*Sports Injuries and Data Mining:*

*In an era of abundant data and techniques, which ones to use?*

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*Abstract***—Sports injuries are an inherent risk in competitive sports with high levels of contact or impact. A variety of parameters has been examined as risk factors for sports injuries. In the context of IoT, streams of data are produced from wearable devices and non-wearable equipment paving the way for the use of AI and ML applications to predict sports injuries and refine prevention strategies. In this report the core parameters are presented and the AI and ML models employed for the examination of those parameters are summarized.**

***Keywords: data mining; sports injury; IoT; wearables; machine learning.***

1. Introduction

Injuries can be considered an inherent risk in competitive professional sports, particularly those characterized by high levels of contact or impact. Despite the implementation of numerous strategies aimed at mitigating these risks, including advancements in training techniques[[1]](https://www.zotero.org/google-docs/?OH8dCk), equipment design[[2]](https://www.zotero.org/google-docs/?w6rk6I), and rule changes[[3]](https://www.zotero.org/google-docs/?5azV43), injuries continue to pose significant challenges for athletes and teams alike. Beyond the immediate physical implications, injuries can have profound psychological and economic ramifications, impacting not only the athletes themselves but also their teams' performance, financial stability, and long-term success[[4]](https://www.zotero.org/google-docs/?295Rfn). Addressing the complex interplay of factors contributing to injury occurrence requires a multifaceted approach, integrating insights from sports science, medical research, and data-driven analytics.

In the realm of injury prevention and management, data mining techniques play a pivotal role in harnessing the vast amount of information available to sports organizations. By analyzing large datasets encompassing diverse modifiable parameters such as biomechanical metrics and non-modifiable factors like injury history, data mining enables the identification of patterns and correlations associated with injury risk. Furthermore, the advent of Internet of Things (IoT) devices has revolutionized data collection in sports, facilitating real-time monitoring of athletes' performance and health status[[5]](https://www.zotero.org/google-docs/?ZjtpIb). Wearable sensors, smart devices, and GPS trackers provide continuous streams of data during training sessions and competitive events, offering invaluable insights into athletes' physical condition, workload, and movement patterns. Leveraging this wealth of data using Artificial Intelligence

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(AI) and Machine Learning (ML) algorithms and models, sports organizations can develop more targeted injury prevention strategies, tailor training programs to individual athletes' needs, and optimize performance while minimizing injury risk.

The remainder of the paper is structured as follows.

Section II presents the selection criteria for the referenced articles.

Section III showcases the variety of parameters captured with IoT, smart devices and computer vision technology for the purposes of sports injury prevention.

Section IV presents the current state on the use of AI and ML applications in sports injury prediction.

Section V discusses challenges and limitations of the field.

Lastly, Section VI summarizes the key elements of the report.

1. selection criteria

The search for relevant studies was conducted using the keywords 'data mining,' 'sports injury,' 'IoT,' 'wearables,' 'machine learning,' as well as combinations thereof. Three reputable digital platforms, namely *Taylor & Francis Online*, *PubMed*, and *IEEE Xplore*, were queried. To be considered for selection, studies had to meet the following criteria:

* Conducted within the last five years (>2019), and
* Published in a journal with an above-average impact factor (>2)

Due to the limited scope of this mini-review, only a subset of the returned studies was included, specifically those that exemplify the state-of-the-art research in the field of data mining and sports injuries.

1. data influx

The IoT has permeated almost every aspect of our lives, with the sports sector being one of them. Within this context, a variety of wearable devices and non-wearable equipment are extensively utilized to monitor athletes' internal and external workload[[6]](https://www.zotero.org/google-docs/?ikgTvH). This enables the capture of crucial information about various dimensions of an athlete’s condition and performance, including biometric data, biomechanical metrics, impact forces, and player movement and positioning on the field. These parameters represent potential injury risk factors, and their analysis can lead to the development of new injury prevention and rehabilitation strategies.

