_t$ are the sequence of data extracted from the image through the CNN process.

A major aspect of these networks is an evolving hidden state that allows them to process current inputs by capturing and using information from earlier time steps in equation (4).

Basic RNN cell:

$$h_t = \sigma(W_h \times [h_{t-1}, X_t] + b_h) \quad \text{(Eq.4)}$$

where h_t is the hidden state at time t. W_h, b_h are the weight and biases for the RNN cell. σ is the activation function.

A succession of vector representations is the usual input to an RNN, and the network processes each input. At each stage, the network keeps context and temporal relationships in the data by updating its hidden state using its present input and the previously hidden state. An output sequence is produced by this method, which can be used for data production, categorization, or prediction, among other things. RNNs excel at processing time-series data, natural language, and other applications where the input order and context are crucial because of their capacity to store and update internal memory.

f. Optimization with Evolutionary Algorithms (EAs)

An evolutionary algorithm is an artificial intelligence (AI) program that attempts to solve issues using procedures like living organisms. Thus, reproduction, mutation, and recombination are processes often linked to biological evolution. An approach to finding optimal or near-optimal solutions to complicated problems, Optimization with EAs

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takes genetic processes and natural selection guidance. Machine learning model hyperparameters and architectural optimization are areas where EAs shine, especially when more conventional gradient-based optimization approaches have failed.

Athlete behaviour identification using evolutionary algorithms entails training models to better process and forecast an athlete's actions based on complicated data sets, including geographical data, physiological parameters, and video footage. The main concept is using EAs to determine the best model parameter and architecture configurations for CNNs and RNNs to better process and understand sequential data. Figure 3 shows the working flow of the EA.

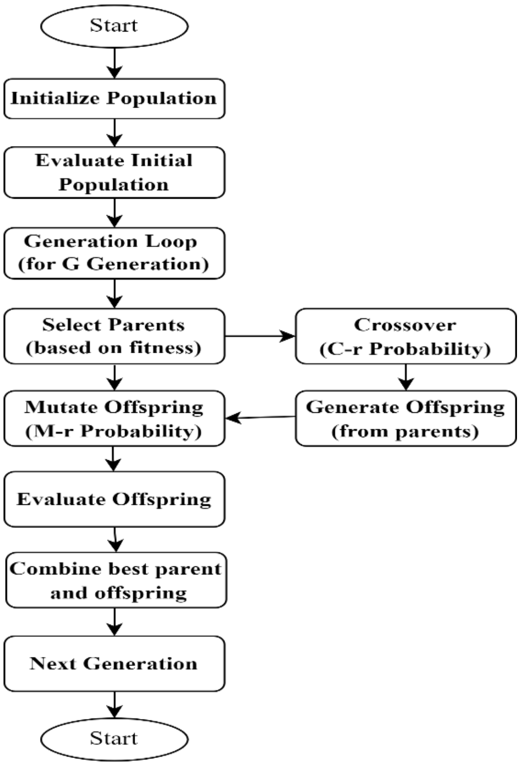

Figure.3 Flowchart for EA

EAs take a biologically inspired approach to find the best settings for deep learning models to analyze athlete behaviour. In this evolutionary strategy for CNN/RNN architecture optimization in sports behaviour analysis, we start with a diverse set of models with different convolutional layer configurations, dropout, and learning rates. A labelled dataset of athlete activities, including running, jumping, and resting, is used to train and verify each model in this population. Reproduction is then limited to the best-performing models, defined as those with the greatest accuracy in behavior recognition. While some progeny experience random mutations, such as changes to learning rates or the quantity of RNN units, new architectures are generated by merging the convolutional layers of one parent model with the RNN layers of another. By incorporating advantageous mutations into the process, the best features of the original models are combined to create the subsequent set of models. The model undergoes a 50-generation evolutionary cycle to fine-tune and improve its performance. Based on how well it detects different player actions in the test data, the best CNN/RNN model is selected after the procedure. This method uses evolutionary algorithms to quickly comb through all the potential model configurations until it finds one that works well for evaluating physical exertion.

