Power System Technology
ISSN:1000-3673

Received: 16-10-2024 Revised: 05-11-2024 Accepted: 22-12-2024

Machine Learning in the Field of Sports Medicine and Rehabilitation Science.

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Abstract

This study examines the application of advanced machine learning (ML) and artificial intelligence (AI) technologies to enhance athletic performance and predict injuries across various sports. By leveraging big data and complex analytical models, ML algorithms can identify key patterns for injury prediction, as well as optimize training and rehabilitation strategies.

AI has been used to develop mathematical models for injury risk assessment in team sports such as football, basketball, and volleyball. Machine learning also plays a crucial role in refining movement techniques and shot execution, for instance, in tennis. Additionally, ML improves sports performance forecasting and optimizes athlete training, assisting coaches and medical professionals in making more informed decisions.

AI technologies demonstrate significant potential in the detection and analysis of electrocardiographic (ECG) data interpretation, including the identification of life-threatening conditions.

Key words: artificial intelligence, machine learning, sports, sports medicine.

Introduction

The vast majority of things in the world around us are easily recognized and classified by humans. He does this thanks to the information available about these subjects. Moreover, a

Received: 16-10-2024 Revised: 05-11-2024 Accepted: 22-12-2024

person can often classify an object quite successfully, even if they have never encountered it before. This is possible due to the extensive knowledge about objects that people have come across before.

Another important introductory point is that the human brain is good at assigning certain quantitative values to the characteristics of an object. The computer, in turn, was designed and created as a tool that facilitates interaction with numbers, as a result of which it is perfectly adapted to work with them.

At the junction of these two assumptions, a hypothesis arises that if you "digitize" the properties of objects by presenting them numerically, as well as accumulate a sufficient sample of successfully classified objects, then the computer is able to build a mathematical model that allows you to independently classify objects based on their "digitized" features. This is how artificial intelligence and various machine learning methods work.

Machine learning is a branch of artificial intelligence, explores the field of knowledge discovery in data [1]. In addition, neural networks are used in deep learning, an additional branch of machine learning, to achieve the same goal. After data collection, a significant amount of time is usually spent formatting and preparing the data for analysis. This includes standardizing data for analysis, removing or interpreting variables with an excessive number of missing values, and performing routine statistical tests to evaluate relationships such as collinearity. These latest technologies are used in many areas of life – engineering, medicine, sports, etc. Artificial intelligence (AI), including machine learning (ML), has revolutionized the analysis of medical data, supporting the diagnosis of various conditions such as gait disorders, Parkinson's disease, stroke and osteoarthritis. [2,3,4,5,6]. Machine learning algorithms are used as a decision support system for the diagnosis of neuromuscular disorders. For example, a study was conducted comparing machine learning methods in an ensemble of bundling and amplification for automatic classification of EMG signals [7]. Bijari et al. In their work, they used the machine learning method for the differential diagnosis of glioblastoma multiforme and brain metastases and found that machine learning based on radiomics can accurately classify these 2 diseases [8]

During life, the human body adapts to the living conditions of a particular individual, as well as to the motor tasks that it regularly encounters. As a result, in combination with different innate data, the organisms of individuals of homo sapiens (or, more simply, modern humans) can vary significantly within the species, even under similar living conditions

Assessing the functional state of the human body is not a trivial task, at least at the stage of setting criteria for this assessment. The most obvious reasons are as follows: firstly, the abundance of innate individual characteristics of a particular person, secondly, the abundance of acquired characteristics, motor habits and skills, and, thirdly, the difference in goals and

Power System Technology
ISSN:1000-3673
Received: 16-10-2024 Revised: 05-11-2024 Accepted: 22-12-2024

directions of development: someone wants to achieve less weight, someone – more strength, someone – endurance or speed. In this regard, the use of machine learning methods in such areas as sports, sports medicine and rehabilitation has recently become increasingly important.

Main part

Machine learning methods

The most popular, due to their simplicity and clarity, among the methods of machine learning with a teacher are linear regression, the method of near neighbors and decision trees.

3.1. Linear regression

A special case of the regression model. This mathematical model is based on a linear equation of the form:

y=f(x, b)+ε, where y is the answer (class of the observed object), x is a row of features of the object (observation), each column of which corresponds to some parameter measured in this observation of the object, b are coefficients for the observed parameters, ε is a random error of the model;

The function f(x, b) for linear regression, in turn, has the following form: f(x, b) = b0 + b1x1 + ... + bnxn for an object that has n features.

