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Article

Predicting sports injuries with machine learning technology: Enhancing athletes' life expectancy through biomechanical analysis

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Abstract: This study investigates the application of machine learning technology and biomechanical analysis in predicting sports injuries to enhance athlete life expectancy. The purpose is to explore the relationships between training practices, previous injuries, biomechanical factors, and athlete engagement with injury prevention technologies. Key issues addressed include the gap between awareness and practical application of these technologies, as well as the need for standardized data collection methods. A quantitative research design was employed, utilizing survey questionnaires distributed to 110 athletes to gather data on their training practices, previous injuries, and engagement with technological tools. Descriptive statistics and correlation analyses revealed significant relationships among the variables, highlighting the importance of effective training practices in reducing injury risks. Findings suggest that while athletes recognize the value of biomechanical assessments and machine learning, there is a need for improved engagement with injury prevention technologies. Recommendations include standardizing data collection protocols, enhancing educational initiatives for athletes and coaches, and addressing ethical concerns related to data privacy.

Keywords: sports injuries; machine learning; biomechanics; injury prevention; athlete engagement

1. Introduction

1.1. Background on machine learning and sports injuries

Machine learning [ML] has transformed several industries, including health, finance, and sports science. ML enhances programs through experience without being programmed [1]. In sports medicine, the application of ML technologies includes injury prediction (shown in **Figure 1**), which has been a major issue of concern among athletes, coaches, and health practitioners. Injury prediction can result in prevention strategies that improve athletes' welfare and effectiveness. When operating on datasets from training sessions, competition, and biomechanical evaluations, an ML algorithm can predict patterns that signal increased vulnerability to injury [2]. This predictive ability is helpful in a field where the physical workload of athletes is likely to increase.

Sports injuries have short-term impacts on an athlete's performance and future career. In each sporting activity, ordinary injuries, including sprains, strains, and fractures, may necessitate long periods of intensive rehabilitation, emotional upset, and, sometimes, early retirement from competitive sports [3]. Sports injuries have financial consequences such that athletes lose their earnings due to injuries, and sports organizations lose funds on medicine and recovery. Hence, implementing ML to predict injuries is a shift in the approach to sports injury management. This approach is critical where sophisticated algorithms can process large amounts of information in the shortest time possible; it is, therefore, likely for the stakeholders in the sports industry to make sound decisions that are pro-athlete health.

Figure 1. AI for predicting injury risk in various sports.

The necessity of injury prediction is not limited to the individual athlete; it also affects teams and organizations. Injury prevention and management strategies are reliable ways of improving performance because the most important players are protected during the season (shown in **Figure 2**). Furthermore, organizations that apply effective data management to prevent injuries may be in a better position than organizations that use conventional tools and methods. Advanced technologies, such as machine learning, effectively prevent athletes' injuries during a sports performance. This transition to data usage for decision-making is complemented by other trends observable in sports science to help train performance metrics continually.

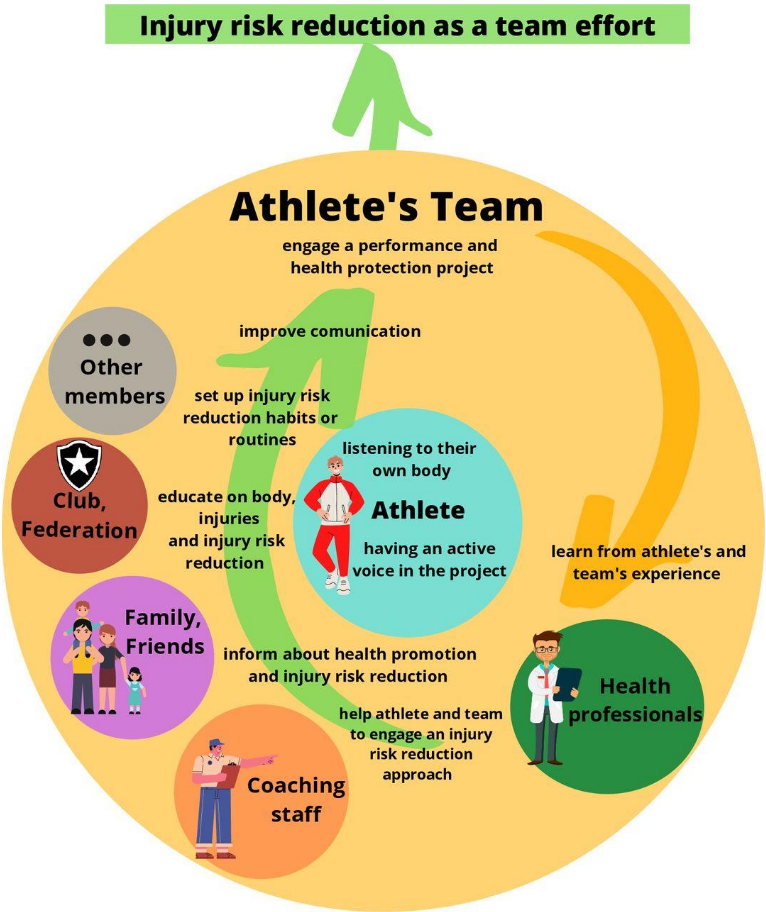

Figure 2. A concept map of the role that health professionals can play in the context of injury to help athletes and their teams to engage in an injury risk reduction approach.

Research on biomechanics reveals that biomechanics is central to studying sports injuries. Biomechanics analyzes motion and force acting on the body during physical activity (shown in **Figure 3**) [4]. Since biomechanics affects things like joint angles, force exertion, and muscle activation during an athletic performance, researchers can pinpoint specific movements that athletically place an athlete at risk for an injury. For example, poor coordination during bouncing activities may cause knee injuries, and poor coordination during running activities may result in ankle sprains. The presented ML models that utilize biomechanical data can help understand these complex relationships between movement patterns and injury presence.

