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Review

A Systematic Literature Review of Intelligent Data Analysis Methods for Smart Sport Training

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Received: 28 March 2020; Accepted: 16 April 2020; Published: 26 April 2020

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Abstract: The rapid transformation of our communities and our way of life due to modern technologies has impacted sports as well. Artificial intelligence, computational intelligence, data mining, the Internet of Things (IoT), and machine learning have had a profound effect on the way we do things. These technologies have brought changes to the way we watch, play, compete, and also train sports. What was once simply training is now a combination of smart IoT sensors, cameras, algorithms, and systems just to achieve a new peak: The optimum one. This paper provides a systematic literature review of smart sport training, presenting 109 identified studies. Intelligent data analysis methods are presented, which are currently used in the field of Smart Sport Training (SST). Sport domains in which SST is already used are presented, and phases of training are identified, together with the maturity of SST methods. Finally, future directions of research are proposed in the emerging field of SST.

Keywords: intelligent data analysis; sport training; smart sport training; data mining; computational intelligence; deep learning; machine learning

1. Introduction

The rapid development of Information Technologies (IT) has had an impact on almost all areas of our lives. Computers, smartphones, smart watches, and other mobile and pervasive technologies change the way we work and how we perceive the outer world. Furthermore, robots are replacing human workers in various industries, especially in the era of Industry 4.0 [1]. There is no doubt that our civilization has to adapt to the many changes that are the consequence of modern technology [2].

Sport training is not an exception, and is also an interesting area, where modern technology is revolutionizing the way athletes maximize their performance and compete on a higher level than ever before. By the same token, with the increase of participation trends in mass sporting events [3], as well as the involvement of people in sporting activities, there is a need for systems/applications that can guide, help, and support people in enjoying their activities [4]. For instance, many people all over the world cannot hire a professional sports trainer due to the many barriers, e.g., financial. On the other hand, extensive research that links intelligent data analysis tools/methods with sport science is building new intelligent solutions that support all phases of sports training. Smart Sport Training (SST) is a type of sports training, which utilizes the use of wearables, sensors, and Internet of Things (IoT) devices, and or intelligent data analysis methods and tools to improve training performance and/or reduce workload, while maintaining the same or better training performance. This means that SST implementations range from simple tasks, such as introducing wearable devices [5] in a sports training session, performing intelligent data analysis of a session, to much more complex artificial trainer implementations, where a coach is replaced by a smart agent which manages all the aspects of training, except for actually performing the proposed exercises for the trainee [6]. The workload reduction can apply either to the athlete or his trainer. For an athlete, an improved training plan means he can achieve better results with the same, or even less, amount of training, and for his trainer, this means the assistance of IT technologies can automate parts of his coaching routine.

The research area that represents the intelligent data analysis methods in the domain of sport training is now becoming very popular. Despite the popularity of this research area, literature on this subject is expanding quickly. In this paper, we compile the latest advancements in this domain. We review the intelligent data analysis methods that are applied in different sports, either individual or team sports. Moreover, we study how mature the studies in the field are when measured according to the technology readiness level [7].

The remainder of this paper is structured as follows. Section 2 outlines the fundamentals of sports training. Section 3 presents a description of the research methodology used to conduct a systematic literature review, Section 4 identifies and classifies the intelligent data methods used in the field. Section 5 presents all the reviewed studies, sorted by the sports in which they were conducted. Section 6 analyzes the findings, and provides answers to the proposed research questions, together with future challenges. The paper is wrapped up in Section 7, where conclusions are drawn.

2. Sport Training

Sports training is a continuous process between an athlete and their trainer. It is a pedagogically organized process where the role of the trainer is one of teacher and organizer, with respect to guiding the athlete's activities, and organizing their training sessions [8]. Training exercises are precisely defined tasks that demand physical effort, and should in some way improve the sports results of the trainee. Multiple training exercises are then organized into complete units called training sessions. The end goal of a training session is the *perfection* of the athlete's abilities, in other words reaching their natural potential. The continuous process of training can be broken down briefly into the following four phases [6]:

- **Planning** refers to the prescription of the proper exercise units. The cycle of sports training sessions are focused around the competition calendar. It is the phase in which the trainer prepares the exercise schedule for the athlete.
- **Realization** is the *execution* phase of the prepared exercises. The roles of the trainer in this phase are: preparing (potential) equipment, conducting a psychophysical evaluation of the athlete before the session, monitoring the intensity of the session, and improving tactics in team based sports. The exercise data needed for further analysis are recorded in this step.
- **Control** is a comparison of the exercises actually performed by the athlete versus the planned exercises. This can be completed by the use of video analysis and contemporary computational technology. In individual sports, a bio-metric performance analysis can be performed, whereas notational analysis systems are used in team sports.
- **Evaluation** is the measurement of the athlete's performance. Two kinds of evaluations exist: (1) The evaluation of the single training load (short-term performance analysis) and the (2) evaluation of the total training cycle load (long-term performance analysis). The evaluation is the comparison between set goals versus achieved results, and the amount of planned versus actually performed exercises.

The interconnection and continuous transition between the four mentioned phases is seen in Figure 1. Each cycle should provide the athlete with improved results. Since sports training is an activity of at least two parties, notably the trainer and the athlete, various computational-based approaches can be used to aid the decision-making of the trainer, or replace him altogether by introducing a virtual assistant. This allows the athlete to choose from a variety of possible training regimes without the need for employing an actual person to aid them in their training.

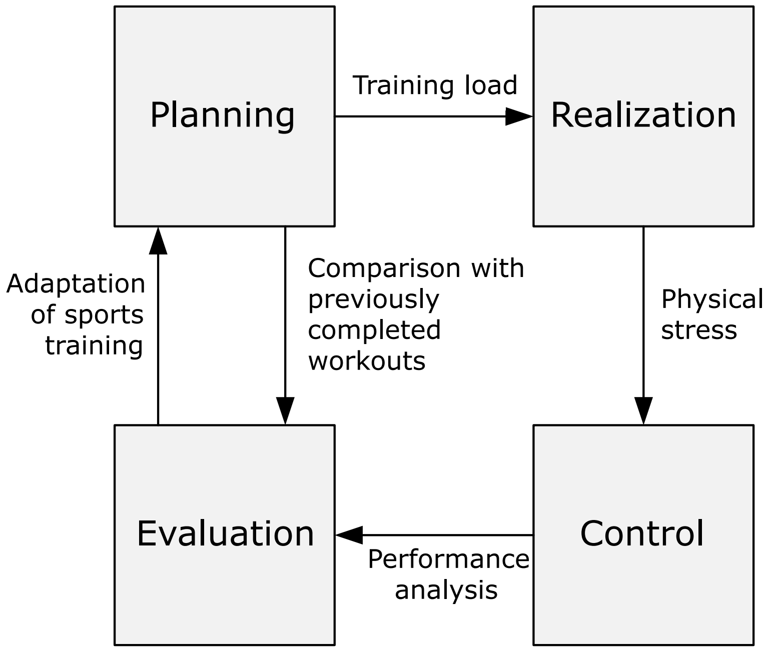

Figure 1. The four phases of sport training.

3. Research Methodology

We followed the Systematic Literature Review Guidelines in Software Engineering [9] to conduct this review. The goal of this review was to: (1) Identify how modern smart applications and methods assist athletes and trainers in sports training and (2) how fast the theoretical knowledge is transitioning into practical real-world use cases. Based on the study goals, the following Research Questions (RQ) were formulated:

1. RQ: How do smart applications influence the process of sports training?
   (a) RQ: In which phases of sports training are smart applications utilized?
2. RQ: Which sports are the most supported?
3. RQ: Which intelligent data analysis methods are the most utilized in smart training applications?
4. RQ: How mature are the research ideas of smart training applications in practice?

The literature search was conducted between **12 March 2020** and **18 March 2020**. The standard search string used to identify literature was:

> ("sport") **AND** ("training" **OR** "tracker" **OR** "logger" **OR** "diary" **OR** "trainer") **AND** ("data mining" **OR** "computational intelligence" **OR** "artificial intelligence" **OR** "big data" **OR** "machine learning").

There were some differences in the search strings used between databases, due to different query languages and limitations between scientific paper databases. The databases queried are shown in Table 1 with their corresponding number of results; the results are shown prior to the exclusion of duplicates and prior to their evaluation based on inclusion and exclusion criteria.

Table 1. Databases with search results and total after removed duplicates.