The b parameter is selected so that the lines delimit the objects between the classes. The selection of this parameter is the process of training a network based on a regression model (Figure 1).

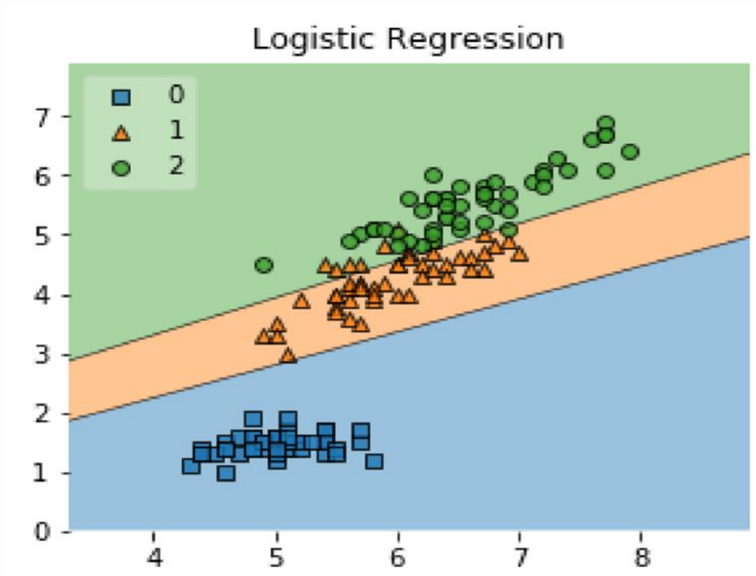

Figure 1. Graphical representation of linear regression.

Power System Technology
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3.2. K-nearest neighbors algorithm, k-NN

This method is also based on the representation of points in the coordinates of their features. However, the division into classes does not occur in hyperplanes. In the k-nearest neighbors method, each new object is classified according to a majority vote on k-neighboring objects with already known classes.

There are also weighted versions of this method, where closer objects are more important in the classification process than more distant ones.

Due to the use of the term "distance", it is necessary to define it. Most often, the Euclidean distance is used for the k-nearest neighbors method. Signs are usually normalized in this case, because otherwise more sparse signs will change the distance more strongly than more dense ones, which can reduce their weight in the final mathematical model. On the other hand, if there are clearly important features that should be paid more attention to when building a model, these features can be highlighted by adding the "weights" of the axis.

An important parameter of this method is the number of nearest neighbors by which the class of a new object is determined. The selection of the number of neighbors, as well as space metrics, is the process of configuring a computer expert system for the nearest neighbors method (Figure 2).

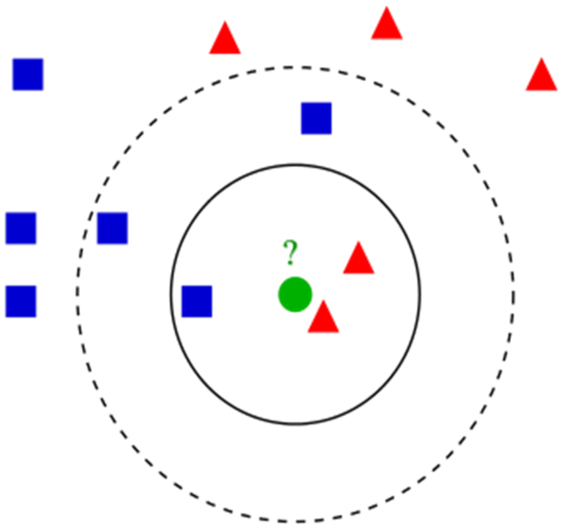

Figure 2. K-nearest neighbors algorithm. The illustration about the importance of the number of neighbors to determine the class of an object.

3.3. Decision trees

This method is based on multiple binary choices, depending on which we iteratively move further down the tree along the right or left branch until we reach the leaf containing the answer — the class of the object being defined (Figure 3).