Variables related to cardiovascular health are pivotal in biometric data collection for athletes. Metrics such as heart rate (HR), blood pressure (BP), and maximal oxygen consumption (VO2 max) are central to cardiac monitoring[[7]](https://www.zotero.org/google-docs/?dWDm2S). Additionally, advancements in sensor technology have enabled the measurement of more nuanced variables, including cardiac conduction and blood flow changes[[8]](https://www.zotero.org/google-docs/?GkJVdM). In [[9]](https://www.zotero.org/google-docs/?zwAcRp), Fanous et Dorian examine the intricacies of utilizing wearables for cardiac monitoring in athletes, highlighting concerns regarding their potential misuse. The authors emphasize that athletes represent a unique population with distinct characteristics, underscoring the need for a more refined classification of the devices used, considering their specific features, as well as of the athletes themselves. In regards to the selection of the device and the interpretation of the data generated thereof, they suggest seven dichotomies that need to be considered for an appropriate selection as well as for enhanced confidence in the tool’s “findings”. Examples of the aforementioned dichotomies refer to whether the device “is employed for diagnosing disease or for monitoring known pathology” and whether it “is applied to an asymptomatic or to a symptomatic athlete”. With respect to the particularities of the athletes and more specifically to why they constitute a niche population, the authors make a case by quoting the assertion of Bayes’ Theorem, according to which the effectiveness of a diagnostic tool in forecasting outcomes is primarily determined by how common the disorder is within the population under examination. In asymptomatic athletes, the occurrence rate of sudden cardiac arrest (SCA) is very low, rendering the device prone to yielding a lot of false positive results, which in turn would potentially entail further unnecessary investigations and treatments. On the other hand, in symptomatic athletes the utility of most devices is limited, as they are mostly restricted to single-lead tracings, which are not sufficient for detecting abrupt heart rate changes. All in all, an athlete-centered approach is warranted to maximize the benefits of the available technologies.

Another type of biometric data under examination in the context of sports injury prevention is body core temperature. Both wearable sensors and ingestible capsules have been utilized to predict or diagnose exertional heat illness (EHI). According to the 2023 expert consensus statement from the American College of Sports Medicine, there has been no significant decrease in deaths attributed to exertional heat stroke (EHS) among athletes[[10]](https://www.zotero.org/google-docs/?uePTgT). A recent review on wearable and ingestible technology concerning EHI[[11]](https://www.zotero.org/google-docs/?FcTrsb) summarizes studies employing this technology as an evaluation and prevention strategy. A noteworthy discovery is the variability in measurement accuracy, partly due to the diverse proprietary algorithms used to estimate core temperature. Additionally, factors such as body composition, clothing, and sweat can introduce limitations and lead to inaccurate measurements. Specific wireless communication requirements also exist, as some devices demand a recorder to be within a specific range. Overall, while body core temperature monitoring shows promise, caution is advised regarding reliance on its predictive accuracy. Moreover, recent research suggests that combining it with gait instability could enhance sensitivity and specificity for EHI detection[[12]](https://www.zotero.org/google-docs/?KHuQoz).

Kinetic, kinematic and biomechanical metrics have been extensively collected as they offer valuable, sport-specific insights into the load experienced by athletes. In [[13]](https://www.zotero.org/google-docs/?ygltEt), the authors, with the use of a dual-g sensor attached to the distal medial tibias of ten soccer athletes, measured the impact load, step count and cumulative bone stimulus during a series of soccer-related tasks. In [[14]](https://www.zotero.org/google-docs/?mXgxxN), the authors used wearable shoe sensors to measure tibial forces in nine recreational runners, as tibial bone stress injury, often encountered by runners, is a prevalent overuse injury caused by repetitive tissue forces. In [[15]](https://www.zotero.org/google-docs/?LTeGuF), peak knee flexor force and position displacement were measured using a force plate and a linear encoder respectively Fifteen elite soccer and track and field athletes were tested performing the Nordic hamstring exercise (NHE), which has been found to reduce hamstring injury risk. In [[16]](https://www.zotero.org/google-docs/?aWMMMj), a list of knee injury risk factors were captured during cutting and landing tasks using a three-dimensional motion capture system and force plates. Twenty five elite female handball players were assessed after the implementation of neuromuscular training. In general, excessive impact loads pose a threat and can be injurious to musculoskeletal tissue. However, as it is demonstrated through the above mentioned studies, there is an inherent difficulty of assessing those loads in real-time, in the field, due to the characteristics of the employed equipment.

