The Role of Artificial Intelligence in the Diagnosis and Prediction of Sports Injuries Using Portable Devices

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Abstract. This review provides detailed information on the current advancements in artificial intelligence in sports scenarios, including injury prediction, motion detection, and performance optimization. The AI diagnostic applications showcase ML and DL techniques, such as RFs, SVM, CNN, and ANN, which are all applied to forecasting injuries in various sports by integrating different data provided by individuals. Several sensor-based technologies emphasize the importance of inertial measurement units and sensor fusion in motion detection across a wide range of human joints. Meanwhile, in the sport of hammer throw, real-time biomechanical feedback is developed, aiming for more precise and accurate results. Generally, AI not only benefits athletes safely and thoroughly, but also promotes the sport medicine field to take a step forward by offering data and more research. The future of AI is optimistic and promising in the field of sports medicine, and the review has already identified ways to tackle several challenges that remain unresolved in the current situation.

Keywords: Artificial intelligence, sports injury, wearables, sensors.

1. Introduction

Sports are growing more popular among people of all ages; however, sports injuries often accompany participation in sports across all age groups. The physical impacts of such injuries can seriously affect a person's performance, sports longevity, and overall well-being. It is crucial for everyone to have early prediction, assessment, and effective recovery tactics.

Traditionally, detection and treatment have relied on hospital-based devices, which faced accessibility and financial issues, such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), among others [1]. While these approaches are effective, they are often bulky in size and volume, time-consuming, and inaccessible in environments where immediate decision-making is needed. On the other hand, the integration of Artificial Intelligence (AI) with the field of sports medicine has shown a tendency to make significant progress in predicting and diagnosing sports-related injuries. First, machine learning (ML), which enables systems to learn from past data and generate predictions without explicit programming, is at the core of AI injury prediction [2]. Large and complex dataset problems are well-suited for DL models, which can automatically discover complex patterns without the need for manual feature extraction [2]. For example, due to the poorly performing real-time system and low-accuracy sport injury monitoring systems, an SVM classifier that owns a real-time injury monitoring system has been developed [3].

Moreover, sensor-based technologies have been developed for motion analysis by attaching various sensor types to the human body, resulting in inertial measurement units (IMUs) that offer versatility in terms of configurations [4]. Karnuta et al. created 84 models to predict seven distinct clinical outcomes using six algorithms: logistic regression, random forest, k-nearest neighbors, naive Bayes, XGBoost, and a top-three ensemble. These results covered total injury risk and injuries to the knee, back, hand, foot/ankle, shoulder, and elbow in the following season [5]. Real-time biomechanical feedback systems developed by Wang et al. for in-field applications will replace subjective (experience-based) training and learning of human motor abilities with objective (science-based) methods [6]. Such a translation is very beneficial for hammer-throw instruction, which still relies on coaches' observation and experience [6]. Thus, for real-time biomechanical feedback training in the hammer throw, a wearable sensor system with AI was created. Including

several technologies mentioned above, AI in healthcare has gained significant attention and experienced rapid growth over recent decades. Modern sports medicine emphasizes practical applications of sports, which are crucial for injury prevention, enhancing athletic performance, and advancing recovery methods.

The purpose of this review is to examine the current state of AI applications in the diagnosis and prediction of sports injuries using portable devices. It will combine evidence from existing studies, compare the strengths and limitations of different technological approaches, and identify their further development. By introducing AI algorithms to predict sports injuries across various body parts, an injury monitoring system utilizes an algorithm, injury analysis using sensor-based technology, a wearable sensor system that provides real-time feedback, and sensing wearable technology to optimize performance.

2. Method

2.1. Application of Machine Learning (ML)

Machine learning algorithms excel in forecasting sports injuries by determining intricate connections between risk factors, such as training intensity, prior injuries, and physical performance metrics.

2.1.1 Random Forest (RFs)

In order to predict the lower-extremity musculoskeletal injury risk in student athletes, an RF model was used for analyzing joint strength, postural stability, flexibility, previous injury history, and demographics. It is reported that the RF model's prediction accuracy for sports injuries was 79%, emphasizing the significance of the identification of risk factors such as hip external rotation strength and hip adductor strength [2].

2.1.2 XGBoost

XGBoost excels in handling complex, multidimensional data, providing predictions that are precise and highly accurate. Combining XGBoost with futsal and football has made great progress in predicting and optimizing the performance of players. For instance, a study created a model that could differentiate between acute injuries and overuse using preseason data, such as anthropometric measurements, motor coordination, and physical performance metrics [2]. To be specific, in youth football players, XGBoost has become the most effective algorithm by having the ability to distinguish large datasets and different types of injuries.

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2.2. Application of Deep Learning (DL)

When working with data from wearables, video analysis, or sequential performance measurements, deep learning methodologies are beneficial for predicting sports injuries.