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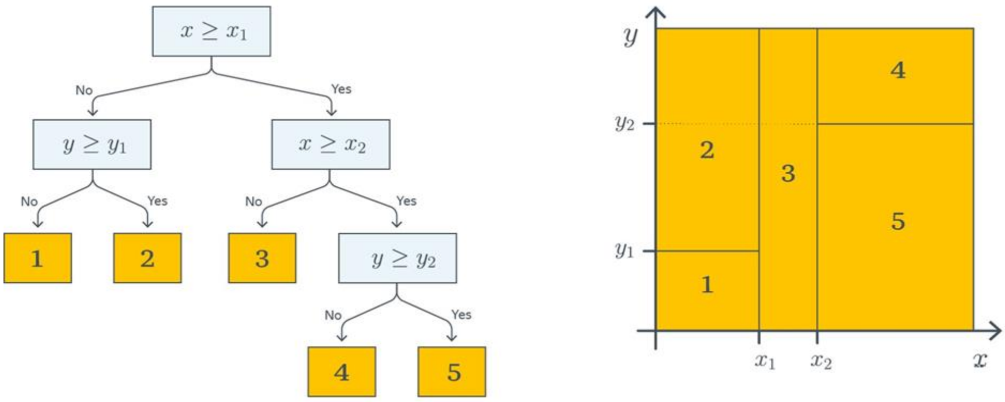

Figure 3. An example of classification by the decision tree method for a point on a plane depending on its coordinates.

The training of the decision tree model consists in selecting such conditions at the nodes of the tree in order to get to the leaves of the tree as quickly as possible, that is, to receive an answer.

Of the important nuances of this mathematical model, it should be noted that the answer is "piecewise" — the tree divides the hyperplane into sections, but it is not able to estimate the proximity of the answer to the boundary (Figure 4**)**. Moreover, decision trees are not capable of extrapolation, that is, of making predictions outside the boundaries of the training sample, which means that you need to be sure that the data on which the model will be used lies inside the training sample.

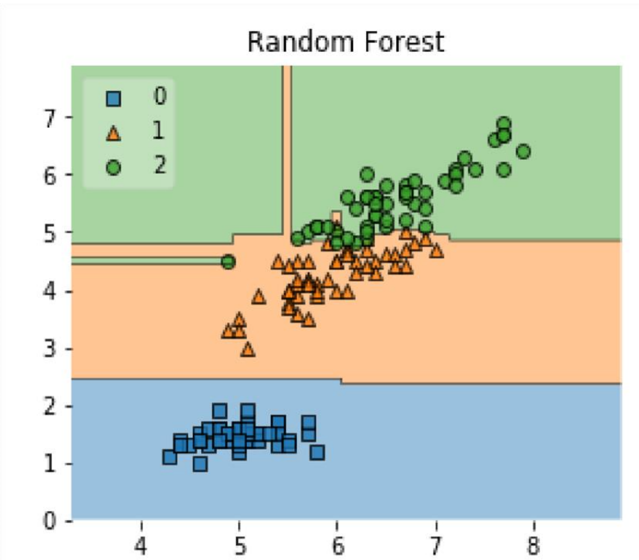

Figure 4. An example of dividing a set of objects into classes using decision trees.

Power System Technology
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3.4. Neural network, NN

There are also neural network models. These networks are based on "neurons" – nodes with multiple inputs and one output connected to other similar nodes. Depending on the input data, the output of the neuron changes. Learning consists in choosing the optimal connections, the number of hidden layers, and the function (dependence of output data on input signals) of each neuron (Figure 5).

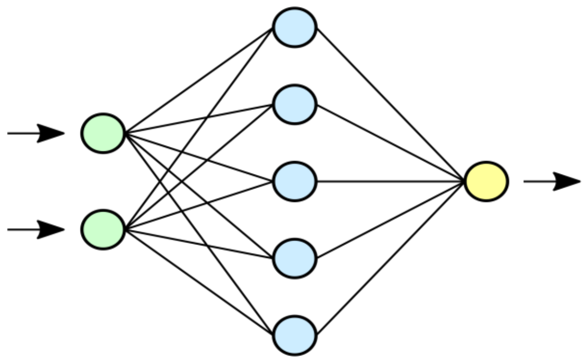

Figure 5. ***The simplest example of a neural network. The circles in the diagram are neurons. Green – input, blue – hidden (inner) layer, yellow – output. In more complex networks, the number of hidden layers may be greater.***

Neural network models often allow for more accurate results, including through a variety of methods and architectures for their construction, but they often require significantly more time and computing power for training. Also, as the complexity of the model increases, it becomes almost impossible to track the principle of decision-making, which makes it difficult to configure and debug the model.

