Artificial Intelligence A tool for sports trauma prediction

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Artificial intelligence. A tool for sports trauma prediction

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ABSTRACT

Injuries exert an enormous impact on athletes and teams. This is seen especially in professional soccer, with a marked negative impact on team performance and considerable costs of rehabilitation for players. Existing studies provide some preliminary understanding of which factors are mostly associated with injury risk, but scientific systematic evaluation of the potential of statistical models in forecasting injuries is still missing. Some factors raise the risk of a sport injury, but there are also elements that predispose athletes to sports injuries. The biological mechanisms involved in non-contact musculoskeletal soft tissue injuries are poorly understood. Genetic risk factors may be associated with susceptibility to injuries, and may exert marked influence on recovery times. Athletes are complex systems, and depend on internal and external factors to attain and maintain stability of their health and their performance. Organisms, participants or traits within a dynamic system adapt and change when factors within that system change. Scientists routinely predict risk in a variety of dynamic systems, including weather, political forecasting and projecting traffic fatalities and the last years have started the use of predictive models in the human health industry. We propose that the use of artificial intelligence may well help in assessing risk and help to predict the occurrence of sport injuries.

Injuries affect negatively performance in sports. In professional sport, injuries to key players costs teams millions in salary and lost revenue, and can make the difference between success and failure [11]. All too often, nevertheless, sporting teams take a simplistic solo approach to injury detection, with each team attempting to discover those hidden variables and metrics that can accurately 'predict' the risk of injury to particular players [8]. Historically, academic work on injury forecasting has been deterred by the limited availability of data describing the physical activity of players. Nowadays, the Internet of Things has the potential to change rapidly this scenario thanks to Electronic Performance and Tracking Systems (EPTS), new tracking technologies which provide high-fidelity data streams extracted from every training and game session. [17]. Some factors raise the risk of a sport injury, but there are also elements that predispose athletes to sports injuries [6]. The biological mechanisms involved in non-contact musculoskeletal soft tissue injuries (NCMSTI) are poorly understood. Genetic risk factors may be associated with susceptibility to injuries, and may exert marked influence on recovery times [7]. Rehabilitation and preventative efforts should be centered on a thorough knowledge of risk factor etiology and on the knowledge of how such factors contribute to sports injuries. Predictive factors of sports injuries are some biological variables: the as yet not well defined relationship between all these biological variables can help to produce a health profile or a personalised diagnosis [9].

The relationship between training workload and injury risk has been widely studied. For example, in rugby, players are a high injury risk when their workloads are increased above certain thresholds. To assess injury risk in cricket, Hulin et al. propose the Acute Chronic Workload Ratio (ACWR), i.e. the ratio between players' acute and chronic workload. When the acute workload is lower than the chronic workload, cricket players are at a low risk of injury. In contrast, when the acute/chronic ratio is higher than 2,

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players have an injury risk 2–4 times higher than players in whom this ratio is lower than 2. Hulin et al. and Ehrmann et al. find that injured players, in both rugby and soccer, show significantly higher physical activity in the week preceding the injury compared to their seasonal averages.

Athletes are complex systems, and depend on internal and external factors to attain and maintain stability of their health and their performance. Organisms, participants or traits within a dynamic system adapt and change when factors within that system change [1]. Scientists routinely predict risk in a variety of dynamic systems, including weather, political forecasting and projecting traffic fatalities [14]. Ideally, the modeling for each forecasting model involves sophisticated statistical assessment, complex/multiple simulation studies, allowances of time-related changes, and distinctly large sample sizes [9]. Sports injuries occur within a dynamic system, and all too often we have ignored the dynamic nature of the system (for example, changes in force production performance, or accounting for factors such as contact injuries) when trying to predict injury. Classically, we assume that baseline characteristics such as strength, balance and flexibility would predict an injurious event, independent of their internally driven change, and often independent of external factors.

The prevention, diagnosis and management of sports injuries are crucial in both professional and amateur sports. Injuries occur as a consequence of extrinsic and intrinsic factors. For example, the extrinsic factors that may influence a soccer player's predisposition to injury include the design of the playing field, the characteristics of the ball, air temperature, altitude, and the time of the match; the intrinsic risk factors for NCSMTIs include age, sex and prior injuries [12]. Despite rigorous controls over many extrinsic and intrinsic factors, a wide range of inter-individual differences exists in number and degree of injuries and in recovery time, suggesting that other factors, including genetic variations, may exert an important influence on these differences [7].

The canonical approach to predict injury risk has been linear regression [11]. While suitable for simple models, linear regression is unable to capture the complex, non-linear interplay between multiple input features. A given sport action will depend on the task to be undertaken, and personal and environmental constraints. A coach should aim to train athletes to adapt their behaviour to constantly changing and often unpredictable environments and situations [15].

In practice, we are attempting to model a very complex system, the human body, inputting in the model many variables and signals. It would be desirable to train artificial intelligence models which exploit non-linear relationships between observable variables to approach complex phenomena such as soft-tissue injuries.

With this in mind, their inherent characteristics make Artificial Neural Networks well suited to be applied to this issue, as they are able to model very complex systems and form disjointed decision boundaries in a large dimension space [4].

