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Research on Information Processing System of Sports Combination Training Model Based on Machine Learning and Neural Network

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Abstract

Information processing systems in sports and training applications are backboned by artificial intelligence for non-human intervening and accurate analysis. The fitness, performance, etc. outcomes are delivered by the system through learning implications over the different inputs. However, the recommendation/ prediction outcomes are down-surged in analyzing similar information due to learning complexity and non-adaptable outcome. Therefore, the problem is resolved by fragmenting and processing the information using a similarity measure. Therefore,

this method is named as Sliced-Information Processing with Analogous Learning (SIP-AL). In this method, a neural network is used for deciding the processing feature for better accuracy. In the contrary case of down-surges, the information slicing based on an analogous point is performed. This prevents the continuity between redundant and continuous data preventing errors.

Keywords: Data Slicing, Information Processing, Neural Network, Sports Training

Introduction

An information processing system is a system that takes information in one form and produces or processes it into another form. Information processing system provides various services and process for various fields which enhance the efficiency and performance of the system [1]. In sports, an information processing system is mainly used to train the data and process the information to achieve a certain goal [2]. The information processing system uses movement response to get the information and process the information which forms proper output for the sports environment. An information processor is used in every processing system to train the dataset and produce an optimal set of data for the data analysis and identification process [3]. Information processing systems are commonly used for the decision-making process to find out the exact details about sports information to provide a proper set of information for various processes. Information processing systems are used in sports environments to train a large amount of data and provide an appropriate set of data for data analysis and management processes. Information processing system collects data and information which are related to sports and manage it in an efficient manner [4, 5].

Information slicing is a process that divides or segments the larger information into smaller segments which reduces the latency rate in the data analysis process. Information slicing plays a major role in various fields and applications which need to find out the optimal and actual set of data for analysis and management processes [6,7]. Information slicing is also known as information dicing which divides the information into an appropriate set of data. The feature extraction technique is used in slicing methods which find out the important details about sports events and provide keywords or frames for the slicing process [8]. In sports and training, a huge amount of data is collected from various fields and applications, effective set of data is identified using the data slicing process. Pattern recognition technique is used in the information slicing method which finds out the necessary and needed a set of data among a huge amount of data. The pattern recognition process reduces the latency rate in the data analysis process which improves the effectiveness and efficiency of sports and training-related applications [9, 10].

Sports data processing is a process that performs an analysis process that contains data such as sports events, players' information, performance, strength, and weakness [11,12]. The data analysis process improves the performance and reliability of sports industries. Sports data processing systems manage both group and individual performance of sports which provide the necessary set of data for various processes [13]. ML approach is also used for the decision-making process in sports data processing system which analysis every detail of sports events and produce a final set of data for the data processing system [14, 15].

Related Works

Zhang et al. [16] introduced a big data monitoring system for sports health management. Microcomputer processing is used in the proposed system to improve the scope and efficiency range which provide proper services for the users. The proposed method is a sports healthcare system, which conducts various tests and services to find out the health condition of users. Big data monitoring system increases the accuracy rate in the detection and identification process which monitor every detail about the users and provide an effective set of data for various process.

Weiwei et al. [17] proposed an improved random forest and genetic algorithm (RF-GA) method for the classification of sports action. GA is used to improve the accuracy rate in the optimization process. Sports-based actions are collected based on 3D data and provide an optimal set of parameters for the classification process. The principal component analysis (PCA) process finds out the actual details and reduces the latency rate in the analysis process. Experimental results show that the proposed method increases the overall efficiency and effectiveness of the sports action classification process.

Zhao et al. [18] introduced a wearable sports posture measurement system using the Internet of Things (IoT). The proposed method identifies the sports postures, gestures, and measurements of sports which provide actual information of users to the coach. The proposed method is an online monitoring device that finds out the exact details which are related to sports gestures and provides the necessary set of data for the data analysis process. When compared with other methods, the proposed wearable posture measurement system increases the accuracy rate in the monitoring process which improves the overall performance of the system.

Xie et al. [19] proposed real-time monitoring of big data sports teaching data using a complex embedded system. The proposed method is mostly used in the sports industry which needs an internet connection. The proposed monitoring system monitors every detail of the sportsman by understanding the gestures, postures, and position of users via wearable devices. The proposed method increases the efficiency and feasibility of the system.

Qian et al. [20] introduced a new data mining technology for the sports training index analysis process. The proposed mining model is used to analyze the data which are collected from the analysis process. Deep learning technology is also used here to analyze the data which are needed for the data mining and monitoring process. The proposed method increases the accuracy rate in the analysis process which improves the capability and scalability of the manning process.

Liang et al [21] proposed a fitness state of sports training method based on a self-organizing neural network. The self-organizing theory has various characteristics which contain new details about sports. The neural network model is used here to find out the exact detail about the activities of a user which provide effective services to users. The sports data training process needs an actual set of data for analysis and identification process. The proposed method improves the efficiency and feasibility of the sports training adaptation process.

Wu et al. [22] introduced a short-term memory (LSTM) neural network-based cognitive computing system for the sports training pattern recognition process. The proposed method uses LSTM to reduce the error rate in data processing and improves the effectiveness rate in data that are needed for the training process. Experimental results show that the proposed method increases the accuracy rate and efficiency rate in the sports data training process.

Yuan et al. [23] proposed a sports decision-making model using data mining and a neural network. The proposed model is mainly used to increase the accuracy rate in the decision-making process in sports. Data mining technology is used here to find out the exact details which are needed for the decision-making process. The proposed method improves the performance and efficiency of the sports decision-making process which provides appropriate services for the users.

Meghji et al. [24] introduced an algorithm for automatic detection and quantifying the change of direction (COD) incident angles in sports. An inertia measurement unit (IMU) sensor data is used in COD incidents which find out the actual angle and degree of turns and direction which are occurred in particular sports. The signal computation processing technique is used here to identify the changes in angles. The proposed algorithm increases the overall performance and effectiveness of the monitoring process.