Database Name	URL	No. Total Results	No. Included Results
ACM Digital Library	dl.acm.org	33	20
IEEEXplore	ieeexplore.ieee.org	316	41
ScienceDirect	sciencedirect.com	113	16
Scopus	scopus.com	490	87
Google Scholar	scholar.google.com	17,900 (270)E	43
Total			180

The abstracts of the studies were all inspected to include/exclude the studies from the review. There were some necessary modifications to search strings. The ScienceDirect database allows a maximum of eight Boolean operators per search field, so the search string was split for the abstract and full text conditions. All the results were inspected on all databases except for Google Scholar, where the results were shown by relevancy, and the search was stopped once there were no more included (relevant) studies on two successful pages −20 results, and this criteria was satisfied after 270 inspected results.

All the database results were checked for duplicates, and after removal, 181 results remained. The duplicates between database pairs are seen in Table 2, where it can be seen that all the databases had at least one duplicate when compared with Scopus or Google Scholar. That is because Scopus and Google Scholar merely index documents found on other databases, and do not host them.

Table 2. Databases' matrix with duplicates shown between each database:database pair.

	ACM DL	IEEEX	ScienceD.	Scopus	G. Scholar
ACM Digital Library	/	0	0	1	1
IEEEXplore	0	/	1	10	3
ScienceDirect	0	0	/	3	6
Scopus	1	10	3	/	7
Google Scholar	1	3	6	7	/

The selection and exclusion criteria were specified, and limitations were examined with respect to determining as complete and actual a state of the field as possible.

Selection criteria:

- The research addressed sport training, sport trainers, or sport trainees.
- The research was peer reviewed.
- The research addressed sport as *an athletic activity requiring skill or physical prowess and often of a competitive nature* [10].
- The research used at least one of the intelligent data analysis technologies (e.g., data mining, computational intelligence, big data, and machine learning).

Exclusion criteria:

- The research was not in the English language.
- The full text of the research was not available on the digital library or any of the subscription services.
- The research only addressed activity recognition from a leisure perspective (e.g., general health).

Limitations:

- The research was limited to the five scientific databases/search engines: ACM Digital Library, IEEEXplore, ScienceDirect, Scopus, and Google Scholar.
- The research had to be available prior to 12.03.2020, when the indexing of potential articles was conducted.

- Google Scholar results were searched until there were at least two consecutive pages of non-relevant results (20), so a total of 270 results were inspected.

The attributes identified for each study are shown in Table 3. When research proposed general solutions/models for sport training across multiple disciplines but the model was tested and/or used only on a specific discipline or athletes from a specific discipline, that discipline was identified as the only sport of application in the Table. Differentiation between team and individual sports was done on an individual basis, and was determined from each piece of research individually (e.g., tennis may in some cases refer to 1 vs. 1 matches, and in another to 2 vs. 2 matches). The training phases presented were referenced from [6], and their maturity was identified according to the [11] abstraction of H2020 European Union Technology Readiness Level (TRL) [7]. The proposal [11] mapped the nine levels of TRL to the four ordinal values:

- Idea (TRL 0–3).
- Validation (TRL 6–7).
- Production (TRL 8–9).

Table 3. Attributes screened in the reviewed studies.

Attribute Category	Attribute	Range
Reference	Reference no.	[citation number]
	Authors	-
	Title	-
	Year of publication	-
Sport	Type	individual, mixed (e.g., tennis in pairs), team
	Name	name of the sport
Research	Methods used	algorithms identified in Section 4
	Focus	-
	Result	-
Training phases	Planning	0—not addressed, 1—idea, 2—prototype, 3—validation, 4—production
	Realization	——— | | ———
	Control	——— | | ———
	Evaluation	——— | | ———

By inspecting the title, keywords and the abstract 207 studies were initially selected for review, out of which 27 were duplicates. The remaining 180 studies were selected for full text inspection. However, we could not find the full text for 25 of the studies, but this is of no concern, since the unavailable studies were of dubious origin, and we did not detect them to be cited in any of the papers (when inspected on Google Scholar). Of the 155 fully available studies, 109 were selected as relevant for our literature review and 46 were excluded. The whole review process is shown briefly in Figure 2.

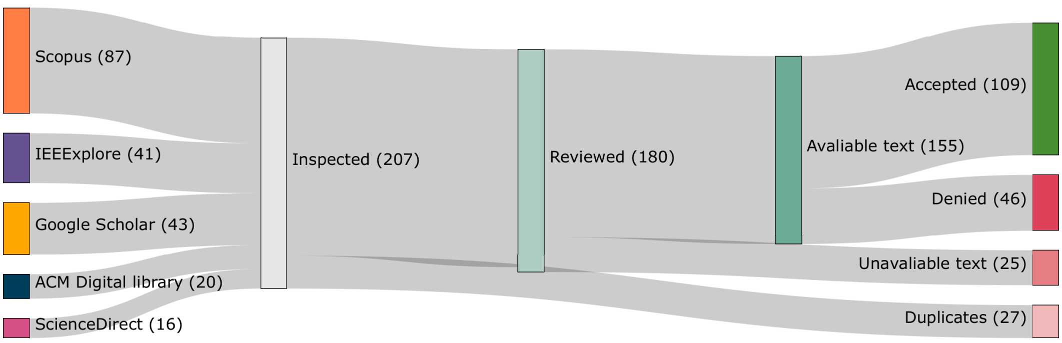

Figure 2. Review process.

The field of smart sports training has been rising in popularity over the last few years, as demonstrated in Figure 3. The first identified study was from the year 2006, and between 2006 and 2012, one to four studies were published in the field each year. Its popularity started increasing sharply from the year 2013 onward, with no less than four research studies in any of the following years. Of the research studies, 23 and 22 of them in this review were published in 2018 and 2019, respectively, which contrasts sharply with previous years. The data for 2020 are of a different shade and hue, since the year is still in progress and we anticipate more research to be published.

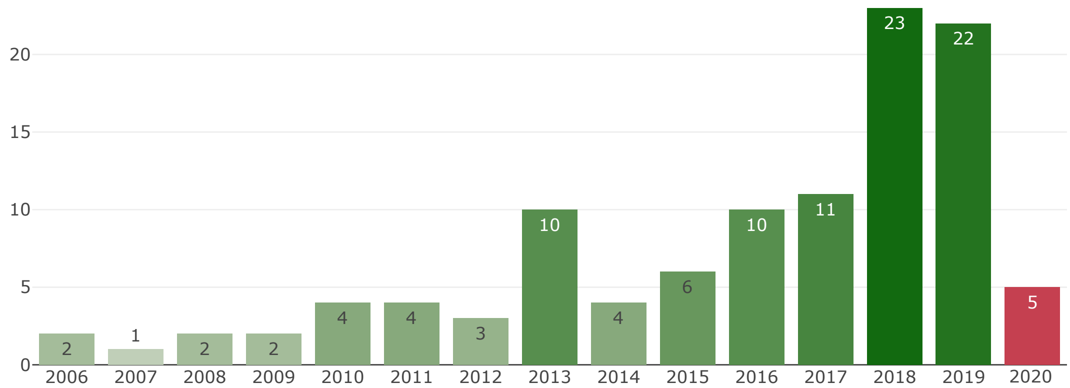

Figure 3. Number of studies published per year included in the literature review.

The results of literature search analysis are provided in the next sections.

4. Intelligent Data Methods Used in Studies

The objective of this section is to present the intelligent data analysis methods that were used by the researchers in the domain of smart sport training. Following the recent practice of intelligent method taxonomies proposals on other highly domain specific fields, such as intrusion detection [12], very large-scale integrated circuits and systems [13], program binaries [14], diabetes management [15], the same practice, and establishment of a novel taxonomy of intelligent methods is proposed in the domain of SST. The proposed taxonomy is based on the methods identified and currently used in the domain and may be extended as the domain grows and matures in the future.

