Prediction and Management of Physical Injuries Caused by Gym Equipment and Facilities Using a Support Vector Machine (SVM) Algorithm

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Abstract

Purpose: This study aimed to predict and manage physical injuries caused by gym equipment and facilities using the SVM algorithm.
Method: This study was of a developmental-applied type. The snowball method was used to select the subjects. Subjects were asked to answer the questionnaire online and send it to friends and acquaintances of athletes. The validity of the instrument was confirmed through the opinions of university professors and convergent validity. Cronbach's alpha was used to check reliability. The sample questionnaire included 612 athletes in the age group of 18 to 60 years. 158 people were healthy, 54 people had head injuries, 211 people had leg injuries, and 189 people had hand injuries. The SVM algorithm was used to classify people. In addition, MATLAB software version 2022 was used for data analysis. The evaluation was conducted based on the clutter matrix and accuracy criteria.
Results: The results showed that the SVM algorithm can predict head, arm and leg injuries with 74.6% accuracy and 73.2% accuracy, respectively.
Conclusion: This study showed that by discovering hidden patterns and relationships in the data, this algorithm can probably be used correctly to improve the quality of sports facilities management to prevent physical injuries of athletes.
Keywords: Sports Facilities, Prediction, SVM, Physical Injury.

Introduction

Supervising the performance of sports is a fundamental issue in the management of sports venues and teams (Chelladurai, 2014). One of the important duties of the board of directors is to maintain the health of sports teams and reduce the risk of injury (Organization, 2022). Machine learning is the scientific study of mathematics and statistical models and enables computers to use data to learn automatically and make better decisions (Nozari & Sadeghi, 2021). Machine learning has been used in many areas of science: healthcare and financial industries such as image recognition and cancer diagnosis; stock market forecasting and customer turnover prediction (Faritha Banu et al., 2022). In some fields, such as sports, the effective use of machine learning is in its early stages. Technological advances in data collection and storage are increasingly advancing in sports science (Chmait & Westerbeek, 2021). The method of multi-camera filming and tracking systems and electronic performance in addition to wearable sensors and the use of questionnaires have allowed doctors, managers of sports teams, and coaches to collect more accurate physical and technical data from sports equipment and venues (Rault, Bouabdallah, Challal, & Marin, 2017).

These data can be used to predict and manage injury factors in gyms, but increasingly they are being used to better understand the cause of injuries (Rossi et al., 2018). Sports injuries are very common in various sports among elite and recreational athletes, affecting health and performance and may even cause life-long problems (Bullock, Collins, Peirce, Arden, & Filbay, 2020). Sports injuries can lead to pain, loss of play or work time as well as reduced mobility, and prolonged absence from matches with associated effects on team performance and financial consequences (Leventer, Eek, Hofstetter, & Lames, 2016). In particular, gym facilities, sports equipment, such as shoes and gym flooring and the distance from the floor to the wall might lead to loss of manpower, increased costs due to medical treatments and extensive rehabilitation as well as poor quality of life (Harifi & Montazer, 2017). Several factors are associated with the development of injuries during sports training or competition. The use of machine learning to predict sports injuries has also been highlighted by recent reviews (Rossi, Pappalardo, & Cintia, 2021; Van Eetvelde, Mendonça, Ley, Seil, & Tischer, 2021).

For specific sports applications, SVMs have been trained using modifiable metrics such as training load, performance techniques, psychological and neuromuscular assessments, and immutable metrics such as anthropometric measurements, previous injury history, and genetic markers to accurately predict future injuries (Rodas et al., 2019; Van Eetvelde et al., 2021). Identifying injury risk factors such as these allows coaches and medical personnel to modify training loads, regimens, and techniques to prevent future injuries (Dijksma, Sharma, & Gabbett, 2021). For instance, the 2018 paper by Rudy et al. used several ML algorithms, including SVM, to evaluate identified risk factors in hamstring compression injuries (Ruddy et al., 2018). In another 2018 paper by Carey et al., also on the prediction of hamstring injury and risk factors, SVM significantly benefited from data preprocessing, although it ultimately outperformed simple logistic regression (Carey et al., 2018). Using non-physiological data, a 2017 paper predicting in-game injuries in Premier League soccer found SVMs to be the most accurate of the algorithms tested including logistic regression, multilayer perceptron, and random forest (Landset, Bergeron, & Khoshgoftaar, 2017). However, in recent literature, including two 2021 papers comparing the performance of ML algorithms, SVMs have been found to be less effective than other algorithms (Meng & Qiao, 2023; Shen, 2021). Despite this, SVMs might still be valuable given their suitability for predicting high-dimensional datasets, particularly when combined with other techniques as shown in the 2022 paper by Wang et al. (Wang & Lyu, 2022).