BARCELONA FC construct a multi-dimensional model to forecast whether players will be injured based on their recent training workload. The construction of the injury forecast consists of two phases. In the first phase (training dataset construction), given a set of features S, a training dataset T is created where each example refers to a single player's training session and consists of: (i) a vector of features describing both the player's personal features and his recent work- load, including the current training session; (ii) an injury label, indicating whether (assigned a value of 1) or not (assigned a value of 0) the player gets injured in the next game or training session. In the second phase (model construction and validation), a decision tree learner is used to train an injury classifier on the training dataset T. Injuries involve great economic costs to the club, given the expensive process of recovery and rehabilitation of the injured players. Injury prevention can reduce these costs by avoiding the injury, which will improve team performance and the player's mental state, as well as reducing the seasonal costs of medical care. We estimate that 139 days of absence during the seasons are consequent to injuries, corresponding to 6% of the working days. Players returned to regular physical activity within 5 days in 15 instances out of 23 injuries, while only 6 times a player needed more than 5 days to recover [18].

Machine learning models which account for non-linear relationships have become very successful in areas such as vision and natural language, both heard and written, that require to understand complex patterns through raw-level data [13]. Artificial neural networks are able capture complex patterns in a hierarchical way, identifying non-linear functions of the observed variables through a data-driven learning process that would be impossible to achieve through linear models [5].

A distinction must be made between predicting injuries and predicting injury risks. Injuries are binary events - in a particular session, a player is either injured or not injured. The task of accurately predicting whether a player will be injured in a given session is extremely difficult, as a multitude of factors are statistically associated to an injury, many of which cannot be predicted nor measured, but these factors are not necessarily causative of injury. There is no way to know whether a healthy player will land awkwardly on a given section of the playing field during next match. Conversely, we cannot predict whether an at-risk player will be put in a situation that will result in an injury. Instead, we attempt to measure the injury risk of a player [3].

However, for some injuries [e.g. hamstring strain and patellar tendinopathy (PT)], these techniques have not yet yielded consistent identification of risk factors [2]. These inconsistencies confirm how complex most of human health conditions are. In this sense, we need a broader approach to better understand the complex relationships between risk factors/predictors and injuries. Recently, a complex systems approach has been used to predict complicated problems in medicine, biology, economics, and social sciences [1].

This approach may be the only option if we accept the non-linearity and complexity of sports injuries and their predictability.

Declaration of Competing Interest

The authors declare that there are no conflicts of interest.

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References

[1] Hulme A, Finch CF. From monocausality to system thinking: a complementary and alternative conceptual approach for better understanding the development and prevention of sports injury. Inj Epidemiol 2015;2–31.
[2] Meeuwisse WH, Tyreman H, Hagel B, et al. A dynamic model of etiology in sport injury: the recursive nature of risk and causation. Clin J Sport Med 2007;17:215–9.
[3] Higgins JP. Nonlinear systems in medicine. Yale J Biol Med 2002;45:247–60.
[4] Plsek P, Greenhalgh T. Complexity science: the challenge of complexity in health care. BMJ 2001;323:625–8.
[5] Kelso JAS. Coordination dynamics. In: Meyers RA, editor. Encyclopedia of complexity and system sciences. Berlin: E & Springer-Verlag; 2009. p. 1537–64.
[6] Bahr R, Krosshaug T. Understanding injury mechanisms: a key component of preventing injuries in sport. Br J Sports Med 2005;39:324–9.
[7] Pruna R, Artells R, Ribas J, Montoro B, Cos F, Muñoz C, et al. Single nucleotide polymorphisms associated with non-contact soft tissue injuries in elite professional soccer players: influence on degree of injury and recovery time. BMC Musculoskelet Disord 2013;14(221).
[8] Lippi G, Longo UG, Maffulli N. Genetics and sports. Br Med Bull 2010;93:27–47, doi:http://dx.doi.org/10.1093/bmb/ldp007 Epub 2009 Feb 9. Review.

[9] Kambouris M, Ntalouka F, Ziogas G, Maffulli N. Predictive genomics DNA profiling for athletic performance. Recent Pat DNA Gene Seq 2012;6(December (3)):229–39.
[11] Maffulli N, Longo UG, Berton A, Loppini M, Denaro V. Biological factors in the pathogenesis of rotator cuff tears. Sports Med Arthrosc Rev 2011;19 (September (3)):194–201.
[12] López-Valenciano A, Ayala F, Puerta JM, DE Ste Croix MBA, Vera-Garcia FJ, Hernández-Sánchez S, et al. A preventive model for muscle injuries: a novel approach based on learning algorithms. Med Sci Sports Exerc 2018;50(May (5)):915–27.
[13] Senders JT, Staples PC, Karhade AV, Zaki MM, Gormley WB, Broekman MLD, et al. Neurosurgical outcome prediction: a systematic review. World Neurosurg 2018;109(January):476–86.
[14] Kruse C, Eiken P, Vestergaard P. Machine learning principles can improve hip fracture prediction. Calcif Tissue Int 2017;100(April (4)):348–60.
[15] Liu NT, Salinas J. Machine learning for predicting outcomes in trauma. Shock 2017;48(November (5)):504–10.
[17] Ehrmann FE, Duncan CS, Sindhusake D, Franzsen WN, Greene DA. GPS and injury prevention in professional soccer. J Strength Cond Res 2015;30:306–7 pmid:26200191.
[18] Rossi A, Pappalardo L, Cintia P, Iaia FM, Fernàndez J, Medina D. Effective injury forecasting in soccer with GPS training data and machine learning. PLoS One 2018;13: e0201264.

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