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Cloud-based deep learning-assisted system for diagnosis of sports injuries

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Abstract

At both clinical and diagnostic levels, machine learning technologies could help facilitate medical decision-making. Prediction of sports injuries, for instance, is a key component of avoiding and minimizing injury in motion. Despite significant attempts to forecast sports injuries, the present method is limited by its inability to identify predictors. When designing measures for the avoidance of work-related accidents and the reduction of associated risks, the risk of injury to athletes is a crucial consideration. Various indicators are being evaluated to identify injury risk factors in a number of different methods. Consequently, this paper proposes a Deep Learning-assisted System (DLS) for diagnosing sports injuries using the Internet of Things (IoT) and the concept of cloud computing. The IoT sensors that compose the body area network collect crucial data for the diagnosis of sports injuries, while cloud computing makes available flexible computer system resources and computing power. This research examines the brain injury monitoring framework, uses an optimal neural network to forecast brain injury, and enhances the medical rehabilitation system for sports. Using the metrics accuracy, precision, recall, and F1-score, the performance of the proposed model is assessed and compared with current models.

Keywords: Deep Learning, Sports Injury, Prediction, Sports, Cloud Computing, Internet of Things (IoT)

Introduction

The sports industry generates an annual revenue of over 157 billion dollars globally. The annual income in the United States alone is 62 billion dollars [1]. The Internet of Things (IoT) creates vast and varied data sources, but these sources are not currently being utilized to support particular measures [2, 3]. This is the case despite the fact that the IoT has immense potential to boost the development and emergence of athletes. The research done so far reveals that improper treatment of injuries sustained by children and adolescents as a result of sports may have a negative influence on the pleasure of life and their ultimate health. Musculoskeletal problems are the leading cause of persons being chronically unable to work and needing medical care in the United Nations [4].

The traditional methods of treating sports injuries concentrate mostly on subjective assessments, which do not seem to be able to restore the neuro-mechanical functioning to a level that reduces the risk of further injury, while also enhancing function [5, 6]. Object identification would lead to a better study of certain athletes who have adjustable hazard variables, offering a chance to avoid sporting mishaps that would otherwise result in lifelong disability. Recent studies [7, 8] have shown a connection between a prior history of concussions and an elevated risk of musculoskeletal injury. In addition to this, the presence of a previous football injury was anticipated to result in a 5.9% increased risk of future concussions. According to the findings, congestion has long-lasting and harmful effects on the neuronal acquisition that occurs in the input layer [9]. However, the particular mechanism through which a

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mild traumatic brain injury leads to an increased risk of physical harm has not yet been identified. Enhanced data collection methods that are able to identify even the most subtle breakdowns in neuromechanical functioning might be of assistance in this regard [10, 11].

Cloud computing is a form of distributed computing where large data computing processing programs in broken down into numerous small programs through the "cloud network" and processed and evaluated through the system made up of different servers. Cloud computing has been a very welcome addition to the sports industry. It has been applied in numerous ways, from studying the real-time parameters of athletes to using data to enhance the performance of the team. When a certain community's risk factors for high susceptibility are assessed, it is possible to compute the likelihood that members of that demography would sustain a sports injury [12]. When it comes to constructing reliable prediction models for an outcome measure [13], one of the most important factors is the adoption of an appropriate injury assessment test. Some screens may give prediction performance over a wide range of demographics. Nevertheless, the work performance that is associated with high risk may vary for different types of injuries and numerous groups specified by sports, gender, or competitive level [14, 15]. During a test of single-leg postural balance, the authors used an IoT device to quickly accelerate the body weight in three dimensions at a frequency of 100 Hz. During this injury risk screening procedure, the data collected was combined with the athletes' self-reported perception that they were at risk due to past injuries. Additionally, the longitudinal monitoring of the players' gaming exposure was conducted during the preseason. The data collected from the IoT sensors worn by the player and held on the cloud platform could predict how likely a player is to injure themselves in the next match. The cloud platform digests the collected data before sending it to the central system for prediction. A major limitation of this study is that it only uses deep learning to assess and prevent the risk of injury to an athlete. No study is done how to mitigate it in the event that it occurs.

The findings of this study provide a significant amount of genuine evidence about the prevention of sports injuries. The following are the main contributions of this paper:

- It demonstrates how injury risk checking may be carried out in a manner that is more efficient and effective.
- It provides a mechanism for classifying the risk of harm that takes into account different data sources, such as the history of injury, information collected by IoT, and information from injury monitoring that was gathered retrospectively.
- It illustrates a personalized method to decreasing the risk of injury that is targeted at a deficiency detected in the screening experiment.
- It has the potential to effect the avoidance of accidents in games that are caused by similar physical demands to those applied in sporting activities.

The remainder of this research article is organized as follows: The history of the process of assessing injuries sustained by athletes is presented in Background of the diagnosis of sports injuries section. In proposed Deep Learning-Assisted System (DLS) section, the DLS is presented and implemented. Software analysis and performance evaluation section provides a demonstration of the software analysis and performance assessment of the suggested model. Conclusion section concludes the work and discusses the possible future applications.

Background of the diagnosis of sports injuries

Sports injuries have always been a hot issue in the field of international sports science and sports medicine. Since 1994, the sports medicine community has proposed the linear multi-factor sports injury cause model, the dynamic multi-factor sports injury cause model, the sports injury complex model, and other sports injury cause mechanism models. Some progress has been made. However, because most studies on the etiology of sports injuries are driven by problem assumptions, which are verified, interpreted and simulated through experimental science, theoretical science, and computational science research paradigms. Although it can effectively identify injury risk factors and provide important information for the interpretation of sports injuries on a theoretical level, it cannot effectively prevent and predict sports injuries in practice [16]. The reason is that in previous studies, scholars often used small sample size data to extrapolate complex injury causal relationships, and used limited data to simulate the pathogenesis of sports injuries under complex conditions. Traditional multivariate statistical methods cannot capture the dynamics, surging and multiplicity of sports injuries [17].

With the development of sensing technology, the foundation for sports science research has been laid. In the context of a big data environment, how to effectively use information and obtain hidden, effective and understandable knowledge from massive data is very important to effectively prevent sports injuries. As an important part of data science, machine learning (ML) adopts a research paradigm that is completely different from the traditional scientific research paradigm. The performance of the data is continuously improved, and the data is learned and mined to obtain the potential laws and phenomena of the data [18]. Compared with traditional statistics, the biggest advantage of machine learning lies in the processing and prediction of high-dimensional and large-scale data. The flexible functional form of machine learning can adapt to different data structures and better predict injury [19]. Machine learning techniques can be divided into supervised learning and unsupervised learning. Unsupervised learning can make predictions on datasets without corresponding outcome variables, while supervised learning uses a dataset with known outcome variables to identify patterns and predict result variables. Since the outcome variables in sports injury research are usually known, supervised learning techniques are more suitable for sports injury research [20]. Presently, the application of machine learning in sports injury research mostly focuses on competitive athletes, and the algorithms involved in the study are mainly random forest, neural network, support vector machine, and decision tree. Through the data collection of sports injury risk factors reported in explanatory research, the collected data is preprocessed to obtain a normalized dataset, which is then divided into a training set and a test set according to a certain proportion. Machine learning algorithms are applied to the training set. The data is used for learning, and an optimal model is obtained by repeatedly optimizing the model, and the model is put into injury prediction and identification [21].

The application of machine learning in sports injury prevention focuses mostly on two aspects:

- Identifying risk factors for sports injuries and explicating the link between risk variables and injury outcomes [22–33].
- Determining the appropriate machine learning model for injury prediction.

The incidence of sports injuries is the consequence of numerous variables acting in concert. Meeuwisse et al. classified the risk factors for sports injuries as internal risk factors, external risk factors, and inciting events [22]. Meeuwisse argued that the most effective strategy to avoid sports injuries is to remove as many internal risk factors as possible prior to exercise. To guarantee the stability and repeatability while building a multiple linear regression model using conventional statistical techniques, the number of predictors must be smaller than the sample size, and the predictors must grow more independent of one another [23]. Due to these issues, classical multiple regression cannot make optimal use of prospective predictors, and cannot mine the data to its fullest extent. As a novel statistical tool, machine learning can capture the interaction impact between numerous predictors, and offer a foundation for identifying sports injury risk factors and studying injury etiology. In [24], this authors used the random forest algorithm to model and predict the technical and tactical statistics and injuries of NBA players for two seasons. Using the algorithm, they extracted five significant sports risk prediction features: the average speed of the athletes in the game, the average speed of the athletes in the season number of games, the average distance run in games, the average minutes played per game, and the average points. In [25], the authors used the variance expansion factor to assess the multicollinearity of each predictor and, used XGBoost to model it with SHAP (Shapley Additive Explanations) scores to evaluate and explain the predictors. They identified a total of 38 injury predictors for players, and 15 injury predictors for goalkeepers. They were able to accurately forecast sports injuries.