According to Figure 4, our taxonomy comprises of five main groups (some algorithms can be counted in more than one group e.g., Artificial Neural Networks. In our case, we put artificial neural networks in the machine learning group, since most of the studies that reported the use of Artificial Neural Networks also used the other machine learning methods, e.g., Decision Trees in the same study), from which the used algorithms were identified:

- **Computational Intelligence** methods [16]:
  - –Evolutionary Algorithms: Differential Evolution (DE) [17].
  - –Swarm Intelligence Algorithms: Bat Algorithm (BA) [18], and Particle Swarm Optimization (PSO) [19]).
  - –Fuzzy systems [20].
  - –Simulated annealing [21].
- **Data Mining**:
  - –conventional Data Mining methods, i.e., Apriori [22].
  - –Machine Learning: Conventional machine learning methods, i.e., Decision Trees (DT) [23], adaptive boosting [24], Random Forests (RF) [25], Gradient Boosting (GB) [26], K-Nearest Neighbors [27] (k-NN), Support Vector Machine (SVM) [28], Artificial Neural Networks [29] (ANN), hierarchical clustering [30], and k-means clustering [31].
- **Deep learning** [32]: Recurrent Neural Networks (RNN) [33], Long Short-Term Memory (LSTM) [34], Convolutional Neural Networks [35] (CNN).
- **Other methods**: Case-Based Reasoning (CBR) [36], Dynamic Time Warping [37] (DTW), Bayesian Networks (BN) [38], Naive Bayes (NB) [38], Markov chain [39], generalized additive

models [40], Gaussian process [41], Linear Regression [42] (LR), regularized logistic regression [43], linear discriminant analysis [44], and spline interpolation [45].

Some research did not define the algorithms used clearly, just the field from which they were (e.g., [46], or used custom non-conventional algorithms (e.g., [47]), in such cases the method used was identified as *custom* and *data analysis field from which the method was* (e.g., [47] custom data mining algorithm). In cases where the data analysis method used was not clearly visible and an accurate determination was not possible, the slash sign ('/') was used in the table.

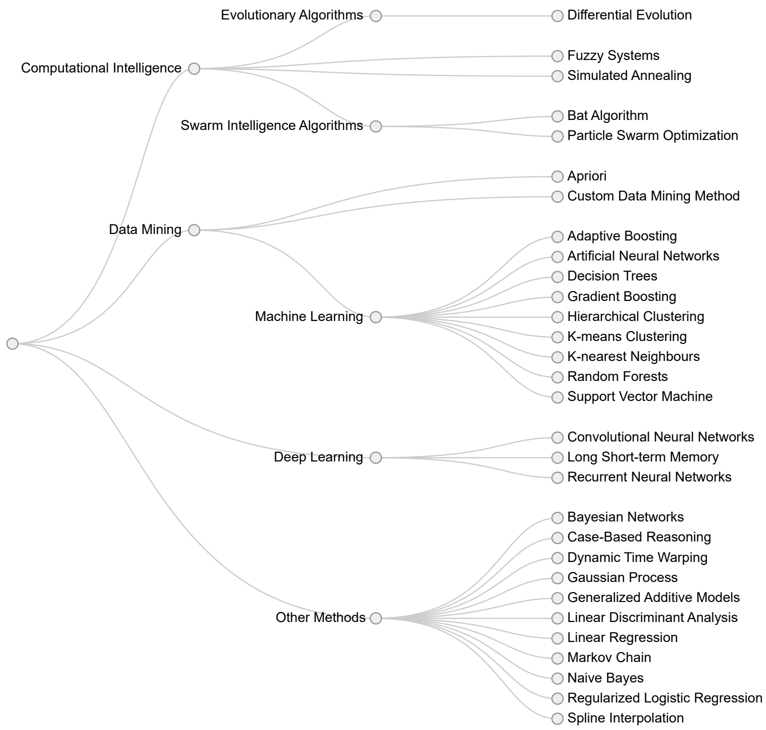

Figure 4. Taxonomy of methods used in smart sport training.

5. Review of Sports

The following sports were detected in the literature review: Aikido, archery, badminton, basketball, climbing, counter-movement jumping, cricket, cycling, fencing, fitness (gym), (American/ Australian) football, golf, hammer throwing, handball, hockey, jumping, karate, kick-box, rowing, running, cycling, shooting, ski jumping, skiing, soccer, swimming, table tennis, Tai-chi, tennis, triathlon, volleyball, weight lifting, and yoga. The remaining research was unrelated to a specific discipline, and was concerned with sports training in general. This research was placed in the General category. Some sports were investigated much more than others, as is shown in Figure 5, which may be due to their popularity among athletes and regular people, or they may simply be easier to evaluate, and were, as such chosen by researchers. The most popular sports for research were: soccer (12 papers), running (11), and weight lifting (9).

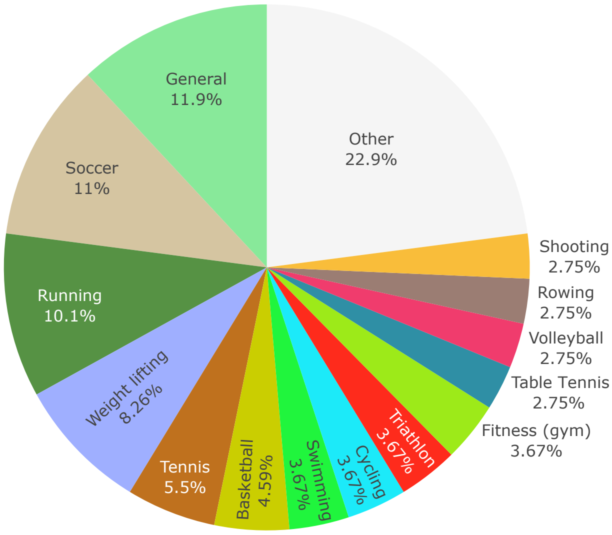

Figure 5. Identified research by the relative frequency of sport it was applied on, rounded to three significant digits.

We have also divided the sports by their participation into three categories: (1) Individual sports, which are sports where the participant normally competes against other individuals and not as a part of a team; (2) mixed sports, where the individual sometimes competes individually against other individuals, but may, in some competitions, be part of a duo (e.g., Tennis) or a team (e.g., Ski Jumping), and (3) team sports, where the individual is always part of a larger team and competes against other teams. We have classified the identified sports in the following way:

- Individual—aikido, archery, climbing, jumping, fencing, fitness (gym training), golf, hammer throwing, karate, kickboxing, rowing, running, shooting, skiing, swimming, Tai-chi, tennis, triathlon, weight lifting, and yoga.
- Mixed—badminton, cycling, rowing, ski jumping, table tennis, and tennis.
- Team—basketball, cricket, (American/Australian) football, handball, hockey, soccer, and volleyball.

The research related to the General category (unrelated to a particular sport) was not classified according to individual, mixed, team division. Most of the studies were related to individual type sports (54,6%), as seen in Table 4. This may be because it is much easier to control all the experiment variables with individuals, and it is also much easier to receive consent for studying from individuals than from whole teams where every individual has to consent.

Table 4. Division of studies by sport type.

Sport Type	No. of Studies	% of Studies (General Studies Excluded from Count.)
Individual	53	54.6
Mixed	17	17.5
Team	27	27.8
Total	97	100

The identified research is separated and presented by sport (alphabetically sorted) in the following subsections. The research of each sport is presented in a separate table, together with the methods used and the maturity of their implementation, for all sports for which three or more research studies were identified. The sports for which there were less than three studies identified are presented in Section 5.14. For clarity, the following abbreviations for sport training phases presented in Section 2 are used in the table data: Planning, Realization, Control, and Evaluation.

5.1. Basketball

Table 5 presents research on smart sports training done in the domain of basketball. All the studies were at least partially concerned with the realization phase of the sports training; in [48] this meant recognizing the actions performed during training by the use of a wearable device, for [49] which meant the creation of a Virtual Reality (VR) environment. Only one study [50], was concerned with the evaluation phase of sports training for more than an idea level of study; the study was concerned with the evaluation of actions performed by players and the effect it had on the game score. The only research that was at least partially related to three of the training activities was [51], where a comprehensive web information system was presented for sports statistics and analysis. There was, however, no presentation of the system by any practical means.

Table 5. Identified studies in the domain of basketball.

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[48]	SVM	Recognizing the basketball training type automatically by sampling data from a battery powered wireless wearable device equipped with motion sensors, by using the SVM classifier.	99.5% accuracy of activity recognition with the SVM algorithm on the examined data-set.	0	2	1	0
[49]	DTW	A VR training system is presented helping users to learn sport gestures in the case of basketball.	A bio mechanical training regimen was developed and amateur users were interviewed.	0	2	1	0
[52]	k-NN; RF	Use of a wrist watch wearable device that records movement. A model was built to classify the actions of basketball players.	The Random Forest model was found to be the most accurate.	0	2	2	0
[51]	/	Proposal of a web based information system called Basketball Coach Assistant (later BCA) for sports statistics and analysis.	The proposal and prototype were described.	0	1	1	1
[50]	Apriori	Identification of commonly used technical actions in basketball games to provide reference for the training of players and coaches, based on Apriori algorithm model generated association rules.	The system's usage in practice was demonstrated.	0	0	0	2

5.2. Cycling

No studies in the domain of cycling addressed all four stages of sports training, as seen in Table 6. All of the studies addressed the planning stage of sports training, which is not surprising, since data can be captured easily and existing data sets exist [53]. The research analyzed the cycling session from the coach/manager perspective [54], where the identification of athletes with high potential in cycling was done. The obtained objective of the best results does not necessarily mean the best results for the athlete, but rather the best results for the organization the athlete is representing. One of the studies [55] addressed nutrition planning for optimizing training performance.

