Feature Selection and Machine Learning Based Fatigue Detection for Track and Field Training

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ABSTRACT. *Due to the different intensity of track and field training, excessive fatigue often occurs in athletes, which poses a serious threat to health. Thus, fatigue detection for track and field training is urgent. Electroencephalographic (EEG) signals are the gold standard for detecting fatigue, but EEG-based fatigue detection approaches have invalid features, making the detection inefficient. To deal with the above issues, this paper designs a fatigue detection model for track and field training based on feature selection and machine learning. Since the EEG signal contains a large number of ocular artefacts, the multi-channel EEG is decomposed and reconstructed by Independent Component Analysis (ICA) to obtain a pure EEG. Meanwhile, the EEG is transformed into a two-dimensional image using the wavelet transform, and the multi-channel CNN is used for deep feature extraction. Then the random forest is introduced to select the important features, delete the redundant features, construct the important feature vector space, and finally introduce the relaxation variables in the SVM classifier to transform the classification problem into the optimal solution of the quadratic programming problem to gain the final classification outcome. Experiments imply that the offered model has an average classification accuracy and F1 value of 93.61% and 92.57%, respectively, which is 5%–22% higher than the comparison model, and can efficiently achieve the detection of fatigue in track and field training.*
Keywords: Fatigue detection; Feature selection; Independent component analysis; Feature extraction; SVM classification

1. **Introduction.** Athletics training is a process that alternates between fatigue and recovery. Under moderate training intensity, fatigue can be slowly recovered according to the body's mechanism, but excessive training intensity can lead to over-fatigue, which can cause damage to the body's functions and put athletes at risk [1]. Brain fatigue

and psychological fatigue are potential risk factors for falls [2], adversely affecting motor coordination and muscle reaction time, leading to postural instability and altered gait [3]. In daily track and field training, we should plan the training goals scientifically and should not over-exercise. The fatigue test should be carried out comprehensively to ensure that the athletes can carry out track and field training healthily. Therefore, fatigue detection in track and field training can scientifically and effectively improve the level of individual track and field and ensure the quality of track and field training.

1.1. **Related work.** Athletic training fatigue detection is mainly divided into subjective evaluation methods and objective detection approaches [4]. The most commonly used subjective assessment method is the Karolinska Sleepiness Scale (KSS) [5], which classifies athletes' fatigue on nine levels from wakefulness to fatigue. Zhang et al. [6] administered the KSS self-assessment to athletes and then took the average as the fatigue level before and after running to further reduce the side effects of the self-assessment method. Among the subjective self-assessment methods, there are also the Short Fatigue Questionnaire (SFQ) [7] and the Childs Fatigue Scale (CFS) [8], which have the advantages of simplicity of use and versatility, but have the subjectivity of the athletes, which affects the authenticity of the test results.

Compared with the subjective evaluation approach, the objective detection method can avoid most of the interference of human factors can better detect the degree of fatigue of athletes. Objective methods are divided into biochemical and physiological measures [9]. Biochemical measurements are mainly used to determine the fatigue level by detecting the changes in the concentration of urine and blood [10], but this measurement method is mostly invasive and damaging to the human body, so it is not suitable for continuous fatigue detection. Physiological measurement is to detect the human body's electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG) and other physiological signals [11]. Due to the high temporal separation rate of the EEG signal, it is considered as the 'gold standard' for fatigue detection [12], and is often combined with Machine Learning (ML) models for fatigue detection. Yang and Ren [13] developed a real-time exercise training fatigue detection method based on EEG channel power spectral density [14] and sample entropy [15]. Hasan et al. [16] explored the classification potential of decision trees for fatigue detection, where the EEG signal features were used as inputs to a decision tree classifier, but the accuracy of the detection was not high. Worsey et al. [17] proposed the use of a K-nearest neighbor classifier to quantify training fatigue with an accuracy of 82.26%. Wang et al. [18] used a support vector machine classification algorithm to track alpha waves in EEG to identify training fatigue, and achieved better detection results.