Using logistic regression as a starting point in [26], the authors modeled the demographic parameters, athletic ability parameters, physical examination parameters, and non-contact injuries of basketball players and floorball players using random forests in an attempt to apply the predictive ability of machine learning to detect and predict ability-based sports injury risk factors. Although the accuracy of random forest and logistic regression for predicting sports injuries was not sufficient, the risk variables for sports injuries revealed by the random forest and logistic regression method were similar to those reported in prior interpretative research. In [26], the authors noted that despite the fact that the prediction accuracy of the models established in the study is still relatively low, machine learning methods can be used to identify sports injury risk factors, and demonstrate the predictive power of injury risk factors identified in previous interpretive studies. In [27], a dynamic Bayesian network was used to model the training load parameters of track and field athletes and lower extremity non-contact injury. It presented the correlation between the training load and lower extremity non-contact injury in the form of network topology, explaining the training from a holistic standpoint. Using a Markov blanket function, the link between study parameters and injury risk, as well as how loading affects the development of non-contact lower limb injuries over time, were discussed. The findings generally support the "training injury paradox" presented in [28] indicating that training load is a significant predictor of non-contact injury. Applying machine learning to the analysis of risk factors for sports injuries may enhance understanding of the mechanism behind sports injury causation, improve the detection of injury predictors with predictive capacity, and build the groundwork for future research on sports injury prevention.

The incidence of sports injuries is often attributable to the patient's own internal injury risk, which renders the patient vulnerable to harm and external hazards. The injury consequences could be produced by instigating events. If a patient's sports injury risk and injury propensity can be anticipated in advance, modifications may be done in a timely manner to prevent the incidence or worsening of sports injuries. In [30], the authors monitored football players for 23 weeks utilizing GPS-based external monitoring of training load, and built a non-contact injury prediction model using three distinct algorithms: decision tree, random forest, and logistic regression. By comparing the performance of the three algorithms in predicting sports injuries, it was discovered that the decision tree classifier can detect approximately 80% of injuries with approximately 50% precision, significantly better than random forest. The prediction model lowered FC Barcelona's injury-related expenditures despite the fact that its predictive accuracy was not adequate. In [31], a Multi-Layer Perceptron (MLP) neural network model was developed for non-contact injury of Chinese rugby players using demographic data such as age, gender, action pattern screening, and evaluation score data. There is a general belief that the MLP neural network plays a significant role in sports. The use of injury prediction models is promising. The author believes that although the overall prediction accuracy of the model is good, the disease-free prediction accuracy is poor, which may result in a highly specific model that is difficult to implement in practice. In addition, the tiny sample size makes the network challenging. In [34], the authors proposed a sport training auxiliary system based on the concept of cloud computing and the requirements of modern sports training. This system illustrates the effect of training on performance, and improves the unbalanced resources of regional sports. [35] discussed the application of the Hadoop cloud platform in prediction of sports performance and injury. In [36], the authors proposed an electricity and power generation storage device for next-gen technologies, including deep learning for better computation. [37] develops a model for the support of preservation of the privacy of public auditing and a secure cloud storage system. In [38], the authors deliberated on providing security for health information making use of the Modular Encryption Standard (MES) and its different security layers. [39] discussed how deep learning algorithms can improve the detection of cyberbullying.

In [25], the injury prediction of hockey players was modeled using the XGBoost algorithm. This led to the assumption that regression analysis should not be the main criteria for injury prediction analysis. Using anthropometric measurements and physical ability assessments, the authors in [30] performed preseason evaluations of football players in the U10 to U15 age categories. Based on the results of the preseason testing, XGBoost was utilized to develop an injury prediction model with an 84% accuracy rate. When the model was evaluated using the test data of 147 athletes, the recall rate, precision rate, and F1-score were all 85%, indicating that the model's precision and sensitivity are adequate. Machine learning offers significant potential for injury risk assessment in top athletes, and may be used for the development of injury prevention measures in order to identify players at a greater risk of injury [30]. In conclusion, the application study of machine learning in sports injury focuses mostly on identifying risk factors for sports injuries and predicting sports injuries. It not only compensates for the limitations of traditional statistics in processing multi-factor and nonlinear data, but also provides a more complete depiction of the pre-injury appearance, which is beneficial for clinical injury risk assessment and coaching. It also provides a foundation for employees to make timely training adjustments.

Proposed Deep Learning-Assisted System (DLS)

A randomized controlled research design was made available to participants one month before the beginning of the preseason practice sessions, and fifty football club players joined in the study as a result. The data gathered from each of the 45 participants was used to collect and evaluate a variety of interconnected datasets. Football players had a median age of 21.2 years, varied in length by 1.3 years, with heights that ranged from 189.7 cm to 5.9 cm, weights that averaged 134.36 kg (106.4 kg), and with a degree determined by the average weight of 46.4kilos, respectively. The ethical committee ensured that the research procedures were acceptable before the experiments were allowed to begin.

Figure 1 is an illustration of the block diagram model that was used to obtain data and construct the injury prediction model. Every athlete's perception of their functional ability to attain 0–100 settings on the 10-point Sports Fitness Indicator (SFI) was taken one month before the beginning of the preseason training sessions. A higher rating is a result of an increased SFI, while a lower rating is the result of the repercussions of previous injuries.

An in-depth examination of the player's leg strength and ability to maintain postural stability was carried out a few days before the first preseason practice session. The purpose of this test is to determine how well low-muscle reactions are synchronized in order to simultaneously stabilize adjacent joints (including lumbopelvic tendons,

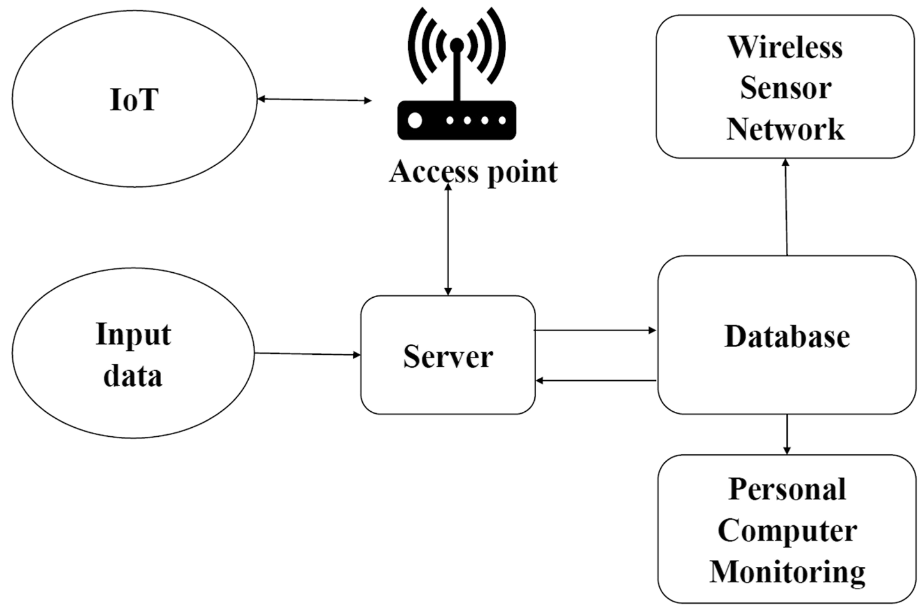


Fig. 1 Block Diagram Model of the Proposed DLS

hips, knees, and ankles), while simultaneously maintaining a correct trunk location, 145° knee angles, and a low heel altitude for ten minutes. The test is carried out independently. An IoT device's accelerator output was placed in a band around the athlete's upper torso along with the scapulae in order to analyze the degree to which the movement of the athlete's body mass effects the athlete's postural balance. The IoT device wirelessly sent the results of the tests to a secure server. The three-dimensional velocity was measured at a frequency of 100 Hz (new values stored every 0.02 min).