2.2.1 Convolutional Neural Networks (CNNs)

In the field of baseball, the use of AI is transformative, especially focusing on statistical analysis. For CNNs, which are effective at coping with complicated and large datasets, handling player mechanics and performance becomes a key role, such as pitch sequences, swing motions, and fielding patterns. This algorithm made high-dimensional data easier to interpret while improving the accuracy of predicting injury risks associated with the sport [2]. On the other hand, the application of CNNs presents a little difference among other sports, like basketball or handball, which mainly

focus on real-time and dynamic analysis; the use in baseball is prone to static motion analysis, giving precise information about players' actions and strategies.

2.3. SVM-based Human Target Action Recognition Method

The human action recognition method begins with video detection, where video data is analyzed for human movements. It then proceeds to human joint detection, using both training and testing data to identify joints. The detected data are subsequently transmitted to a polynomial fitting analysis to determine the connections between joints [3]. Next, the mean of the training data is calculated as a reference point, followed by demeaning the original values to adjust for data position and orientation. An additional step involves applying data dimensionality reduction techniques to enhance processing efficiency and speed up model training. Finally, the processed data are fed into an SVM classifier for classification and identification [3].

2.4. Sensor-based Technology

Among the sensors used, inertial measurement units (IMUs) provide versatile configurations. The three internal sensors can operate together or separately. Specifically, accelerometers, gyroscopes, and magnetometers are utilized. Sensor fusion approaches, which are used in the evaluation of rehabilitation, injury assessment, and injury detection, were used in 38% of studies overall—for example, an arthrometer, EMG, camera, plantar pressure, and IMU [4].

2.4.1 Injury Detection

Three studies identified knee and ankle joints using sensor-based motion analysis [4]. In 2017, researchers in the United States investigated knee sprains using advanced sensors, including EMG, cameras, and pressure measurements, within a laboratory setting. A few years later, in 2021, scientists in Iran also focused on knee injuries. Still, their work was conducted in a clinical environment, emphasizing the use of cameras and pressure sensors in team sports. In the same year, researchers in Hong Kong turned their attention to ankle sprains, utilizing inertial measurement units (IMUs) and statistical methods to gain a better understanding of these common injuries.

2.4.2 Injury Assessment

Eighteen investigations in all were carried out with the aim of evaluating injuries. Sensor fusion was employed in 44% of the studies to evaluate motion in relation to injury assessment. None of these studies utilized machine learning techniques, while one incorporated signal processing methods. Regarding study settings, 28% (n=5) took place in clinical environments, 61% (n=11) in laboratory conditions, 5.5% (n=1) on sports fields, and another 5.5% (n=1) involved both laboratory and clinical settings.

2.4.3 Rehabilitation Evaluation

In order to assess rehabilitation, twenty-one studies were presented. Two studies concentrated on a combination of team and individual sports, one on flexible team sports, and one on individual sports, and 47% of the research focused on team sports. In 52% (n = 11) of the investigations, joint sprains were examined. The knee is the subject of every study on the many types of joint sprain injuries. Ninety percent (n = 19) of the research looked at rehabilitation using statistical analysis.

2.5. Performance Optimisation

2.5.1 Prediction of Athletes' Injury Risk Before the Event

Karnuta and colleagues developed 84 predictive models employing six different algorithms—logistic regression (LR), random forest, k-nearest neighbors, naïve Bayes, XGBoost, and an ensemble of the top three methods—to forecast seven clinical outcomes [5]. These outcomes included injuries in the next season such as knee, back, and elbow injuries, as well as overall injury risk. The models achieved prediction accuracies of approximately 70% for baseball players and up to 94.6% for hockey players, outperforming conventional regression approaches in 93% of cases.

2.5.2 During the Event: Optimizing Athletes' Performance

Li et al. present a specially designed "artificial intelligence assistance system" that enhances decision-making within games across three distinct tiers: the database layer, the processing layer, and the display layer [5]. The database component collects tactical information into a comprehensive data warehouse, which the processing layer then analyzes to produce visual decision outputs for the user. They also explain dynamic options that assess the likelihood of various situations by requiring the input of in-game settings, as well as to determine the most effective substitutions, tactical combinations, and other strategic data points. Furthermore, by gathering multidimensional physiological data through a network of body sensors, this wearable platform provides real-time corrective feedback, facilitating quicker and more accurate decision support.

2.5.3 After the Event

In a study led by Bloomfield and team, researchers employed machine learning methods to analyze data gathered from wearable devices used after patients underwent total knee replacement surgery [5]. They modeled different metrics captured by these devices to find relationships with higher patient-reported outcome measures (PROMs), which are associated with improved functional clinical results post-surgery.

2.6. A Wearable-Sensor System in Hammer Throw

The sensor and the receiver are the two nodes that make up the system. To gather data in the field and transmit it to a receiver node, athletes might wear the sensor node device around their waist. A custom printed circuit board (PCB) that can be inserted or linked to an Arduino microcontroller, an XBee wireless communication module, two IMUs, and a small load cell helped to reduce the physical size of the wearable gadget. An on-board IMU was used to collect the vertical waist displacements because the prior design of the optical infrared sensor was not always vertically toward the ground during a hammer-throw movement. An integrated IMU is used in the current architecture to improve data accuracy [6].