Table 6. Identified studies in the domain of cycling.

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[55]	PSO	Proposal of method for generating eating plans for athletes.	An eating plan generation method proposal, based on Particle Swarm Optimization.	2	0	0	0
[56]	BA	Method for sports training sessions, where the training plans are generated using the Bat Algorithm according to data obtained from a sports watch while cycling.	The construction of a training plan generation model based on the previous performance data of an individual athlete.	2	0	0	0
[54]	BN	Machine Learning models to assist cycling experts in the decision-making processes for athlete selection and strategic planning in the track cycling omnium.	A Bayesian Belief Network model was constructed to predict the future final standings of cyclists in each cycling event category.	2	0	0	2
[57]	LSTM	A Proposal for an artificial coaching system for road cycling athletes, able to follow and tailor their training plans automatically, based on a Machine Learning algorithm.	The virtual coach provided personalized training plans of comparable quality to human experts.	2	2	2	0

5.3. Fitness (Gym Training)

Fitness (gym training) is a great environment for conducting research on SST since the environment can be controlled and a lot of training can be done on devices, which allows for the much easier control of variables. The athletes (e.g., [58–60]) can easily be equipped with different wearable devices or sensors to measure their exercise data accurately. None of the research was concerned with the control and evaluation phases of SST, as seen in Table 7. A lot of research is done on classifying the movement being conducted, and a repetition count of the exercises (e.g., [58,59]).

Table 7. Identified studies in the domain of fitness.

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[59]	k-NN; SVM; BN; DT	Comparison of different algorithms used to determine the activity being conducted in the Fitness Center by using data from a smart wrist wearable device.	Deep Exercise Recognizer model constructed from received measurements and combined individual Machine Learning models.	0	2	0	0
[60]	k-NN; SVM; DT	An automatic indoor exercise recognition model for both in gym and home usage scenarios. Classified activities are Biceps curl, Chest fly, Row, Push up, Sit up, Squat and Triceps curl.	Accuracy of 95.3% and 99.4% was achieved for activity recognition and repetition count, respectively.	0	2	0	0
[61]	BA	Planning fitness training sessions.	A fitness training session generation method that takes into account muscle groups, intensity and repetition, so that a balance between muscle groups is achieved for best results in training for a triathlon.	2	0	0	0
[58]	Adaptive Boosting	The demonstration of a wearable system, based on a fabric force mapping sensor matrix, which can measure the muscle movement during various sporting activities, demonstrated with the case of leg workout exercises.	81.7% accuracy was achieved after 24 different leg workout sessions.	0	2	0	0

5.4. Rowing

None of the research in rowing was concerned with the planning phase of SST (Table 8). The research ranged from VR supported rowing simulators that were designed with a combination of use for a rowing training machine ([62]) to the longitudinal range analysis of training data in rowing [47].

Table 8. Identified studies in the domain of rowing.

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[47]	Custom Data Mining	Time series (one year of rowing training data) data analysis, to obtain the knowledge rules from the training data of rowing through analysis.	Model that determines if the individual over or under trained	0	0	2	2
[63]	Apriori	Analysis of the association between the different training items of (rowing) athletes in different time segments during training in the method of time series data analysis.	Discovery of some rules regarding training and future performance.	0	0	2	2
[62]	DTW	Automated feedback implementation, to decrease the number of mistakes made by trainees, on a VR supported rowing simulator.	The learning rate of the requested velocity profile was significantly higher for the experimental group compared with the control group.	0	2	2	0

5.5. Running

Running was the second most popular sport for research of SST and a total of 11 research items were identified and analyzed (Table 9). All four stages of SST were addressed in the domain of running. There were also some methods presented for post analysis of runners' performance (e.g., [64,65] to identify where running speeds were inadequate. Since the whole act of running when not in a stadium means that the user moves quickly through the environment and does not stay in the same area, the trainers are limited in providing direct feedback during the training. This problem has been solved by the use of wearable sensors and feedback devices, which provide feedback instantly to the athlete, just as is the case with fatigue detection systems [66] and the targeting of heartrate planning systems [67] and virtual coach systems [68].

Table 9. Identified studies in the domain of running.

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[69]	Simulated annealing	Planning the optimum running speed of an athlete, by estimating the physical effort needed at each part of the competitions and training.	An example of the application of a data-driven approach to the development of an adaptive decision support system for sports training, based on a case of estimating the optimum running speed of an athlete.	2	2	1	1
[68]	/	A proposal for a wearable personal training system which supports the user's outdoor fitness activities with context-aware and user adaptive advice, based on sensed context, a user model, and knowledge elicited from a personal trainer and a Sport Physiologist.	A proposal by a training expert was developed to guide the user towards optimum training.	1	1	1	1
[65]	DE	A post hoc analysis of sport performance in a marathon run	A method that determines where an athlete underperformed (lost time) when their results are weaker than expected, based on GPS running data.	0	0	0	2
[64]	DE	A post hoc analysis of an athlete's performance (time trial) based on their heart rate.	25 different strategies identified by the Differential Evolution algorithm on how to reduce time deficits in each kilometer of the course.	0	0	0	2
[70]	k-NN	The implementation of an ambient intelligence system applied to the practice of outdoor running sports, with support for personalized real-time feedback for sports practitioners.	The system provided real time feedback (with up to 70% accuracy) based on terrain, temperature and slope.	0	2	2	0
[66]	ANN; GB; LR	Fatigue detection and warning system to prevent injuries from occurring during training.	Models, trained on a longitudinal dataset of runners, were able to predict the Rate of Perceived Exertion accurately.	0	2	0	0
[71]	GB	Predicting the finishing time of athletes for 800m and 5000m runs based on exercise (wearable) and nutrition (diary) data.	With a small sample, the GBM algorithm proved more accurate than the SVM, LR, RF and DNN algorithms.	0	2	2	2
[72]	/	Assessment of the kinematic features of a standardized endurance running test using novel ETHOS (Inertial Movement Units) sensors.	A minimum set of two acceleration sensors attached to the athlete's foot and hip were sufficient to derive kinematic features that allow for a distinction between experienced and inexperienced runners.	0	2	2	0
[73]	BN	The presentation of a system that formulates an optimized interval training method efficiently for each individual by using Data Mining schemes on attributes, conditions, and data gathered from an individual's exercise sessions.	The users who followed the proposed system training plans burned 29.54% calories compared with the Tabata interval training protocol.	2	2	2	0
[67]	SVM; k-NN; Spline interpolation	Demonstration of the feasibility of ambient intelligence technologies applied to outdoor sports practice.	A system which chosen user track to adjust the difficulty of running has achieved 80% success rate in runners maintaining their target heart rate in training.	0	2	0	0
[74]	SVM	Proposal for an athlete performance prediction-model and Sports Science training plan based on an SVM built model	SVM predicted the running results of athletes with 90% accuracy.	0	0	1	2

5.6. Shooting

All three studies in the field of shooting were related to the realization training stage as seen in Table 10. The main method of improving shooting training is the use of augments to replace real weapon ammo with IT-supported training devices, so that actual ammo does not need to be used. This, in turn, improves the safety of the training grounds, reduces training costs due to replacing real ammo with simulated shots, and enables advanced analysis of training data.

Table 10. Identified studies in the domain of shooting.

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[75]	/	The design and implementation of a computer-aided shooting training and instructing system for trainees and coaches.	The device was accurate, and allows for the replacement of parts for shooting training (with live ammunition) with a virtualized component.	0	2	1	0
[46]	Custom Data Mining algorithm	Design and implementation of a shooting training and intelligent evaluation system by image acquisition.	A system was developed which can be used on 95 different military-style rifles. The system provided automatic target-scoring and analysis of the shooter's technique.	0	3	2	2
[76]	Fuzzy	Proposal for a shooting trainer system solution, based on the requirements received from the shooters and trainers, which consists of hardware and software components.	The top level architecture of the system was presented.	1	1	1	1

5.7. Soccer

Soccer is arguably one of the most popular sports in the world, with up to 43% of the world's population watching or playing it to some extent [77]. Soccer was also the most popular individual sport researched in the SST research, and was the focus of research in 12 different papers (Table 11). All of the training stages were researched at least once in the field of soccer training research, with one research study [78] related to all the phases of training research. Some of the main researched topics include: injury prediction, prevention and recovery [79–81], match analysis [82–84], and performed training analysis [85–87].