Jerk is the three-component of movement that represents the accelerated rate of change (an indication of motion smoothing). It has been shown to be a reliable predictor of the capacity to maintain postural stability. The average root mean square (RMS) value of jerking was measured for each game over the course of a 10-s testing period. Inside of each plant, the overall value of the jerks RMS was measured over a testing time period of 10 s. The general value jerking RMS was found. The value "x" in the data is used to determine the instantaneous velocity (in seconds). The acceleration is represented by Eq. (1) below:

$$p_x = \frac{\sqrt{{p_i}^2 + {p_j}^2 + {p_k}^2}}{p_i + p_j + p_k} \tag{1}$$

The velocity in three-dimension is denoted as $p_i, p_j and p_z$. The jerking value at period x + 1 is denoted in Eq. (2):

$$S_{x+1} = \frac{p_{x+1}}{\Delta x} - \frac{p_x}{\Delta x + \beta} \tag{2}$$

The current and next velocity of the player is denoted $p_x and p_{x+1}$. The player position displacement is denoted Δx, and the deviation is denoted as β. Jerking RMS (S^x_{rms}) between beginning and end of the diagnostic test is assessed and expressed in Eq. (3):

$$S^x_{rms} = \frac{\sqrt{{s_x}^2 + {s_y}^2 + {s_z}^2}}{M \times (s_x + s_y + s_z)} \tag{3}$$

The three-dimensional speed is denoted as $s_x, s_y ands_z$. The total number of measurements is M, x represents the axial level i, j, or k. The overall evaluation for the RMS jerking is expressed in Eq. (4):

$$S_{rms} = \frac{{s_x}^2 + {s_y}^2 + {s_z}^2}{3} \times \frac{s_x + s_y + s_z}{\beta} \tag{4}$$

The three-dimensional speed is expressed as $s_x, s_y ands_z$. The scaling factor is denoted β. As suitable joint inclinations are achieved, the earliest stage of the test management produces a ready posture, which imposes little effort. As soon as the 'test site' has been determined, a timer is started to count down the remaining minutes. The subject will be provided with physical contact information in order to maintain the optimal posture while taking the exam. The procedure will be redone for ten seconds if the subject does not maintain the right test posture, which is defined as deviating by less than 12 degrees from the required knee test inclination.

During the process of administering a clinical diagnostic, it demonstrates the order in which events occurred, as well as the data analysis performed by the IoT systems. The participant is monitored both at the beginning of the game and during the whole of it to ensure that they maintain the appropriate test posture for the entirety of the game. After an athlete has successfully completed an evaluation, the data collected by IoT is uploaded to the athlete's register. In order to provide injury forecasts, the information is first integrated into the findings of the SFI survey, followed by data on sport participants and injury incidents. This demonstrates the event sequencing as well as statistical analysis that can be performed utilizing IoT devices while clinical diagnostics are being administered. During the first and comprehensive examination, the subject is observed to ensure that they maintain the appropriate test posture for the whole test. When an accurate test is carried out, the information obtained from IoT is to be uploaded to the athlete's record. After that, the information is included in the conclusion of an SFI questionnaire, as well as the records of sports participants and injury incidents.

Breaks, deformations, lacerations, abrasions, and overuse symptoms were excluded from the studies in order to narrow the focus on injuries that are more likely to result from poor neuromechanical responses to the stresses placed on muscles and joints during movement. Different degrees of engagement in games are potential problems that may obscure or mask an important relationship between a probable major predictor and injuries, as there was reported to be a 5–10 times higher risk of injuries for involvement in the real football matches as opposed to practice. Only at the conclusion of the season was each athlete's total number of matches played (MP) recorded to the central system. This was done to account for the varying levels of experience among the athletes. It was mentioned as planned displays that there will be sports and workshops. The reception operational feature (ROF) research was used to find gaps in the scoring of SFIs, the number of jerks, and the total amount of matches played in order to provide the groundwork for categorizing players as high-risk or low-risk. The cross-tabulation testing was performed for each conceivable binary prediction, and the odds ratios were computed as a result (OR).

The suggested data learning system's sports injury prediction model is shown in Fig. 2. An IoT device is first utilized to monitor the athlete's arrival, and then another device is used to gather data from the athlete. The athlete is tested for a certain amount of time, and the study also takes into account any past injuries. The present state of the athlete's fitness is evaluated, as is the likelihood of incurring an injury in the foreseeable future. In order to find any links that may exist between binary forecasters, a step-by-step logistic regression analysis has been carried out. Additionally, an evaluation of each predictor's individual effect on the sensitivity and specificity of a multivariate model has been carried out. In order to confirm the significance of any group that was comprised through the logistic regression framework, a Cox Timetable Regression Analysis (CTRA) was utilized. This allowed for the prediction of the immediate likelihood of the first injury over the course of the period, as well as the determination of the relative risk for high-risk and low-risk categories.

The medical histories of 12 out of the 45 players that were monitored were documented as having had a maximum of 8 sprains or migraines during the course of the preseason and the 14-game regular season. The majority of the injuries that were seen were classified as various types of sprains (Ankle-8, Knee-2, and Shoulder-2). Indicators of risk for injuries were found to include a low SFI rating (Lo-SFI), a high user scoring function (USF) rating (Hi-UFS), and a high number of matches played (High-HP). The cross-tabulation analyses revealed that the interacting effects of low SFI and high UFS were more significant, and the odds ratio (OR) was found to be 8.74. The influence of the association was substantial. In addition, the OR for Hi-GP has been reported to be 3.26. Simply put, athletes who have competed in eight matches or more have a greater risk of injury than their counterparts who have taken part in less than eight matches.

Sports injury prevention procedure

It is a necessary first step to identify the potential injury, but it offers limited direction on how to create a risk-reducing strategy for the athlete. A preparational examination has to include screening techniques that assess the degree to which the effects of the pre-injury continue to have a bearing on the individual's performance capacity. This research reveals that testing results could provide a functional estimate of the probability for injury incidence during the following season. They also revealed that the procedures to identify the cuts in the categorization of dichotomous risk of accidents are validations based on injury information that is only accessible after some part of the cohort is injured. As a consequence of this, the capacity to reduce the risk of harm won't be available until the season after the model was developed.

According to the results of current research, a prospective analysis of the correlations between test findings and previous injuries will be able to produce accurate binaries risk estimates for future applications. This provides an overview of the framework of an ongoing approach