Moreover, the development of portable systems has allowed gathering dynamic biomechanical information from the trainees and participants during practice and actual contests [5]. Motion sensors such as accelerometers, gyroscopes and pressure sensors enable recording an athlete's biomechanics in a natural environment. The abundance of this data allows the machine learning algorithms to pick up on the early signs of changes in movement patterns that might lead to more instances of injury than can be afforded. By incorporating these data streams into decision-making models, coaches and medical staff can use derived strategies to change biomechanical faults or training volumes.

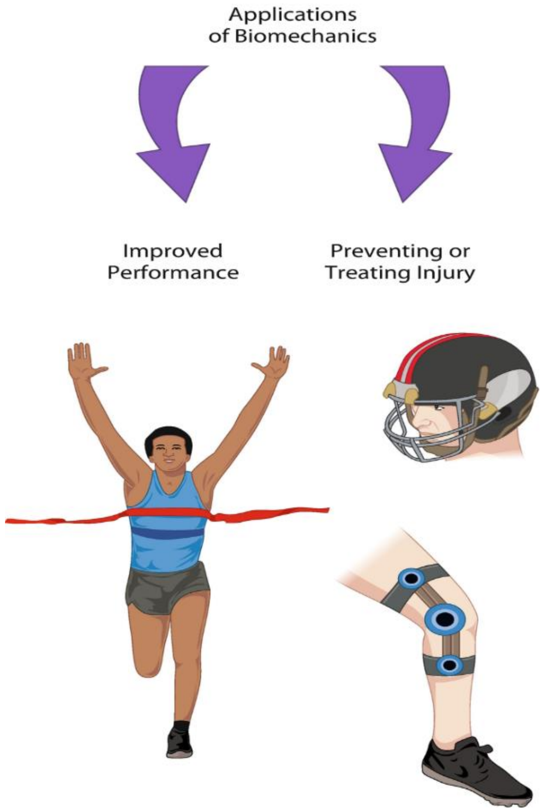

Figure 3. Biomechanics of human movement.

1.2. Research problem and objectives

The primary research problem addressed in this study is the challenge of accurately predicting sports injuries using machine learning technologies informed by biomechanical analysis. The objectives include:

1) To develop predictive models that incorporate biomechanical data to forecast injury risks.
2) To evaluate the effectiveness of these models in real-world athletic settings.
3) To assess how improved injury prediction can contribute to athlete longevity.

This research has the potential to enhance athlete safety and performance through informed training practices and injury prevention strategies.

1.3. Scope and limitations

The present research aims to explore the use of ML technologies in different sports disciplines with special regard to biomechanics as a potential predictor of injury occurrence. Some limitations include possible bias in data selection, fluctuations in the reaction of athletes to training loads, and the use of standardized databases across various sporting disciplines. Furthermore, although the ML has rich prediction capabilities, its capabilities may be limited by data quality and access.

2. Materials and methods

2.1. Research design

This research adopts a quantitative research approach to establish a framework for predicting the occurrence of sports injuries through ML algorithms. The quantitative method makes gathering and measuring figures easier, which helps compare contributing factors to injury rates. For training loads, previous injuries, and biomechanical parameters, athletes completed survey questionnaires as part of the study's data collection. This approach helps apply strategies to draw conclusions and efficiencies about the efficiency algorithms in predicting injuries.

The research design adopted is a combination of cross-sectional research design. Cross-sectional questionnaires were used to study subjects' present training habits and incidence of injuries. This approach could be beneficial primarily because it increases the study's reliability by making it possible to examine the dynamics of the effects resulting from variations in training and biomechanics on injury risks over time.

2.2. Participant selection

The subjects selected for this study comprised males and females from different sporting disciplines in the country. The selection criteria included participants 18 to 35 active in competitive sports in amateur or professional leagues. Selection criteria involved the number of trained years above six months so that the participant in training loads and its corresponding injuries in sports was not a novel concept to the participant.

Specific survey data was gathered: Age, gender, the type of sport, the competition level, the frequency of training and participation and history of injuries. These data points are useful when determining the background against which injuries happen and the precise characteristics of individual sports related to elevated risk. Moreover, participants were categorized according to the type of sport played, whether team sports such as soccer or individual such as athletics, to enable cross-sectional comparisons. This stratification is necessary to ensure that the approach to injury prevention is informed by the biomechanical and kinetic stress inherent in each sport.

2.3. Sample characteristics and data collection methods

The sample number of various sporting disciplines (team and individual sports) involved was 110 athletes. Participation was based on such criteria as age, competition level (amateur and professional), and at least 6 months of training experience. For recruitment, it contacted sports organizations, training academies, and university athletic programs.

An online survey was conducted, and the data was emailed or spread across sports networks to extend the accessibility and convenience of participation. The questionnaire covered demographic details, training habits, injury history, radical awareness, and learning-based injury prevention technologies. Wearable sensors were used to collect self-reported data on biomechanical data from participants through training sessions to supplement and complement data from self-reports. Informed consent and confidentiality of the data were strictly upheld based on ethical considerations.

Quantitative data was gathered through survey questionnaires to gain specifics on athletes' training schedules, previous injuries, and biomechanical characteristics.

The questionnaires were electronic, which ensured that all participants could easily access and fill them out on this page. Questions were, therefore, included, like weekly training hours, the type of exercises done, rating of perceived exertion and history of past injuries.

Further, it was useful to collect objective biomechanical data using wearable sensors during training practice, which will supplement self-reports. These sensors can quantify movement kinematics and kinetics in real-time, including joint angles, acceleration, and impact forces important to an athlete's movements during performance. The use of both subjective and objective data assures the validity of the results, as different sources of information are used in the study.

2.4. Data analysis techniques

The data collected was then analyzed using several SPSS. The analysis included regression analysis, correlation analysis, and descriptive analysis techniques, which were also discussed.

Regression analysis: This technique determined how different independent variables, such as training loads, influence and correlate with the dependent variables by giving incidences of injuries. By archiving these relationships statistically, a researcher can estimate the probability of injury given different parameters pertaining to training.

Correlation analysis: Descriptive analysis compares the strength and significance of the relationship between the different variables of the data set. For instance, it can help determine whether participant injury rates are higher when organizations train employees in large volumes.