The use of artificial intelligence and machine learning methods in sports and medical practice

Over the past decade, several articles have proposed models for assessing the risk of injury in athletes. The first injury risk model was developed by Gabbet et al. in 2010, who modeled the risk of soft tissue injury using a one-dimensional approach [9]. This risk was assessed by assessing the training load endured by the athletes during the competitive season (i.e. the cumulative amount of stress perceived by the player during one training session). In this study, the authors suggested that football players who perform a high training load are 70% more likely to get injured compared to players who have been subjected to a low training load. In addition, Gabbet, Hulin et al. In the last decade, they continued their research, finding a link between acute training load (i.e., the average training load for about one previous week) and injury risk [10,11,12,13].

Received: 16-10-2024 Revised: 05-11-2024 Accepted: 22-12-2024

The use of machine learning methods in sports provides sports organizations and coaches with vital information about athletes' performance, as well as generates a huge amount of data to optimize athletic performance [14,15]. The extensive data obtained serves as a catalyst, allowing coaches to improve their training decisions and strategic approaches, and sports doctors to improve their treatment and rehabilitation [16]. The results obtained through the application of machine learning models can help coaches and sports managers in predicting and evaluating athletes' performance, identifying sports talents, evaluating game strategies, and more. For example, Pappalardo et al. The performance of the players was assessed using a data-driven approach [17]. In this study, the authors developed a machine learning model for predicting match results, in order to identify the impact of various events (the number of passes, throws and tackles) committed by a football player during the game on the final victory. Using the obtained weights, the authors calculated the score by applying the dot product between the previously determined weights of the functions and the values these functions take in a particular match played by a particular player. Moreover, Sałabun et al. developed a multi–criteria model (for example, the Characteristic Objects Method - COMET) to evaluate the effectiveness of players according to their position on the field based on match statistics [18]. In addition, the COMET approach has also been proposed in several articles to evaluate swimmers' progress during the competition season, demonstrating good accuracy compared to other models previously proposed in the scientific literature [19,20].

At the moment, machine learning has been used in several areas of research to identify talents in tennis, as well as to prevent sports injuries in football, skiing, baseball, basketball, and volleyball [21,22,23,24,25,26,27]. In addition, machine learning has also been used to predict match results [28,29].

He`s investigation introduces the characteristics and causes of sports injuries of young football players are analyzed and a text classification algorithm based on machine learning is used to create a simple model for predicting sports injuries [30]. The results showed that incorrect technical actions, inattention during the game, excessive training load and physical fatigue directly affected the likelihood of injury. Also, thanks to the use of machine learning methods in the aforementioned study by Robles-Palazón et al., a screening model based on six field indicators, which showed moderate validity, was developed to identify young football players at risk of minor injury [22]. The developed screening model made it possible to successfully identify every second (true positive indicator = 53.7%) and three out of four (true negative indicator = 73.9%) players with a high or low risk of injury throughout the season, respectively, using a subset of six indicators based on field conditions (medial knee displacement during jumping from a springboard, asymmetry of the maximum vertical on the ground), reaction force during landing, asymmetry of the projection angle in the frontal plane, estimated using a pull-up jump, asymmetry of passive internal hip rotation (ROM) and knee joint dorsiflexion (ROM).

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A study by Radovanovich et al. proposed a model for predicting skiing injuries using the trajectory features of a ski lift [24]. Ski trails tend to vary in width, length, difficulty, and geographical location on the mountain, leading to different skiing patterns. The correlation between these patterns and various types of ski injuries has been studied. The results showed that skiing injury during the next hour on a particular ski slope can be predicted with an AUC of ~0.76, which is ~15% better than classical approaches such as logistic regression and decision trees.

In a study by Lu et al. The use of ML for predicting muscle strain injuries in NBA athletes from 1999 to 2019 was studied [31]. This study compares traditional logistic regression methods with ML models such as random forest and extreme gradient boosting (XGBoost) to assess injury risk. The aim of the study was to improve the understanding of risk factors and contribute to the improvement of injury prevention strategies in professional basketball. Based on the results, the XGBoost machine achieved the best performance compared to logistic regression in predicting lower limb muscle tension. A study by Duarte Ayala et al. It considered the use of artificial intelligence and machine learning methods to predict, identify and classify athletes with ankle injuries [32]. The accuracy of the study has reached 90.0%, which makes it possible to use these methods in practice. De Leeuw et al. We have implemented a machine learning approach to study individual indicators of training load and well-being, which can predict the occurrence or development of injuries from excessive use in professional volleyball [27]. The results showed that monitoring the load during jumps is an important step towards preventing excessive loads in volleyball.