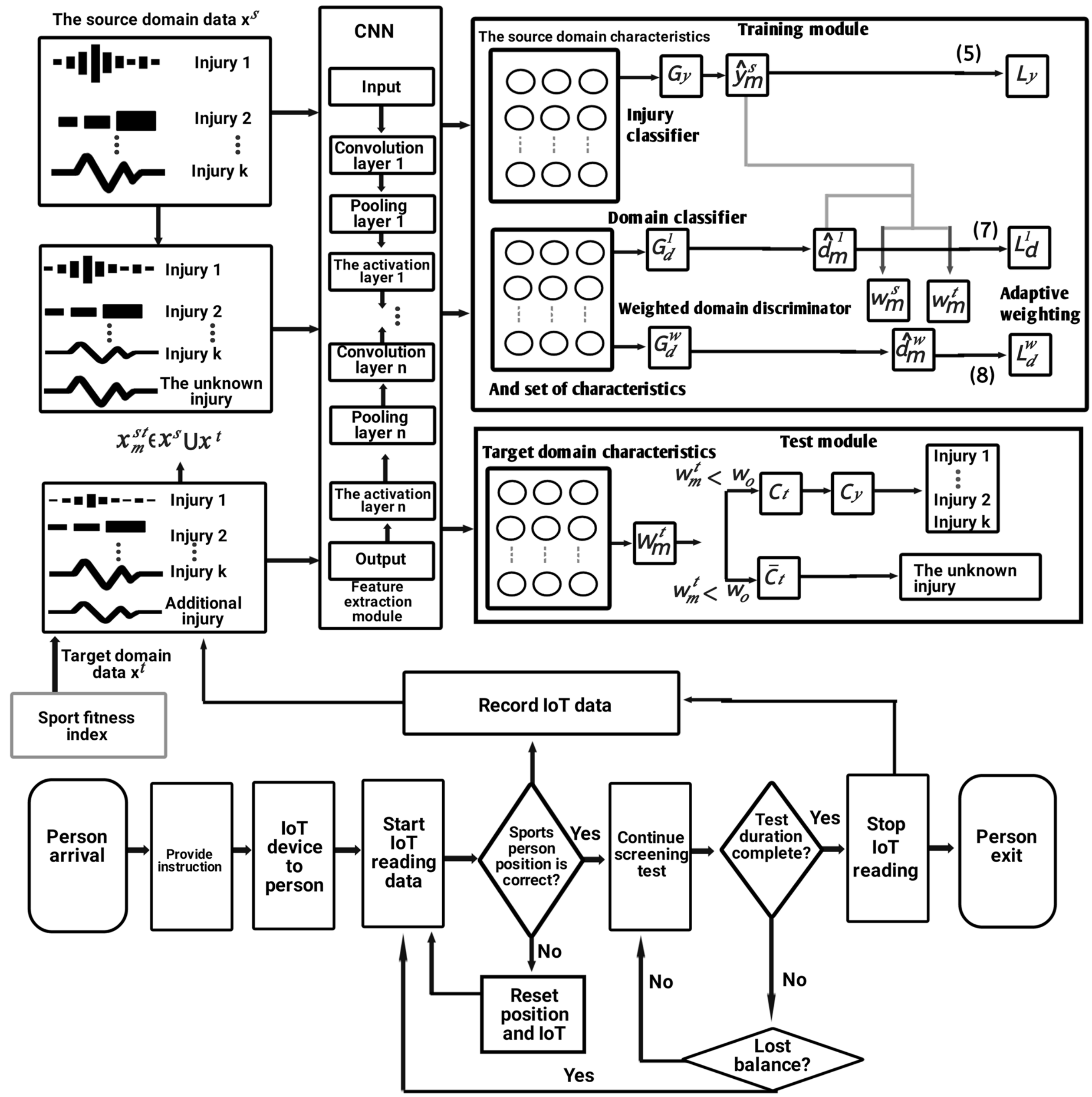


Fig. 2 Sports Injury Prediction Model of the Proposed DLS. Note: G_y: Injury classifier. $G_d^{'}$: Domain classifier. G_d^{w}: Weighted domain discriminator. $\widehat{y}_m^s$: Sample label prediction probability. $\widehat{d}_m^{'}$: Sample domain prediction probability. w_m^s: Source domain sample weight. w_m^t: Target domain sample weight. w_0: Sample weight threshold. C_t: The target domain shares the set. $\overline{C_t}$: Unknown set of target domain. L_y: Injure classification loss function. $L_d^{'}$: Domain classification loss function. L_d^{w}: Weighted domain classification loss function. $\widehat{d}_m^{w}$: Weighted sample domain prediction probabilities

that was recommended via sequential risk assessment as a means of protecting individuals from getting hurt.

Figure 3 presents the results of the risk score analysis performed on the proposed DLS. It includes pre-participation evaluation, injury monitoring, post-season assessment, post-training assessment, and individual participant assessment modules, among others. Using the prior data and other machine learning approaches, a prediction may be made on the probability of future harm. For the suggested model to be able to quantify the effects of injuries, it must assume a post-season evaluation that is made up of the same components as the pre-participation assessment. Assessed weaknesses need to be addressed by tailored off-season training

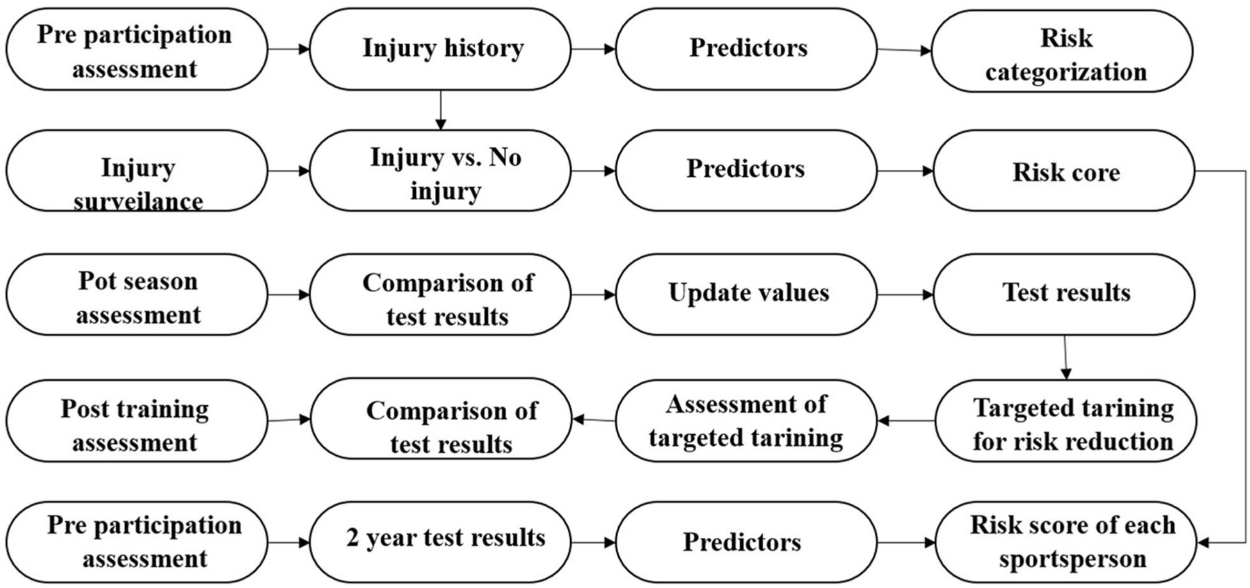


Fig. 3 Risk Score Analysis of the Proposed DLS

programs, enhancing the risk information for a certain athlete population. If the results of diagnostic tests taken during a post-training assessment (PTA) were compared to the results of the risk score, it would be possible to demonstrate that risk prevention education is effective.

The only physical examination that was done for this study focused on the participant's ability to maintain their posture while standing on one foot. However, in order to examine a number of different aspects of an athlete's capability to perform, additional diagnostic tests were used. Previous research has demonstrated that time-tailored posture assessment is an easy and effective technique to evaluate the degree to which weariness is connected with the risk of accidents. The unilateral test is a tool that may be used to examine the ability of an athlete to support one side of their body weight while their legs and ankles are bent at a 90-degree angle and placed on the floor. This position requires the athlete to have both legs and ankles on the floor. The horizontal reclining trunks provide a means by which the persistent impact of the quadriceps, hip extender, and back extender may be evaluated in a bending position of 90 degrees, with the ankles and hips remaining in their normal positions. Only a small percentage of competitors are able to maintain either the horizontal or reclining positions for more than two minutes while they are under pressure.

Binary injury worry classifications are defined in terms of cut-overs produced for these tests. These cut-overs may also serve as beginning training targets for the purpose of increasing performances to the extent that they exceed the cutoffs in order to reclassify as being at a low risk. Basic neurocognitive (brain data processing effectiveness) testing of a sportsman can also be an addition to an accident risk assessment. This is because it has been shown that there is a high risk of musculoskeletal injuries as a consequence of an accident, as well as the danger of additional disruption. For example, the flanking test consists of providing verbal or mouse-clicking responses to a series of brief, directed presentations shown on a laptop screen or to the expressions displayed on the screen when the device is tilted to the right or left. A test like this might potentially be incorporated in the IoT-based data analysis project for the purpose of reducing injuries. The accuracy of a response and the amount of time that elapses between the presentation of the stimulus and its execution are both indicators of efficiency. Aside from its potential value in the future for determining the frequency of severe injuries, it could also be put to use in sporting events or practices to determine the extent to which an effect has influenced the standard capacities of the top players, as indicated by a previous risk clinical diagnosis. This would be in addition to its potential use for determining the frequency of severe injuries.

Real-time sports injury analytics models

The integration of cognitive and behavioral analysis into the monitoring of real-time injury data in sports models is essential. Early in this investigation, the data acquired from survey questions, detectors, and accident records were reviewed. The small size of the prediction algorithm is the most significant disadvantage associated with the findings. Due to the extremely theoretical nature of the hypotheses that are required for estimating the investigation power of injury prediction research, a systematic method in the creation of multifactorial models reduces the number of results events to at least ten. Each event predicts a parameter that corresponds to the number of factors included in the injury forecasting model.

The criteria was violated by the suggested modeling of two different variables (15 injuries). However, for any of its binary risk categories that were included into the modeling, the threshold for the OR that was considered to be 80% confident was not more than 1. The prospective verification of this forecasting model is comprised of the largest possible cohort of athletes who are available to be tested for risk and monitored for future injuries. In the subsequent analysis, participation in the co-variant training program on personal risk reduction will be used to analyze the likely link to baseline findings test variables. These injury prediction models will become more accurate over time when more kinds of diagnostic tests and data collecting for subsequent assessments are carried out. As a result, athletes who stand to benefit the most from preventive care will be better protected as a result.

In the future, research may focus on other types of diagnostic tests that have already been authorized. The tests consist of either a single or even a double squat, and they are designed to evaluate injuries to the lower limbs, as well as test the upper limbs ' ability to stabilize the linked chain. Various tests for monitoring the athlete's outcome measures from numerous resources, including the information from sensing devices used during sport engagement, may be continuously updated now that IoT systems are increasingly prevalent and cost-effective. In the end, data mining technology will enable the rapid transmission of individualized injury concern ratings based on frequently updated criteria. Additionally, this technology will be able to detect any changes in the condition of top players that are the result of new ailments or improved functionality as a result of training.