In most studies, data were analyzed using traditional statistical methods, such as Pearson correlation coefficients, multiple regression, and general linear models with partial correlation coefficients. A recent systematic review showed that several factors, including biological and anthropometric characteristics (older age, gender), history of previous injuries, longer training periods, limited experience in the sport, lack of coaching, supervision and extensive participation in competitions increase the risk of injury. Yang et al. (2022) in their study entitled *Prevention of sports injuries in the process of physical fitness exercises* divided the factors of sports injuries of athletes into 4 first-order causes (human, material, managerial and social) and 8 second-order causes (coach, athletes, venue facilities, sports environment, human management and management physical, national, local, and family), and 23 third-level causes (i awareness of coaches' safety training, ability to teach, and athlete's physical condition) (Yang, Cheng, & Su, 2022) by using the fading model analysis algorithm. Majumdar et al. (Majumdar, Bakirov, Hodges, Scott, & Rees, 2022) investigated non-contact injuries using decision trees as a machine learning algorithm. The authors used 954 data records (each data record contained information on the daily training load of the players) from 80 training sessions and 18 variables to predict sports injuries.

Lövdal et al. (2021) (Lövdal, Den Hartigh, & Azzopardi, 2021) investigated non-contact soccer injuries from what they called high-intensity training. Using 65 variables and the SVM algorithm, the authors reported an accuracy score of 83.5%. Lopez Valenciano and his colleagues (2018) (López-Valenciano et al., 2018) used 52 important variables in their questionnaire to predict injury and considered the three key variables of lower limb muscle injury history in the last season, maximum knee flexor torque and reduced sports motivation as effective factors in predicting sports injuries. Ayala and colleagues (2019) reported 66 variables that were important for predicting sports injury (including history of hamstring strain injury in the previous season, sleep quality, decreased sense of accomplishment, and passive hip flexion range with knee) (Ayala et al., 2019).

According to the above studies, it is necessary to collect greater data on skeletal injuries caused by equipment and the condition of sports facilities in order to better understand their origin and etiology, and to identify risk factors and preventive measures related to injuries. They are also needed to increase the level of safety and better serve the active athlete population participating in indoor sports and facilitate the development of injury prevention strategies. The use of multivariate statistical methods and machine learning (despite their obvious utility for understanding complex, multidimensional problems) has been largely neglected (Araújo, Couceiro, Seifert, Sarmento, & Davids, 2021). Few studies have used machine learning techniques to understand and predict injuries caused by the equipment and condition of sports venues, and so the main goal of the present research was to predict and manage injuries in sports venues using the SVM algorithm.

Materials and Methods

This developmental-applied study was a survey-based descriptive epidemiological study designed to collect data on physical injuries caused by factors related to sports venues in Iran. This study used an electronic, anonymous and self-made questionnaire that had 58 factors of injury, which were modified according to the opinion of university professors and with the help of scientific articles in the field of predicting indicators of sports injuries. 15

factors were determined as the main factors of physical injury. They were selected based on the facilities and conditions of sports halls. The questionnaire consisted of three sections. The first part included items related to general demographic information (gender, age, height, and weight). The second part comprised of specific questions on sports and training conditions (including shoe size, sports, professional and amateur athletes, and quality of shoe material). The final part, focused on the occurrence of damage due to factors related to sports hall facilities (lighting, sports equipment, cleanliness and hygiene, ventilation, flooring quality, and distance between the wall and the playing field). Its validity was checked by experts in the related field. Experts were asked to review the questionnaires and provide feedback. Based on the feedback received from the experts, several changes were made to the questionnaire. Considering that Cronbach's alpha is a method to measure reliability by comparing the amount of common variance or covariance among the items that constitute the tool with the amount of overall variance, the reliability of the questionnaire was checked with Cronbach's alpha. The Cronbach value of the questionnaire was 0.86, which indicates a high reliability value (Sharma, 2016).