Descriptive analysis: The basic data analysis methods included measures of central tendency and dispersion that offer an overview of the trainees' average training loads, the incidence of injuries, and respondent demographics. By establishing such a methodology, this paper lays down the groundwork for using more advanced ML techniques in the future.

The incorporation of these analytical tools enables proposing a coherent perception of the impact that various aspects have on athlete injury likelihood.

2.5. Ethical considerations

There are justifications to why ethics are considered very important before researching human subjects. In collecting the data, permission from the relevant ethical committees of the universities will be sought to uphold ethical conduct in research. In this regard, participants will need to read or receive a written notice about the general facts of the study as well as its specific purpose, methods, possible drawbacks, and advantages.

Participants were given a consent form, and if they agree voluntarily, they will participate in the study. Hence, people understand their participation and data-usage rights in their totality to the letter. Finally, the participants can opt out of the study at any given time with no consequences. Further, to address privacy concerns, all participant data collected will be stripped of their identity, and the results returned will only be in aggregated form.

By encompassing these ethical considerations in the study, the research shall ensure the highest ethical standards in research conduct, and the participant's welfare is central to the research process. This section will, therefore, offer a good account of materials and methods without compromising on the word limit imposed.

3. Impact of machine learning on injury prediction

3.1. Analysis of machine learning algorithms in injury prediction

ML, now a standard tool in analysis, provides algorithms that can analyze these diverse data sets on sports injuries. In the application of a given body of data, the most popular machine learning techniques include Support Vector Machines (SVM), decision trees, and gradient boosting methods; these have yielded considerable results towards identifying the risk factors for injury (as depicted in **Figure 4**) [6]. For example, SVMs have been used in injury prediction, where independent variables were taken depending on training loads and techniques and dependent variables that cannot be changed, including genetic factors and past injuries. Research has shown that through these parameters, SVMs can be used to classify athletes depending on the risk factor [7]. This can help coaches and medical personnel decide on training schedules depending on the risk factors. However, the performance of the chosen method depends on the data preparation and the specific field of the sport under consideration, underlining the consideration of the algorithm choice and the subsequent planning. Machine learning models can accurately predict football-related injuries by analyzing player-specific data such as muscle fatigue and joint stress, significantly improving injury prevention strategies compared to traditional approaches [8]. Similarly, Majumdar et al. [9] emphasized integrating multiple data sources, such as training load and match intensity, into predictive models to refine risk assessments for athletes across various sports.

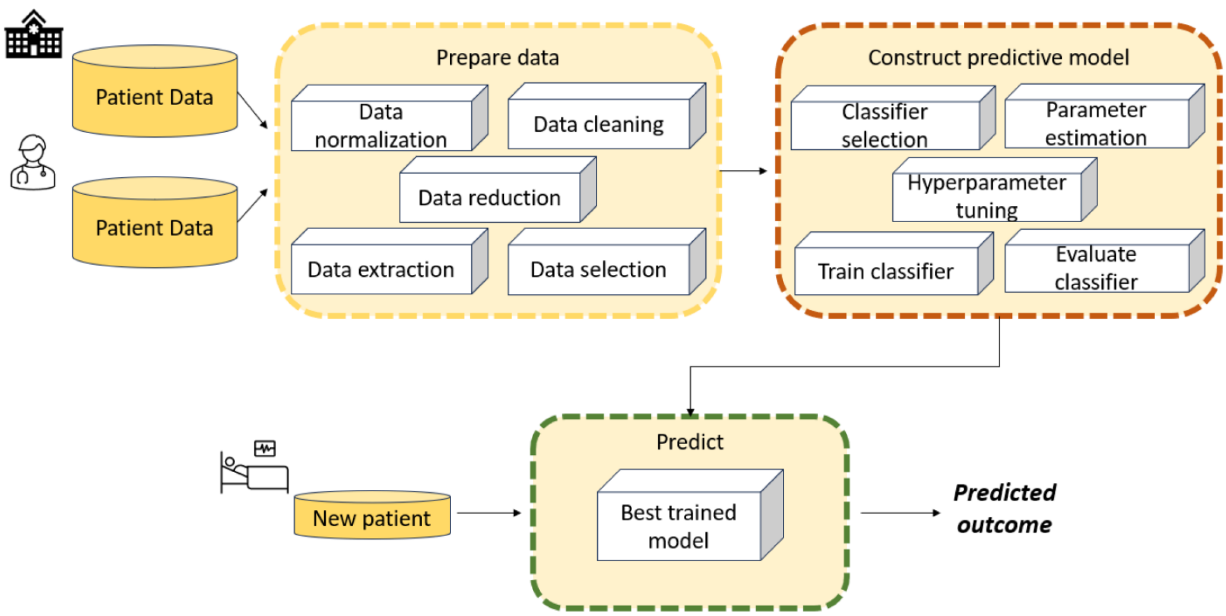

Figure 4. Typical stages in the development of an ML model such as an SVM to solve a classification or regression problem.

Gradient boosting techniques, such as XGBoost, have been the subject of research for their predictive capabilities. For instance, a work dealing with new injuries in learners playing college football reached 91.9% precision using XGBoost [10]. This algorithm is well-suited for injury prediction because it can address interactions between multiple variables within the same algorithm. Moreover, gradient-boosting techniques are more accurate in predicting sports injuries than logistic regression models, and therefore, sports injury prediction is adopting more complex ML techniques. The specific incorporation of these algorithms and large data sets in current and future research suggests improved accuracy as these algorithms are fine-tuned.

3.2. Case studies demonstrating machine learning effectiveness

There are various cases that demonstrate how ML can be effectively used in the prediction of sports injuries in different kinds of settings. For example, a relatively recent cross-sectional study of youth soccer players used an XGBoost model, showing that the model accurately predicted injuries with a precision and recall rate of approximately 84% and 83%, respectively [10]. This research showed that the new generation of ML algorithms can accurately identify acute and overuse injuries and emphasized the importance of this discriminator in designing efficient injury prevention strategies. Another example of AdaBoost in action works to classify the likelihood of injuries in CrossFit enthusiasts; the model AUC was 77.93% [10]. These studies underscore how the applications of machine learning methods cut across various sporting disciplines and how these can help design efficient injury prevention measures.