It is quite possible that the effectiveness of injury prevention measures will see a significant boost if a strategy like this for enhancing a population-specific prediction model with data collection is used. The dataset that was used in this study demonstrates how effective IoT systems are in reducing the risk of injuries. However, there is just a little amount of data that supports the wider perspective effects of the intensity of exercise (frequencies of high-impact congestions). These variables need to be included in the multivariate injury risk assessment as covariations in order to be accurate. It does not provide access to a multi-program dataset that includes coding for a variety of different kinds of exercise or rates of practice. Further research will be a beneficial alternative if multi-program relationships and information exchange can be established.

Diagnosis of athletes' injuries

Aiming at the problem of human injury diagnosis, the concept of shared set and unknown set was introduced [16], and a human injury diagnosis method using deep transfer learning and adaptive weighting was proposed. The method consists of a feature extraction module, a training module and a testing module, as shown in Fig. 3. The feature extraction module uses the deep convolutional neural network to extract human injury features, while the training module uses the transfer learning idea to identify unknown injuries in the target domain through sample adaptive weighting. In the test module, the source domain injury diagnosis knowledge is transferred to the target domain.

Definition of shared set and unknown set

Within the context of the suggested procedure, "C" stands for the shared set, and "C-" for the unknown set. It is reasonable to anticipate that as a result of training, the samples of the shared health state in both the source domain and the target domain will be partitioned into shared sets, whilst the samples of additional harm states in the target domain will be partitioned into unknown sets. In the shared set, the diagnostic information from the source domain may be utilized to determine the state of health of the samples from the target domain. In the unknown set, the samples from the target domain with further injuries are categorized as having unknown lesions.

Feature extraction module

The feature extraction module maps human samples to a high-dimensional feature space. The module consists of a convolutional neural network that takes $\{x_i^{\mathrm{s}}\}_{i=1}^{n_{\mathrm{s}}}$ as input to the union of source $\left\{x_m^{\mathrm{st}}\right\}_{m=1}^{n_{\mathrm{st}}}$ and target domain data. $\{x_j^{\mathrm{t}}\}_{j=1}^{n}$ The feature extraction module is expressed as G_f, then the deep abstract feature of the union is $x_{\mathrm{f},m}^{\mathrm{st}}$

$$x_{\mathrm{f}m}^{\mathrm{s}} = G_{\mathrm{f}}\left(x_m^{\mathrm{s}}\right) \tag{5}$$

In the formula, when the *mth* input sample is the source domain data, the union feature $x_{\mathrm{f},m}^{\mathrm{st}}$ can be expressed as $x_{\mathrm{f},m}^{\mathrm{s}}$.

Training module

The training module primarily makes use of the extracted high-dimensional injury features to train the injury classifier with the capability of distinguishing the health status, and to train the domain classifier with the capability of distinguishing the domain characteristics. After that, a weighted domain discriminator is developed in order to discover unknown injury samples inside the target domain. Among them, the injury classifier is denoted as G_y, the domain classifier is denoted as $G_d^{'}$, and the weighted domain discriminator is denoted as G_d^w.

Injury classifier

The injury classifier G_y takes the source domain features $x_{f,m}^s$ as input, and uses the supervised learning method to realize the classification of human body injuries. Let the injury classifier be expressed as G_y, and its structure design can be found in [34]. The probability prediction matrix corresponding to the source domain features is:

$$\widehat{y}_m^s = G_y x_{fm}^s \tag{6}$$

According to Eq. (6), combined with the real fault labels of the source domain features, the loss function of the injury classifier can be expressed as:

$$L_y = \frac{1}{n_s} m = 1nsL\left(\widehat{y}_m^s, y_m^s\right) \tag{7}$$

L is the cross entropy loss function; y_m^s represents the real injure label of the mth sample.

Domain classifier

The domain classifier $G_d^{'}$ aims to measure the domain information of human data samples, discriminate whether it belongs to the source domain or the target domain, and complete the training through domain confrontation. The classifier takes the union feature $x_{f,m}^s$ as input and obtains the predicted probability of the sample field:

$$\widehat{d}_m^{'} = G_d^{'}\left(x_{fm}^s\right) \tag{8}$$

According to the above domain information, the loss function of the domain classifier is expressed as:

$$L_d^{'} = \frac{1}{n_{st}} \sum\nolimits_{m=1}^{n_{st}} L\left(\widehat{d}_m^{'}, d_m\right) \tag{9}$$

In the formula, d_m represents the real domain label of the mth feature. When it is 0, it represents the target domain, and when it is 1, it represents the source domain.

Weighted domain discriminator

A feasible idea for identifying unknown injury samples in the human target domain is based on the adversarial training of traditional domain discriminators [40]. During the training process, the samples are adaptively weighted, and the difference between the target domain shared set and the source domain is increases. Domain similarity suppresses the similarity between the unknown set of the target domain and the source domain. It also controls the degree of domain similarity measured by the sample weight. Then, by setting the weight threshold, the shared set samples and the unknown set samples in the source domain and the target domain are distinguished. Therefore, referring to [40], a weighted domain discriminator is designed with a loss function as follows:

$$L_d^w = \frac{1}{n_{st}} \sum\nolimits_{m=1}^{n_{st}} L\left(\widehat{d}_m^w, d_m\right) = \frac{1}{n_s} \sum_{m=1}^{n_s} \omega_m^s 1b\left(G_d^w\left(x_{f,m}^s\right)\right) + \frac{1}{n_t} \sum_{m=1}^{n_t} \omega_m^t 1b(G_d^w(x_{f,m}^t)) \tag{10}$$

G_d^w represents the weighted domain discriminator. Its network structure is the same as that of the domain classifier, and the output is $\widehat{d}_m^w$; $x_{f,m}^t$ is the feature of the target domain sample; n_s represents the total number of source domain samples; n_t represents the total number of target domain samples; ω_m^s represents the source domain sample weight; ω_m^t represents the target domain sample weights.

The domain sample weight in Eq. (10) is the key to effectively identify unknown injury samples in the target domain, and it can measure the similarity of the input sample and the source domain data distribution. The source domain samples are the most comparable to the source domain data distribution. The target domain shared set and the source domain have the same health status samples, and their distributions are relatively similar. Therefore, there should be a logical relationship between the source domain sample weight ω_m^s, the target domain shared set sample weight $\omega_m^{c_t}$, and the unknown set sample weight.$\omega_m^{\overline{C_t}}$

$$\omega_m^s > \omega_m^{c_t} > \omega_m^{\overline{C_t}} \tag{11}$$

The superscript s represents the source domain; C_t represents the target domain shared set; $\overline{C_t}$ represents the target domain unknown set.

It is clear that if the injury prediction information entropy of the injury classifier and the domain prediction probability of the domain classifier in the training process can be used to calculate the sample weight, and if the logical relationship of the sample weight in Eq. (11) can be adaptively matched, then it is possible to control the degree to which the samples share a domain with the target domain. It would also be possible to identify the unknown set of samples in the target domain. This can be seen by looking at the following:

(1) The entropy of the injury prediction information: The degree of accuracy with which the injury classifier can detect injury samples may be evaluated with the help of the information entropy. If the injury prediction information entropy is lower, then it implies that the injury label of this sample can be determined more easily. If it is higher, it indicates that the injury label can be determined less easily. The entropy of the information may be computed as:

$$H\left(\widehat{y}_m\right) = -\sum \widehat{y}_m 1b\widehat{y}_m \tag{12}$$

where is $\widehat{y}_m$ the prediction result of the injure classifier on the sample.x_m

Since the injury classifier is trained on the data from the source domain, the label of the source domain sample is the easiest to determine, and its information entropy is the smallest. The target domain shared set sample has the same health status as the source domain, its label is easier to determine, and its information entropy is the smallest. Finally, since the source domain sample is used to train the injure classifier, the information entropy of the target domain sample is the smallest. The information entropy is low, and the unknown set of the target domain has the highest information entropy. This is because the unknown set of the target domain does not have the same health condition as the source domain. Therefore, the relationship between the injury prediction information entropy and the $H\left(\widehat{y}_m^{C_t}\right)$ sum of the $H\left(\widehat{y}_m^{\overline{C_t}}\right)$ source domain samples, the target domain shared set samples and the target domain unknown set samples are:$H\left(\widehat{y}_m^s\right)$

$$H\left(\widehat{y}_m^s\right) < H\left(\widehat{y}_m^{C_t}\right) < H\left(\widehat{y}_m^{\overline{C_t}}\right) \tag{13}$$