As the neural networks explosively growing, many researches have extracted effective information from EEG signals with the help of neural networks. Gu et al. [19] firstly constructed a dynamic brain network by using CNN for mutual information between each EEG channel, and finally completed the fatigue detection, which can effectively detect fatigue state. Li et al. [20] proposed an AlexNet CNN model fatigue detection algorithm, which uses EEG features to detect fatigue and obtains high detection accuracy. Since EEG signals contain a large amount of feature information, Feature Selection Algorithm (FSA) is important to eliminate their irrelevant features, improve detection accuracy and reduce computational overhead in classification. Karvekar et al. [21] used genetic optimisation algorithm to select the extracted EEG features and put them into SVM to identify the fatigue with an accuracy of 85.7%. Min et al. [22] extracted the time-frequency characteristics of EEG signals, and principal component analysis to select the

features with high contribution in the EEG as the final features, and implemented the training fatigue detection through SVM.

1.2. **Contribution.** To objectively and accurately evaluate the real fatigue, and to address the issue of feature redundancy in existing research, which results in poor detection accuracy. This paper suggests a fatigue detection model for track and field training based on feature selection and ML. The innovative work of the model is mainly reflected in the following four aspects.

(1) For the goal of removing the electrooculographic (EOG) artefacts from the EEG signal, the multichannel EEG data were decomposed into the sum of independent components by the independent component analysis (ICA) method, and the pure EEG was obtained by removing the EOG component and reconstructing the rest of the component signals.

(2) The EEG signal is transformed into a 2D image dataset using continuous wavelet transform, and the EEG image is feature extracted using multi-channel CNN to obtain global features. And the importance of the features is scored using the method of ranking importance in Random Forest (RF), and the low correlation invalid features are deleted to construct the important feature vector space.

(3) Introducing relaxation variables into the SVM classifier, transforming the classification problem into an optimal solution of the quadratic programming problem, and using the important feature vector to judge the fatigue state to obtain the final classification results of fatigue detection for track and field training.

(4) The experimental outcome imply that the average classification accuracy and MAE of the suggested model are 93.61% and 0.61, respectively, which are better than the comparison model. Meanwhile, it is verified that the introduction of feature selection method is of great significance to improve the fatigue classification performance.

2. **Theoretical analysis.**

2.1. **Feature selection methods.** A large number of features will bring the issues of increased computation, model complexity and the existence of a large amount of redundant information. However, the FSA can reduce the feature dimension of the original data without affecting the classification accuracy by evaluating the importance of all features in the original data set and discarding irrelevant and redundant features in order to retain a subset of effective features.

The relationship between the amount of characteristics and the effectiveness of the classifier is implied in Figure 1, when the amount of features is less than a certain value, the effectiveness of the classifier is strengthened with the increase of the amount of features, and when the amount of features is greater than a certain value, the effectiveness of the classifier is weakened with the increase of the number of features [23].