The following simple formula was used to calculate the adequate sample size in the present epidemiological study:

$$\mathrm{n} = \frac{1.96^2}{\delta^2} p(1-p)$$

Where n represents the sample size, p is the estimated prevalence and δ is the margin of error. The minimum sample required to conduct this study was 512 people and the exclusion criteria for selecting the participants were: (1) they had trained independently outside the gym or outside of Iran; (2) they had trained alone or in an unauthorized gym; 3) they had incurred an injury in the hall due to non-sports performance; (4) they were under 18 years of age; (5) they were affected by chronic osteoporosis diseases; and (6) they did not complete the questionnaires.

The statistical population of this study consisted of 1052 athletes who participated in the online call (whats app, Instagram, Telegram,) by completing the questionnaire. The sample included 612 athletes aged 18 to 60 years (221 (36%) women and 391 (64%) men (see Table 1)). In this research, the task of predicting injury was considered as a two-class classification problem. The participants in this study were divided into two groups: (1): healthy participants (not injured during exercise) and (2) athletes who reported being injured while exercising in the gym.

To perform efficient data mining, in addition to the need for appropriate data, appropriate data mining methods and algorithms should also be used. SVM data mining algorithm is a supervised machine learning algorithm that can be used for both classification and regression problems. However, this algorithm is mostly used in classification problems. For the optimal use of data, they should be altered in a way that is suitable for data mining algorithms (Osisanwo et al., 2017). The numbers zero and one were used for the questions that had answers with qualitative measurement criteria. In the SVM algorithm, each data sample was drawn as a point in the n-dimensional space on the data scatter plot (n is the number of features that a data sample has) and the value of each data feature specified one of the coordinate components of the point on the plot. Finally, by drawing a straight line, different and distinct data were grouped. SVM can solve non-linear classification problems easily (Fasihi, Tartibian, & Eslami, 2022). This method can be very useful in cases where two classes of the same data cannot be separated with straight lines (Figure 1).

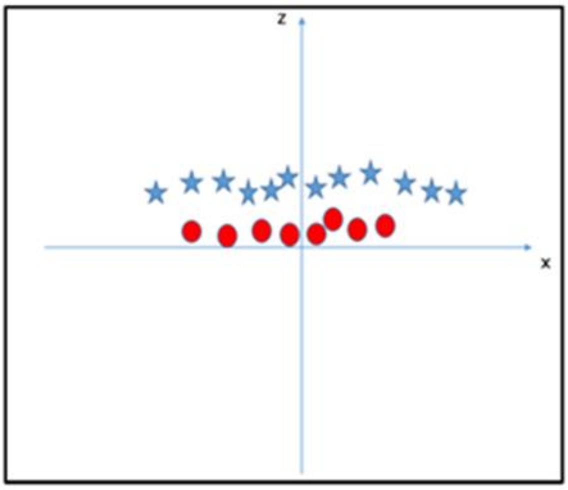

Figure 1. Classification method of the SVM algorithm.

Table 1 shows the accuracy and precision criteria based on the data evaluation method in which accuracy is equivalent to "how much of the selected samples are correct" and "how much of the correct samples are correctly selected".

Table1. Data evaluation method.

		Correct values	
		positive	negative
Predicted values	Positive	True positive (TP)	False positive (FP)
	negative	False Negative (FN)	True Negative (TN)

Algorithm performance was evaluated based on accuracy and correctness. The accuracy of the algorithm shows its value in prediction, which is obtained from the number of correct predictions divided by the total number of predictions (relationship 1). The accuracy of the algorithm shows its ability to separate sick and healthy people from each other and is obtained by dividing the number of predictions by the number of predictions in each row (relationship 2) (Fasihi, Tartibian, Eslami, & Fasihi, 2022).