4. Results and discussion

a. Experimental Setup

The first step is collecting the data, which comprises pulling sports-related videos from the UCF50 dataset. The clips will be resized, normalized, and enhanced as part of this pre-processing. The model architecture comprises a pre-trained CNN for feature extraction in space, an RNN for feature analysis in time, and all layers linked for classification. The objective of the EA is to enhance the model's structure and hyperparameters. The search space has several parameters that may be customized, including activation procedures, training rates, dropout rates, CNN and RNN layer specifications, and many more. Starting with fifty distinct model configurations, this procedure employs a fitness metric that prioritizes validation accuracy over processing speed. Some evolutionary processes that guide the population towards the best designs include hyperparameter randomization, regular component crossings, and natural selection.

b. Performance metrics

Here we'll compare SA-EAMDL to some more traditional methods, such as Ant Colony Optimization (ACO) [12], Deep Learning-Deep Belief Network (DL-DBN) [13], and Class Aware Network (CANet) [14], by looking at their performance metrics like convergent rate, accuracy, precision, recall, F1 score, and more. These approaches are perfect for comparison because they include combinations, deep learning, and customized neural networks—all of which are vital to the study of athletic behaviour. Their exceptional academic success serves as an example to others. Methods such as SA-EAMDL encompass action identification, movement analysis, and behaviour clustering, all of which are important components of sports analytics. The advantages of the proposed SA-EAMDL framework, which include RNNs, evolutionary optimization, and CNNs, can be more clearly shown by contrasting it with these approaches.

i. Accuracy, Precision, Recall and F1 Score

Precision: The precision P metric shows what proportion of the system's positive predictions were correct. Equation (5) accomplishes this.

$$P = \frac{TP}{TP+FP} \tag{Eq.5}$$

where TP (True Positives) is a real-life behavior that is accurately recognized by the model, FP (False Positives) is a non-existent behavior that is falsely identified by the model.

Recall: Equation (6) yields the recall, denoted as R. The recall measures the proportion of correct predictions relative to the number of positive cases.

$$R = \frac{TP}{TP+FN} \tag{Eq.6}$$

where TP (True Positives) is a real-life behavior that is accurately recognized by the model, FN (False Negatives) if a model misses a real-world behavior.

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F1 Score: An equitable evaluation of each statistic is provided by the $F1$ Score is obtained by calculating the harmonic average of both recall and accuracy using equation (7).

$$F1 = 2\left(\frac{P \times R}{P + R}\right) \quad \text{(Eq.7)}$$

where P and R are obtained from equation (5) and equation (6) respectively.

Overall Accuracy: The percentage of accurate (positive and negative) predictions among all the model's predictions is known as overall accuracy (A). This is essential for all approaches to prevent false alarms. Equation (8) could achieve this.

$$A = \frac{(TP + TN)}{TP + TN + FP + FN} \quad \text{(Eq.8)}$$

where TN (True Negatives), a model accurately detects that a particular behavior is not present.

Table 1 Accuracy, Precision, Recall and F1 Score Comparison Analysis

Method	Accuracy	Precision	Recall	F1 Score
ACO	0.80	0.75	0.79	0.79
DL-DBN	0.82	0.79	0.84	0.83
CANet	0.85	0.85	0.86	0.90
SA-EAMDL	0.95	0.94	0.96	0.95

When comparing the models, SA-EAMDL stands out as the most effective one, outperforming all others based on the given metrics. The best balance between precision and recall is indicated by its greatest F1 Score, and its dependability in forecasting positive outcomes and capturing real positives is emphasized by its high specific precision and recall scores. Though ACO and CANet do reasonably well, especially regarding recall and precision, they are inferior to SA-EAMDL in terms of accuracy and balance. On the other hand, DL-DBN needs major work or new strategies to increase its performance because it continuously gets poor results across all criteria.

c.Convergence Rate

An optimization algorithm's convergence rate is how close it gets to its ideal solution. Knowing how fast the applied approach may converge to an optimal or near-optimal solution for tasks like action recognition, behaviour clustering, and movement analysis is critical in the context of athlete behaviour analysis. Equation (9) shows how the convergence rate is calculated.

$$\rho = \lim_{k \to \infty} \left(\frac{\|x_{k+1} + x^*\|}{\|x_k - x^*\|}\right) \quad \text{(Eq.9)}$$

where ρ is the convergence rate, x_{k+1} is the solution at iteration $k + 1$, x_k is the solution at iteration k. x^* is the optimal solution. $\|.\|$ denotes the norm, typically the Euclidean norm. Figure 4 displays the results of the comparison regarding the Convergence Rate. SA-EAMDL might get to an ideal solution faster than ACO and DL-DBN, as the desired function value drops sharply. The SA-EAMDL system could benefit from the addition of CNNs, RNNs, and EA to improve learning and accelerate convergence. A comparison of convergence rates allows one to assess the practicality and efficiency of various approaches to real-time analysis of athlete behavior. In selecting the best approach for

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such issues, a faster convergence is essential, since it means faster results with less computing expense.