Zhang et al. [25] proposed a design and data analysis method using the Internet of Medical Things (IoMT) for sports information acquisition systems. IoMT identifies various characteristics and collects a necessary set of data for the data analysis process. The client information management system contains the personal data of users and the terminal node is the place where the data analysis process takes place. The communication process plays a major role in collecting information for the analysis process. Experimental results show that the proposed method increases the feasibility and reliability of the system.

Zhang et al. [26] introduced a human motion ping-pong recognition method using a machine learning classification algorithm. Inertial data is used in the proposed method which contains angular velocity, angles, acceleration, and magnetic induction level of humans via the wearable watch. Machine learning algorithm provides a better detection recognition process which reduces the latency rate in the computation process. The proposed method increases the accuracy rate in the recognition process which improves the efficiency and effectiveness of ping-pong games.

Cao et al. [27] proposed a high-dimensional multi-objective optimization strategy using a directional search for the decision-making process in sports. First, the optimization process finds out the information which is needed for the decision-making process. Multi-objective optimization strategy train various set of data to find out the actual decision space for the decision-making process. The proposed strategy reduces the error rate in the decision-making process which improves the performance and feasibility of the system.

Zadeh et al. [28] proposed a new sports injury prediction method using wearable technologies and data analysis processes. The proposed identifies the injuries based on a certain set of features. Features such as heart rate, signs, conditions, situation, and mentality of user's information are collected via wearable devices. The proposed method increases the accuracy rate in the prediction process which improves the efficiency and robustness of wearable devices.

Proposed SIP-AL Method

The proposed information processing is based on the individualities performed according to the category of sports and adapts to its environment by pursuing his roles and tasks. The goals and the outcomes provide motivations for cooperation that must be independent of personal goals. This behavioral demand increases coordination between individuals and teams. With the direct communication dynamic factors namely workload and pressure are managed by planning actions under time pressure and high workloads. Fig. 1 presents the proposed method in a training scenario.

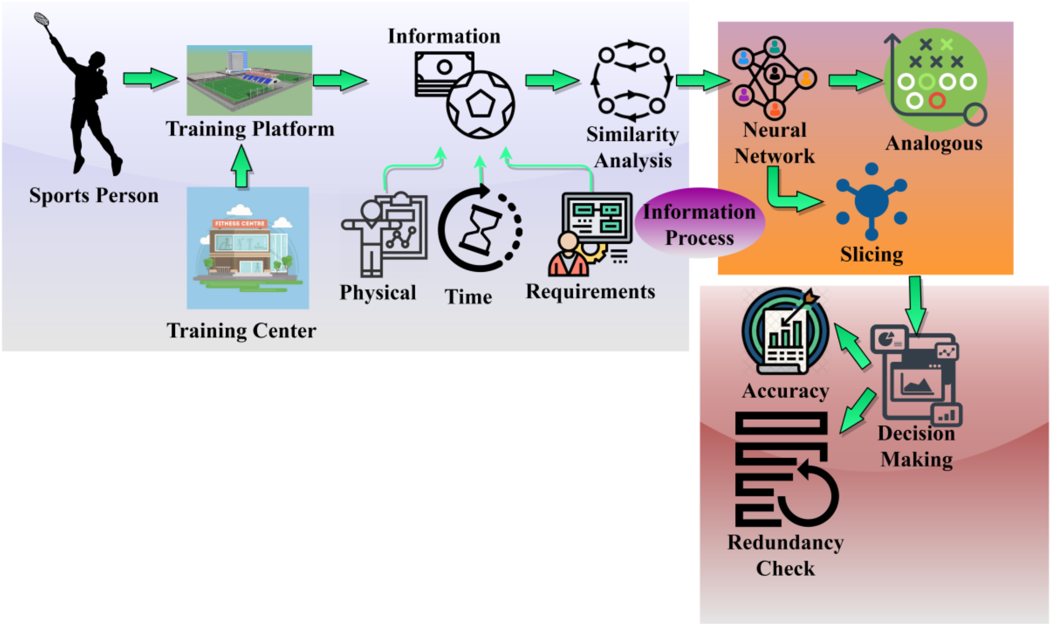

Fig. 1. Proposed SIP-AL Method

The sportsperson attending the training is analyzed for his/her motion actions, and performance using external and body-mounted sensors. These are observation sensors that generate information related to physical, time, and player requirements (Refer to Fig. 1). It is analyzed based on their emotions that are represented by state transition models by finding the boundaries for their gestures. These motions are represented in sequences that are denoted as in Eqn (1)

$$P = (P_s, P_p, P_e)$$

(1)

From Eqn (1) P denotes the motion sequences, P_s start state, P_p denote the performing state and P_e denote the end state of the motion. The boundaries of the motion are stated by the start and end of the motion. The performing state is said to be the relevant motion which is said to happen between the start and the end motion. The sequence of the state for the sports and its sequence of steps between the start and the end motion is shown in Eqn (2)

$$P = (P_s^1, P_p^1, P_e^1)$$

(2)

$$P = (P_s^2, P_p^2, P_e^{N-1})$$

(3)

$$P = (P_s^N, P_p^N, P_e^N)$$

(4)

The above Eqn (2), (3), and (4) show the transitions and overlapping of the motions. It represents the motion model with N motions and its sequence of states corresponding to the inputs of the individuals according to the behavior of the individuals and the mental models are used to discuss information that describes and predicts the events for social interactions. It explains the operation of the system for the individuals to understand. These mental models differ from each other based on the type of sport and its environment considering the individuals in the team. It reflects the beliefs of the individuals about the team operations which are correlated to each individual. The experiences gained from the sport and the individuals on the team will maintain a set of beliefs that are considered mental models.