The aim of the study was Calderón-Díaz et al. The aim was to identify biomarkers of muscle injuries in professional football players using biomechanical analysis using several ML algorithms, such as decision tree (DT) methods, discriminant methods, logistic regression, naive Bayes algorithm, support vector machine (SVM), k-nearest neighbor (KNN), ensemble methods, reinforced and packed trees, artificial Neural Networks (ANNS) and XGBoost [33]. In particular, XGBoost is also used to get the most important functions. The data obtained emphasize that the variables that differentiate the groups most effectively and can serve as reliable predictors for injury prevention are the maximum hamstring muscle strength and stiffness of the same muscle. Also, in a study by Papageorgiou et al. The complexities of NBA players' injuries and recovery times are discussed in detail using advanced DM and ML techniques, such as DBSCAN, isolation forest, and Z-score [34]. The analysis of associative rules, in particular using the Apriori algorithm, revealed significant correlations between the types of injuries and the duration of recovery, as well as between socio-demographic and financial consequences [35]. For example, injuries such as hip, foot, and groin injuries resulted in shorter recovery periods, highlighting the effectiveness of treatment and rehabilitation protocols in the NBA. In addition, this analysis revealed the key importance of rest periods for the recovery of players, as evidenced by the high probability of players

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returning within 0-10 days after injuries. This discovery suggests a potential strategic advantage in using rest periods to keep players healthy and continue their careers. In addition, the results of the study by Papageorgiou et al. It is shown that the duration of recovery is related to the physical characteristics of the players, such as height and weight [34]. This highlights the importance of individual treatment and rehabilitation plans that take into account the specific physical profile of each athlete. Such personalized approaches can lead to the development of more effective and customized injury recovery strategies.

Machine learning is widely used in lawn tennis, making it possible to improve the technique of tennis players, in particular, such an element as serving. The introduction of tracking technology such as Hawk-Eye in tennis has opened access to rich datasets that have been used by researchers to predict game performance and parameters, especially those related to serving [36]. In singles, an analysis of serve patterns shows that serve accuracy has a greater impact in the game than speed. [37]. As for doubles, the tracking data shows that the placement and direction of the serve strongly affect the effectiveness and expectation of returning players [38,39]. In a study by Vives et al. the key characteristics of direct serve in men's professional doubles tennis were identified [40]. The pitch angle proved to be a crucial variable, while the distance from the bounce of the ball to the sideline also mattered. These results are consistent with previous studies of doubles tennis. It has been observed that the optimal feeding angle from 5.7° to 8.7° significantly increases the probability of direct feeding. In addition, maintaining the distance from the bounce of the ball to the sideline from 0 to 28 cm increased the probability of success. The serve rate in doubles tennis had less impact compared to singles tennis. These results are consistent with previous research on serving in singles tennis, which showed that if the serving angle was less than 5.88°, the serve would be repeated with a probability of 92.52% [37]. The effective application of the values found for variables such as pitch angle, line distance, or speed will determine the structure of specific training tasks and help identify specific game patterns [38].

In the specialized literature, the use of artificial intelligence technologies for analyzing big data in the field of sports activities is justified as one of the significant and effective tools for improving the quality of health and motor performance of novice and professional athletes [41,42,43]. IT technologies have also found their application in the training of wrestlers. Thus, as a result of a study by Nagovitsyn et al. the systematic analysis of the program created at the previous stage to predict the competitive results of young wrestlers in the intelligent Orange system allowed us to determine the basic classification for predicting sports results [44]. The practical significance of the research on the implementation of neural networks and ML algorithms has been confirmed by reliable experimental data, which can improve the quality of sports selection of young wrestlers and will contribute to the timely personalization and adjustment of the training process of young athletes.