To gather the vertical wrist displacements, an additional IMU has been incorporated into the system. The hammer-throw handle's narrow end still has the tiny load cell implanted in it, soldered in place. A special easy-to-release attachment on the handle allows the hammer to be thrown away in a full hammer-throw movement. When the receiver node's extra XBee module is linked to a laptop-like device, it is capable of receiving, processing, and analyzing the data collected by the sensor node device. [6].

3. Comparison and Future Prospects

3.1. Comparison

3.1.1 Machine Learning (ML)

Through the combination of numerous machine learning approaches, including RF, SVM, and KNN, sports experts can accurately forecast injury risk and identify intricate patterns. Because of these methodologies' qualities, they may be applied in a variety of ways and can be tailored to the unique data features of each sport. Additionally, ML methods pleasantly handle moderate datasets; they focus on relatively small or medium-sized datasets, which can be helpful when samples are in short supply or limited. However, compared to DL models, ML methods are not as capable as DL models when it comes to tackling complex and non-linear relationships.

3.1.2 Deep Learning (DL)

When data are sufficiently provided, DL performs better than ML methods in injury prediction and movement predictions because DL models can incorporate a large amount of data, like wearables, sensors, videos, and so on. In biomechanics, this allows for the prediction of joint angles or forces by using fewer sensors, as can be seen in the hammer throw system. Nevertheless, one of

the challenges that DL methods face includes the high cost of computational resources; using DL for real-time or on-field applications may not be a good choice. Plus, DL methods usually require large and varied datasets in order to perform their best function, but in sports scenarios, data are always fragmented.

3.1.3 Support Vector Machine Classifier

SVM classifiers handle small datasets as a binary classifier. According to a study analyzing the results of sport injury monitoring, with results of 94.2%, 92.5%, and 96.0%, the study demonstrates that the SVM algorithm ranks the top among all other nine methods (RFs, KNN, and so on) in terms of accuracy, sensitivity, and specificity. However, although SVM classifiers offer fast training speed, they must ensure their pipeline operates without errors (mentioned in part two); if one of the processes fails, the system will generate inaccurate results. Last but not least, compared to deep learning methods, SVMs are less flexible in coping with complicated sports movements, such as the hammer throw.

3.1.4 Sensor-Based Technologies

Traditional sensor-based technologies, such as IMUs, Electromyography (EMG), arthrometers, and so forth, still play a significant role in biomechanical monitoring. These sensors can be used on various body parts (upper limb, lower limb, trunk, etc.), which helps to understand which part of the body is monitored the most and how well it performs. Thus, promoting the designs of new systems. However, for example, IMUs can be easily drifted during movements, hence influencing the player's experience. Furthermore, most prediction methods are statistical and lack machine learning and complex algorithms. This can lead to limited development potential and prevent them from being cutting-edge in the field.

3.1.5 Wearable-Sensor System in Hammer Throw

Wang et al. proposed a system for use in an on-field sport scenario. Compared to sensor systems, it reduces the athletes' burden by using two IMUs plus a load cell. Compared to pure deep learning methods, it incorporates a design that fits an actual sport. However, its limitation stems from data diversity, as all data comes from a single athlete. Besides, although fewer sensors help reduce movement constraints, some issues still remain unsolved, such as ensuring that IMUs are properly fixed in place.

3.2. Future Prospect

To begin to understand the significance of AI in long-term impacts, future studies will primarily focus on managing longitudinal studies of the integration of AI on risk prevention and athlete health among a wide range of sports medicine studies [2].

More involvement from a range of stakeholders, including hospitals, insurance companies, and wearables manufacturers, is needed to incorporate wearable technologies and artificial intelligence into healthcare systems [5].

The next phase will involve integrating a vertical GRF measurement module into the multimodal wearable system that piloted using a dual-chain biomechanical model [6, 7-10]. Furthermore, extracting a variety of motion features from different motor skills using surface electromyography is one of the study's objectives, in order to identify significant motion patterns that demonstrate intra- and inter-limb motor coordination [6].

For sensor-based technologies, advances in miniaturization and wearability are essential. Meanwhile, by introducing more advanced sensor fusion algorithms, IMU drift will be mitigated, thus enhancing the accuracy of the data.

4. Conclusion

This review aims to explore the current use of AI in diagnosing and forecasting sports injuries through portable technology, thereby strengthening the relationship between sports injuries and medical care. The paper synthesizes recent research on advanced AI algorithms, wearable sensors, and IMUs, emphasizing their combined importance in injury prevention, detection, and enhancing performance. By demonstrating the high efficiency and accuracy of AI-driven approaches, some motion tracking systems and advanced algorithms have been validated and are used in numerous research studies. However, limitations include unstable data, restricted environments, and the requirements that systems need for data, among others. In the future, longitudinal studies will be conducted more frequently, and the miniaturization of specific technologies will be implemented, ultimately benefiting the progress in sports medicine.

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