It is obtained by subtracting the values from the unit values and multiplying them by 100. The resultant score denotes the level of concentration that represents the behavior of the individual at that current point in time. The concentration levels are subjected to the roles and workload of the individual. The detection of the motion follows procedures in which the motion states represent the input of the individual and the state pattern is extracted from the estimated sequence states. The estimated states for the sequence of the vectors and the state probabilities are shown in Eqn (5)

$$A = (a_1, a_2, \ldots, a_m)$$

(5)

$$B = (b_1, b_2, \ldots, b_m)$$

(6)

$$b_c = (b_c^0, b_c^1, \ldots, b_c^d)$$

(7)

From the above Eqn's the sequence *A* with *m* vectors and *B* probabilities of the sequence where b_c^d is the probability of the sequence B at c th state with an input sample of d $(0 \leq c \leq N)$ and $c = 0$ where it denotes the state that is considered to be unknown. Due to the variances in the motions for the sports, it is not possible to represent all the motions as input sequences within a fixed-length m. To reduce the computation complexity, the input sequence cannot be increased rather than the fixed length. Rather, the probabilities of sequences are aggregated regarding the time as shown in Eqn (8)

$$\gamma(\alpha) = (\ldots, b_{\alpha-m-2}^{\alpha-3}, b_{\alpha-m-1}^{\alpha-2}, b_{\alpha-m}^{\alpha-1}, b_{\alpha-m+1}^{\alpha}, \ldots, b_{\alpha}^{\alpha})$$

(8)

The probability of the input sequence b_S^α with sample s estimated at time α where $(\alpha > 0)$. From Eqn (8) the motion is extracted by identifying the resemblance similarity index defined by the motion model. In Fig. 2, the state probability for m vectors is represented.

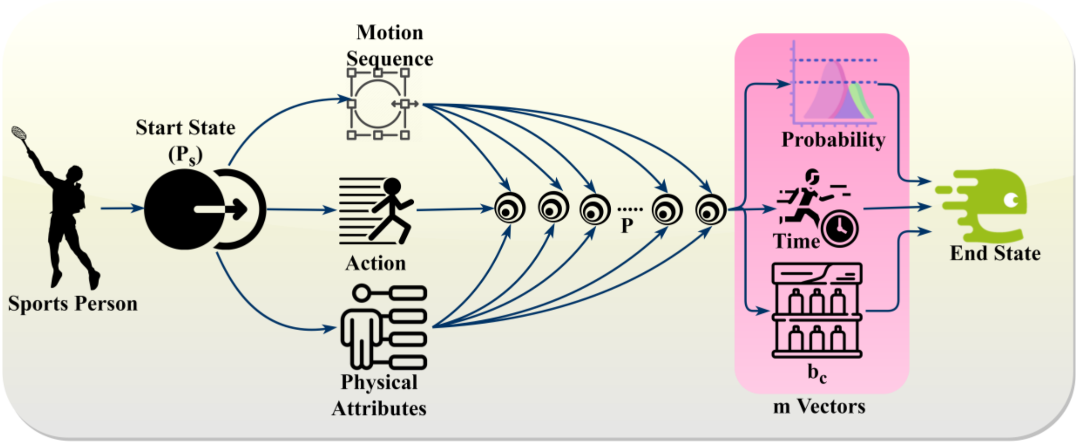

Fig. 2. State Probability for m Vectors

The inputs $\gamma, A,$ and physical attributes are used for state modeling as in Fig. 2. The vectors are based on $\gamma(\alpha)$, time (between P), and b_c are identified through the motion sequences (A), actions (B), etc., from $P_p \,\forall\, \gamma(\alpha)$. This representation is performed if the observation is inconsistent/ unsimilar to the previous observation in P. Based on the motion model, individuals are allowed for some tasks to calculate physical fitness by mentioning the changes according to their age. The effects of the task are monitored by varying the duration of the task and by increasing the task in specified time duration as a fitness function along with their concentration. These time-specified fitness values with their motions are also sequenced together. The reaction time and movement time for the fitness function of the individuals are calculated as shown in Eqn (9)

$$\eta = (\tau \times \varpi \times \rho \times \psi)$$

(9)

Similarity Analysis

For the similarity function analysis, the data sequences are analyzed resembling the fitness conditions in terms of behavior and motion models. These sequences are based on the estimation of spatial responses of the individuals that are independent of each other. This spatiotemporal analysis uses a linear model based on conditions with activity patterns for the dissimilarities. The sequences with their conditions are compared for estimating the dissimilarities based on the task and its oriented motion models. These dissimilarities of sequences with all the conditions are grouped to visualize the similarity of sequences. Using an exploratory visualization technique, sequence patterns are organized for indicating the correlations between the sequences. A dissimilarity matrix is formed which brings a close relation in identifying the factors that determine the behavior of the individual and their fitness function. Fig. 3 presents the similarity analysis process representation.