To overcome this limitation, accelerometers and GPS trackers are also used in the quest for capturing an athlete’s load. Accelerometers gauge acceleration forces, allowing for the quantification of an athlete's movements and the corresponding energy consumption, as well as for the discovery of particular biomechanical patterns. At the same time, an athlete’s movements along with the covered distances can be captured also with the use of GPS trackers, providing further insights on the experienced physiological load. In [[17]](https://www.zotero.org/google-docs/?M7hTWS), the relationship between impact accelerations, peak forces and loading rates was assessed using a pelvis-worn accelerometer and force platforms. Fifteen ballet dancers were examined performing ballet maneuvers, revealing a strong association between the studied variables, while fatigue was confirmed as a confounding factor. In [[18]](https://www.zotero.org/google-docs/?p3pKKM), a GPS tracker and a triaxial accelerometer unit were employed to measure the position-specific workload in female soccer. Technical skills drills and playing as a defender were found to incur the highest median player load (PL).

The utilization of wearable sensors and non-wearable equipment for data collection extends beyond the core parameters outlined here. Achieving a comprehensive understanding of the factors contributing to injury and illness requires a multifaceted approach. This approach should be athlete-centered and sport-specific, taking into consideration the complex interplay of various factors. While the abundance of data offered by IoT technology is undoubtedly advantageous, it also presents challenges. These challenges include the need to rectify device features and methodological processes for capturing the desired parameters accurately. It is crucial to recognize that the goal is not merely to collect more data. Therefore, our eagerness for data collection should not overshadow the importance of refining and leveraging existing data effectively.

1. AI & ML at the service of sports injuries

Data generated in the framework of IoT align with the concept of Big Data, as they are produced at high rates, continuously, and from diverse sources. In this context, AI and ML models play a crucial role in the data mining process of knowledge extraction as they perform well at handling complex datasets and scale more efficiently compared to traditional analytics. Along those lines, such models have been harnessed to improve the efficacy of injury prediction and prevention strategies.

According to the findings of three recent reviews on AI and ML applications in sports injury prediction[[19]](https://www.zotero.org/google-docs/?0M1rOq), [[20]](https://www.zotero.org/google-docs/?utDNKk), [[21]](https://www.zotero.org/google-docs/?bTqy4G), the use of such models is exhibiting an upward trend. In the oldest review cited[[19]](https://www.zotero.org/google-docs/?G4b1hN), Claudino et al. (2019) outlined the prevalent, at the time, AI techniques and methods used for injury risk assessment and performance prediction. Across 15 injury risk assessment studies, artificial neural networks, decision tree classifiers and support vector machines (SVM) were identified as the most commonly used techniques with the best performance. Regarding the injury related variables that were assessed, the most prevalent ones were training load, various knee injury causes as well as ground reaction forces. What was underlined by the authors as a challenge for the future was the integration of all the injury risk related variables in the AI models to come. In other words, a refinement of the data to be analyzed and the employed models thereof, providing a deeper and a more comprehensive approach.

In their study[[20]](https://www.zotero.org/google-docs/?MNV94w), Van Eetvelde et al. applied a more focused approach compared to Claudino et al,. concentrating exclusively on studies that examined injury occurrence or injury type as outcome variables. Given the categorical nature of the outcome variable, the base models were rendered as classification models with tree-based and SVM as the most utilized ones. Also in this review, various risk factors were examined and although there was little consistency in the reported important predictors, the features which were reported more frequently were previous injury and higher training load. Moreover, while eight of the 11 studies reported appropriate to good performance of the ML prediction models, the authors of the review identified several methodological deficits related to the small sample sizes, preprocessing phase, and dependency between training and test datasets. They highlighted that the reported predictive performance should be regarded with caution, as it may not solely reflect the inherent quality of the ML analysis. For example, evaluation measures such as accuracy, sensitivity, specificity are based on an injured - not injured distinction, while probabilistic scoring rules would be more informative.