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Artificial intelligence technologies are also used in sports medicine. For example, the use of artificial intelligence in ECG interpretation has a significant history, and recent advances noted by Adasuriya et al. demonstrate the potential of artificial intelligence to significantly improve the detection and analysis of complex heart diseases using advanced algorithms, offering a more sophisticated, accurate, and predictive approach to ECG interpretation in athletes [45,46]. Common parameters used to evaluate the effectiveness of artificial intelligence methods in ECG include accuracy or positive predictive value, sensitivity, specificity, area under curve (AUC), c-statistics, and F1-statistics [47]. Various artificial intelligence technologies have been developed to detect various heart diseases using ECG. Bellfield et al. highlighted a critical problem in ML applications for sports cardiology: small sample sizes and unbalanced data often lead to overfitting and reduced generalizability, undermining the reliability of models for accurate diagnosis of heart defects in athletes [48]. The role of artificial intelligence in ECG interpretation is to redefine diagnostic approaches, in particular due to its ability to identify both known and new physiological patterns, thereby improving diagnostic accuracy [49]. Key to this evolution are physiological experiments and in silico modeling tools such as significance maps and generalized competition networks, which are crucial for refining ECG models with enhanced artificial intelligence (AI-ECG) [39]. Adetiba et al. We have developed an automated model for detecting heart defects in athletes using ECG and artificial neural networks [50]. The study involved 40 participants, both athletes and non-athletes, to cover various heart conditions such as tachyarrhythmia, bradyarrhythmia, and HCM. The ECG data was preprocessed and analyzed using ANNs, while the Levenberg–Marquardt algorithm demonstrated excellent performance. During the research, a neural network model was successfully developed, achieving accuracy, sensitivity and specificity of 90.00%, 91.96% and 97.06%, respectively. Several studies have demonstrated that artificial intelligence ECG techniques are superior to doctors of various specialties in accurately detecting arrhythmias. Martínez-Sellés et al. reported 98% accuracy in detecting and classifying arrhythmias [45]. Artificial intelligence has proven effective in detecting life-threatening arrhythmias, potentially reducing analysis time in emergency departments and helping pinpoint the cause of ectopic ventricular contractions.

References

1. Martin RK, Pareek A, Krych AJ, Maradit Kremers H, Engebretsen L. Machine Learning in Sports Medicine: Need for Improvement. J. ISAKOS, 2021.
2. Phinyomark A, Petri G, Ibáñez-Marcelo E, Osis ST, Ferber R. Analysis of Big Data in Gait Biomechanics: Current Trends and Future Directions. J. Med. Biol. Eng. 2018.
3. Begg R, Kamruzzaman J. Neural networks for detection and classification of walking pattern changes due to ageing. Australas. Phys. Eng. Sci. Med. 2006.

Power System Technology
ISSN:1000-3673
Received: 16-10-2024 Revised: 05-11-2024 Accepted: 22-12-2024

4. Wahid F, Begg RK, Hass CJ, Halgamuge S, Ackland DC. Classification of Parkinson's Disease Gait Using Spatial-Temporal Gait Features. IEEE J. Biomed. Health Inform. 2015.
5. Lau H-y, Tong K-y, Zhu H. Support vector machine for classification of walking conditions of persons after stroke with dropped foot. Hum. Mov. Sci. 2009.
6. Laroche D, Tolambiya A, Morisset C, Maillefert JF, French RM, et al. A classification study of kinematic gait trajectories in hip osteoarthritis. Comput. Biol. Med. 2014.
7. Emine Yaman, Abdulhamit Subasi. Comparison of Bagging and Boosting Ensemble Machine Learning Methods for Automated EMG Signal Classification. BioMed Research International, 2019.
8. Salar Bijari, Amin Jahanbakhshi, Parham Hajishafiezahramini, Parviz Abdolmaleki. Differentiating Glioblastoma Multiforme from Brain Metastases Using Multidimensional Radiomics Features Derived from MRI and Multiple Machine Learning Models. BioMed Research, 2022.
9. Gabbet T. The development and application of an injury prediction model for noncontact, soft-tissue injuries in elite collision sport athletes. J. Strength Cond. Res. 2010.
10. Hulin B, Gabbet T, Blank P, Chapman P, Bailey D, Orchard J. Spikes in acute workload are associated with increased injury risk in elite cricket fast bowlers. Br. J. Sports Med. 2014.
11. Hulin B, Gabbet T, Lawson D, Caputi P, Sampson J. The acute:chronic workload ratio predicts injury: High chronic workload may decrease injury risk in elite rugby league players. Br. J. Sports Med. 2016.
12. Gabbet T, Hulin B, Blanch P, Whiteley R. High training workloads alone do not cause sports injuries: How you get there is the real issue. Br. J. Sports Med. 2016.
13. Gabbett T. The training-injury prevention paradox: Should athletes be training smarter and harder? Br. J. Sports Med. 2016.
14. Morgulev E, Azar OH, Lidor R. Sports Analytics and the Big-Data Era. Int. J. Data Sci. Anal. 2018.
15. Hammes F, Hagg A, Asteroth A, Link D. Artificial Intelligence in Elite Sports—A Narrative Review of Success Stories and Challenges. Front. Sports Act. Living, 2022.
16. Papageorgiou G, Sarlis V, Tjortjis C. Evaluating the Effectiveness of Machine Learning Models for Performance Forecasting in Basketball: A Comparative Study. Knowl. Inf. Syst. 2024.
17. Pappalardo L, Cintia P, Ferragina P, Massucco E, Pedreschi D, Giannotti F. PlayeRank: Data-driven performance evaluation and player ranking in soccer via a machine learning approach. BMC Sports Sci. Med. Rehabil. 2018.