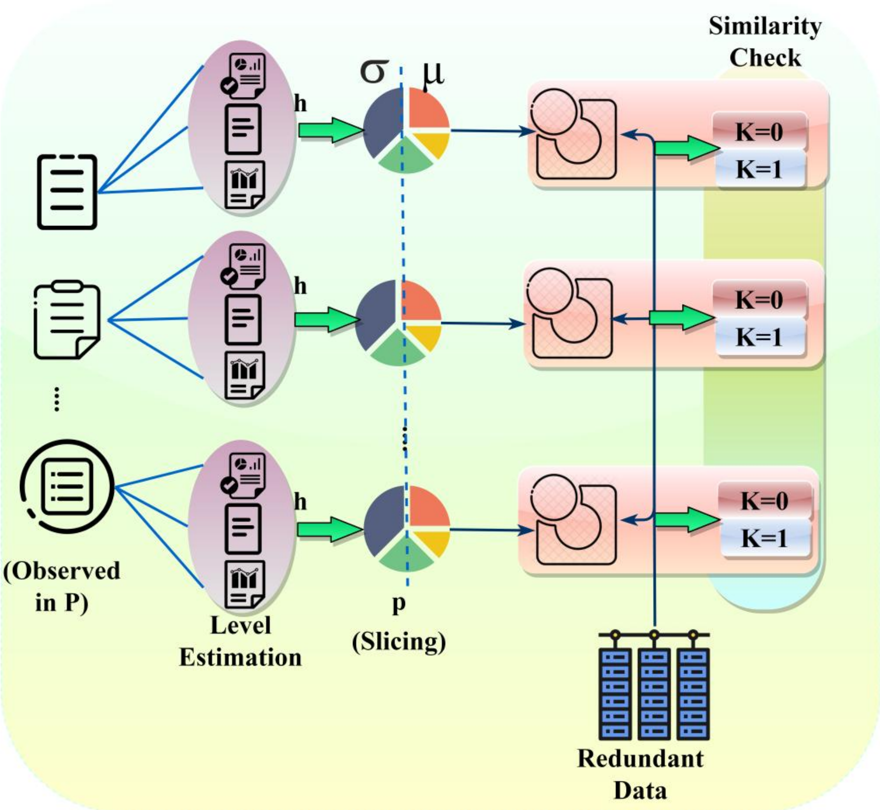

Fig. 3. Similarity Analysis Representation

The data observed in P is organized $\forall\, \gamma$ for identifying h using equation (8). From the identified h, σ and based slicing $\forall\, p$ is performed for performing the similarity check. This check is performed between σ and $\mu \;\forall\, p$ such that h is the same as the previous P_S or in P. The final verification is either $k = 0$ or $k = 1 \;\forall\, P \in p$ and hence b_c is instigated (Refer to Fig. 3). From the extracted motions of individuals with time stamps and their descriptions of the sport, its environment is analyzed for similarity. The roles of individuals in sports differ from each other, so a list of data with the individual position and timestamps is maintained. From these data, high similar spatiality and less similar spatiality are analyzed. Based on the local align algorithm, the similarities are identified in the sequences. An editing function is used to identify individual sequences for equality and inequality and decision-making by editing the sequences. Similarity analysis between sequences is measured by the following Eqn (10)

$K(\sigma, \mu) = \sum_{j \in J} K_j(\sigma, \mu)\omega_j$

(10)

A dataset is utilized for the behavioral and motion models. The goals and tasks of the individuals and the actions for achieving the goals promptly are maintained as sequences. Each individual has their plans for achieving the game towards the team. By the action and counteraction of the opposite team, huge data is extracted from the sport. As the sequences of models are of larger data, the similarity functions are analyzed. These sequences are used to build a dataset that is used for training and testing for its performance in accuracy, decision making, and redundancy check.

Neural Network for analogous learning

A neural network is of the input layer, output layer, and hidden layer to generate the slices of sequences and to achieve better performance. The neural network is a fully connected network with neurons connected to the input layer. The analogous learning is depicted in Fig. 4.

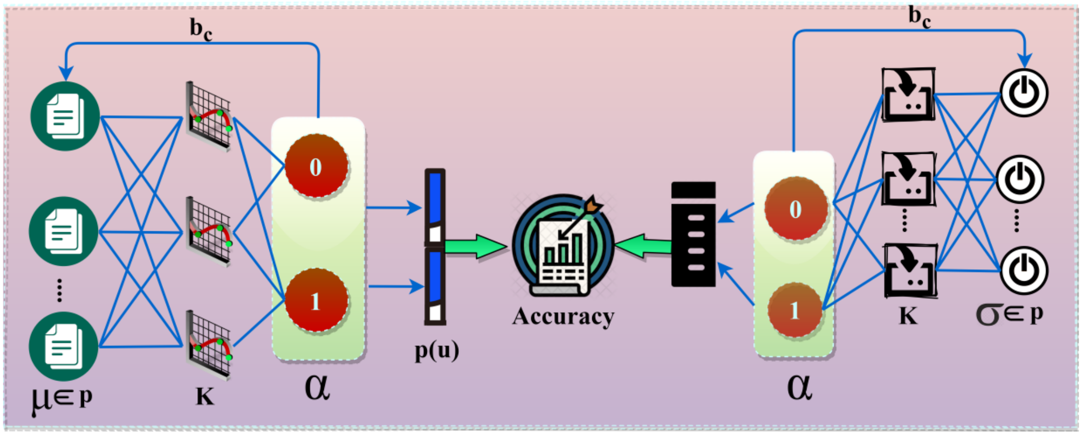

Fig. 4. Analogous Learning

The maximum accuracy is estimated based on assigning weight and bias from $\mu \in p$ and $\sigma \in p$ learning as in Fig. 4. The processes need to be analogous for improving the accuracy before $p(u)$ and a standard output post $p(u)$. The sigmoid is responsible for validating the accuracy through b_c such that K is invariably maximum. It is to be noted that the sigmoid is used if either of μ (or) σ is imbalanced. The analysis of the sequences undergoes operations such as responsive field functions, weights corresponding to the field functions, and the operations at the sigmoid function. The responsive field functions deal with the fully connected layers represented in the vertical set of neurons and the input sequences are connected to hidden neurons. Based on the input, the weighted and the bias functions are estimated for slicing of input sequences that are shown in Eqn (11)

$$p = \phi\left(q + \sum_{e=0}^{4} \sum_{f=0}^{4} V_{e,f}\, R_{x+e,y+f}\right) \quad (11)$$

From the above Eqn (11) p is the output from the hidden layer, ϕ is the activation sigmoid function used to estimate as shown in Eqn (12)

The sigmoid layer maps the convolutional layer and the output layer which helps in particular to analyze the physical fitness function with the max-value function. From the output layer, the sequences are sliced through analogous learning which is based on the information from the similarity analysis.

Self-Assessment

In this sub-section, the self-assessment using the variable representations is discussed. The impact of $P-(P_s-P_e)$, p , and $(A+B)$ over sequence probabilities, fitness validation, $p(u)$, and redundancy are analyzed. In this analysis, the dataset from [29] is used for identifying training T1 to T5. In Table 1, a short description of the dataset and its fields are provided.

Table 1. Dataset Description

Parameter	Value
Name	CrossFit Data
Tables	2
Fields	36
Statistics Span	2013-2015
Training (T1, T2, T3, T4, T5)	Running, Deadlift, Back Squat, Snatch, Pull-Ups
Persons	Male= 194927, Female= 136129

Based on the above, first, the analysis of the probability sequence and analyzed $h\%$ for the varying P_S to P_e is presented in Fig. 5.