Various machine learning approaches, such as DGCN, consistently predicted high-risk athletes by analyzing past failure history and current athletic activity (shown in **Figure 5**) [2]. Although many algorithms might be valid, there are issues with transferring models across the sports context because of differences in data acquisition methods and athletes. Tackling these issues is fundamental to progressing the use of ML techniques in real-world scenarios.

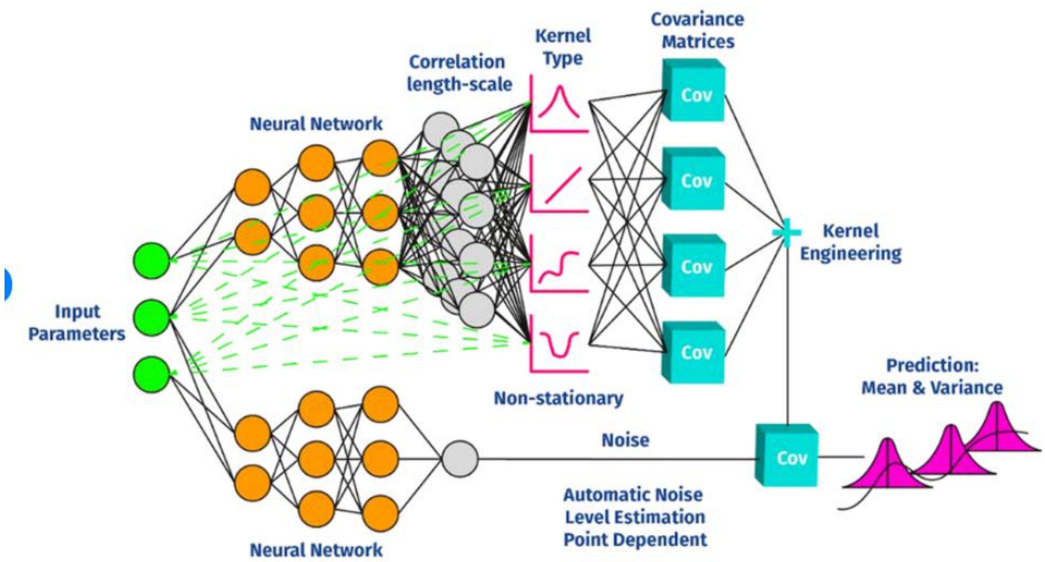

Figure 5. Dynamic graph convolutional network model [2].

4. Athlete engagement and performance outcomes

4.1. The role of athlete engagement in performance

Athlete engagement is a multifaceted phenomenon that meaningfully affects performance in sports. Current literature also points at athlete commitment and perceived performance parameters as key indicators that enhanced commitment leads to better performance. For example, in the boarding school athletes' study, there was a high positive correlation ($r = 0.861$, $p = 0.001$) between engagement and perceived performance; this means students in boarding school sports participate more and will rate their performance higher [11]. This relationship thus emphasizes the role of promoting an effective atmosphere in athletes, enhancing their commitment levels and, hence, their performance in the area. In addition, it has been associated with psychological aspects, including self-confidence and commitment. The two factors are essential if one is to deliver their best.

Based on the research, they adopted the theoretical framework from the Self-Determination Theory (SDT) to explore athlete engagement in self-determination as well as acknowledge the role of the basic psychological need satisfaction, namely autonomy, competence, and relatedness, in promoting the athlete's optimal functioning [12]. Sports enthusiasts who feel that their exercise environment meets or fosters these needs tend to report enhanced levels of engagement that will, in turn, enhance their performance. Thus, developing the conditions that foster these psychological needs is likely to help improve athlete interest and performance, respectively, in general. Based on this relationship, coaches and sports organizations should focus on processes that seek to enhance athlete participation and create the right environment that enhances the highest performance.

4.2. Engagement dimensions and their impact on performance

The dimensions of athletes' engagement are dedication, confidence, vigor, and enthusiasm, as well as how they impact performance. These dimensions have been found to moderate different sociodemographic characteristics, including gender, age, and competitive-level determinants of engagement among athletes [12]. For instance, the various degrees of overall engagement are general with higher levels of competitiveness, and the samples are more engaged in these dimensions if the athletes are younger males. It indicates the need for specific training methods regarding the differences in athletes.

Furthermore, much discussion has concerned the connection between engagement dimensions and performance results. Confidence has become an influential factor; self-confidence influences athletes' participation in training sessions and competitions [13]. Similarly, vigor, which is energy physically and emotionally, has been linked positively with increased pace and tenacity during tedious tasks. Therefore, understanding the effect of these dimensions on overall engagement allows coaches to use specific interventions to improve certain aspects of athlete engagement concerning certain objectives of performance enhancement.

4.3. The impact of engagement on injury prevention and recovery

Injury prevention and recovery also involve another critical factor: Athlete engagement. The focus suggests that committed, active employees are more likely to follow the standards of care meant for the prevention of injuries and follow rehabilitation measures that are prescribed to them. Research carried out among youth athletes determined that the engagement variable predicted a positive experience in the sport, resulting in lower rates of burnout and injuries [12]. This discovery indicates that stimulating the environment in which training occurs may improve performance and likely lead to improved health status due to decreased injuries.

Likewise, during injuries and subsequent rehabilitation, the engaged athletes recover and follow recommended procedures better than their peers. This higher psychological investment with increased levels can help develop a more favorable attitude towards recovery processes, thus, faster return-to-play times. Coaches and the sports medicine team should understand the value of keeping an athlete interested during rehabilitation periods through motivational techniques that relate the athlete to their sport. This can help reduce loneliness or impatience, which is common when recovering.