1) $$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN}$$

2) $$\text{Precision}= \frac{TP}{TP+FP}$$

The data set was transferred to MATLAB version 2022 in Excel format and analyzed.

Results

The variables identified based on the results of scientific articles and surveys of orthopedic specialists, indoor sports team doctors, coaches, and gym managers are shown in Tables 2 and 3. The variables of hall light, sports hall equipment, hall cleanliness and hygiene, ventilation, shoe size, hall floor quality, distance from the wall to the playing field, sports field, and whether they were a professional and amateur athlete and the shoe material quality worn were considered qualitative and discrete, while the variables of age, height, weight, body mass index were considered quantitative and continuous.

Table 1. Quantitative variables of subjects.

indicators	Mean ± standard deviation
Age (years)	39.44 ± 19.66
Height (cm)	168.87 ± 7.35
Weight (kg)	60.83 ± 15.64
Body mass index (kg/m2)	25.37 ± 5.17

Table 2. Qualitative variables of subjects.

Characteristic	type (discontinuous)
Gym floor condition	1 quality 0 poor quality
Gym ventilation	1 appropriate 0 inappropriate
Gym light	1 standard 0 non-standard
Gym sports equipment	1 standard 0 non-standard
Salon cleaning and hygiene	1 standard 0 non-standard
The distance between the wall and the playground	1 standard 0 non-standard
sports field	1 standard 0 non-standard
Professional and amateur athlete	1 professional 0 amateurs
The quality of the shoe material	1 quality 0 poor quality
gender	1 man 0 women
Coach supervision	1 Present 0 absent

30% of the data was considered for testing and 70% for the training of the algorithm. The SVM algorithm was used to predict injured people. The results of the clutter matrix of this algorithm are shown in Figure 2.

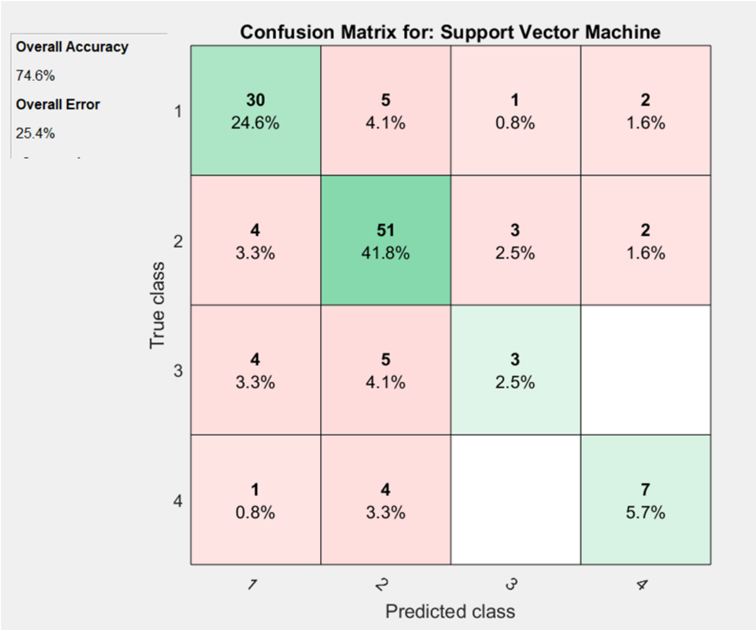

Figure 2. SVM algorithm clutter matrix.

The results showed that the SVM algorithm can predict head, and arm and leg injuries with 74.6% accuracy and 73.2% accuracy, respectively.

Discussion

The risk of injury from physical activity can interfere with the enjoyment of participation and reduce the long-term health benefits that physical activity can provide. Injuries can lead to negative changes in daily activities, lost work time, poor quality of life, disability, or in severe cases, death. It has been proven that sports facilities play an important role in managing the prevention of sports injuries. The most important issue is to be aware of injuries because prevention is better than cure. For this reason, early identification of all types of sports injuries caused by factors that threaten safety in sports venues is vital. For this reason, data mining is crucial in diagnosing and predicting physical injuries (head, arm and leg injuries). An issue that has been less addressed is the use of data mining in the prediction and management of physical injuries caused by the structure and defects of sports facilities and equipment. The purpose of this research was to provide a model to determine the type of physical injuries in the gym using the SVM algorithm. The findings of this study can predict the probability of injury before the game and provide evidence for the design and development of an injury prevention strategy (C. Huang & Jiang, 2021).