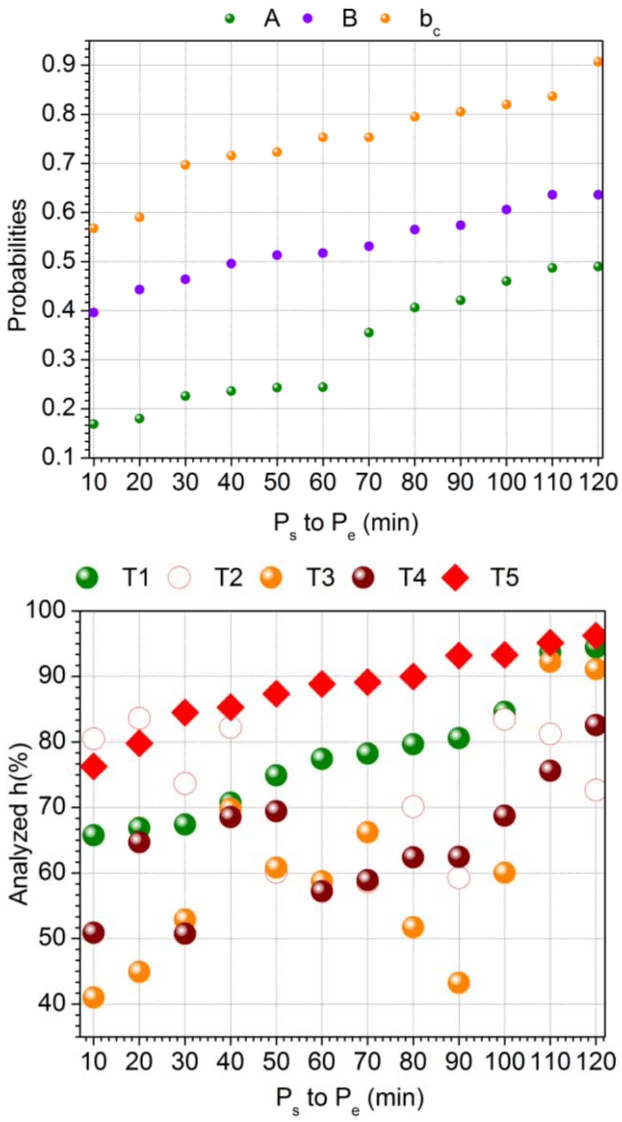

Fig. 5. Sequence Probability and Analyzed $h\%$ for P_S to P_e

Fig.5 presents the sequence probability (for A, B, b_c) and identified $h\%$ observed in P_S to P_e interval. In the $P = (P_S - P_e)$, the b_c requirements post the analogous learning is identified for improving the $h\%$. As the $h\%$ increases, the $\gamma(\alpha)\ \forall\ A, B$ and b_c is forward shifted. That is, P relies on A from which B is moved on, and the common b_c is then induced. This is achieved based on $K(\sigma, \mu)$ and $p \in \sigma$ and $p \in \mu$. As the learning requires the analogous $K(\sigma, \mu)$: max $\forall\ K = 0$ or $K = 1$ using $p(u)$. Therefore, as b_c increases, the $p(u)$ is induced for reducing $K = U$ instance in P. Hence the $h\%$ is better for different training actions considered. Fig. 6 portrays the $K(.)$ and $p(u)$ analysis for the varying p.

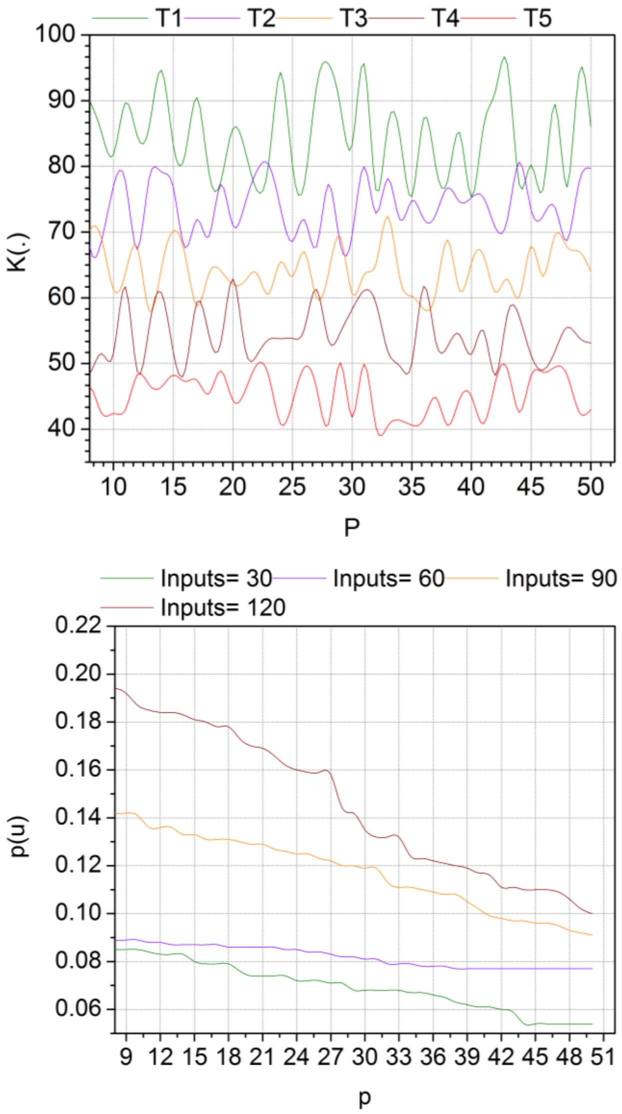

Fig. 6. $K(.)$ and $p(u)$ Analysis for varying p

The analysis for different training actions and inputs over $K(.)$ and $p(u)$ for varying P is given in Fig. 6. The p variation is classified for $p \in \sigma$ and $p \in \mu \,\forall\, \gamma(\alpha)$. Based on $A, B,$ and b_c, the p is performed. As mentioned earlier, the state vector representations are realigned for $\gamma(\alpha)$ such that $h\%$ is modified based on $K(\sigma, \mu)$. This is varying $\forall\, T_1,\ T_2, T_3, T_4$ and T_5 such that $p(u)$ is organized for improving the accuracy. In the $p(u)$ as the input varies the biasing of $p \in \sigma$ or $p \in \mu$ or both is performed for improving $h\%$. Therefore, the proceeding instance relies on this factor for preventing errors, and hence, the $p(u)$ is high for high inputs. Fig. 7 illustrates the redundancy ratio for varying $(A + B)$.