5. Biomechanical factors in injury prediction

5.1. Understanding biomechanical risk factors

Biomechanical factors are also key in injury prediction and prevention because biomechanics represents a set of principles describing the mechanics of movement in athletes. Hence, earlier studies have presented certain specific biomechanical risk factors (BRF) that have been seen to attach probability to the occurrence of the probability of injury most vividly when analyzed within the context of high-impact sports. For instance, ground reaction forces and stride lengths are considered good predictors of running injury risks. A recent study based on mobile technology and using a machine learning approach for data analysis showed that foot pressure, muscle activation and other parameters were correlated with developing running-related injuries among 84 active runners [14]. Combining these biomechanical findings with state-of-the-art prediction algorithms resulted in an 88.37% accuracy rate in this study, which provided a proof of concept of the benefits of mixing traditional biomechanics with current machine learning techniques to improve injury prediction.

Furthermore, the literature also focuses on how these intrinsic and extrinsic factors might interact to cause injury. Intrinsic factors are those internal to the athlete and may include things like muscle strength, flexibility and other physical attributes, while extrinsic factors are outside the athlete and may consist of things like shoes and the training surface. For instance, the wrong shoes can change an athlete's kinematics at all levels, leading to extra stress in some joints and tissues. For this reason, understanding these factors is imperative and critical when developing injury prevention strategies unique to each athlete [15]. Concentrating on such intrinsic and extrinsic biomechanical risks allows for constructing more evidenced and comprehensive views of performance variables in athletics-based research.

5.2. Biomechanics of common sports injuries

Biomechanics of most sports-related injuries can be examined to determine how movements in certain sports increase the likelihood of an injury. Knee injuries, especially those involving the anterior cruciate ligament (ACL) (shown in **Figure 6**), are common in sporting activities that include issues of cutting and jumping [16]. The study shows that any change in these mechanics, including the wide base of support, increased knee valgus, or incorrect landing, predisposes one to develop ACL injuries. Interventions and neuromuscular training programs have helped modify these biomechanical discrepancies and minimize ACL injury risks among athletes.

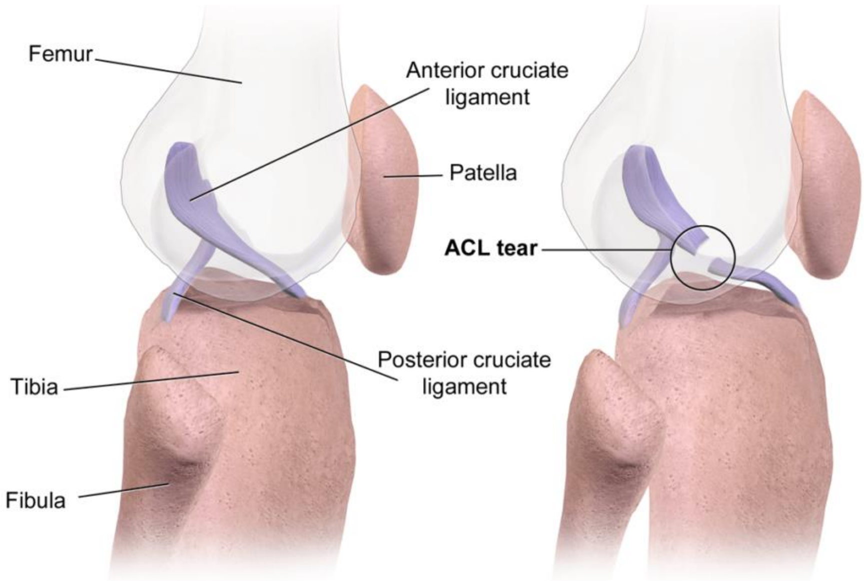

Figure 6. Sample of anterior cruciate ligament (ACL) injury that can occur in sporting activities.

Moreover, training errors have been attributed to biomechanical components of overuse injuries and muscle imbalance. For instance, running-related overuse injuries (ROIs) are often prevented by strain build-up on particular tissue touchstones without reasonable rest. There have been efforts to define biomechanical parameters with some degree of BRF, including kinematic and kinetic variables extracted from motion capture data from ROIs. Such parameters include ground reaction forces and pressure mapping information that unequivocally demonstrate an athlete's biomechanics under varying training loads. Knowledge of these relationships is essential to creating effective prevention strategies for overuse injuries in tennis through training practices and equipment modification.

5.3. Integrating biomechanics with injury prediction models

Biomechanical analysis with machine learning technologies is proposed as the next frontier in injury prediction research. Lyubovsky et al. [8] demonstrated that combining motion capture data with deep learning techniques could identify subtle movement inefficiencies that increase injury risks, allowing for early intervention [8]. Newer techniques have established that biomechanical data can be analyzed using machine learning techniques in a manner that makes it difficult for classical statistical techniques to pick up. For instance, using GBDT, LSTM, and SVM in an ensemble manner in a biomechanical input-based machine learning model for the prediction of running-related injuries (shown in **Figure 7**) [17]. This approach leverages the features offered by the various algorithms to improve predictive capability substantially.