Table 11. Identified studies in the domain of soccer.

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[88]	RF; LR; ANN; SVM	Estimate future goal scoring performance and shots attempted for soccer players, based on past performance.	A model to predict goals scored, based on total shots attempted.	0	0	0	1
[84]	/	Recording player positions in a match with the use of a wearable device and visualizing them by placing them on a heat map.	A model incorporating sensor data recordings and output on a heat map was developed.	0	0	0	2
[79]	SVM; Gaussian Process; ANN	A model for predicting the recovery time after the injury of soccer players, based on the parameters regarding the player and the injury.	No single method was found to be significantly better than the other two. Somewhat accurate predictions can be acquired.	2	0	0	0
[78]	K-means clustering	Smart Coach user adaptation model to assist with recommendations in user training.	System was developed, and is going to be tested at two soccer clubs.	1	1	1	1
[80]	k-NN; SVM	Developing a Machine Learning predictive system for early injury detection and prediction was based on athletic load data.	A player individualized probability mapping of possible future injuries was presented.	2	2	0	0
[83]	Custom Data Mining algorithm	A soccer tactics Data Mining algorithm using an improved association rules mining algorithm.	The proposed algorithm effectively distinguished between different types of soccer tactics.	0	0	0	1
[89]	LR, RF, ANN	A Machine Learning model to determine the performance of a soccer player at a particular playing position.	The ANN model achieved 79.01% accuracy.	1	0	0	0
[81]	DT	Soccer player injury forecasting by extracting training load data and physical attributes.	A set of rules were proposed for evaluating and interpreting the relation between injury risk and training performance in professional soccer.	2	3	2	0
[86]	DT; RF, SVM, GAM, LR, k-NN	Predicting the Rate of Perceived exertion from GPS training data of players in a soccer club.	GPS data was used to uncover the training workload of players in a professional soccer club during a season. The proposed Ordinal predictor was accurate and precise in medium RPE value (i.e. between 4 and 7) but was not consistent in the extreme values (i.e. below 4 and above 7).	0	2	2	0
[85]	RF	Detecting the in-season short-term training cycles in an Italian elite soccer team.	The soccer training cycles detected were composed of two kinds of training: high and low intensity training loads performed in the days long before, and close to, the match.	2	3	3	0

Table 11. *Cont.*

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[82]	Apriori	Algarve Cup 2012 Germany vs. Japan match analysis supported with Data Mining	Identification of general playing patterns key combinations and players in a soccer match that have a positive impact on scoring opportunity.	0	0	0	1
[87]	LSTM	Deriving peaks in soccer players' ability to perform from subjective self-reported wellness data collected using the PMSys system.	LSTM RNN model could predict the performance peaks with an accuracy of at least 90%.	2	0	0	2

5.8. Swimming

Swimming research was concerned mostly with the realization phase of the SST, as seen in Table 12. One of the topics [90] was related to the recruitment of potential swimmers'. Wearable devices for evaluating actual training were used in [91,92].

Table 12. Identified studies in the domain of swimming.

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[91]	/	Evaluation of swimmer training performance by recording the exercise with a wearable sensor and analyzing the data.	Measurements were performed and the measurement of the critical stroke rate was proposed via use of the wearable.	1	2	1	1
[93]	Fuzzy	Data Mining the available data in the domain of Swimming and proposing a set of fuzzy rules "IF (fuzzy conditions) THEN (class) regarding swimmer's feelings after their training session.	The proposed Machine Learning tool acquired the rules from the data with an almost 70% accuracy rate.	0	1	1	0
[92]	DT; ANN	Proposal for a methodology for the automatic identification and classification of swimmers' kinematics (swimming strokes) information, retrieved from sensors, during interval training of competitive swimming.	The accuracy of the stroke style classification by both the multi-layered Neural Network (NN) and the C4.5 Decision Tree were 91.1%.	0	2	2	0
[90]	ANN	To establish neural form models assisting the recruitment process in sport swimming, based on swimmers' physical attributes and standardized athlete results.	Kohonen's networks showed that through the use of independent variables, they could group subjects accurately into categories, which after a year, achieved very good, average and very weak performances.	3	0	0	0

5.9. Table Tennis

None of the table tennis SST research addressed the planning and evaluation training phases of sports training as shown in Table 13. Virtual reality training with the use of VR goggles for use in table tennis amateur players was presented and proposed in [94]. Since the primary equipment the player uses is a table tennis racket, most of the important movement is concentrated in the upper limb movement. Two studies [95,96] related to table tennis executed training data measurements with the inertial movement unit sensors, fixed on the players' hands.

Table 13. Identified studies in the domain of table tennis.

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[95]	SVM; BN; RF; k-NN;	Table Tennis stroke detection and stroke type classification using inertial sensor data, were trained and tested by SVM; Linear Kernel (LIN); Radial Based Function (RBF) kernel; k-NN.	An SVM based algorithm yielded the best results with a classification rate of 96.7%.	0	2	0	0
[96]	LSTM	A Deep Learning-based coaching assistant method, for providing useful information in supporting Table Tennis practice on data collected by an Inertial Movement Unit sensor.	Experimental results showed that the presented method can yield results for characterizing high-dimensional time series patterns.	0	2	0	0
[94]	/	Investigating the use of virtual reality training to improve Table Tennis skills.	VR training improved participants' real-world Table Tennis performance significantly compared to a no-training control group in both quantitative and quality of skill assessments.	0	3	3	0

5.10. Tennis

The research in the domain of Tennis addressed all four phases of SST as seen in Table 14. The authors of [97] presented an interesting way of analyzing a tennis game, it was one of the only two studies discovered by our review to use sound recordings as a way of analyzing a game and its events. Similarly to the discipline of table tennis , the use of inertial movement unit sensors was also pervasive in this field (e.g., [98–100]).

Table 14. Identified studies in the domain of tennis.

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[98]	Fuzzy	Use of Artificial Intelligence on sports coaching with the example of tennis coaching.	A tennis coaching prototype that rates each swing based on input data.	0	1	2	0
[97]	ANN	Recognizing events of a tennis game from sound recording.	A system that identifies the main events of tennis games based on sound recordings.	0	0	0	2
[99]	ANN	The recognition of tennis strokes by using a sensor for data collection and ANN for activity recognition.	A trained ANN model for the recognition of 9 different tennis strokes. Basic recognition achieved, recognition of advanced motion is still a work in progress.	0	2	1	0
[101]	Apriori	Associative Rules proposal on tennis strokes mined from the data of a professional female athlete.	Rules about an athlete were discovered, and using these rules in the future was proposed.	0	0	0	2
[102]	LSTM	A Deep Neural Network model classification model of action recognition in tennis, from video data.	A 3-layered LSTM network was able to classify fine-grained tennis actions with high accuracy (between 81.23%–88.16%)	0	2	0	0
[100]	SVM	An automated method for quantifying shot counts, and for discriminating shot types among elite tennis players using an Inertial Movement Unit sensor and video recording data.	Binned shots (overhead, forehand, or backhand) were classified with an accuracy of 97.4% while a 93.2% accuracy rate was achieved for the classification of all 9 shot types.	0	2	2	0

5.11. Triathlon

The triathlon is a multidisciplinary sport which consists of cycling, running, and swimming stages, so it should be noted that the mentioned research is at least partially relevant to the triathlon discipline. None of the research addressed the realization stage of SST as displayed in Table 15. The focus of the two studies [103,104] was related to predicting the time in which the athlete will complete each part of the triathlon race. The triathlon discipline [103,105] was the only field where the particle swarm optimization method was used.

Table 15. Identified studies in the domain of triathlon.