In the most recent of the cited reviews[[21]](https://www.zotero.org/google-docs/?cgAT2U), Amendolara et al. focused on the performance of specific algorithms. They observed that the use of K-nearest neighbor (KNN) has been downgraded to the role of a comparison algorithm. However, they highlighted that current, more sensitive sensors allow for better precision in data collection, favoring the use of KNN. Regarding another similarly simple algorithm, K-means, they noted that it is mostly used in the preprocessing and exploration phases rather than as a predictive algorithm. Moreover, decision trees and random forest models were found to offer certain benefits. Decision trees enable deep feature exploration with sufficient classification accuracy, while random forests show increased predictive accuracy at the cost of reduced transparency and underperformance with high-dimensionality data. With respect to the latter, support vector machines (SVMs) offer advantages, especially when constructed as ensemble models. Finally, Gradient Boosting and AdaBoost were shown to have increased predictive capabilities compared to classic regression. Moreover, when combined with decision trees, they tend to be more transparent than neural networks. Nonetheless, neural networks are ranked as the most accurate and powerful ML algorithms currently available, despite their increased complexity.

Overall, a point made in all the review studies is that although the use of AI and ML applications is growing, it is still in its infancy. The variety of ML applications indicates that there is no one-size-fits-all approach. Since each algorithm has its pros and cons, a combinational use is often promoted. However, there are some universal elements, both data-wise and methodology-wise, that are lacking, perplexing and impeding this way the real-world validation of these algorithms in the field of sports injuries.

1. challenges & limitations

The purpose of this report was to present the core parameters examined as injury risk factors in the context of sports injuries and to summarize the AI and ML models employed to examine those parameters.

To start with, the purported data abundance does not necessarily indicate high data quality. Theoretically, we have vast amounts of data at our disposal; however, not all of it can be leveraged, as some may stem from unreliable IoT devices or be poorly configured and annotated. The reliability and performance of wearable devices vary, and the use of poorly reported proprietary algorithms for their configuration prevents robust analysis of their efficacy. This leads to the perpetuated use of questionable devices solely for the sake of data collection. Additionally, there is a scarcity of available primary data regarding certain confirmed risk factors, such as biomechanical parameters. These parameters are often captured in vitro with small sample sizes and are sport-specific. Consequently, studies analyzing these parameters rely on artificially crafted datasets, which might explain their low generalizability[17].

For AI and ML models to operate properly, large, finely tuned datasets are needed. Several researchers repeatedly highlight that open-source repositories with uniformly annotated data and common protocol standards could meet the needs of these data-hungry models. However, only the future will reveal whether such an endeavor will be successful or end up being a wild goose chase. The lack of such datasets sets the stage for other methodological shortcomings commonly encountered, like overfitting, inconsistent validation techniques, and poorly chosen evaluation metrics. Moreover, direct comparison of the absolute performance of different algorithms cannot be made unless they are applied in the same manner on identical datasets, necessitating transparent reporting of the algorithmic formulation for a more reliable evaluation.

Current technologies such as cloud computing[[22]](https://www.zotero.org/google-docs/?jdWzcN) and blockchain[[23]](https://www.zotero.org/google-docs/?ie3W21) can be valuable tools for refining suggested architectures and constructing a comprehensive, all-encompassing framework, paving the way for the aforementioned open repositories. Furthermore, blockchain technology, on top of data management and sharing, could also be particularly useful with respect to data privacy by providing safeguarding mechanisms, crucial when dealing with health-related data. In conclusion, as emphasized by Tee and McLaren[[24]](https://www.zotero.org/google-docs/?804Afc), the complexity of sports injury prevention calls for better processes, not singular solutions. The particularities of different sports contexts and athletes highlight the need for sport-specific models that learn from previous intervention cycles, rather than a universal solution applicable to all sports and athletes.

1. conclusions

An array of parameters is used in AI and ML applications to predict sports injuries and improve prevention strategies. Although AI and ML offer certain advantages, there are methodological elements that need to be improved for these models to produce more insightful results.

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