There are three main types of feature selection methods: filtering, encapsulation and embedding [24]. Filtering methods only judge the relationship between features, but not the relationship between features and the prediction target, such as chi-square test and mutual information method. The encapsulation method selects the combination of features with the best classification result through the classification result of a subset of features by the classification model, i.e. judging the relationship between the features and the predicted target, e.g. genetic algorithm. Embedding methods such as Decision Tree (DT), RF, etc., use the characteristics of the classification model itself to select important feature combinations. In this paper, the extracted EEG feature data is used to remove unimportant features using RF, then combined with the model to achieve feature selection while improving the model classification capability.
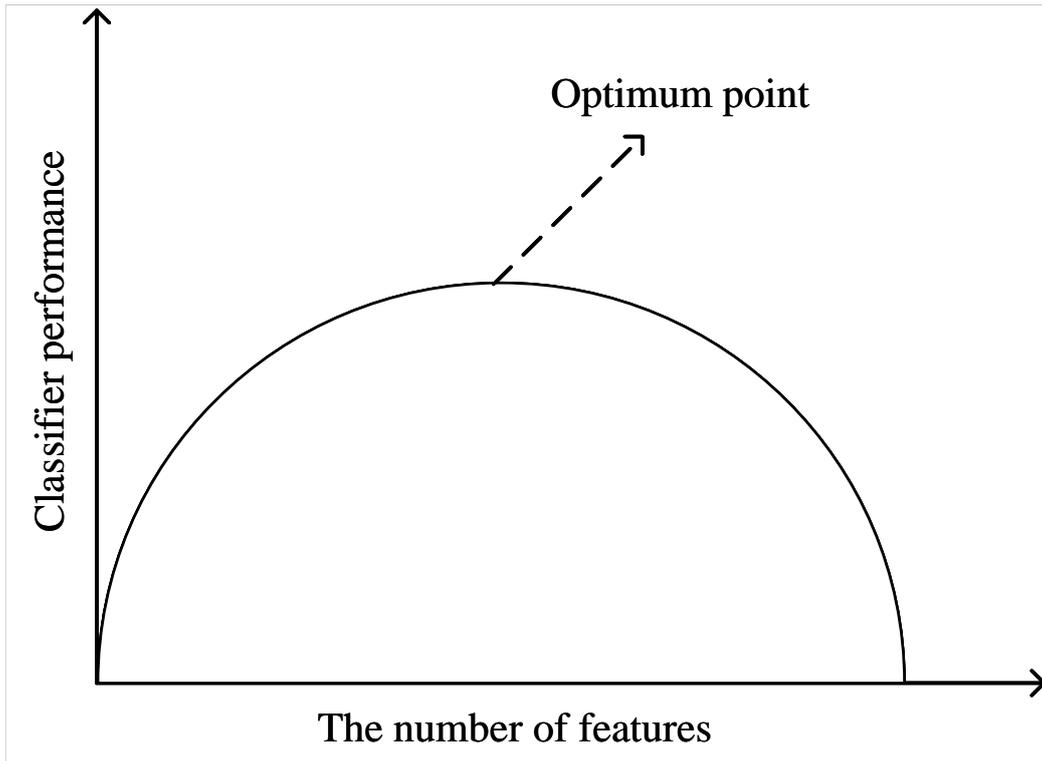
Figure 1. Plot of number of features versus classifier effectiveness

2.2. Support vector machine.
SVM is one of the most representative ML methods [25], and compared to neural network-based classification methods, SVMs have better interpretability and are easy to implement and adjust for optimization in practical applications. Therefore, SVM is used to classify the fatigue state of track and field athletes in this paper.

Given a binary classification issue, assume that the input space of the issue is different from its feature space. Let the training set be

$$T = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\},$$

where $x_i \in \mathbb{R}^{n+1}$, $y_i \in \{1, -1\}$. When $y_i = +1$ is specified, x_i is a positive example; when $y_i = -1$, x_i are negative examples. As shown in the leftmost subplot of Figure 2, the SVM achieves classification based on the separation hyperplane ($\circ$ denotes a positive case and $\times$ denotes a negative case).
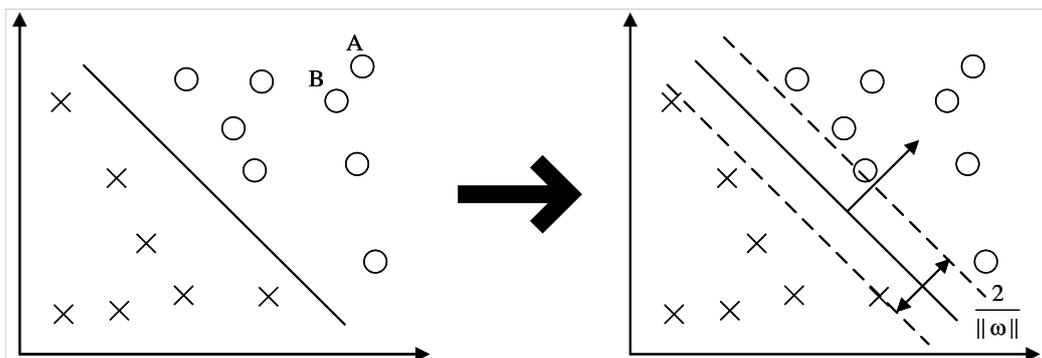

Figure 2. SVM classifier schematic diagram

Assume that the classification hyperplane obtained by learning is $\omega^* \cdot x + b^* = 0$, where ω^*, b^* are the parameters to be determined. The related classification decision function is as follows, where $\text{sign}(\cdot)$ is the sign function.