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[106]	PSO	Planning the training sessions for triathlon	Training session plan (multiple sessions) generation method for preparing for a triathlon.	2	0	0	0
[105]	DT	Decision Tree classification of eating suggestions during a longer endurance race.	A Decision Tree model was built to aid in the decision making process during a race, based on welfare, weather, heart rate and distance.	0	0	0	2
[103]	PSO	Presentation of an automatic framework for modeling preference times, based on previous results of athletes for a particular race course with the Particle Swarm Optimization algorithm.	A Particle Swarm Optimization model was developed from which an athlete can determine their preference times for an Ironman triathlon	0	0	1	2
[104]	RF; k-NN; DT; BN; SVM; LR; Linear Discriminant Analysis	Predicting the level of the in-exercise loads by the use of Machine Learning methods (linear regression, Linear Discriminant Analysis, k-nearest neighbors, Decision Tree, Random Forest, Gaussian naive Bayes, support-vector machine) for monitoring energy expenditures in athletes.	The k-NN classifier was found to be the best predictor, but the data are not generalizable, and need to be studied further.	0	0	2	0

5.12. Volleyball

The volleyball-related SST research contained two studies [107,108] which addressed training in full, addressing all four stages of training concurrently, as seen in Table 16. Some [107,109] of the research was more focused towards team training, as to what to improve in the team to improve results, and some with improving individuals [109].

Table 16. Identified studies in the domain of volleyball.

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[107]	MC; LR	Improving the team performance of a (specific) volleyball team, through identifying specific skills to improve in training.	Ball blocks were found to be determinable to their team performance, so their use in training was recommended.	2	1	1	3
[109]	LSTM	Arms, hands and wrists, standing posture and timing recognition by the use of wearable (Inertial Measure Unit and EMG sensor) and video cameras and classification of disallowed moves so that feedback is provided in training sessions.	The proposed model proved beneficial for beginner players. It was possible to describe the setting action with IMU and EMG sensors and the usage of performance classes.	0	2	0	0
[108]	k-NN	SAETA AmI system for professional team sports training presentations. Developing decision-making systems for different aspects of player training, providing automated real time feedback to coaches and athletes.	The system use in practice was presented. The system detection process of player jumps (which has a 93% rate for true positives and 100% accuracy for true negatives) was described in depth.	1	2	2	2

5.13. Weight Lifting

Weight lifting is similar to fitness (gym training), a fairly static discipline where movement is limited. It was the third most researched SST discipline and a total of nine research studies were published as seen in Table 17. The research was focused largely around the use of inertial movement unit sensors in a lot of studies [110–112]. Interestingly, one [113] of the studies put sensors on the equipment instead of the trainee.

Table 17. Identified studies in the domain of weight lifting.

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[114]	ANN	A prediction of a female power-lifter's performance, based on their applying their bio-metric data to an ANN model.	A prediction model was built that gives an estimation of a best dead-lift performance.	0	0	2	2
[111]	CNN	A training system was developed for Weight Lifting exercises. It contained fatigue and a posture warning system, based on CNN, to warn users about incorrect postures or high fatigue.	A solution was developed that warns users of incorrect movements and fatigue, based on readings from sensors and cameras.	1	2	1	0
[112]	SVM	Classification of Weight Lifting exercise by an SVM model currently performed from data worn on a single wrist wearable device.	94,36% accuracy achieved in classifying between 9 different exercises.	0	2	0	0
[110]	Markov Chains, SVM, k-NN	Accurate and real time tracking of select/the use of wearable gyroscope and acceleration meter sensors (based on Inertial Measurement Units).	The system can identify Weight Lifting exercises with a delay of 300 ms and count their repetitions with high accuracy.	0	2	0	0
[115]	CNN	A prototype of a system for extracting poses from weightlifting sport training videos.	Deep Key Frame Extraction (DKFE) was presented for sport training video analysis.	0	2	2	0
[113]	ANN	Artificial Neural Network (ANN) model to automatically evaluate exercises in weight training, by receiving data from sensor placed on Weight Lifting machines.	ANN model automatically differentiated between improper and proper execution of machines and provided feedback.	0	2	2	0
[116]	Fuzzy	The Fuzzy logic approach to evaluate if Weight Lifting exercises on machines are being executed correctly.	Fuzzy rules regarding proper training execution on machines were proposed combining time duration, velocity, and displacement of equipment parts.	0	0	1	0

Table 17. *Cont.*

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[117]	RF	Assessing and providing feedback on Weight Lifting exercises with sensor support and a trained Random Forest model.	Users using the system made less mistakes doing Weight Lifting exercises than when not using the system.	0	2	2	0
[118]	CNN	Presentation of the key pose recognition method, based on Deep Learning.	The learned system could classify users lifting weights in one of the four poses with over 95% accuracy.	0	2	0	0

5.14. Other Sports

In the other sports category, all the sports were included which had two or less studies addressing their training. As such, the sports of aikido, archery, badminton, climbing, counter movement jumping, cricket, fencing, (American/Australian) football, golf, hammer throwing, handball, hockey, karate, kickboxing, ski jumping, skiing, Tai-chi, and yoga, which contained less research regarding their domain (N < 3), are presented here and shown in Table 18. The field research ranged from injury prediction and identification [119,120], to pose recognition and evaluation [121–123], virtual coaching and coaching assistants [124–126], and VR systems [127,128].

Table 18. Identified studies of other sports.

Ref.	Sport	Research SST Methods	Focus	Results	Training P	R	C	E
[129]	Aikido	CBR	Presentation of an AI-Virtual Trainer educative system on a case of Aikido lessons. The system proposes varied lessons to trainers, via the utilization of case-based reasoning.	The system can propose training tasks based on requested training objectives, without repeating the same exercises.	2	0	0	0
[130]	Archery	SVM	Predicting the class of archers based on the chosen performance variables using the SVM model.	Archers were split between low and high potential and a 97.5% classification accuracy rate was found.	2	0	0	2
[131]	Badminton	LR	To design a mobile application, which will serve as a virtual trainer and provide the athlete with dietary, exercise and health related advice, based on his profile.	A developed solution for managing stress and health, generating exercise and training schedules, suggesting meals by using the example of badminton.	3	1	3	2
[132]	Climbing	/	A system for automatic route recognition on a climbing wall is proposed using a Inertial Measurement Unit sensor.	The system was developed and tested. It was very accurate for ascent-only climbs, but only limited in use when the ascent was combined with a descent.	0	2	0	0
[133]	Climbing	/	Wearable device based on the feedback of an online survey of climbers. Verification of the device by a case study in a climbing gym. Investigating best notification channels for real time notifications during a climb.	The most suited notification channel was sound, directly followed by vibrotactile output.	0	1	0	0
[134]	Jumping	ANN	Artificial Neural Network (ANN) model to determine the effect of 15 weeks of resistance training on changes in countermovement jump (CMJ) performance in male track and field athletes.	A model was built that predicted performance increase based on weekly volume load.	0	2	2	2
[124]	Cricket	Fuzzy, ANN	Developing an Artificial Intelligence based cricket coach, that amateur cricketers can use to practice and gain expertise in cricket, particularly in batting, bowling and fielding.	The system can suggest the best strokes as well as bat movements and can train fielders with regard to every aspect of training.	2	2	1	0
[135]	Cricket	SVM	Identification of the optimal set of attributes (of cricket players), which impose the high impact on the results of a cricket match.	Player attributes were determined based on their effect on the end result of a cricket match.	2	0	0	2

