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ORIGINAL

ATHLETE HEALTH MANAGEMENT BASED ON DATA-DRIVEN DECISION SUPPORT FOR INJURY PREVENTION AND TREATMENT

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ABSTRACT

Due to the special characteristics of competitive sports, high-level athletes are more prone to psychological problems as their mental and physical bodies are subjected to long-term psychological pressure and high-intensity stimulation challenges that are difficult for ordinary people to experience. The emergence of these problems will directly affect the athletes' competitive level and potential, and may even end their athletic careers prematurely, causing irreparable damage to themselves. This paper proposes a data-driven machine learning approach for injury prevention and treatment decision support. The advantages of the machine learning method mainly lie in the following: firstly, the whole process of machine learning, from feature selection to analytical modelling and up to prediction, is tightly focused on the data, and will not be interfered by the a priori knowledge, so it can effectively extract the unattended influencing factors which are difficult to be found in the traditional method, so that the feature selection process can be more accurately completed, and it can effectively support the scientific athlete's health management.

KEYWORDS: Athlete Health Management; Data-driven Decision Support; Injury Prevention; Injury Treatment

1. INTRODUCTION

In the 1970s, health management (Health Management) emerged in the United States. Subsequently, athlete health management gradually developed in developed countries such as the United Kingdom, Germany, France, and Japan, and formed an industry with wide and deep coverage (Brenner & Chen, 2018; Klimeck et al., 2023). Economically applicable prescription agreements are signed between medical insurance institutions and medical institutions in order to ensure that insurance customers enjoy lower medical expenses; in medical insurance institutions, through a series of systematic athlete health management for medical insurance customers, disease control is ultimately achieved The occurrence or deterioration of the accident can greatly reduce the accident rate and medical expenses of insurance institutions, thereby achieving the purpose of reducing medical insurance compensation to customers (Ferguson et al., 2021). With the development of society and the continuous changes and updates in the actual business content of insurance, athlete health management has gradually developed into an independent system and operation, and professional health management companies have begun to replace traditional medical institutions (Labrague, 2021). Health management companies cooperate with medical insurance institutions as third-party service agencies, or directly provide systematic and professional health management services for a fee to individuals in need (Boyle & Leon, 2002; Hartley et al., 2016). As an emerging concept, athlete health management was introduced to my country in the 1990s, and Chinese scholars also have different opinions on the concept of health management. As early as 1994, scholar Su Taiyang started from public health services and pointed out that health management aims to improve health and use effective management methods to improve the health of individuals and society (Khan et al., 2020; Nowbar et al., 2019). In terms of personal health awareness, lifestyle and personal behavior, health management uses modern medical achievements and management methods to improve personal health and quality of life in a purposeful, planned and organized manner. Athlete’s health management is a process of comprehensively rectifying the adverse factors in the health of individual athletes and social groups (Hajifathalian et al., 2020; Ungar & Theron, 2020). Health management is the entire process of comprehensively monitoring, analyzing, evaluating, providing health consultation and guidance, and intervening on health risk factors for the health of individuals or groups. Its purpose is to mobilize the enthusiasm of individuals, groups and the entire society, and effectively utilize limited resources. Resources to achieve maximum health effects. From the perspective of health investment, health management is a health service that actively, continuously and systematically manages human health based on the needs of health investors and health assessment conditions (Fink et al., 2020; Sattar & Valabhji, 2021). Health management is centered on controlling factors that affect health, which include both variable and non-variable risk factors (Kang et al., 2020; Soroya et al., 2021). Tertiary prevention (Aghili et al., 2021) is the treatment of disease and prevention of disability (also known as clinical prevention), after the occurrence of the disease, through a series of measures to promote the recovery of the corresponding functions of the body, and ultimately to achieve improved quality of life, prolonged life expectancy, and reduce the mortality rate (Dash et al., 2019; Nayak et al., 2021). The whole service process needs to be combined with the individual's health condition, and the three processes are continuously recycled to achieve the control of health risk factors and the level of health of the organism (Dineen-Griffin et al., 2019; Zhang et al., 2023). The research purpose of this paper is to explain how to use machine learning technology for data analysis and modelling of athletes' health management, and on this basis to establish a universal research method that can obtain high-precision results by simply relying on large-sample data computation, and is not restricted by professional fields. The main contributions are as follows:

1. This paper investigates an athlete health state prediction method based on improved Bayesian filtering for a single source of information with a single failure mode, which can be used to construct a prediction model using the amount of equipment's individual athlete's health monitoring and can robustly predict the health state of the equipment's individual athlete under a single degradation failure mechanism.