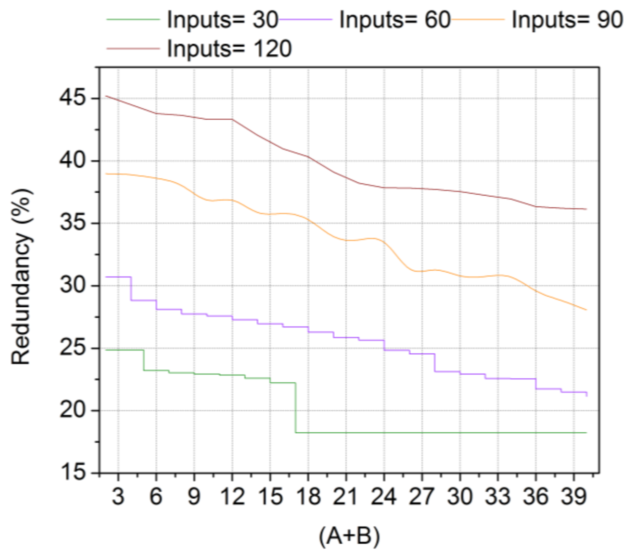

Fig. 7. Redundancy Ratio for varying $(A + B)$

Fig. 7 presents the redundancy ratio for $(A + B)$ instances for varying inputs. The joint state transitions for $m\, vectors \in (A + B)$ cumulatively reduce the redundancy. Based on $\gamma(\alpha)$, the p and learning $\forall\, P(u)$ are performed for improving A and B. This relies on non-redundant data in any $P \in (p_s - p_e)$ such that repetition is not permitted. Therefore, as the inputs vary, the $\gamma(\alpha)$ distinguisher A, B, and b_c such that redundant data is not in both A, B or b_c.

Performance Assessment

The dataset provided in [29] that is described above is used for analysis. The metrics accuracy, error, processing rate, redundancy, and processing time are analyzed by varying the inputs and similarity factors. For a comparative analysis, the methods DAS-IoT [26], PCA-RF-GA [17], and DOA+LSTM [22] are used.

Accuracy

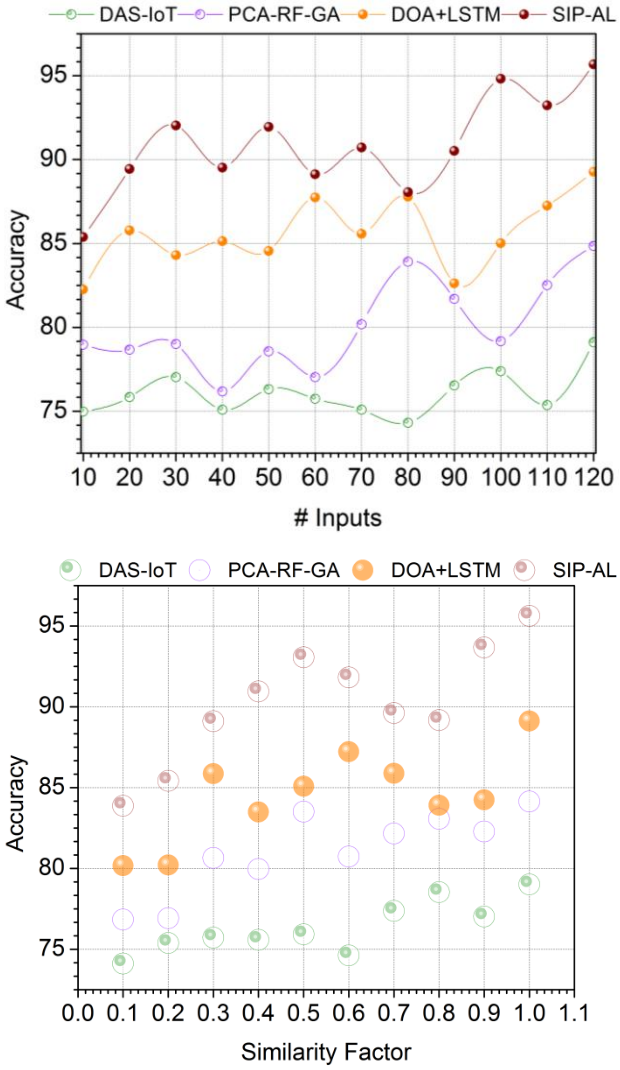

Fig. 8. Accuracy Comparisons

The data extracted from individuals based on behavior analysis, fitness function, and motion models are evaluated for their accuracy with the proposed slicing-based technique. For the improvement of accuracy, a local align algorithm performs search operations of sequences extracted from individuals. From the graphs, it is evident that the proposed slicing-based analogous learning achieves higher accuracy (Refer to Fig. 8).