$$f(x) = \text{sign}(\omega^* \cdot x + b^*). \tag{1}$$

In SVM, the distance from a point to the separating hyperplane represents the degree of confidence of the model in its classification prediction, as shown in Figure 2; if point A is further away from the separating hyperplane compared to point B, then the model has a greater certainty that the classification of point A is correct. As a result, for hyperplane (ω, b), the interval of sample point (x_i, y_i) as a function of the hyperplane is as follows.

$$\hat{\gamma}_i = y_i(\omega \cdot x_i + b). \tag{2}$$

The hyperplane is spaced as a function of the data set T as $\hat{\gamma} = \min_{i=1,2,\ldots,n} \hat{\gamma}_i$. The original issue can be formulated as the following optimization issue.

$$\begin{cases} \max_{\omega,b} \; \gamma = \min_{i=1,2,\ldots,n} \; \gamma_i \\ y_i(\omega \cdot x_i + b) - 1 \geq 0 \end{cases} \tag{3}$$

Equation (3) is a convex quadratic programming problem for which there exists a unique solution ω^*, b^*. This paper will use the Sequential Minimization Optimization (SMO) algorithm [26] to solve ω^*, b^*. This yields the separating hyperplane $\omega^* \cdot x + b^* = 0$ and the categorization decision function $f(x) = \text{sign}(\omega^* \cdot x + b^*)$.

3. Preprocessing and feature extraction of EEG signals.

3.1. **EEG artefact removal based on independent component analysis.** As a low-frequency complex signal, the EEG signal is highly susceptible to environmental interference in the signal acquisition process, so it is necessary to remove the artefacts. According to the frequency domain characteristics of EEG signals, ICA [27] is used to remove other components of EEG signals and CNN is used to perform multidimensional feature extraction of pure EEG signals. EEG is a complex signal that consists of multiple signals superimposed on each other, and EOG, EMG and other signals that are not related to EEG need to be eliminated. For example, track and field athletes' muscle soreness and swallowing during training can interfere with the EEG signals, and ICA, which linearly mixes and separates independent sources from multiple sensors into a number of non-interfering and independent components, has been used in physiological signal de-artifactualization studies and has achieved good outcome.

If the athlete has N sources during the track and field training, the mixed signal can be considered as a square array, i.e., $S = M$, where S is the model dimension and M is the input data dimension. Assuming that each component of the original EEG is unaffected and independent of each other, and all of them satisfy the Gaussian distribution, and the k linear combinations of k independent components $s_1, s_2, \ldots, s_k$ are $x_1, x_2, \ldots, x_k$, having

$$x_j = m_{j1}s_1 + m_{j2}s_2 + \cdots + m_{jk}s_k. \tag{4}$$

Each mixing x_j and independent component s_k are random variables, observation vector $x = (x_1, x_2, \ldots, x_k)^T$, original signal vector $s = (s_1, s_2, \ldots, s_k)^T$, coefficient matrix $M = (m_{ij})$, $1 \leq i \leq k$, $1 \leq j \leq k$, then the mixing model is expressed as $x = Ms$. After obtaining the M matrix, the inverse matrix $M^{-1} = P$ of M is then computed, and the independent component $s = Px$ is computed, and the sigmoid is used as the cumulative

distribution function of the components independent of the original function, then there is

$$p(s) = p_s(Px)\,|P| = |P| \prod_{i=1}^{k} p_s(w^T x), \tag{5}$$

where $p_s(\cdot)$ denotes the probability density and w denotes the random variable, obtained from the great likelihood estimation. Finally, the gradient descent method [28] is used to calculate the P-value, and each independent component of the original signal is obtained by $s = Px$. The ICA algorithm can be used to decompose the multichannel EEG data into the sum of independent components, and the pure EEG can be obtained by removing irrelevant components and reconstructing the remaining component signals.

3.2. Multi-dimensional EEG feature extraction based on wavelet transform and CNN..

After obtaining the pure EEG signal, this paper uses wavelet transform [29] to convert the EEG signal into a 2D image dataset, and then uses multi-channel CNN to perform multi-dimensional feature extraction on the EEG to improve the detection effect of the subsequent model. CNNs are able to perceive local features using convolutional layers compared to traditional feature extraction methods and synthesize local operations at a higher level to obtain global features.