2. In this paper, an improved traceless Kalman filter based on Kalman filtering and linear adaptive strategy is established to construct a prediction model of athlete's health status indicator, which can adaptively adjust the model noise term; then, based on the consideration of uncertainty in the model or algorithm parameters, robust athlete's health prediction is achieved using the established prediction model.

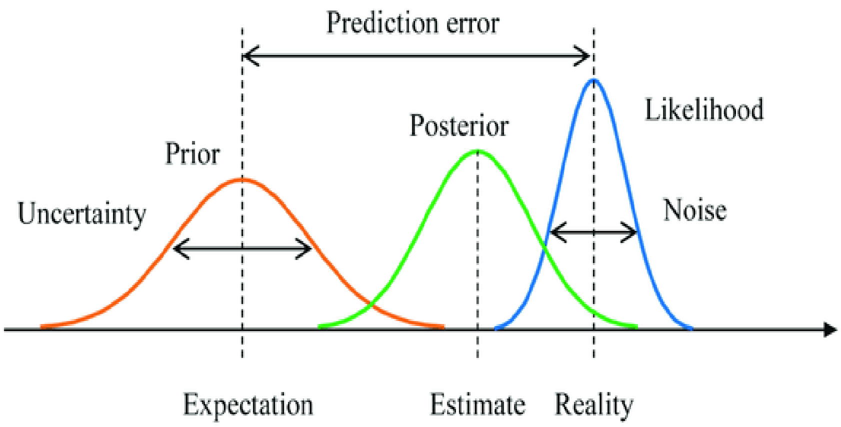

Figure 1: Schematic representation of a Bayesian model.

2. Methodology

Among the Bayesian filtering methods (as shown in Figure 1), traceless Kalman filtering has a more balanced effect in terms of accuracy and computational efficiency in dealing with nonlinear models, and has been better applied in athlete health prediction. The traditional traceless Kalman filtering method characterises the nonlinear degradation process of athlete health through a state space model. The state-space model consists of two nonlinear equations, i.e., the state transfer equation and the measurement equation. The state transfer equation is used to characterise the non-linear change pattern of the degradation indicator of the athlete's health; the measurement equation is used to characterise the non-linear relationship between the monitoring quantity and the degradation indicator. However, when the monitoring quantity is used as the degradation indication quantity, the monitoring value and the degradation indication quantity may have a linear relationship, i.e., the measurement equation is a linear equation. This is due to the prediction error introduced when directly using a traceless Kalman filter to process athlete health predictions containing linear measurement equations. In addition, uncertainty in the parameters of the prediction model or algorithm can lead to fluctuations in the prediction results, which can severely limit the scope of application of health prediction methods for athletes. In this paper, a robust athlete health prediction method is proposed to reduce the error and volatility of prediction results. Firstly, an improved traceless Kalman filter is established to construct a prediction model for athlete health indications based on Kalman filtering and linear adaptive strategy, in which a linear adaptive strategy is used to adaptively adjust the model noise term; then, a robust athlete health prediction is achieved using the improved traceless Kalman filter; finally, the effectiveness of the proposed method is verified.