Error

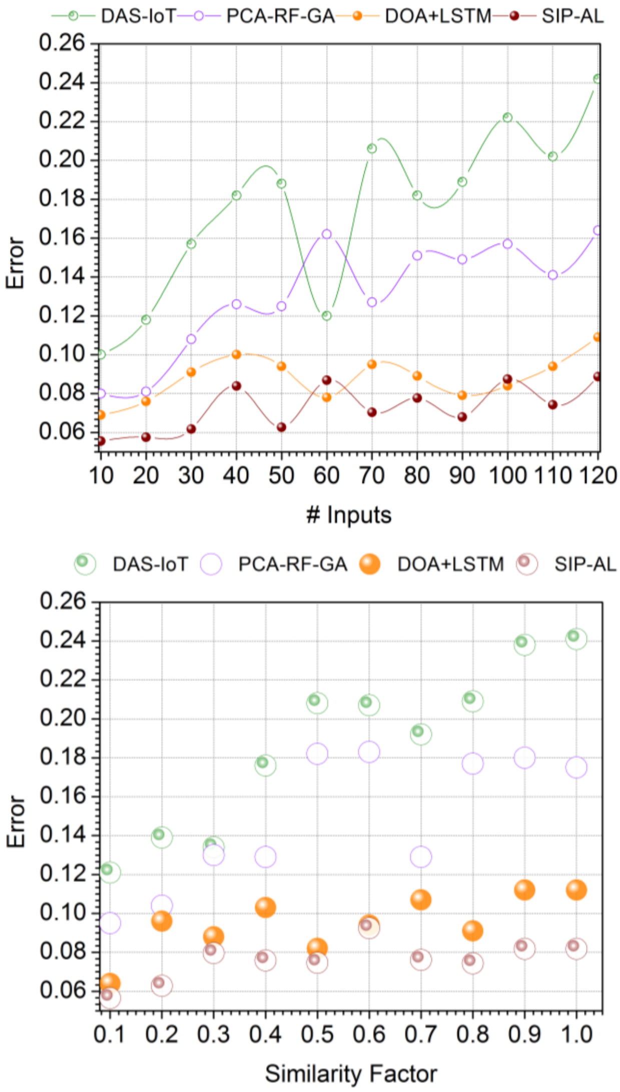

Fig. 9. Error Comparisons

The errors generally occur due to data extraction from the individuals. That is due to the labeling of sequences considering their mental motion models and fitness performances due to their roles. To overcome these error interventions, the proposed technique provides values to the sequences that are monitored based on the behavior analysis, mental models, and fitness functions. The actions and reactions of the individuals in the sport as time progresses are sequentially monitored and analyzed for resemblances of sequences. Based on the resemblances the sequences are valued. These valued sets of sequences are used for training the neural networks. To further reduce the errors, weights and biasing functions in the neural network are determined based on the input dataset. From, the results it is clear that the proposed technique combats the errors in the dataset (Refer to Fig. 9).

Processing Rate

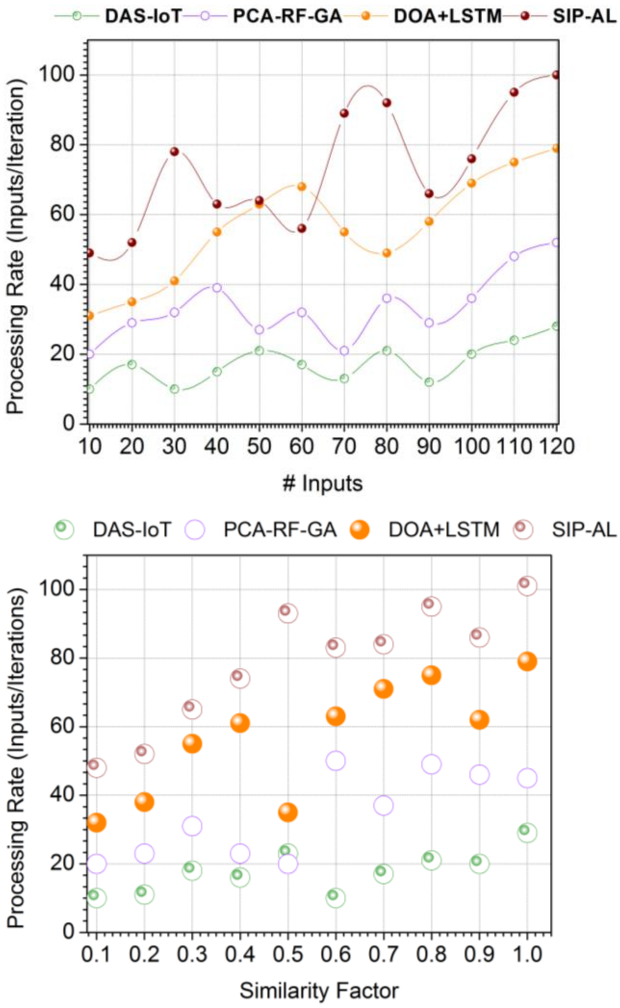

Fig. 10. Processing Rate Comparisons

The processing rate of the neural network depends on the learning rate that increases the network performance. These data with values are given as the input for slicing the information. The slicing of data happens through the neural network from learning the input data. This sequentially arranged data amplifies the processing rate of the network The comparative analysis of the processing rate over the varying inputs and similarity factors are presented in Fig. 10.