Power System Technology
ISSN:1000-3673
Received: 16-10-2024 Revised: 05-11-2024 Accepted: 22-12-2024

18. Sałabun W, Shekhovtsov A, Pamučar D, Wątróbski D, Kizielewicz B, et al. A Fuzzy Inference System for Players Evaluation in Multi-Player Sports: The Football Study Case. Symmetry, 2019.
19. Więckowski J, Kołodziejczyk J. Swimming progression evaluation by assessment model based on the COMET method. Procedia Comput. Sci. 2020.
20. Więckowski J, Dobryakova L. A fuzzy assessment model for freestyle swimmers—A comparative analysis of the MCDA methods. Procedia Comput. Sci. 2021.
21. Nijenhuis SB, Koopmann T, Mulder J, Elferink-Gemser MT, Faber, IR. Multidimensional and Longitudinal Approaches in Talent Identification and Development in Racket Sports: A Systematic Review. Sports Med.-Open, 2024.
22. Robles-Palazón FJ, Puerta-Callejón JM, Gámez JA, De Ste Croix M, Cejudo A, et al. Predicting Injury Risk Using Machine Learning in Male Youth Soccer Players. Chaos Solitons Fractals, 2023.
23. Rossi A, Pappalardo L, Cintia P. A Narrative Review for a Machine Learning Application in Sports: An Example Based on Injury Forecasting in Soccer. Sports, 2021.
24. Radovanović S, Petrović A, Delibašić B, Suknović M. Ski Injury Predictions with Explanations; Springer: Berlin/Heidelberg, Germany, 2019.
25. Piergiovanni AJ, Ryoo MS. Early Detection of Injuries in MLB Pitchers from Video. In Proceedings of the 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Long Beach, CA, USA, 16–17 June 2019.
26. Taborri J, Molinaro L, Santospagnuolo A, Vetrano M, Vulpiani MC, Rossi S. A Machine-Learning Approach to Measure the Anterior Cruciate Ligament Injury Risk in Female Basketball Players. Sensors 2021.
27. de Leeuw A-W, van der Zwaard S, van Baar R, Knobbe A. Personalized Machine Learning Approach to Injury Monitoring in Elite Volleyball Players. Eur. J. Sport Sci. 2022.
28. Sukumaran C, Selvam D, Sankar M, Parthiban V, Sugumar C. Application of Artificial Intelligence and Machine Learning to Predict Basketball Match Outcomes: A Systematic Review. Comput. Integr. Manuf. Syst. 2022.
29. Huang M-L, Li Y-Z. Use of Machine Learning and Deep Learning to Predict the Outcomes of Major League Baseball Matches. Appl. Sci. 2021.
30. Kai He. Prediction Model of Juvenile Football Players' Sports Injury Based on Text Classification Technology of Machine Learning. Mobile Information Systems, 2021.
31. Lu Y, Pareek A, Lavoie-Gagne OZ, Forlenza EM, Patel BH, et al. Machine Learning for Predicting Lower Extremity Muscle Strain in National Basketball Association Athletes. Orthop. J. Sports Med. 2022.
32. Rocío Elizabeth Duarte Ayala, David Pérez Granados, Carlos Alberto González Gutiérrez, Mauricio Alberto Ortega Ruíz, Natalia Rojas Espinosa and Emanuel Canto

Power System Technology
ISSN:1000-3673
Received: 16-10-2024 Revised: 05-11-2024 Accepted: 22-12-2024

Heredia. Novel Study for the Early Identification of Injury Risks in Athletes Using Machine Learning Techniques. Journal: Appl. Sci., 2024.