Assuming that $f(t)$ denotes the amplitude of the preprocessed EEG as a function of time t, and $\varphi(t)$ is the mother wavelet that satisfies $\int_{-\infty}^{+\infty} \varphi(t)\,dt = 0$, a different function can be obtained by translating and telescoping the function φ as

$$\varphi_{a,b}(t) = a^{-\frac{1}{2}} \varphi\left(\frac{t-b}{a}\right), \tag{6}$$

where $a, b \in \mathbb{R}$, $a \neq 0$; a is used to control the shape of the wavelet function and is called the expansion factor, and b is used to control the displacement of the function and is called the translation factor. For the EEG signal $f(t)$, the wavelet transform is shown in

$$W_f(a,b) = (f, \varphi_{a,b}) = a^{-\frac{1}{2}} \int_{-\infty}^{+\infty} f(t)\,\varphi\left(\frac{t-b}{a}\right) dt. \tag{7}$$

The coefficients $W_f(a,b)$ of each wavelet transform can be obtained by the inner product of a series of wavelet functions and signals obtained by successive a and b. The signals are projected on a set of wavelet functions formed by wavelet basis expansion and translation, which constitutes a two-dimensional EEG image.

The CNN is adopted to perform a convolution operation on the 2D EEG image to gain a characteristic map with the number of channels c. The feature compression A operation is then performed using global average pooling and squeezing each feature channel along the spatial dimensions as

$$z_c = F_{\text{sq}}(u_c) = \frac{1}{W \times H} \sum_{i=1}^{W} \sum_{j=1}^{H} u_c(i,j), \tag{8}$$

where z_c represents the compressed feature information of the c-th channel feature, u_c represents a channel feature in the feature map X, H and W stand for the height and width of the characteristic map respectively, and $u_c(i,j)$ represents the feature points at different locations in the channel. Then the feature excitation $F_{\text{ex}}(\cdot, w)$ operation is performed by learning the parameter w. A weight is generated for each feature channel to indicate the importance of the feature channel, and the formula is described as follows.

$$s = F_{\text{ex}}(z, w) = \delta\big(g(z, w)\big) = \delta\big(w_2\,\sigma(w_1 z)\big), \tag{9}$$

where g denotes the fully connected operation, δ and σ denote the Sigmoid and ReLU activation functions respectively, w_1 and w_2 represent the weights of the two fully connected levels respectively. Finally, the original features in the multichannel dimension are recalibrated to obtain the final EEG multidimensional features as shown in

$$\tilde{x}_c = F_{\text{scale}}(u_c, s_c) = s_c \cdot u_c, \tag{10}$$

where s_c represents the weights.

4. Track and field training fatigue detection based on feature selection and machine learning.

4.1. Multidimensional EEG feature selection.
Relied on the EEG characteristics extracted by the above CNN, this paper uses FSA to remove the redundant features, selects the important features to form the key feature vector space, which is used as the input to the SVM classifier, introduces the slack variables, establishes the quadratic programming function, and obtains the results of the fatigue detection of the track and field training by solving for the optimal solution to the function, so as to improve the detection efficiency.

Characteristic option is important for training efficient models. Any unnecessary features accelerate the calculational consumption of training and the threat of model overfitting, reducing the generalization performance of the method. Thus, in this paper, RF is used to remove low relevance invalid features and high redundancy features, and the importance of the features is scored relied on the method of RF ranking importance. The framework of the designed fatigue detection model is shown in Figure 3.

Assuming that the feature vectors extracted by CNN are $F_m = \{f_1, f_2, \ldots, f_m\}$, h_i are the corresponding labels, the Gini significance [30] of a characteristic f is delimitated using RF to be the total of the impure improvements of each node n in each tree S that use f.

$$I\{f\} = \sum_S \sum_n \Delta\text{Gini}(n, S). \tag{11}$$

The optimal segmentation leads to a reduction of the Gini index defined as

$$\Delta\text{Gini}(n) = \text{Gini}(n) - p_l \Delta\text{Gini}(n_l) - p_r \Delta\text{Gini}(n_r), \tag{12}$$

where $\text{Gini}(n) = 1 - \sum_{k=1}^{K} p_{n,k}^2$, $p_{n,k}$ denote the proportion of category k in node n, n_l and n_r stand for n's child node, p_l and p_r stand for the ratio of the instance size to the total instance size.