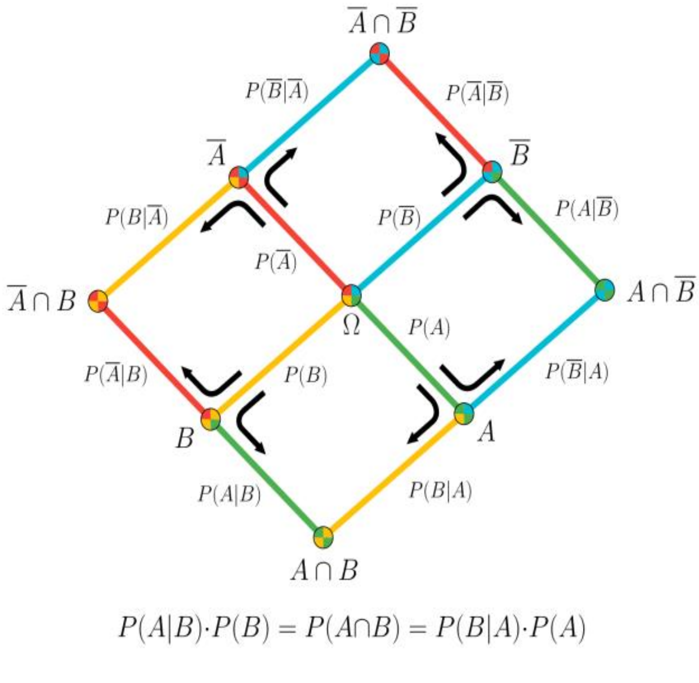

Figure 2: Schematic representation of the Bayesian computational process.

2.1 Athlete Health Prediction Based on Traceless Kalman Filtering

Bayesian filtering is a class of method system widely used to deal with athlete health prediction, which not only can effectively deal with the uncertainty in prediction, but also has a set of standardised Bayesian updating framework.

Commonly used Bayesian filtering mainly includes Kalman filtering, extended Kalman filtering, traceless Kalman filtering, particle filtering and so on. Kalman filter is the most basic filtering method and can only be used for linear models. Through the improvement of Kalman filter, extended Kalman filter and traceless Kalman filter are proposed and used to deal with nonlinear models; among them, extended Kalman filter uses Taylor series expansion to linearise the nonlinear model, and then uses Kalman filter to deal with the nonlinear model; traceless Kalman filter uses UT transform to deal with the nonlinearity, which can obtain higher prediction accuracy compared with extended Kalman filter.

Unlike the above two types of improved filters, particle filtering utilises sequential Monte Carlo methods to deal with nonlinear models. Although particle filtering generally has better prediction accuracy, the sequential Monte Carlo method it uses leads to its high computational overhead. Therefore, in this paper, trace-free Kalman filtering is used to deal with the prediction of athlete health in the single-source information single-failure model. In the traditional athlete health prediction method based on traceless Kalman filtering, the following three main steps are included. Firstly, for arbitrary athlete health data, the stochastic degradation process is characterised by building a state-space model:

$$\begin{cases} x_k = f(x_{k-1}) + w_k \\ y_k = h(x_k) + v_k \end{cases} \tag{1}$$

Where and are the state transfer and measurement equations, respectively; is the time-step subscript; the state quantity is an unobservable measure of this degradation process at the moment; and the monitoring quantity is an observable measure of this degradation process at the moment. Then, based on the historical information, the parameters of the SSM model are initialised, including the mean $\hat{x}_0$ and covariance P_0 of the initial state quantity x_0, and the noise quantity covariance Σ_w and Σ_v. Based on the monitoring data $[y_1, y_2, \cdots, y_k]$,the mean $[\hat{x}_1, \hat{x}_2, \cdots, \hat{x}_k]$ and covariance $[P_1, P_2, \cdots, P_k]$of the state quantity $[x_1, x_2, \cdots, x_k]$ at different moments can be recursively estimated by the traceless Kalman filtering method.

Finally, based on the information about the state quantity of the current moment kt, the state quantity of the future moment is predicted recursively using the Finally, based on the state quantity information of the current moment kt, the state quantity $[\hat{x}_{k+1}, \hat{x}_{k+2}, \cdots, \hat{x}_m]$ at future moments can be predicted recursively using the state transfer equation of the SSM model. if the state quantity $\hat{x}_m$ reaches the threshold value of the athlete's health state at the moment t_m , the time interval between the moments t_m and t_k is the predicted value of the athlete's health. The general athlete health prediction in single source information single failure mode can be solved directly using the above untraceable Kalman filtering method.