Redundancy

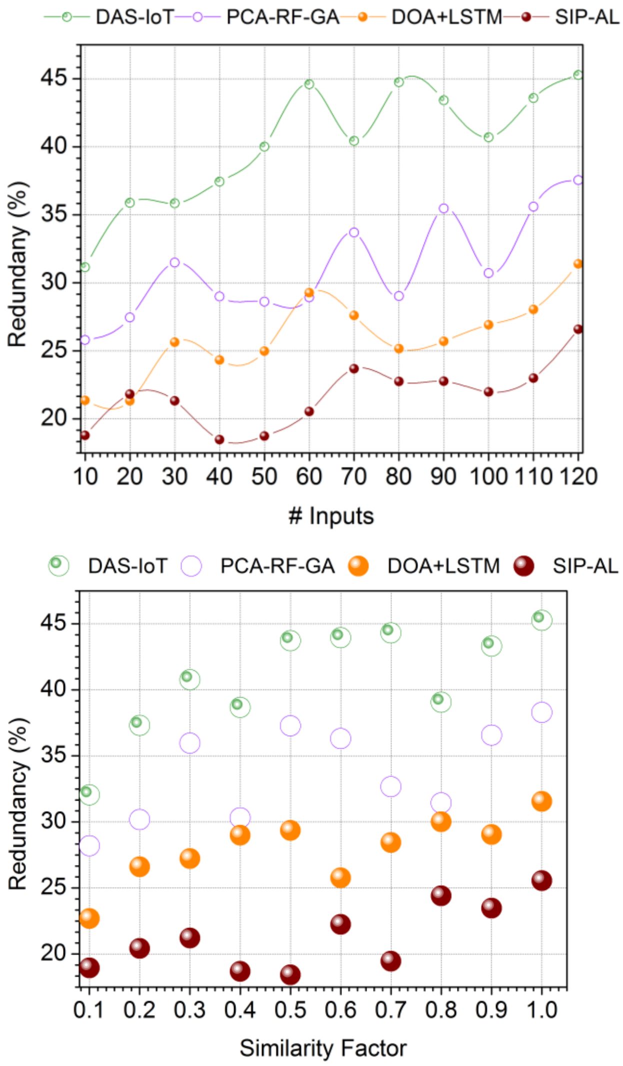

Fig. 11. Redundancy Comparisons

Due to the data set obtained from the similarity analysis that is used for training the neural networks the redundancy of the proposed is reduced. The slicing function which is proposed makes the network effective in modeling the input data. This slicing function maintains the responsive field functions and their corresponding weights functions which reduce the effect of retraining of input data. The analogous learning based on two different factors for p influences the non-redundant occurrences in $A + B$ for which the replications are confined. In this analysis, the learning process is performed based on p for all observations in P. Therefore, for the varying inputs and similarity factors, the proposed method achieves less redundancy (Refer to Fig. 11).

Processing Time

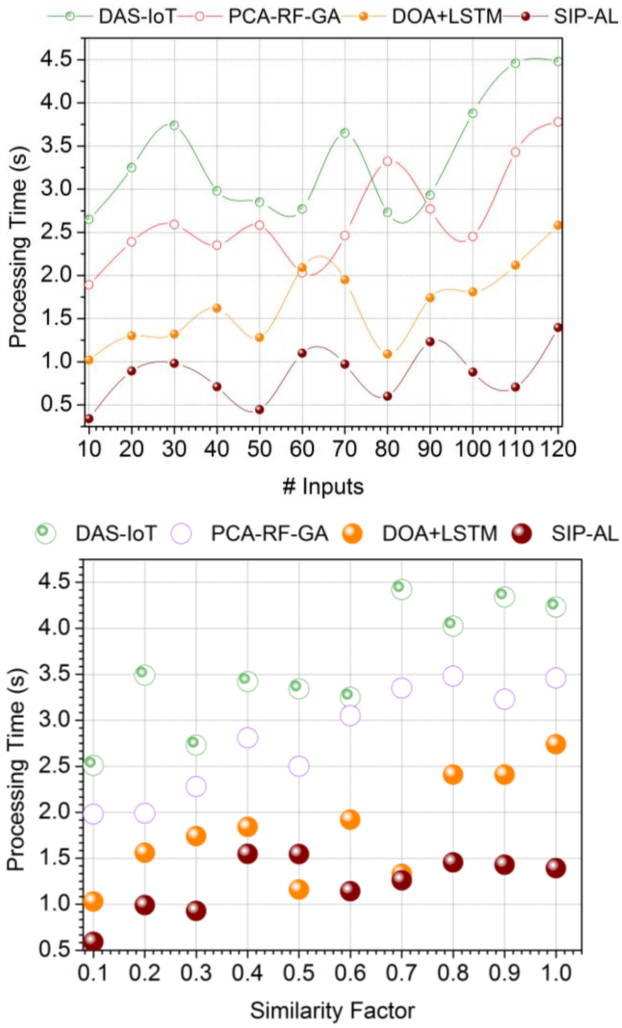

Fig. 12. Processing Time Comparisons

The analysis for processing time under varying inputs and similarity factors is presented in Fig. 12. The processing time of the neural network based on the input data is analyzed. As the number of epochs increases, the processing rate increases. To enhance the processing time, a hyperparameter function is used which decreases the processing rate of the neural networks. The proposed technique deals with the similarity analysis before the data is given as the input to the neural network. This makes the learning rate of the neural network easier based on which the proposed slicing function with analogous learning takes place. The proposed based functions achieve better accuracy even with the increased number of epochs in the neural networks with lower processing time. Tables 2 and 3 present the comparative analysis results with inference.

Table 2. Comparative Analysis for # Inputs

Metrics	DAS-IoT	PCA-RF-GA	DOA+LSTM	SIP-AL
Accuracy	79.1	84.85	89.27	95.682
Error	0.242	0.164	0.109	0.0887
Processing Rate (Inputs/Iteration)	28	52	79	100
Redundancy (%)	45.26	37.55	31.39	26.587
Processing Time (s)	4.48	3.78	2.58	1.395

Inference: The proposed method improves accuracy and processing rate by 11.28% and 15.67% and reduces error, redundancy, and processing time by 8.29%, 11.48%, and 10.21% in order.

Table 3. Comparative Analysis for Similarity Factor

Metrics	DAS-IoT	PCA-RF-GA	DOA+LSTM	SIP-AL
Accuracy	79.01	84.14	89.12	95.62
Error	0.241	0.175	0.112	0.0818
Processing Rate (Inputs/Iteration)	29	45	79	101
Redundancy (%)	45.26	38.29	31.55	25.547
Processing Time (s)	4.23	3.46	2.74	1.392

Inference: The proposed method improves accuracy and processing rate by 11.53% and 8.25% and reduces error, redundancy, and processing time by 9.42%, 12.82%, and 9.98% in order.

Conclusion

This article introduces sliced information processing with analogous learning for improving the accuracy of training applications in sports. The proposed method reduces the complexity of varying sports data analytics for providing better training. In the information processing method, analogous neural learning is employed based on similarity measures for preventing errors. Based on the sequence probabilities the available data is used for identifying the fitness level through data slicing. In this slicing process, the sigmoid function is used for verifying the similarity and training the neural network. The data vectors are used for modeling the analogous states in detecting various training data from the sportsperson. In the recurrent process, the upcoming probabilities based on analyzed fitness levels are used for further slicing and improvements. Therefore, the processing rate is improved without deviating sequences; the processing time is reduced.

Data Availability Statement

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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