(2) Field prediction probability: This probability is the output value of the domain classifier, which measures the probability that the sample belongs to the source domain. The relationship between the domain prediction probability of the source domain sample, the target domain shared set sample and the unknown set sample $\widehat{d}'(x_m^s)$, $\widehat{d}'(x_m^{C_t})$ and. $\widehat{d}'(x_m^{\overline{C_t}})$ is:

$$\widehat{d}'(x_m^s) > \widehat{d}'(x_m^{C_t}) > \widehat{d}'(x_m^{\overline{C_t}}) \tag{14}$$

(3) Weight calculation method: According to the injury prediction information entropy and the domain attribute prediction probability, the sample weight calculation formula can be obtained by:

$$w_m = W(x_m) = \widehat{d}'(x_m) - \frac{H\left(\widehat{y}_m\right)}{T} \tag{15}$$

T represents the number of samples in each training, so that the sample injury prediction information entropy is normalized to between 0 and 1 to ensure that it is on the same scale as the domain prediction probability value. From Eqs. (13) and (14), it can be seen that the weights calculated by Eq. (15) have a relationship.

$$Wx_m^s > Wx_m^{C_t} > W\left(x_m^{\overline{C_t}}\right) \tag{16}$$

The weight relationship obtained by Eq. (16) matches the weight logic relationship designed by Eq. (9), so a reasonable threshold can be set to distinguish the shared set and the unknown set of the target domain.

Test module

In the test module, the target domain unknown set is identified by setting a reasonable threshold. The interference of unknown samples is eliminated, and the injury classifier obtained by training the source domain data is used to identify the target domain shared set human samples. The formula is:

$$\widehat{y}_m = \begin{cases} G_y\left(x_{f,m}^t\right), if\, \omega_m^t > \omega_0, then, x_{f,m}^t \in C_t \\ UnknownInjury, if\, \omega_m^t < \omega_0, then x_{f,m}^t \in \overline{C_t} \end{cases} \tag{17}$$

where is ω_0 the threshold to distinguish the shared set and the unknown set of the target domain.

Objective function of the injury diagnosis method

By synthesizing the loss functions of the human injury classifier, the domain classifier, and the weighted domain discriminator, the optimization objective of the diagnosis method is obtained

$$\min\left(L_y + L_d^{'}\right);\, \max L_d^w \tag{18}$$

After acquiring the monitoring data in the human source domain and target domain, the normalization method is used to preprocess the data first. The Adam method is then used to optimize Eq. (18) to complete the training of the human injury diagnosis method.

Clustering algorithm for risk analysis

Convolutional neural networks correlate to the three primary layers of large datasets, defined in detail in the following subsections.

Convolutional layer

Neural networking, for all intents and purposes, maintains a certain screen resolution and serves as the other component in the convolutional layers throughout the conversion. For example, the first layer inversion of a conventional convolutional network typically consists of a convolutional layer with a dimension of $5 \times 5x4$. When calculating a forward propagating layer, the layer must do regular two-dimensional calculation on the information that it receives as input. During this part of the calibration process, you will need to compute the product that consists of the point in the center of the convoluted core and the relevant input data component.

After going through a few different conversion procedures, the amount of information that is outputted will be cut down. The dimensions of the extracted characteristics and the contents of the source data are both very challenging at this point, although the size of the data item itself has been reduced.

Figure 4 presents the results of the injury prediction study performed on the proposed DLS. When doing the pre-participation testing, the prior injury records are consulted, and when conducting the injury prediction analysis, preseason practice and practice session games are utilized as data sources. The injury risk assessment that has been projected is shown on the coach's monitor. In the current neural network learning method, it is necessary to review and acquire new knowledge about the variables that are located in the convolutional core of the convolutional diagram. Convolutional layers are defined by their weight pooling and their local connection; the two most important characteristics. When doing the actual calculation for the convolution, you will need to provide a certain scaling factor variable at the same time.

If the step size is 1, the associated core will move by only one pixel. However, if the step size is 2 or more than 3, the associated core will move by more than one pixel. The corresponding slip doesn't travel more than 2 pixels. When taking into consideration the data analytics of athletic healthcare as an example, the information on the convolutional layers of information processing is as follows: assuming that the provided text amount meets Eq. (19) of the massive data of healthcare. The matrix of active coefficients is denoted by the associated y n.

$$Y = \{y_1, y_2, \cdots, y_n\} \tag{19}$$

The predicted active coefficient element is denoted as y_n. The outcome of the convolution of each data in the matching score is shown. The combination K matrix for the equivalent K_n may be represented in Eq. (20) if the correlating convolution core is n and the accompanying window region is A_n.

$$K_n^i = ty_n + \exp(-1) - A_n \tag{20}$$

The associated $\exp(-1)$ is a divergence, and the vector of connections between the weight level and the convolution level for t is $\exp(-1)$. The predicted active coefficient element is depicted as y_n. The current game timing is denoted as t.

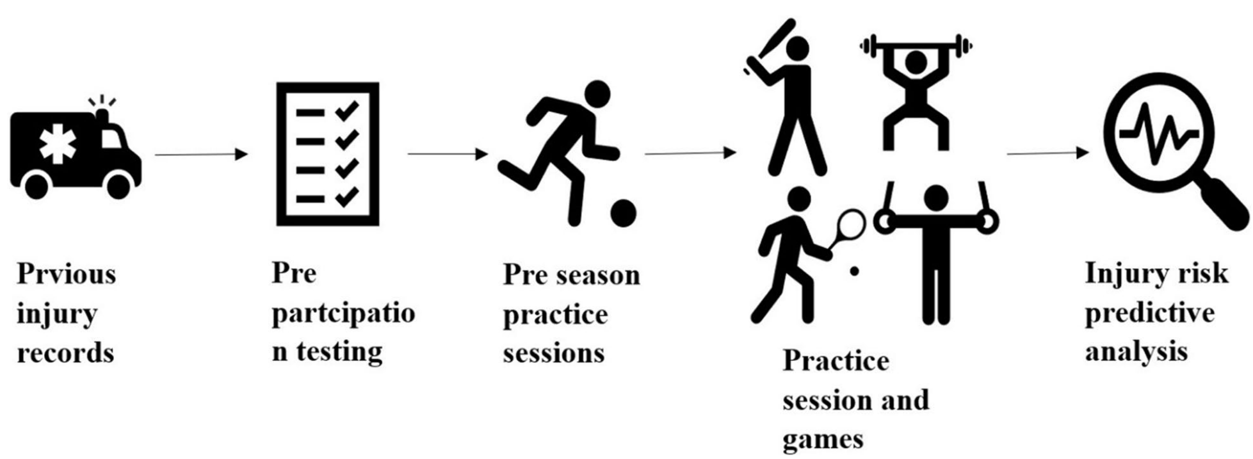


Fig. 4 Injury Prediction Analysis of the Proposed DLS

Pooling layer

The pooling layer primarily includes the K_n vector combination from the convolutional layers in which Eq. (21) can represent the highest value of n elements in the K_n matrix:

$$K_n^i = \tanh\left(\frac{K_n^i}{K_n}\right) \tag{21}$$

The highest element in the matrix is denoted as K_n. The current element in the pooling layer is denoted K_n^i. The working of the convolutional layers is separated into convolution layers and a related pooling layer. In the analysis of massive sports medical information, the maximum pooling procedure is typically employed. The major problem is that data in vast amounts of sports therapy is not precisely the same, but the relevant data is multifunctional and complicated.

Knowledge layer

The knowledge layer is an essential structural layer beneath the convolutional layers, corresponding to the convolution layers' outputs, and is interconnected to the neurotransmitters between the two adjacent layers. Equation (22) shows the respective data processing function:

$$K_n^i = TP + \exp(-4) \tag{22}$$

where the k_n is the pooling layer's production matrix, the K of the associated vector shows the output values of the whole connection layer and the p and t equivalent to the relevant divergence.

Output layer

The output layer depends mainly on the soft optimum rating output to be classified. It has to choose the appropriate classifier model while categorizing. Two standard categorization algorithms are available to correlate to the linear regression in Eq. (23) and the transfer function in Eq. (24):

$$f(t) = \frac{\exp(t) - \exp(-t)}{\exp(t) + \exp(-t)} \tag{23}$$

$$f(t) = \frac{1}{1 - \exp(-t)} \tag{24}$$

The $exp(t) and exp(-t)$ matching in the equation are the computed variables for the present time and the last time. In this way, the injury score of the athlete can be predicted.