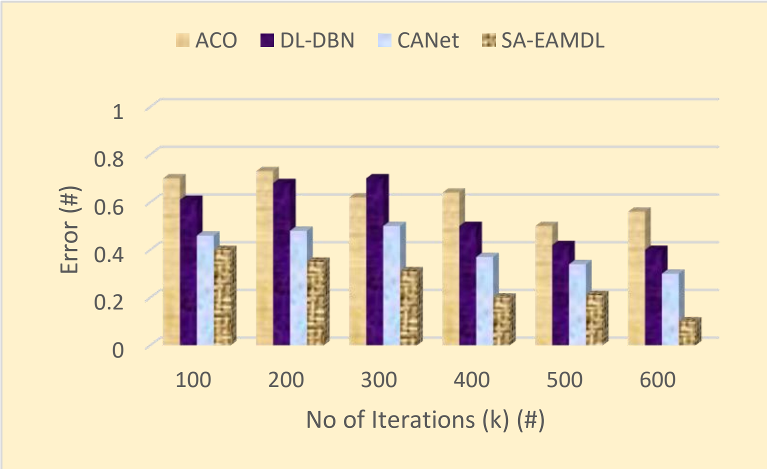

Figure. 4 Convergence Rate Analysis

d. Computational Efficiency

Computational efficiency in evaluating an activity is defined as the rate and accuracy with which data may be processed and inferences drawn regarding the movements, activities, and general behavior of an athlete. Algorithms that efficiently manage large datasets can also give insights rapidly while utilizing fewer computational resources.

Runtime, Using the time required for an algorithm to analyze data and generate outputs as a metric, computational efficiency may be measured in this context using the equation (10).

$$Runtime = f(n) \qquad \text{(Eq. 10)}$$

where $f(n)$ is the function that describes the increase in runtime as the size n of the input data increases.

The amount of operations needed by the method to attain a specific accuracy level is another way to quantify computing efficiency:

$$Efficiency = \frac{Output\ Quality}{Computational\ Resource\ Used} \qquad \text{(Eq. 11)}$$

where accuracy is the example for $Output\ Quality$ and Time and memory are examples of $Computational\ Resource\ Used$. Figure 5 shows the comparison analysis of computational efficiency over the proposed and traditional methods. Four methods for analyzing athlete behavior are compared here, and their different computing efficiencies are shown. SA-EAMDL is great for time-sensitive real-time analyses since it consistently has a shorter runtime regardless of the input size. Accuracy and efficiency can be balanced using ACO and CANet, making it a good choice for less urgent applications. On the other hand, DL-DBN is more appropriate for deep offline analysis than real-time processing since it may yield more detailed insights despite being slower and more computationally demanding.

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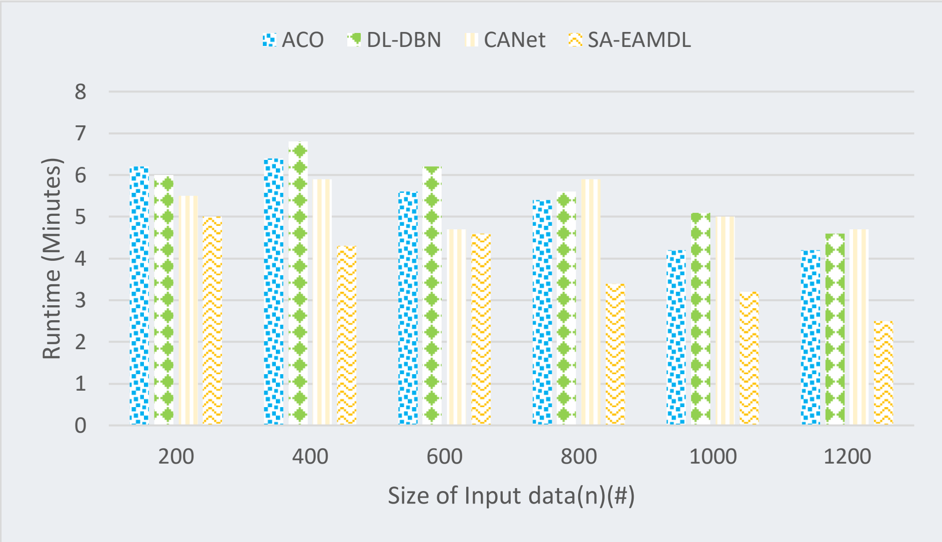