2.2 A health prediction based on improved traceless Kalman filtering

2.2.1 Improved trace-free Kalman filtering

For athlete health data, the nonlinear degradation process can theoretically be discretely represented in the following form:

$$x_k = f_\theta(x_{k-1}) \tag{2}$$

Where θ is a model parameter? In addition, there is a linear relationship between the monitoring quantity y_k and the state quantity x_k of its degradation process. Considering the uncertainties in the degradation process, this type of degradation process can be expressed in the following form:

$$y_k = H \cdot f_\theta(x_{k-1}) + \varepsilon_k \tag{3}$$

where H denotes the linear coefficient between the monitored and state quantities, the model parameter is a random variable, and the noise quantity is set to be Gaussian noise, thus:

$$\begin{cases} x_k = f_\theta(x_{k-1}) \\ y_k = H \cdot x_k + \varepsilon_k \end{cases} \tag{4}$$

In the proposed improved traceless Kalman filtering, Kalman filtering is utilised to process the measurement equation in equation (4). In addition, in the classical traceless Kalman filtering, the noise covariance is set by empirical or historical data. In practice, the noise covariance affects the prediction accuracy and stability of the filtering method; too small a noise covariance can lead to biased prediction results, while too large a noise covariance can lead to dispersion in the filtering method. Therefore, in the proposed filtering method, a linear adaptive strategy is utilised to adaptively correct the noise covariance, which in turn improves the prediction accuracy and robustness of the filtering method.

Based on the historical data, the model parameters are initialised, including the mean $\hat{x}_0$ and covariance P_0, the initial noise covariance Σ_0 of the initial state x_0 .Based on the information $(\hat{x}_{k-1}, P_{k-1}, \Sigma_{k-1})$ at the moment of t_{k-1}, the UT transformation is used to predict the mean $\hat{x}_{k|k-1}$ and covariance $P_{k|k-1}$ of the variable $x_{k|k-1}$, where the random variable $x_{k|k-1} = f(x_{k-1})$. This step consists of the following two sub-steps: (1) In the UT transformation, the distribution of a Gaussian random variable is represented by constructing a finite number of sample points, which are called sigma points. Based on the mean $\hat{x}_{k-1}$ and covariance P_{k-1} of the state quantity x_{k-1} , $2L+1$ sigma points and their weights are generated to characterise the x_{k-1}distribution:

$$\left[x_{k-1}^{i}, W_{i}^{(m)}, W_{i}^{(c)}\right], \quad i = 0,1,\cdots,2L \tag{5}$$

$$\begin{cases} \mathbf{x}_{k\text{-}1}^{0} = \hat{\mathbf{x}}_{k-1} & \\ \mathbf{x}_{k\text{-}1}^{\mathrm{i}} = \hat{\mathbf{x}}_{k-1} + \left(\sqrt{(L+\lambda)\mathbf{P}_{\mathrm{k-1}}}\right) & i = 1,2,\cdots,L \\ \mathbf{x}_{k\text{-}1}^{\mathrm{i}} = \hat{\mathbf{x}}_{k-1} + \left(\sqrt{(L+\lambda)\mathbf{P}_{\mathrm{k-1}}}\right)_{i-L} & i = L+1, L+2,\cdots,2L \\ W_{0}^{(\mathrm{m})} = \dfrac{\lambda}{L+\lambda} & \\ W_{0}^{(\mathrm{c})} = \dfrac{\lambda}{L+\lambda} + \left(1 - a^{2} + \beta\right) & \\ W_{0}^{(\mathrm{m})} = W_{0}^{(\mathrm{c})} = \dfrac{1}{2(L+\lambda)} & i = 1,2,\cdots,L \end{cases} \tag{6}$$

Where the scale parameter $\lambda = a^2(L+k) - L$; L is the dimension of the state quantity x_{k-1}; the scale factor a is generally set to 10^{-3}. 2. Estimation of mean $\hat{x}_{k|k-1}$ and covariance $P_{k|k-1}$, $2L+1$ sigma points $x_{k|k-1}^{i}$ are subjected to a nonlinear state transfer equation to obtain sample points of variable $x_{k|k-1}$ as follows:

$$x_{k|k-1}^{i} = f\left(x_{k|k-1}^{i}\right) \tag{7}$$

2.2.2 Robust Athlete Health Forecasting

When analysing the impact of environmental factors on the health status of athletes, in order to make the predictions of the model match the real situation as closely as possible, we need to find the most relevant features from a large number of environmental factors to model. Due to the large number of environmental variables involved, the very large amount of overall data, and the intention to exclude the influence of manual feature selection, we decided to use the Maximum Information Coefficient (MIC) for automated feature selection. Maximum Information Coefficient (MIC) is a metric specifically designed to measure the degree of association between two variables, including linear or non-linear relationships, for rapid mining of multidimensional datasets, and it not only identifies correlations between different features in a dataset, but also characterises them.