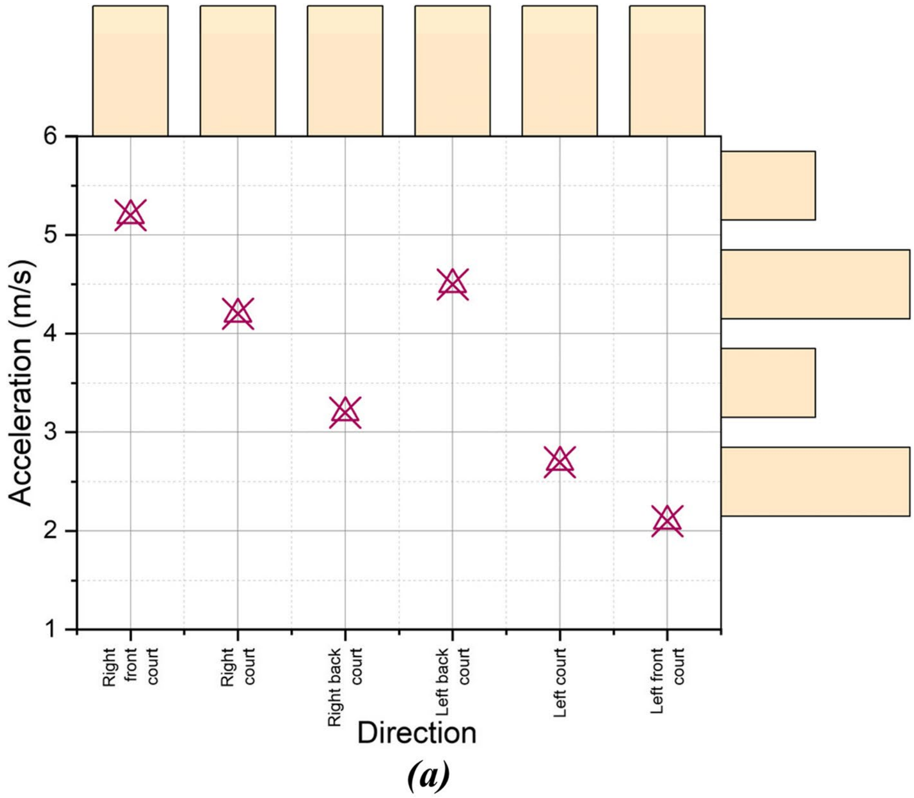
Software analysis and performance evaluation

The database comprises of a list of injuries that have been reported and recorded in accordance with the guidelines. Overall, there were 152 instances, and 10 parameters. It is important to keep in mind that the database's parameter injuries may not represent a final diagnosis but rather a first general evaluation, such as strained muscles or bone injury. As a consequence of this, there was a total of 230 columns and 7 parameters in the model. The variables of the age of the information source for the supplied dataset were classified, and the date parameter was left out of consideration. The days for which access was denied were excluded. For the purpose of the simulation analysis, the simulation characteristics such as accuracy, precision, recall, and F1-score are taken into consideration.

The acceleration analysis of the actual data was represented in Fig. 5(a), and the suggested DLS was depicted in Fig. 5(b). When conducting this study using front- and backcourt models, the researchers took into account the various left and right locations on the court. The provided dataset is used to conduct an analysis of the player's movement and acceleration in a variety of directions. The actual and calculated acceleration of the player in a variety of places on the court, including the front, rear, left, and right positions, is studied and plotted in the figures above. The findings demonstrate that the suggested DLS is accurate across all of the available functional categories.

The acceleration analysis of the proposed DLS is shown in Fig. 6. For the purpose of the simulation study, the various directions in which players may go, such as to the right, the left, the front, or the backcourt level, are evaluated. The physical analyzed acceleration that was measured by the physical meter is studied, and the suggested DLS acceleration that was recorded and tabulated in the above table is compared to the physical analyzed acceleration that was detected by the physical meter. According to the results of the calculations, the suggested DLS has the maximum level of both efficiency and accuracy when it comes to analyzing the motions of the athlete.

The performance analysis of the measured injuries sustained by the athletes is shown in Table 1, and the anticipated injury analysis of the suggested DLS is presented in Table 2. Both analyses may be found in the same document. The injuries sustained by the athletes are tracked for a period of one year, and then the machine learning model is used to assess the projected injuries sustained by the athletes. The results are shown in the table located above. According to the findings, the suggested DLS has the greatest accuracy across the board when it comes to



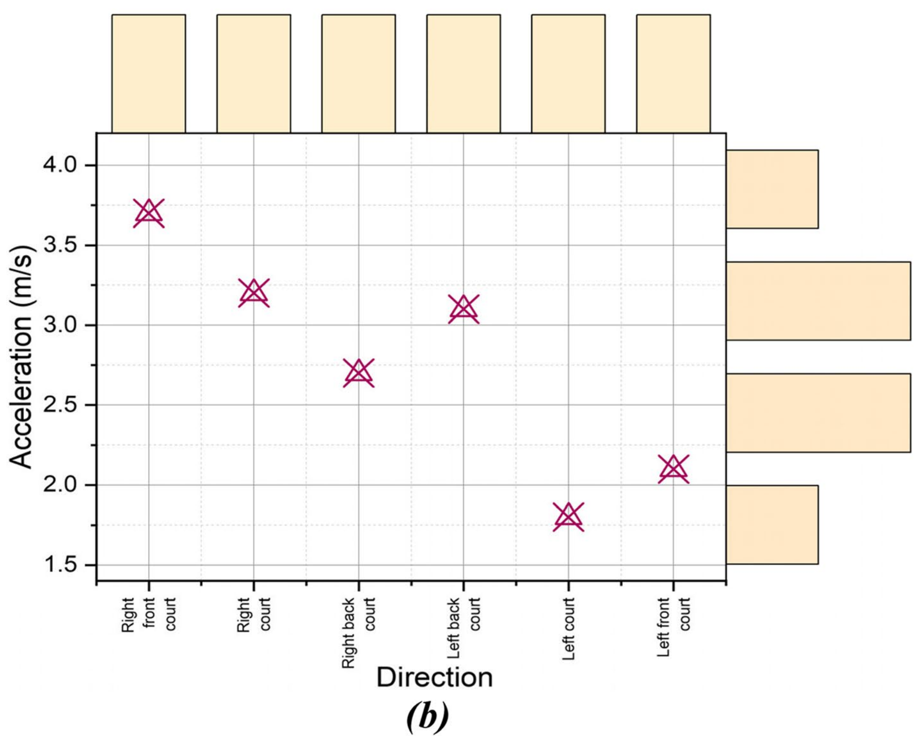


Fig. 5 **a** Acceleration Analysis of the Actual Data. **b** Acceleration Analysis of the Proposed DLS

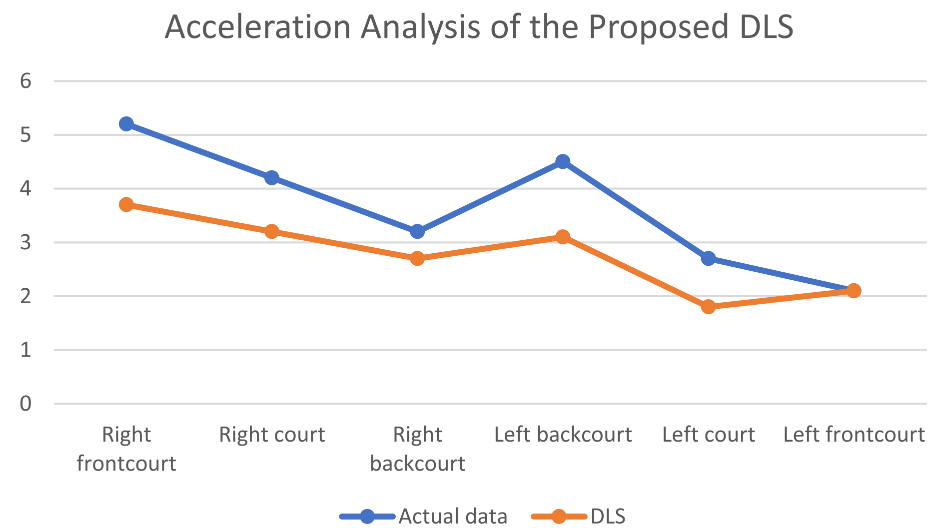


Fig. 6 Acceleration Analysis of the Proposed DLS

Table 1 Performance analysis of the measured injury

Time (month)	1	2	3	4	5	6	7	8	9	10	11	12
Performance (%)	14.9	24.3	32.6	16.5	22.8	38.3	15.0	24.5	28.5	26.7	23.8	17.2