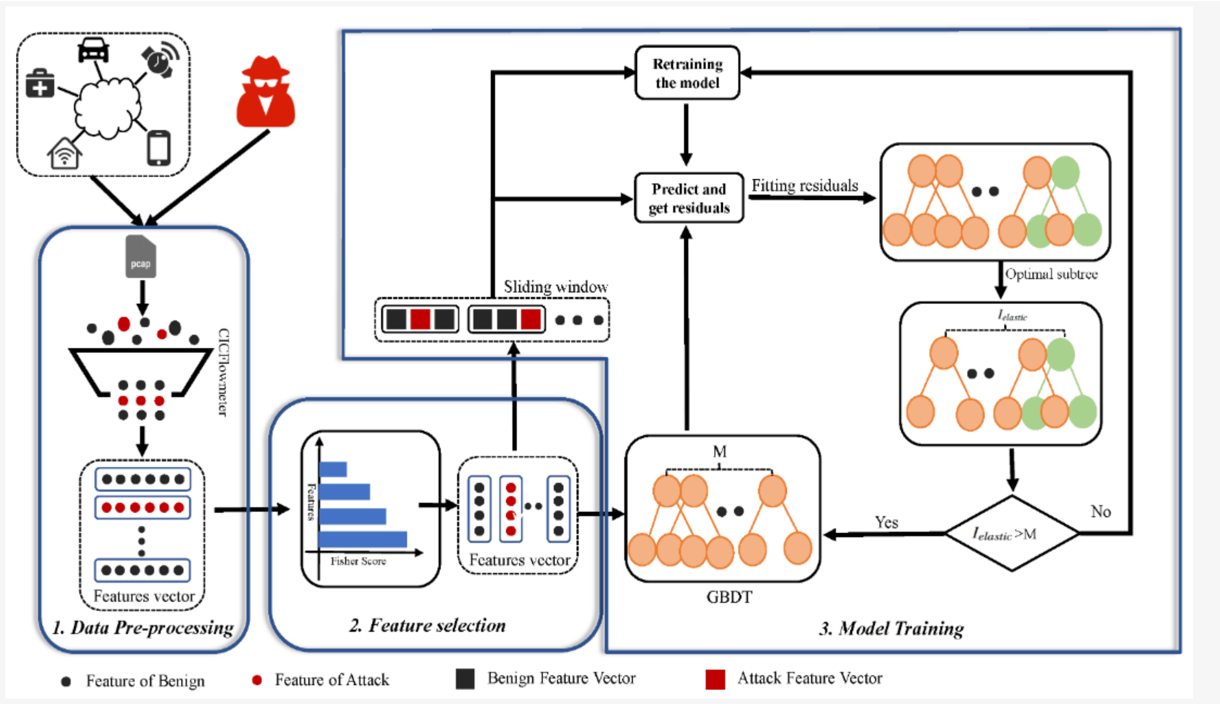

Figure 7. The framework of GBDT-IL.

Moreover, systematic reviews and meta-analyses have shown the importance of additional and more focused studies in this area to investigate specific BRFs related to certain kinds of injuries. Although previous studies have described various risk factors for ROIs, no specific biomechanical factors that may predict more severe injuries have been established. Filling this gap entails including biomechanics in identifying the cause-effect relation between biomechanics and the development of injuries, considering variance in the body structure and movements. Subsequently, by fine-tuning these predictive models through specific studies of BRFs, the practitioners are therefore able to come up with differential injury prevention measures that best suit each of the athletes.

6. Results and discussion

6.1. Results

6.1.1. Descriptive statistics

Table 1 shows the distribution of the study variables as captured by the available descriptive statistics. About 110 participants had complete data for all the measures in the study. The rating of training practices was 3.33 (SD = 0.77), which suggests that athletes had relatively positive attitudes toward training practices in general. The scores obtained ranged from the lowest score of 1.20 to the highest score of 5.00, indicating variability of athletes' perception towards their training regimes. Regarding previous injuries, the mean score was 3.36 (SD = 0.76), interpreted as a moderate acknowledgment of previous injuries, ranging from 1.40 to 4.80.

The mean score concerning biomechanical analysis was 3.43 (SD = 0.56), indicating that athletes perceive biomechanical analyses as necessary during training, ranging from 2.20 to 5.00. For ML Awareness, the mean was 3.81 (SD = 0.45), and all the athletes gave scores from 2.80 to 5.00, showing that athletes have moderate awareness of how machine learning can be used for athlete injury prediction. Last, the mean for engagement with injury prevention technologies was 3.31 (SD = 0.60), as it appeared that participants had engaged with technologies targeted at preventing injuries to a moderate extent, and the scores ranged from 1.80 to 4.80.

Table 1. Descriptive statistics.

Descriptive Statistics					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Training Practices	110	1.20	5.00	3.3273	0.77233
Previous Injuries	110	1.40	4.80	3.3582	0.75667
Biomechanical Analysis	110	2.20	5.00	3.4309	0.55928
Machine Learning Awareness	110	2.80	5.00	3.8109	0.45238
Engagement with Injury Prevention Technologies	110	1.80	4.80	3.3145	0.60242
Valid N (listwise)	110				

6.1.2. Correlations

Table 2 shows the Pearson correlation coefficient of the study variables, where several correlations were identified, although some were significant. Training practices correlated positively and significantly with previous injuries ($r = 0.718$, $p < 0.01$), which means that better training practices are related significantly to fewer previous injuries in athletes. Further, there is a moderate positive relationship between training practices and biomechanical analysis ($r = 0.521$, $p < 0.01$), which means there can be a connection between good training practices and biomechanical knowledge of the athlete.

Table 2. Correlations.

Correlations						
		Training Practices	**Previous Injuries**	**Biomechanical Analysis**	**Machine Learning Awareness**	**Engagement with Injury Prevention Technologies**
Training Practices	Pearson Correlation	1	0.718^{**}	0.521^{**}	0.043	−0.058
	Sig. (2-tailed)		0.000	0.000	0.654	0.550
	N	110	110	110	110	110
Previous Injuries	Pearson Correlation	0.718^{**}	1	0.291^{**}	0.081	0.002
	Sig. (2-tailed)	0.000		0.002	0.402	0.986
	N	110	110	110	110	110

Table 2. (*Continued*).

Correlations						
		Training Practices	**Previous Injuries**	**Biomechanical Analysis**	**Machine Learning Awareness**	**Engagement with Injury Prevention Technologies**
Biomechanical Analysis	Pearson Correlation	0.521**	0.291**	1	0.209*	0.078
	Sig. (2-tailed)	0.000	0.002		0.028	0.420
	N	110	110	110	110	110
Machine Learning Awareness	Pearson Correlation	0.043	0.081	0.209*	1	0.078
	Sig. (2-tailed)	0.654	0.402	0.028		0.421
	N	110	110	110	110	110
Engagement with Injury Prevention Technologies	Pearson Correlation	−0.058	0.002	0.078	0.078	1
	Sig. (2-tailed)	0.550	0.986	0.420	0.421	
	N	110	110	110	110	110

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

The relationship between the previous injuries and biomechanical analysis was also significant, yet less strong; $r = 0.291$, $p < 0.01$, which suggests that athletes with prior injuries are somehow aware of the biomechanics that they are likely to experience or may cause more injuries to them. Correlational analysis showed that machine learning awareness had a positive relationship with biomechanical analysis: $r = 0.209$ ($p < 0.05$), which means that as people have higher MLAs, they would be more familiar with biomechanics.