Table 18. *Cont.*

Ref.	Sport	Research SST Methods	Focus	Results	Training P	R	C	E
[125]	Fencing	BN	Development of a decision support system of the Chinese National Fencing Team based on a Bayesian network.	The model could provide effective decision support for coaches.	1	1	1	0
[136]	(American / Australian) Football	ANN	Estimating the Rate Perceived Exertion (RPE) based on the GPS data of professional Football players by using Artificial Neural Networks.	The Training Load model, could estimate RPE based on GPS movement data, training and previous RPE measurements.	1	2	2	3
[119]	(American / Australian) Football	LR; RF; SVM	Hamstring injury prediction models based on training loads, estimated by GPS, accelerometers and perceived exertion ratings of an Australian football club.	Logistic Regressions were found to be the best performing model for predicting injuries. Poor accuracy was found when data from another football club was applied.	1	2	2	1
[137]	Golf	/	A custom algorithm that estimates swing golf trajectories and rates them based on data from a Inertial Measure Unit sensor and a camera.	The model was presented, whose outputs were swing trajectories and features.	0	2	2	0
[138]	Golf	CNN	Example of golf swing data classification methods based on Deep Convolutional Neural Network (deep CNN) fed with multi-sensor golf swing signals.	The Deep CNN model outperformed the SVM method.	0	2	2	0
[139]	Hammer Throwing	/	Proposal of scientifically described training targets and routes, which in turn require tools that can measure and quantify the characteristics of an effective hammer-throw. The development of a biomechanical feedback device to be used in training of hammer throwers.	The software and hardware architecture of the proposed system was described.	0	1	0	0
[120]	Handball	DT	Lower externity muscle injury risk prediction model from handball players' personal, psychological and neuromuscular data, as well as a comparison between different Decision Tree classifiers.	SmooteBoost ADTree was found to be the best algorithm for predicting injuries.	2	1	2	2
[140]	Hockey	SVM; DT	Identifying differences between individuals in a hockey team and proposing a future match result estimator based on the latest training biometric data.	An SVM based model was built based on the training performance. The model allowed for the prediction of future game outcomes of The University of Virginia's (UVA) varsity field hockey team with 79.8 % accuracy.	0	2	2	3
[141]	Karate	DTW	Investigating repetitiveness of karate kicks of skilled karate practitioners	Ranges of body and joint movement were established for standard karate kicks.	0	2	2	0
[127]	Karate	/	Kinect based VR training system for Karate katas.	The system was presented briefly.	0	1	0	0
[126]	Kickboxing	/	Automated Planning techniques for generating individual training plans, which consist of exercises the athlete has to perform during training, given the athlete's current performance, period of time, and target performance that should be achieved.	The training plans automatically generated by the proposed approach were more detailed and individualized than plans prepared manually by an expert coach.	2	0	0	0
[142]	Kickboxing	k-NN; SVM	Automatic classification by skill level of trajectory data of Kickboxing strike techniques.	73.3% accuracy of classifying strikes by skill level was achieved by k-NN.	0	2	2	0
[122]	Ski Jumping	/	Developing a system for the automatic evaluation of ski jumps on the base of Machine Learning algorithms.	A custom built algorithm for evaluating the performance of individual ski jumps, based on recorded sensor data was proposed.	0	0	0	2
[121]	Skiing	CNN	AI Coach system to provide personalized athletic training experiences for posture-wise sports activities with the case of skiing.	The AI coach system for pose tracking was used by volunteers and a questionnaire reported that they were satisfied with the system.	0	1	1	0

Table 18. *Cont.*

Ref.	Sport	Research SST Methods	Focus	Results	Training P	R	C	E
[128]	Tai-chi	RF; SVM	A VR training system of Tai Chi that analyzes and provides feedback to trainee movements.	The VR training system detected mistakes and corrected trainees, but some of the more subtle mistakes went largely undetected.	1	2	1	0
[123]	Yoga	Adaptive Boosting	Presentation of a Kinect v2 powered interactive system for Yoga pose recognition, with real time direction and picture guidance about the poses to be executed.	6 different yoga poses were identified with 92% accuracy.	0	2	0	0

5.15. General

The *General* research addressed all non domain specific research where the research was not focused explicitly on a particular discipline; the identified papers are shown in Table 19. The use of smart textiles [143] was addressed as part of training data collection. There were also proposals [144,145] of more generalized methods/frameworks regarding SST. Fatigue prediction [146] was done with real-time voice analysis software and is the second study of all the reviewed ones to feature sound analysis. Another unique aspect addressed was the use of machine learning to shorten the standard estimation of cardiopulmonary function by predicting the end result of cardiopulmonary tests [147]. This is an interesting optimization of training, since such tests usually require the maximum exertion of a person under examination, which leaves the athlete tired after the examination and limits his options for further training on the same day.

Table 19. Identified studies unrelated to any particular sport.

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[148]	RF	End-to-end motion analysis system analyzing joint angle and impact acceleration data among athletes with a back injury and uninjured athletes.	Movements that can contribute to knee and back injury was measured and individual movements of athletes wearing an IMU can be classified by the built model.	2	0	0	2
[147]	ANN; k-NN	Use of Artificial Neural Networks and K-Nearest Neighbors to estimate maximum workload in cardiopulmonary tests without completing the whole test.	Shortened test proposal that uses k-NN and ANN to estimate the athlete's ability without completing the whole test, therefore not fully exhausting the athlete.	0	2	2	0
[146]	SVM	Voice-based fatigue detection SVM model, that predicts fatigue levels during a training exercise.	A 91.67% accuracy rate for fatigue was detected. The fatigue was measured with the Rating of Perceived Exertion	0	2	0	0
[149]	BA	Discovering the characteristics and habits of athletes in training	Results of the BatMiner algorithm for association rule mining were presented and association rules were proposed to aid in the decision making of trainers	2	1	1	1
[150]	/	A general approach to design of a automated personal trainer.	A general approach (algorithm independent) for creating an artificial trainer.	0	1	0	0
[151]	NB	Developing a training assistant which helps regular people exercise and monitor their diets.	A generalized app was developed which monitors a person's exercise activity and food intake plans and suggests exercises and nutrition plans.	2	2	2	2
[144]	/	Proposal for a Data Mining tool to guide sports training and provide technical and tactical analysis.	A proposal for a framework for a Data Mining tool is presented to aid coaches and trainees.	0	0	1	1
[152]	BN	Presentation of an inductive approach for dynamically modelling sport-related injuries with a Dynamic Bayesian Network (DBN), on data from regularly monitored athletes.	DBN suggested subjectively-reported stress two days prior, internally perceived exertions one day prior to the injury and direct current potential and sympathetic tone the day of, as the most impact towards injury occurrence.	0	2	2	0
[145]	/	Proposal for a generalized training framework based on emerging technologies.	A personalized training framework proposal based on genetics and regular training monitoring.	1	1	1	1

Table 19. *Cont.*

Ref.	Research SST Methods	Focus	Results	Training P	R	C	E
[153]	K-means clustering, Hierarchical Clustering	Proposal for an integrated Data Mining algorithm based on sports team match data and the generation of individual training regimes to increase their athletes' stamina.	Proposed algorithm with necessary hardware and software equipment for actual use.	1	1	1	1
[143]	k-NN	Textile pressure sensor matrix, that can be integrated into exercise mats to recognize and count exercises done on a exercise mat.	A model for recognition between different standard exercises achieved 82.5% user independent and 89.9% user dependent counting accuracy.	0	2	2	0
[154]	/	A general method to develop an expert system for dynamically adapting workout sessions of athletes was presented. A study of identifying relevant parameters that influence sporting performance was conducted.	An empirical study and self monitoring of athletes led to the rule catalog proposed by the researchers.	1	1	1	1
[155]	LR; RF, DT	Experiment evaluating performance of football players in countermovement jumps (CMJs) and predicting it by using different Machine Learning methods	A correlation between countermovement jump performance and ability to produce greater force in a short period of time was found.	0	2	1	2
[156]	/	Proposal of a model for evaluating fitness level of athletes by measuring their heart rate and GPS location.	Framework that provides a fitness level based on cardiac parameter identification.	0	1	1	2

6. Discussion

The pervasiveness of smart applications has influenced all aspects of sports training. Studies show that the SST is and can be a determining force in transforming all of the four training phases (1.RQ). The most researched training phase was realization, as shown in Table 20. The realization phase is arguably one of the least complex stages where the SST approach can be utilized, because recording the actual data during training can be done mostly by the use of wearable devices. Some multi-purpose wearable devices can be used in multiple domains and can provide sensors for sleep tracking, heart rate monitoring, step tracking, accelerometer, gyroscope, GPS, etc. as presented in [5]. Evaluation phase research was mostly related to longitudinal studies where the training data was compared with the competition performances (e.g., [88,107]). The research related to the training control phase was tightly interconnected with the realization training phase research, especially when measures were introduced to record training data (e.g., [72,91,112,117]).

The least research was related to the planning phase of the training, where the real human coaches still prevail. The planning phase research was related to creating training (exercise) plannin g (e.g., [55–57,61,106,126]), nutrition planning (e.g., [55,151]), and full framework approaches (e.g., [78,131,145]), which were related to all training phases.

Identifying (2.RQ) the most SST supported sports research was presented previously on the Figure 5, where it was shown that the most research was done in the domains of soccer (12 papers • [78–89]), running (11 papers • [64–74]), and weight lifting (9 papers • [110–118]).

The most utilized data analysis methods (3.RQ) were support vector machines (19), artificial neural networks (14), k-nearest neighbors (11), and random forest (11). Based on the taxonomy identified in Section 4, the most widely used methods were in the category of data mining as seen in Figure 6.