We constructed a two-dimensional feature matrix for the Environmental and Mental Health Scale, and next, when calculating the MIC value for each variable, since each resolution division should be calculated for all grid segmentation methods at all possible resolutions, and the amount of calculations will be very large when the total amount of data is large, we adopted an approximate calculation method, i.e., the vertical coordinate axis at each resolution was equidistant After calculating the MIC, the horizontal and vertical coordinate splits are exchanged to recalculate the second MIC, and the maximum value of the two calculations is taken as the final MIC value.

2.2.3 The sample imbalance problem

In machine learning for classification problems, the most commonly encountered problem is the problem of data imbalance, as shown in Figure 3, is the prediction of classification in machine learning, the difference between the various classes is too large, so that the machine learning model in the data learning, the larger class has a greater impact on the model, for example, from the simplest dichotomous classification view of the problem, a total of one hundred data, a small number of classes account for only For example, looking at this problem from the most binary classification perspective, there are a total of one hundred data items in a data set, and the minority class only accounts for 10 of them. If we were only aiming for accuracy, we would have a 90% chance of being correct when predicting this data, even if we blindly guessed all the samples into the correct class, but this defeat the purpose of predicting the minority class, which is usually valued more highly in real-world predictions. For example, in our athlete health prediction problem, the majority of athletes have normal health and very few days of illness, which is exactly the focus of our study. We want the model to learn the underlying characteristics of the athletes' health. Therefore, how to accurately identify the samples in the minority class becomes a key issue in this study.

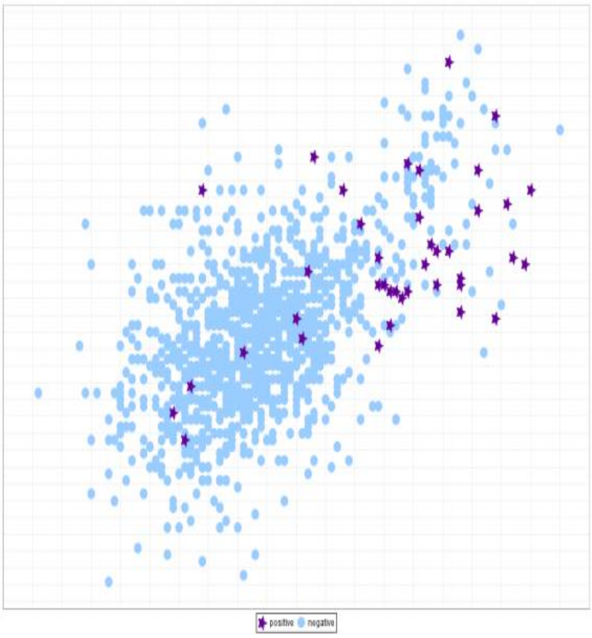

Figure 3: Schematic representation of data sample imbalance

2.2.4 Approache to imbalances

1. Oversampling methods: One of the commonly used methods to deal with data imbalance is the oversampling method, as shown in Figure 4. With the oversampling method, the classes that are in the minority and the classes that are in the majority in the original data are brought to the same number by

increasing the samples of a few classes in the sample. Oversampling increases the sample size and also increases the computational complexity. Random plain oversampling is only one of the simplest forms of oversampling, the purpose is to copy the minority class to the same number as the majority class, which results in an increase in the computational complexity of the training model for machine learning, and simply copying the minority class samples makes the model learning too specific, which is not conducive to improving the generalisation performance, and is prone to overfitting. In order to solve the above problems and the emergence of a representative algorithm to solve the imbalance problem SMOTE algorithm, SMOTE algorithm changed the original simply copy the sample practice, but the use of synthetic data, for a few classes of samples to add noise synthesis of the new samples, to prevent the occurrence of simple random oversampling like overfitting. SMOTE algorithm of the specific process as follows: in a few classes of the selection of a sample x in the minority class and select its k -nearest neighbours to the other minority samples using Euclidean distance as the measure. Determine the sampling multiplicity based on the proportion of imbalance between the minority and majority classes, and randomly select a number of samples x_n from its k -nearest neighbours. Construct a new sample for the randomly selected x_n samples and for the originally selected sample x according to the following formula:

$$x_{new} = x + rand(0,1) * |x - x_n| \quad (8)$$

Following this process of SMOTE algorithm can construct a balanced dataset, but there are problems with this method: the selection of k -value needs to be determined by several experiments, the generated new samples are prone to cause marginal distribution of the data, and also blurring the boundary between the minority class and the majority class, which increases the difficulty of the classification of the model.

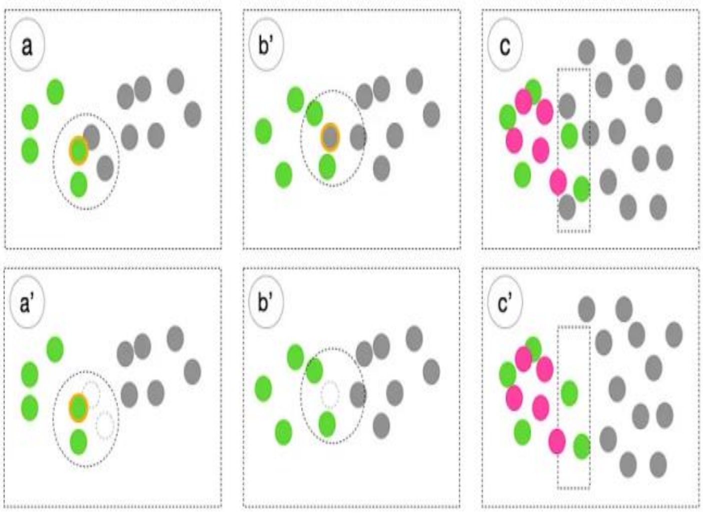

Figure 4: Schematic representation of the SMOTE algorithm

2. Under-sampling method: Another common method to deal with sample imbalance is the under-sampling method, as shown in Figure 5. Unlike oversampling which increases the number of minority class samples, under sampling is handled by removing samples from a class that has a larger number of samples, so that the majority and minority classes become balanced with each other. That is, some sample set m is randomly selected from the majority classD_{maj}, and then the sample set m is removed from D_{maj} and the new sample set$D_{new} = D_{maj} - m$, making the positive and negative examples in the new sample set close to each other. The idea of under sampling is to delete redundant classes, which also results in a reduced amount of data and a lack of information. This method is more feasible when the amount of data is more sufficient and the deletions do not have a large impact on the model. However, when the amount of data is small, this disadvantage becomes apparent. For this reason, the majority of the class samples will generally be put back n times, respectively, with a few classes to form a training set, training n models, and then n models to vote on the test samples. This method solves the problem of missing information to some extent.

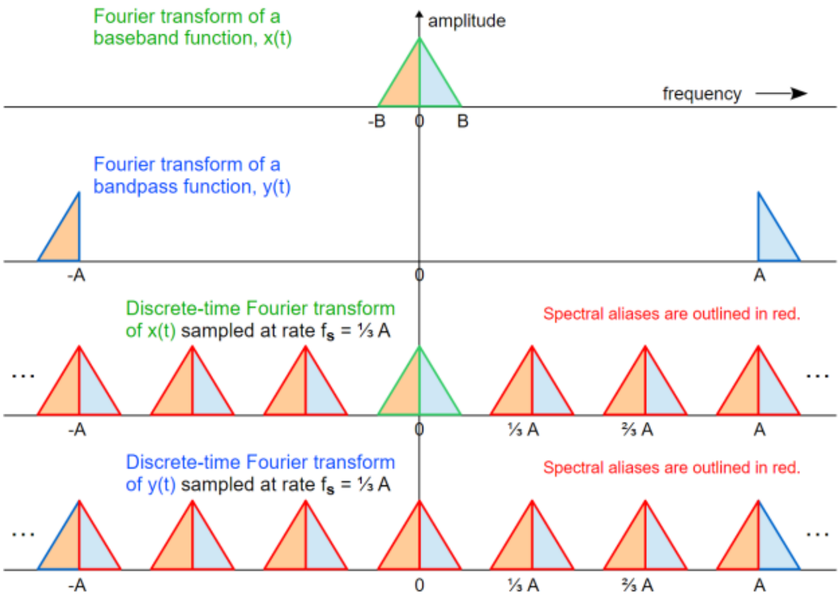

Figure 5: Schematic representation of Under-sampling

3. Experiment and Results

3.1 Evaluation Indicators

Accuracy is the proportion of all predicted samples that are accurate.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{9}$$