Nonetheless, the results did not show any significant correlations between engagement with injury prevention technologies and the other variables. This implies that notwithstanding the athletes' awareness of the availability of injury prevention technologies, the athletes lack the required engagement or compliance to utilize these technologies.

6.1.3. ANOVA results

Table 3. ANOVA[a].

ANOVA[a]						
Model		**Sum of Squares**	**df**	**Mean Square**	***F***	**Sig.**
1	Regression	1.098	4	0.274	0.749	0.561[b]
	Residual	38.459	105	0.366		
	Total	39.557	109			

a. Dependent variable: Engagement with injury prevention technologies; b. Predictors: (Constant), machine learning awareness, training practices, biomechanical analysis, previous injuries.

The study findings regarding the ANOVA analysis (shown in **Table 3**) revealed no meaningful correlation between the level of machine learning awareness, training practices, biomechanical analysis and previous injuries with engagement with injury prevention technologies. The regression model gave an F-value of 0.749 ($p = 0.561$), which indicates that the overall predictors do not account for significant differences in engagement with injury prevention technologies among the athlete population.

6.2. Discussion

6.2.1. Training practices

Retaining training practices obtained a mean score of 3.33 (SD = 0.77), meaning athletes have a good impression of their training schedules. The score range between 1.20 and 5.00 indicates that the athletes' satisfaction varies, and although some athletes score high, showing high satisfaction, some may feel less confident in their practices. Nonetheless, the positive relationship between training practices and previous injuries shows that $r = 7.18$, $p < 0.01$, proving that training can effectively help manage or minimize injuries. These findings suggest that athletes following organized training schedules have few injuries, underlining the direction of following evidence-based training protocols among athletes. This result supports similar research done in the past that suggests that appropriate training can significantly reduce the likelihood of injuries [18] There is a need to establish specific training schedules that consider individuality and the athlete's biomechanical model [16]. Hence, they can improve performance while at the same time diminishing the risk of injuries for athletes, which would lead to longer careers and, in general, better life expectancies.

6.2.2. Previous injuries

The mean score of previous injuries was 3.36 (SD = 0.76), which shows that participants had moderate recognition of the previous injury. The result is equally significant, where the findings of previous studies reveal a positive correlation between previous injuries and training practices ($r = 0.718$, $p < 0.01$) that indicates injury-prone athletes are likely to be more conscious about proper training regimens to avoid any similar mishap in the future. It is essential as the awareness could trigger a behavioral shift in approaches towards training and recovery. Furthermore, comparing the results of the quantitative data, the difference in responses of both groups can be observed: Previous injuries and biomechanical analysis show the correlation coefficient of $r = 0.291$ ($p < 0.01$), which strengthens the assumption that biomechanics remains partially unnoticed by athletes—as a valuable tool for understanding the prevention of injuries.

6.2.3. Biomechanical analysis

The mean score on biomechanical analysis was 3.43 (SD = 0.56), implying that athletes acknowledge the importance of biomechanics in their performance and injury prevention. Moderate to strong correlation was also observed in their training practices and their acceptance of biomechanical assessments ($r = 0.521$, $p < 0.01$). This supports work on the biomechanics of injury-predisposing movement patterns in athletic activity. However, the values obtained for previous injuries were significant; consequently, the results demonstrate that while athletes have specific knowledge about biomechanics, it may not be exploited optimally for preventing injuries based on their histories. Hence, a preliminary study of biomechanics should be integrated into the assessments administered by sports organizations in addition to feedback concerning movement styles and strategies [19]. Incorporating biomechanics into training courses allows a trainer to show an athlete a safer technique that will reduce the chance of getting an injury while at the same time providing optimal performance.

6.2.4. Machine learning awareness

The mean score calculated for machine learning awareness was significantly high at 3.81 (SD = 0.45), which indicates that athletes have a severe recognition of machine learning potential in predicting and analyzing sports injuries. Nonetheless, a low correlation of engagement in injury prevention technologies was observed (M = 68.81, SD = 39.87; $r = 0.078$), which indicates that awareness does not necessarily equal usage or compliance with these technologies in actual environments. This difference is essential to fill the gap; athletes may be aware of the theoretical applications of machine learning tools but may not have the confidence or ability to use them appropriately in training. Indeed, there is a gap in targeting these educational initiatives to help learners understand and operationalize machine learning technologies within athletic domains. Injury prevention ideas for these tools can be gained through workshops or seminars spearheaded by professionals in the field or experts in a specific organization's performance [20]. The case with the innovative technologies is that sports organizations can only be more involved with them if the usefulness of machine learning is promoted more.

6.2.5. Engagement with injury prevention technologies

The engagement with tools used in the prevention of injury was 3.31 out of 4, which is, on average, with moderate use of the tools by athletes with the intention of the prevention of injuries. However, the multiple regression analysis results indicated no strong positive relationship between the level of awareness and engagement levels with other variables. For example, while participants had good awareness of machine learning apps (mean = 3.81), this was not reflected in the level of engagement, let alone compliance, with technologies aimed at injury prevention. This suggests there could be limitations to using such technologies or difficulty motivating oneself to utilize these tools regularly. Sports organizations need to overcome these barriers to increase engagement levels through the availability of resources and support to apply technology in exercise and/or rehabilitation fields. Also, promoting high-tech tools as part of athletes' training can push for better use of such equipment among the athletes, regardless of their classification. Through high levels of involvement with injury prevention technologies, boosted athlete safety and performance results can be achieved.