This is subsequently repeated T times in a random combination of tags h_i to create the invalid significance dispersions of the various features $D^{\{f\}} = \{D_1^{\{f\}}, \ldots, D_T^{\{f\}}\}$. Randomly reordering the labels reduces the Gini importance of all features, so one metric for scoring features is to calculate the percentage of the invalid significance dispersion of the feature that is fewer than the true significance, and the equation for the feature f's rating is shown below.

$$\text{score} = \frac{\text{count}\left(D^{\{f\}} < I\{f\}\right)}{T} \times 100\%, \tag{13}$$

where $\text{count}(\cdot)$ stands for the count of components satisfying the condition, T is the number of repetitions, $D^{\{f\}}$ is the null importance distribution of a set of f, and $I\{f\}$ is the true Gini significance of f_i. Therefore, this score is improved through the initial Gini characteristic significance calculated by RF. Contrasted to the initial Gini significance, the proposed metric is more efficient in choosing characteristics with higher significance.
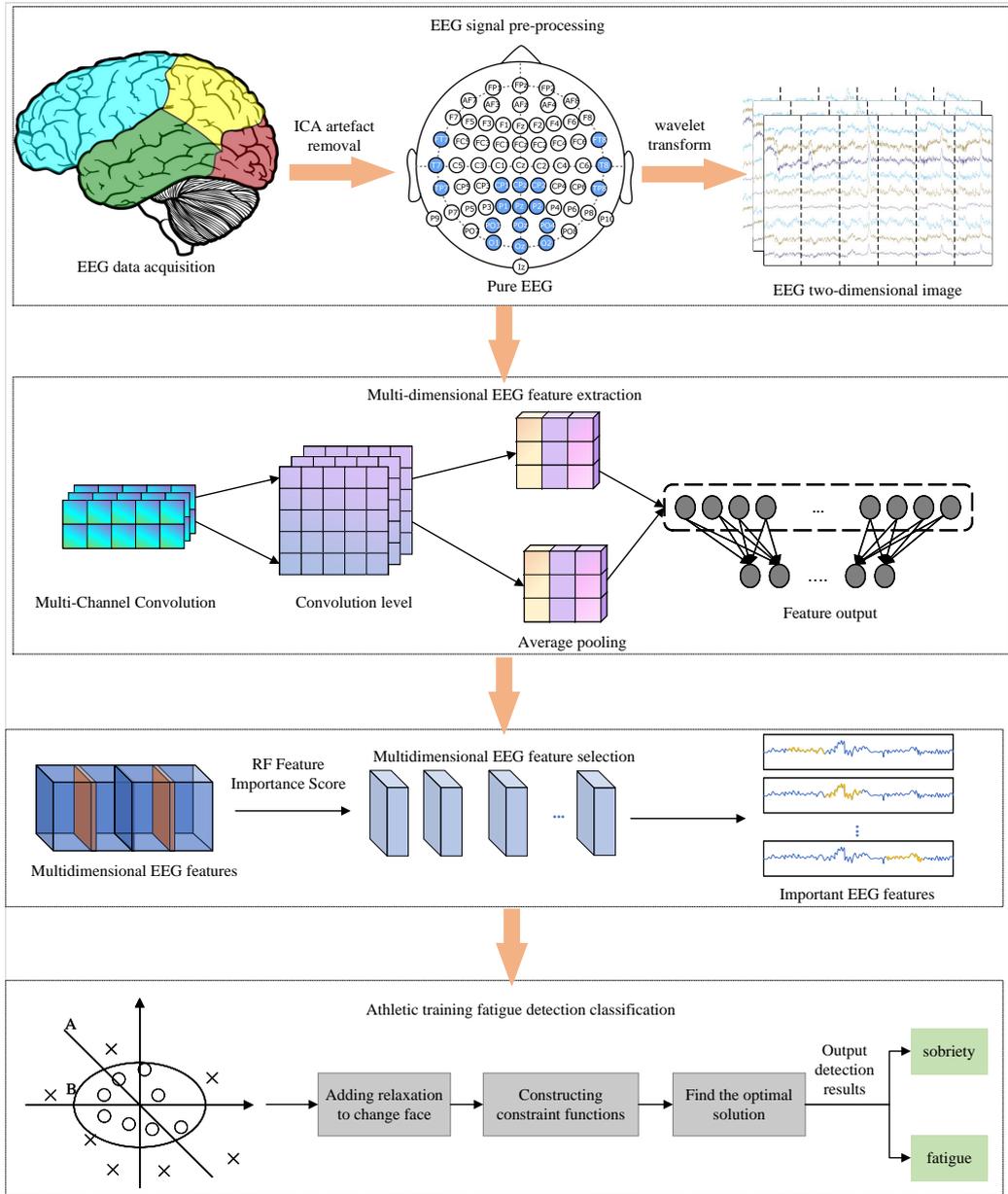
Figure 3. The structure of the designed fatigue detection model