33. Mailyn Calderón-Díaz, Rony Silvestre Aguirre, Juan P Vásconez, Roberto Yáñez, Matías Roby, et al. Explainable Machine Learning Techniques to Predict Muscle Injuries in Professional Soccer Players through Biomechanical Analysis. Journal: Sensors, 2024.
34. George Papageorgiou, Vangelis Sarlis and Christos Tjortjis. Unsupervised Learning in NBA Injury Recovery: Advanced Data Mining to Decode Recovery Durations and Economic Impacts. Journal: Information, 2024.
35. Yakhchi S, Ghafari SM, Tjortjis C, Fazeli M. ARMICA-Improved: A New Approach for Association Rule Mining. In Knowledge Science, Engineering and Management, Proceedings of the 10th International Conference, KSEM 2017, Melbourne, VIC, Australia, 19–20 August 2017; Springer: Cham, Switzerland, 2017.
36. Mecheri S, Rioult F, Mantel B, Kauffmann F, Benguigui N. The serve impact in tennis: First large-scale study of big Hawk-Eye data. Statistical Anal. Data Min. ASA Data Sci. J. 2016.
37. Whiteside D, Reid M. Spatial characteristics of professional tennis serves with implications for serving aces: A machine learning approach. J. Sports Sci. 2017.
38. Vives F, Crespo M, Guzmán JF, Martínez-Gallego R. Effective serving strategies in men’s doubles Davis cup matches: An analysis using tracking technology. Int. J. Perform. Anal. Sport, 2022.
39. Martínez-Gallego R, Crespo M, Jiménez J. Analysis of the differences in serve effectiveness between Billie Jean King Cup (former Fed Cup) and Davis Cup doubles tennis matches. Int. J. Sports Sci. Coach. 2021.
40. Fernando Vives, Javier Lázaro, José Francisco Guzmán, Rafael Martínez-Gallego and Miguel Crespo. Optimizing Sporting Actions Effectiveness: A Machine Learning Approach to Uncover Key Variables in the Men’s Professional Doubles Tennis Serve. Appl. Sci., 2023.
41. Li L, Zhang L, Zhang S. Using Artificial Intelligence for the Construction of University Physical Training and Teaching Systems. J. Healthc. Eng. 2021.
42. Wang T, Park J. Design and implementation of intelligent sports training system for college students’ mental health education. Front. Psychol. 2021.\
43. Kyriazis D, Autexier S, Boniface M, Engen V, Jimenez-Peris R, et al. The CrowdHEALTH project and the Hollistic Health Records: Collective Wisdom Driving Public Health Policies. Acta Inform Med. 2019.
44. Roman Sergeevich Nagovitsyn, Roza Alexeevna Valeeva and Liliia Agzamovna Latypova. Artificial Intelligence Program for Predicting Wrestlers’ Sports Performances. Sports, 2023.

Power System Technology
ISSN:1000-3673
Received: 16-10-2024 Revised: 05-11-2024 Accepted: 22-12-2024

45. Martínez-Sellés M, Marina-Breysse M. Current and Future Use of Artificial Intelligence in Electrocardiography. J. Cardiovasc. Dev. Dis. 2023.
46. Adasuriya G, Haldar S. Next Generation ECG: The Impact of Artificial Intelligence and Machine Learning. Curr. Cardiovasc. Risk Rep. 2023.
47. Somani S, Russak AJ, Richter F, Zhao S, Vaid A, et al. Deep learning and the electrocardiogram: Review of the current state-of-the-art. EP Eur. 2021.
48. Bellfield RAA, Ortega-Martorell S, Lip GYH, Oxborough D, Olier I. The Athlete's Heart and Machine Learning: A Review of Current Implementations and Gaps for Future Research. J. Cardiovasc. Dev. Dis. 2022.
49. Kashou AH, Adedinsewo DA, Siontis KC, Noseworthy PA. Artificial Intelligence-Enabled ECG: Physiologic and Pathophysiologic Insights and Implications. Compr. Physiol. 2022.
50. Adetiba E, Iweanya VC, Popoola SI, Adetiba JN, Menon C. Automated detection of heart defects in athletes based on electrocardiography and artificial neural network. Cogent Eng. 2017.