6.3. Comparison between traditional and predictive models

Traditional injury prediction models use history data, a coach's eyes, and medical judgment to produce predictions; however, predictive models use machine learning to enhance accuracy and adaptability. The comparison table below features some key differences (shown in **Table 4**).

The study used an ML model integrating biomechanical data and historical injury records to predict risks. Unlike traditional statistical models relying primarily on linear or logistic regression, this machine learning approach employs algorithms such as Support Vector Machines (SVM) and Gradient Boosting Decision Trees (GBDT) for superior pattern recognition and predictive accuracy.

Table 4. Comparison between traditional and predictive models.

Feature	Traditional Models	Machine Learning-Based Models
Data Source	Historical injuries, coach reports	Real-time biomechanical data, historical injuries
Prediction Approach	Linear regression, statistical analysis	SVM, GBDT, deep learning
Adaptability	Limited to predefined parameters	Dynamic, learns from new data
Accuracy	Moderate, dependent on manual input	High, recognizes complex patterns
Application Scope	Generalized across all sports	Sport-specific customization
Real-Time Assessment	Not available	Available with wearable technology

7. Current challenges and recommendations

Some research difficulties of using machine learning and biomechanical models in predicting sports injuries include how information is collected, which varies from one sports discipline to another. This variability leads to fluctuations in the observed outcome and the generalization of predictive equations. Various sports activities involve distinct body movements, training and conditioning, and have distinct injury profiles, which makes it challenging to develop a universal model for predicting sports injuries. To manage this challenge, therefore, there is a need for researchers and practitioners to work jointly to establish universal guidelines on data collection procedures that may apply to any given sporting activity. By enhancing the uniformity with which various tools and measures are used, the possibility of comparability between studies will improve, and the accuracy of the predictive models will be refined.

Another problem is incorporating high-tech equipment into conventional training and rehabilitation procedures. Most athletes or trainers may not have sufficient background information or means to apply several machine learning or biomechanical analysis measures to their work. This gap can lead to not leveraging critical technologies that would help expand the effectiveness of injury prevention strategies. To avoid such a problem, sports organizations must spend more on courses to make athletes and all the coaching personnel understand the importance and uses of such technologies. These tools may be completed; therefore, workshops, webinars and firsthand training could help change the culture of the athletic programs.

Also, there are some important ethical issues concerning data protection and permission while using wearable technologies in athlete performance and biomechanics assessment. Concerns about how the data will be used, stored, or shared may make athletes reluctant to engage with the technologies in question. To address these issues, organizations should set complete principles regarding data privacy and the protection of athletes. Disclosure of how information will be used for purposes of injury prediction and performance improvement can help create trust from athletes and foster their engagement in data collection.

Several future recommendations can be proposed to build upon the insights gained from this study. First, it is essential to establish standardized protocols for data collection across various sports disciplines. By creating uniform methodologies, researchers can enhance the comparability of findings and improve the robustness of predictive models. This standardization should involve collaboration among sports scientists, coaches, and technology developers to ensure that the unique characteristics of different sports are adequately addressed. Second, educational initiatives aimed at athletes and coaching staff are crucial for promoting the effective use of machine learning and biomechanical analysis tools. Workshops and training sessions can help demystify these technologies, fostering a culture of innovation within athletic programs. Organizations can enhance athlete engagement in injury prevention strategies by equipping stakeholders with the knowledge and skills necessary to utilize these tools effectively.

Additionally, addressing ethical considerations surrounding data privacy and consent is paramount. Sports organizations must develop transparent policies regarding data management that prioritize athlete confidentiality. Clear communication about how data will be used for injury prediction and performance enhancement can help build trust among athletes, encouraging their participation in data-driven initiatives.

8. Conclusion

8.1. Summary of the findings

This study demonstrates that machine learning and biomechanical analysis can provide the potential of their transformative power to predict and prevent sports injuries. This research integrates advanced algorithmics with real-time biomechanical monitoring in a data-driven approach to reduce injury risk and adapt the athlete's performance. The results suggest that training practice, history of injury, and biomechanical analysis have strong relationships, suggesting that implementing scientifically informed injury prevention strategies is needed. While there is a growing interest in machine learning applications in sports, there has been limited engagement in injury prevention technologies. To fill this gap, it is necessary to design and implement educational programs for athletes and coaches to bridge the gap between knowledge in theory and practice.

Data collection methods can be standardized to improve the accuracy, performance, and adaptability of prediction models to different sports. The broader range of biomechanical variables used in the study is noted for expanding machine learning frameworks. Ultimately, this research will promote personalized injury prevention models to maximize an athlete's longevity and reach optimal performance. The results lay the ground for further research on the use of AI in sports medicine and provide incentives for continuing technology integration in athletic training and rehabilitation.

8.2. Contributions/significance of the study

This study contributes to sports science with its novel approach to using an innovative machine-learning model to capitalize on biomechanical data, pushing the accuracy of injury prediction up a notch. The model enables sport-specific innovation to advance beyond traditional statistical-based approaches by borrowing the power of real-time data from wearable sensors. The research appears to close the gap between biomechanical awareness and sporting involvement in injury prevention technologies, highlighting the strategic need to adopt proactive ways to reduce sporting-related risks. Furthermore, the study provides a comparative analysis of conventional and predictive models that gave the structured framework for future developments in sports medicine. This research increases model reliability and cross-sport applicability by advocating for standardization of data collection methodologies. The study also points out the importance of educational initiatives reflecting the engagement of athletes and coaches in machine learning tools and their usage in training and rehabilitation programs. Taken as a single contribution, this work advances a paradigm change in injury prevention through sports organizations being compelled to adopt AI-based solutions to enhance athlete safety and performance. The first demonstrates machine learning-enabled IR policies to optimize injury mitigation strategies, while the second provides a foundation for future data-driven sports science.

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Ethical approval: The study was conducted in accordance with the Declaration of Helsinki. The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board (or Ethics Committee) of Hefei College of Finance & Economics and Anhui Technical College of Water Resources and Hydroelectric Power. Informed consent was obtained from all subjects involved in the study.

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