Table 2 Performance analysis of the predicted injury of the proposed DLS

Time (month)	1	2	3	4	5	6	7	8	9	10	11	12
Performance (%)	12.1	24.9	34.2	18.7	24.1	32.6	16.3	25.0	29.9	26.9	22.3	16.2

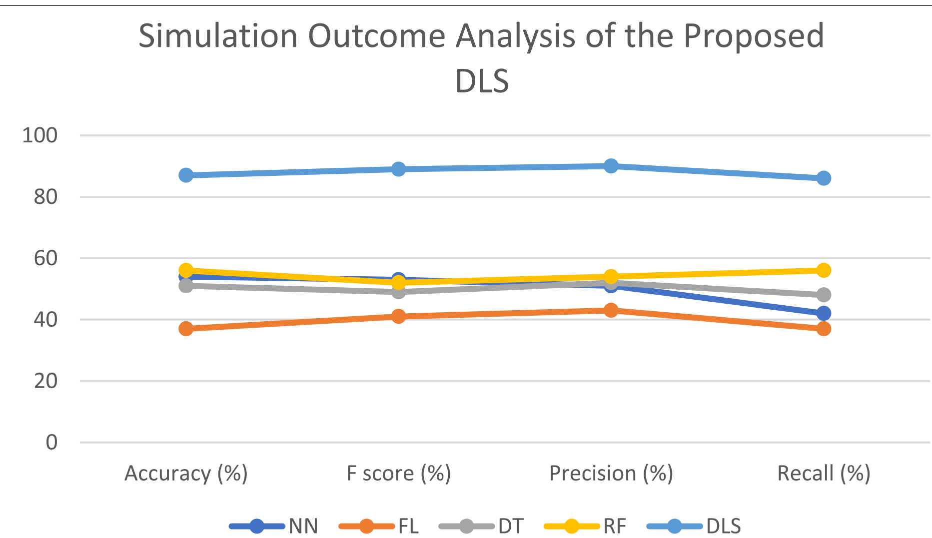


Fig. 7 Simulation Outcome Analysis of the Proposed DLS

forecasting whether or not the athletes would sustain an injury. The likelihood of suffering an injury is thought to be at its highest during the summer months and its lowest during the fall months.

In Fig. 7, you can see an examination of the simulation results obtained by the suggested DLS. The results of the proposed DLS's simulations, including precision, F1-score, accuracy, and recall, are studied and compared with the results of other models, including neural networks (NN), fuzzy logic (FL), decision trees (DT), and random forests (RF). Based on the findings, it appears that the suggested DLS is more effective than the models that are already in use. The results are improved by using the suggested DLS in conjunction with the machine learning model. The proposed DLS demonstrates improved accuracy in predicting the injury.

Figures 8(a) and 8(b), provide an illustration of the suggested DLS's accuracy and F score analysis, respectively. The results of the software, such as accuracy and the F1-score, generated by the proposed DLS are studied and compared to the results generated by previously developed models, such as NN, FL, DT, and RT. The findings of both the existing DLS and the planned DLS are shown in the figures above. The findings demonstrate that the

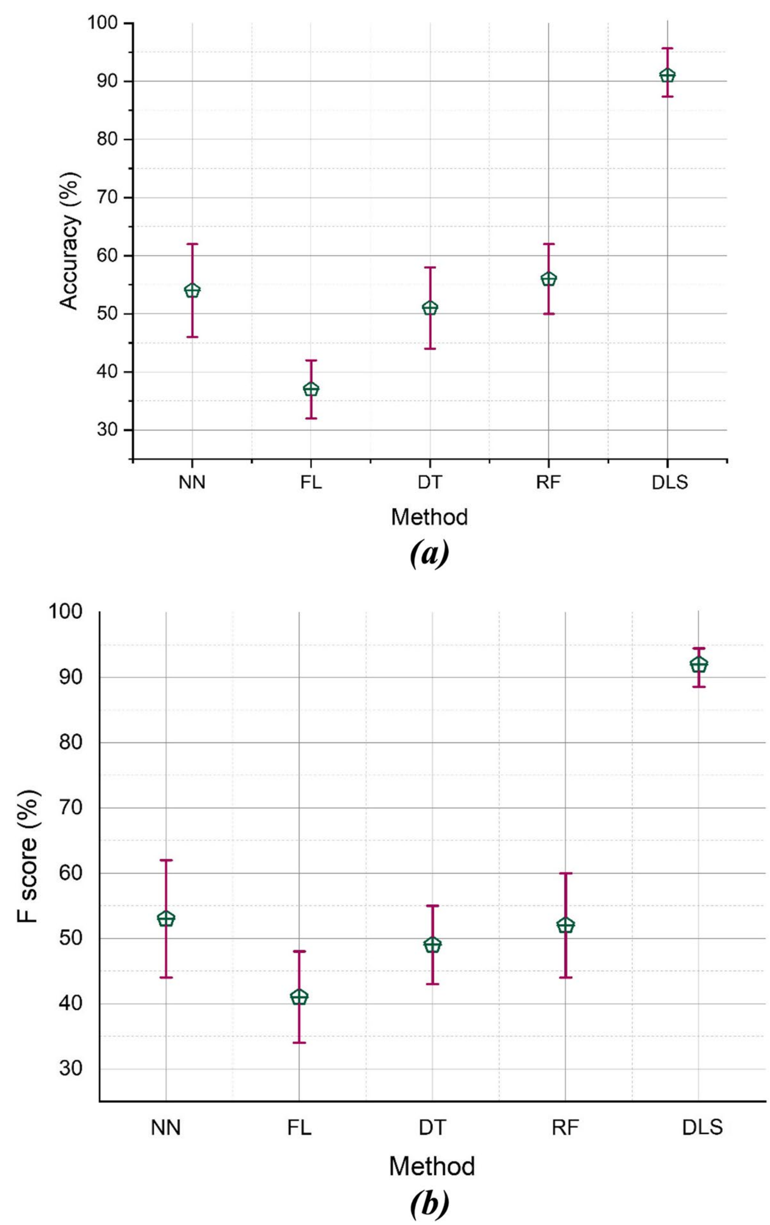


Fig. 8 **a** Accuracy Analysis of the Proposed DLS. **b** F1-Score Analysis of the Proposed DLS

suggested DLS achieves the maximum performance. In comparison to the other models, the accuracy of injury prediction by the proposed DLS, which utilizes a model based on machine learning, is much greater.

In this part, the suggested DLS is given its design and implementation. The results of the simulations, including parameters like precision, accuracy, F1-score, and recall of the proposed DLS, are examined and compared with existing models. The findings provide evidence of the efficiency of the DLS model that was developed.

Conclusion

In this article, a Deep Learning-assisted System (DLS) is presented for the purpose of injury prediction among athletes. The methodologies that were used in this investigation resulted in the production of data that has implications for the growth of athletes ' safety and well-being, as well as potential relevance for other groups. For instance, the strategy that has been suggested may be used to address the alarmingly high rate of musculoskeletal injuries that occur throughout numerous sports. Analyzing the various data acquired via the use of wearable Internet of Things devices and processed through a cloud platform, makes it possible to quickly identify athletes who have a higher risk of being injured. The authors have demonstrated how a binary risk classification model can be applied to the prevention of injuries based on gaming experience, the self-reported persistent effects of a previous injury, and the practical evaluation of single-leg postural stabilization using a range of injury risks. This model was developed to help gamers avoid injuries. The suggested model's performance is analyzed using several metrics, such as accuracy, precision, recall, and F1-score, and is then compared to the performance of current models. The performance of the suggested model is much better than that of the existing models. In the future, we shall consider an AI solution for the challenges of data collection, contractility of AI by the practitioners and explanation of AI real-time results.

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Conceptualization by Jincheng Zhou and Xiaoe Wu; Methodology by Maoxing Zheng; Software by Shanwei Chen and Jincheng Zhou; formal analysis by Dan Wang and Joseph Henry Anajemba. Investigation by Xiaoe Wu; Resources and data collection by Jincheng Zhou; Writing by: Maoxing Zheng; Validation by: Joseph Henry Anajemba and Jincheng Zhou; Funding Acquisition by Dan Wang. The author(s) read and approved the final manuscript.

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Declarations

Ethics approval and consent to participate
The research has consent for Ethical Approval and Consent to participate.

Consent for publication
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Competing interests
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