Precision is the proportion of predictions that are accurate in a positive sample.

$$Precision = \frac{TP}{TP+FP} \tag{10}$$

Recall is the proportion of correctly predicted positive samples to all positive samples.

$$Recall = \frac{TP}{TP+FN} \tag{11}$$

F1 Score is the harmonic mean of the detection and recall rates.

$$F1 = \frac{2 \times Pr\,ecision \times Re\,call}{Pr\,ecision + Re\,call} \tag{12}$$

The AUC value is only an evaluation index of the binary classification model, and the ROC curve is also known as the "receiver operating characteristic curve", ROC is a curve, and the AUC value is an area value enclosed by the ROC curve.

3.2 Experimental results and analysis

The original data was filtered to leave 910 samples, of which 67 were in the minority class. Of these, 20% were designated as the test set and 80% as the training set. 54 samples from the majority category in the dataset were randomly selected to form a balanced dataset with the minority category, which was used to train the data, and the model was evaluated in the test set (which contained 13 samples of the diseased and 169 samples of the healthy).

Table 1: Model prediction effects for under sampled balanced datasets

MODEL	PRECISION	RECALL	F1-SCORE	ACCURACY	AUC
RANDOM FOREST	0.9012	0.7652	0.7845	0.7125	0.7156
LOGISTIC REGRESSION	0.9112	0.7952	0.7952	0.7251	0.7258
GBDT	0.9215	0.8123	0.8011	0.7325	0.7469
OURS	0.9216	0.8236	0.8088	0.7612	0.7962

As shown in Table 1, the under sampled balanced dataset shows that the proposed methodology has the best performance in all four indicators, indicating that the proposed methodology model performs better after the under sampled data are balanced. We took the minority class samples (67 stick) from the 910 data, of which 20% were classified as the test set and 80% as the training set (containing 54), and used an oversampling method to make the minority class in the training set balanced with the majority class samples in the total data. Simple random oversampling simply replicates the minority class samples, which can cause overlearning of the model, so using the SMOTE sampling method, the addition of noise prevented overfitting of the model by artificially synthesising the minority class samples. Oversampling was implemented on the minority classes to increase the number of minority classes to form a balanced sample with the majority classes, totaling 1348 data, and Table 2 shows the model prediction effects for the oversampled balanced dataset.

Table 2: Model Prediction Effect of Oversampled Balanced Dataset

MODEL	PRECISION	RECALL	F1-SCORE	ACCURACY	AUC
RANDOM FOREST	0.9012	0.5368	0.8125	0.7526	0.6874
LOGISTIC REGRESSION	0.9065	0.6198	0.8215	0.7756	0.7025
GBDT	0.9156	0.7659	0.8156	0.7892	0.7512
OURS	0.9268	0.7725	0.8326	0.7932	0.7756

Table 2 clearly shows that the experimental accuracies of the balanced datasets are all improved by oversampling, but the addition of data with SMOTE sampling reduces the AUC values of some models. Overall, the above experimental results fully demonstrate the superiority of the method.

4. Conclusion

Given the special characteristics of competitive sports, high-level athletes are subjected to long-term psychological pressure and high-intensity stimulation challenges that are difficult to be experienced by ordinary people, and thus may be more prone to some psychological problems. Therefore, this paper proposes a data-driven machine learning method for injury prevention and treatment decision support. The advantages of the machine learning method mainly lie in the following: firstly, the whole process of machine learning, from feature selection to analysis and modelling, up to prediction, is tightly focused on the data, and will not be interfered by the a priori knowledge, so it can effectively extract the unattended influencing factors which are difficult to be found by the traditional methods, and thus the process of feature selection can be more accurately completed, and it can effectively support the scientific athlete's health management.

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