Since SST research has experienced such a burst of growth in recent years, a number of papers presented numerous new approaches to sports training. We did not review any of the reviewed approaches in any of the training applications as TRL validation (4.RQ) level research. This may seem surprising, since a lot of applications have been widely used by the general public on Android devices, such as MyFitnessPal [157], Endomondo Running and Walking [158], Google Fit [159], and Apple ecosystem devices, such as Apple Health [160], all of them having over 10 million users. The problem is that such approaches do not share the algorithms and data analysis behind their analysis systems to maintain their competitive advantage. The highest level of TRL achieved was control and, two planning, four realization, three control, and three evaluation research studies reached that level, as seen in Table 21.

Table 20. Count of how many times individual training stages were researched.

Sport	P	R	C	E
Basketball	/	4	4	2
Cycling	4	1	1	1
Fitness (gym)	1	3	/	/
Rowing	/	1	3	2
Running	3	8	7	6
Shooting	1	3	3	2
Soccer	7	5	4	6
Swimming	2	3	3	1
Table Tennis	/	3	1	/
Tennis	/	4	3	2
Triathlon	1	/	2	2
Volleyball	2	3	2	2
Weight Lifting	1	7	6	1
Aikido	1	/	/	/
Archery	1	/	/	1
Badminton	1	1	1	1
Climbing	/	1	/	/
Counter Movement Jumping	/	1	1	1
Cricket	2	1	1	1
Fencing	1	1	1	/
(American/Australian) Football	2	2	2	2
Golf	/	2	2	/
Hammer Throwing	/	1	/	/
Handball	1	1	1	1
Hockey	/	1	1	1
Karate	/	2	1	/
Kickboxing	1	1	1	/
Ski Jumping	/	/	/	1
Skiing	/	1	1	/
Tai-chi	1	1	1	/
Yoga	/	1	/	/
General	6	12	11	9
Total	**39**	**76**	**64**	**45**

Table 21. Count of research by training stage and Technology Readiness Level (TRL) abstracted levels.

	Smart Sport Training Stage			
	Planning	**Realization**	**Control**	**Evaluation**
Idea	14	20	27	15
Prototype	23	52	34	27
Control	2	4	3	3
Validation	/	/	/	/

Since the majority of research done is still in the prototype phase, additional studies are needed in all SST stages and sports to progress towards the control and validation of the proposed ideas. The maturity of SST is very low for phases in sports where no research was found:

- Planning—no research in the domains of basketball, hammer throwing, rowing, table tennis, tennis, climbing, golf, hockey, karate, ski jumping, skiing, and yoga.
- Realization—no research in the domains of triathlon, aikido, archery, and ski jumping.
- Control—no research in the domains of fitness (gym), aikido, archery, hammer throwing, ski jumping, and yoga.
- Evaluation—no research in the domains of fitness (gym), table tennis, aikido, climbing, fencing, golf, hammer throwing, karate, kickboxing, skiing, Tai-chi, and yoga.

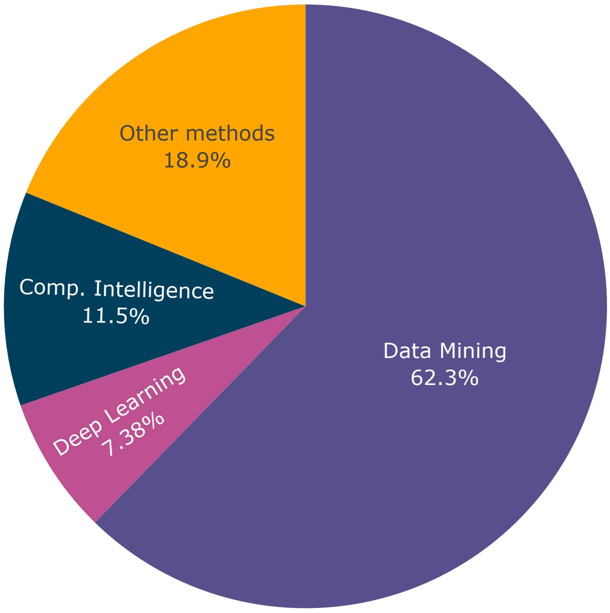

Figure 6. Relative frequency of intelligent methods used by the proposed taxonomy, rounded to three significant digits.

The datasets used in the studies were mostly private data collections, which hinders the ability for verification and validation of published results. Only six studies used and referenced publicly available datasets as presented in Table 22. The vast majority of research used private datasets based on real data. The Dataset column presents the reference to the used dataset, in the Data type column the data were identified as real or synthetic, based on their origin, and in the Studies column, the studies using the mentioned dataset are referenced. All the studies where private datasets were used, or from which we could not identify the used dataset, were classified under the Private dataset rows.

Table 22. Identified datasets and studies using them.

Dataset	Sport	Data Type	Studies
[161]	Soccer	Synthetic	[88,89]
[94]	Table Tennis	Real	[94]
[162]	Tennis	Real	[102]
[163]	Weight Lifting	Real	[114]
[164,165]	Skiing	Real	[121]
Private Dataset	/	Synthetic	[55]
Private Dataset	/	Real	[46,48–50,52,54,56–76,78–87, 90–93,95–101,104–110,112, 113,115–120,122,123,125,128, 130–138,140–149,152,155, 156]

This, however, does not mean that free, open, and public datasets from the domain of SST do not exist. There are already a significant number of them (e.g., [53,166–171]), together with websites that publish sanitized datasets (e.g., [172]), it remains a fact that they are not used enough. If researchers are going to avoid using existing datasets, they should try to ensure publishing as much of their private datasets as possible. A notable mention, although not used in any of the identified studies, is also the data generation methods [173], which could in the future allow easier verification and generation of data. According to our literature review, this research area is still very young, and has experienced increasing and persistent interest among researchers.

Therefore, there are still plenty of challenges for future research. The summarized challenges are:

- **Knowledge transfer into the real-world and validation level research**. There are a lot of research papers that propose planning the training sessions for athletes in various sports. However, most of the papers are concluded with the results in a table, where the results generated by the selected method are shown. However, we do not know how some athletes approach these plans and what the long-term consequences or influence on race results are. Therefore, we encourage researchers to also share their insights of these results in the real-world. Most of the research that was presented reached at most the control phase of TRL and, as such, stopped short of the validation phase. If the field is to gain widespread validity such research is needed, and researchers should try to get in contact with professional athletes more and plan their experiments to capture a wider scope of audience in the field researched.
- **Cooperation with trainers and athletes**: Every athlete is unique and his/her body or mind have different features. How to integrate this component in automatic intelligent solutions still remains a very topical problem. According to our systematic literature review, there are almost no papers that would include the conversation of researchers with athletes and their trainers in the design phase of their experiments.
- **Obtaining test datasets and their dissemination**: The experiments are based on data that could be real or synthetic (i.e., generated artificially). Although a lot of data are available publicly (for example in cycling [53], or soccer [167]), most of the data are still inaccessible, mostly in the domain of individual sports. For that reason, researchers should be encouraged to deposit their data into public repositories, and enable other researchers to access their data.

7. Conclusions

In this paper, we reviewed the latest advances in the development and use of intelligent data analysis methods in the domain of sport training. The purpose of this systematic literature review was twofold. Firstly, we wanted to identify the main intelligent data analysis methods that can be used in different training phases, and, secondly, we wanted to determine which sports are the most supported by these methods.

The study revealed that researchers apply various methods, including computational intelligence, conventional data mining methods, deep learning, machine learning, and some other methods. Computational intelligence algorithms have been rising in popularity in recent years, while the most used intelligent data analysis methods remain support vector machine (19 studies), artificial neural networks (14 studies), k-nearest neighbors (11 studies), and random forest (11 studies). According to this review of 109 studies, we identified that soccer (12 studies), running (11 studied), and weight lifting (10 studies) were the most researched ones. When comparing sports based on participation levels, we have found that over half of the research in this field (54.6%) can be classified as research based on sports for individuals, and that team and mixed sports represent roughly a third of the existing research. The research domain still has a lot of room for improvement, where more validation-level research is needed as well as more publicly available datasets for replicating research and allowing an improvement of methods. Since the field is relatively new, a lot of sports exist with no research in the domain of smart sports training, which offers a wide area of possibilities for research to be made.

Author Contributions: Conceptualization, A.R. and I.F.J.; data curation, A.R.; literature search and review, A.R.; methodology, A.R. and I.F.J.; supervision. I.F.J.; validation: I.F.J. and A.R.; visualization, A.R.; writing, A.R. and I.F.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Javna Agencija za Raziskovalno Dejavnost RS (Research Core Funding No. P2-0057).

Conflicts of Interest: The authors declare no conflict of interest.

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