Figure.5 Computational Efficiency Analysis

e.Temporal Consistency

The cohesion or stability of features or predictions between each frame in a video is referred to as temporal consistency. It indicates that the model's predictions for athlete behavior identification should not fluctuate dramatically or unrealistically from frame to frame. Temporal consistency addresses numerous important sports analytics concerns and is essential for identifying player behavior. Considering that athletes' behaviors usually change gradually rather than suddenly helps to smooth out predictions. In the analysis, this smoothing effect lowers noise and false positives. throughout multi-frame continuous actions such as running or throwing, temporal consistency guarantees cohesive predictions throughout the activity. Incorporating temporal consistency into the SA-EAMDL paradigm improves decision-making, sheds fresh light on sports performance analysis, and yields more trustworthy and accurate assessments of athletes' behavior over time. The consistency loss term is a straightforward tool for expressing temporal consistency as shown in the equation (12).

$$L_T = \sum \|f(x_t) - f(x_{t-1})\|^2 \quad \text{(Eq.12)}$$

where L_T refers to the temporal consistency, $f(x_t)$ is the model's output at frame t, $f(x_{t-1})$ is the model's output at frame $t-1$. Figure 6 shows the temporal consistency analysis. To guarantee temporal consistency in identifying athlete behavior, the SA-EAMDL architecture integrates multiple methodologies. Fundamentally, the Recurrent Neural Network (RNN) captures temporal dependencies by nature, which lays the groundwork for predictions that remain consistent across time. The fitness evaluation in the evolutionary method is enhanced by temporal consistency loss, which means the model can better preserve coherent results across frames. This approach considers the context of the athlete's motions to evaluate sequences of frames rather than individual frames. One of the most important aspects of reliable sports analytics is the ability to make strong and consistent evaluations of player behavior; the SA-EAMDL framework provides this capability through its multi-faceted methodology.

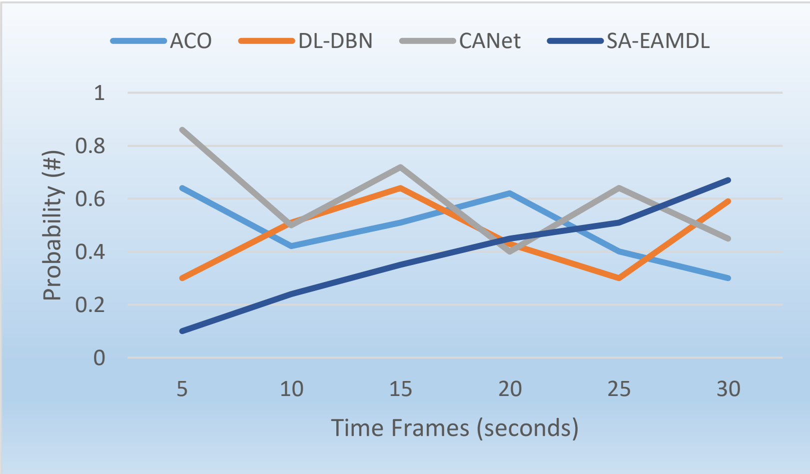

Figure. 6 Temporal Consistency Analysis

5. Conclusion

To overcome the limitations of previous approaches in handling complex, non-linear patterns in performance data from athletes, the SA-EAMDL method is a major step forward in sports data analysis. This state-of-the-art technology combines EA with Meta-Deep Learning, specifically CNNs and RNNs, to enhance the recognition and analysis of athlete behavior. The ability to fine-tune deep learning models ensures exceptional accuracy across diverse datasets, and the framework's ability to detect complicated spatial and temporal patterns enhances the efficacy and accuracy of sports behavior analysis. This state-of-the-art device has the potential to revolutionize performance analysis, training optimization, and injury prevention strategies. The SA-EAMDL system allows for faster, more accurate, and data-driven insights for coaches and athletes, allowing for better training techniques and faster decision-making. Because it can be applied to various sports, the framework's versatility makes it valuable in sports science. The SA-EAMDL system will be a huge step forward in sports analytics and will significantly impact athlete performance, training efficacy, and overall sports science research. Even with the framework's optimizations, creating and maintaining such a sophisticated system might still require substantial computing power. Future innovations are being pursued by SA-EAMDL to revolutionize sports analytics by providing unmatched insights for optimizing performance and preventing injuries.

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