The findings indicated that the SVM algorithm can predict head, and arm and leg injuries of healthy people with 74.6% accuracy and 73.2% accuracy, respectively using 15 risk factors. To the best of our knowledge, this study is the first to provide valuable information on the types of physical injuries (head, hands, and feet) caused by the lack of appropriate management in the construction and maintenance of gym facilities and equipment in a large series of cases. Therefore, cases of various studies that used different risk factors and data mining algorithms to predict sports injuries are presented as consistent and inconsistent studies.

In line with the results of this study, Moustakidis et al. (2022) (Moustakidis et al., 2022) used the SVM algorithm and six risk factors to predict and identify the risk factors of physical injuries in CrossFit. The risk factors of this study included demographic factors (gender), risk factors related to the frequencyintensity of exercise (three variables) and medical history (two variables). Finally, they reported an accuracy of 75.22 and accuracy of 4.61, sensitivity of 83.91 and a specificity of 52.98 for the SVM algorithm. In addition, Kalpaks (2016) (Kampakis, 2016) used the SVM algorithm and the quantitative variable of age and the qualitative variables of type of hall flooring and type of shoes as risk factors in his study entitled *Football injury prediction modeling*; he reported that the SVM algorithm with corresponding accuracies of 67.78 and 74.78 has the best performance in the classification of injuries.

Theron (2020) (Theron, 2020) in his study entitled *Using data mining to predict non-collision injuries in professional football players* reported the highest accuracy score of 0.52 for SVM, which was very poor, based on data of 38 players and the prediction results of decision trees (DTs) algorithms, random forest (RF), SVM, logistic regression (LR). He reported that scores for all the models were low. Low recall scores are as a result of a high proportion of false negatives, meaning algorithmic models are unable to detect damage. His findings were inconsistent with the results of the present study and the probable reason for this discrepancy could be the differences in the number of statistical samples, the number of indicators used and the method of data collection; his study data was obtained through GPS, while the present study data was collected through questionnaires.

Based on the available evidence, the study of Fatholahi et al. (2023) (Fathollahi Parvaneh, Ameri, & Sajjadi, 2023) supports the purpose of this study. They focused on evaluating the quality of recreational and sports facilities in sports venues based on the gap analysis model. In addition, Huang and Wen (2022) (H. Huang & Wen, 2022) reported that presenting a sports injury prevention model for physical education students based on management factors can be effective. In his study, Jiang (2022) (Jiang, 2022) concluded that in complex environments, the risk management of sports venues and the spirit of sports cooperation are prioritized.

The performance of ML models in achieving much higher predictive accuracy can be attributed to the fact that a relatively small number of risk factors are considered and the current dataset lacks quantitative performance-related variables that could provide more precise and measurable information. Taking into consideration the physical condition of the athletes, future research should include data from wearable devices that can quantify the physical abilities of practitioners in sports venues. The findings of this study can predict the probability of injury before the game and provide evidence for management, design and development of injury prevention strategy.

Conclusion

In terms of sample size, this study has the highest number of participants in Iran based on the results of studies in the field of data mining and management of sports facilities for injury prevention. The SVM algorithm was used in this study and its performance was checked in terms of accuracy and correctness. Finally, the current study illustrated that by discovering hidden patterns and relationships in the data, this algorithm can probably be used correctly to improve the quality of sports facilities management to prevent physical injuries of athletes. Overall, a major concern (and a future research topic) was that the studies reviewed here were based on data collected through questionnaires. An important direction of future research will be to test and modify the developed models on data based on quantitative scales to better manage the risk factors of sports venues. Moreover, other aspects of management such as marketing, customer attraction to private salons and factors influencing player attraction to a sports venue can make the most of the predictive capability of machine learning models.

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