Characteristics with scores below the threshold are removed as 'unsignificant character-istics', which donate little to the model, resulting in the final classification of the input feature $F^* = \{f_1^*, f_2^*, \ldots, f_i^*\}$.

4.2. **SVM-based fatigue detection for track and field training.** The issue of detect-ing fatigue state in track and field training is essentially a binary classification problem: that is, the training state of an athlete is classified into two categories: awake and fatigue. Commonly used machine learning classifiers are Bayesian, Fisher and SVM classifiers. Since SVM has a good performance in classification, it is easy to adjust the optimization in real applications. Therefore, SVM is used in this section to classify the fatigue state.

The essence of SVM is to find the optimal solution to a quadratic programming prob-lem. In the classification models in this chapter, the data cannot be completely linearly separable. If a hyperplane is forced to be found to differentiate the samples, the model is susceptible to overfitting. Therefore, a "soft spacing" approach is used, which allows a

small number of samples not to satisfy the constraints of Equation (3). Introducing a new slack variable ε_i, the constraints of the classification model are shown as follows, where $i = 1, 2, \ldots, n$.

$$y_i\left(w^T x_i + b\right) \geq 1 - \varepsilon_i \tag{14}$$

Each fatigue sample has an ε_i. Different values of ε_i characterize the degree to which the sample does not satisfy the constraints of Equation (3), with $\varepsilon_i = 0$ indicating that the fatigue sample is correctly classified; $0 < \varepsilon_i < 1$ indicating that the fatigue sample is in between the separation plane and the fatigue classification model; $\varepsilon_i = 1$ indicating that the fatigue sample is in the separation plane; and $\varepsilon_i \geq 1$ indicates that the fatigue sample is incorrectly classified.

Introducing ε_i cannot be overly relaxed, otherwise it will affect the classification accuracy. Therefore, ε_i is added to the loss function to maximize the separating surface while trying to appear fatigue samples that satisfy the constraints, and the classification model in this chapter is as follows.

$$\begin{cases} \min\limits_{w,b} \dfrac{\|w\|^2}{2} + C \sum\limits_{i=1}^{m} \varepsilon_i \\[2mm] \text{s.t.} \quad y_i\left(w^T x_i + b\right) \geq 1 - \varepsilon_i \end{cases} \tag{15}$$

where $C > 0$ is the penalty parameter to coordinate $\|w\|^2$ and $\sum_{i=1}^{m} \varepsilon_i$.

Equation (16) is simplified by the Lagrange multiplier method to transform it into an unconstrained problem as follows.

$$L(w, b, \varepsilon, \alpha, \beta) = \frac{\|w\|^2}{2} + C \sum_{i=1}^{m} \varepsilon_i + \sum_{i=1}^{m} \alpha_i\left(1 - \varepsilon_i - y_i(w^T x_i + b)\right) - \sum_{i=1}^{m} \beta_i \varepsilon_i \tag{16}$$

where $\alpha_i \geq 0$, $\beta_i \geq 0$ is a Lagrange multiplier, so the fatigue classification problem is converted to a maximum problem of solving

$$\min_{w,b,\varepsilon} \max_{\alpha \geq 0, \ \beta \geq 0} L(w, b, \varepsilon, \alpha, \beta). \tag{17}$$

Since Equation (18) satisfies the KKT condition, there is its dual problem $\max_{\alpha \geq 0, \ \beta \geq 0} \min_{w,b,\varepsilon} L(w, b, \varepsilon,$ such that the partial derivative of Equation (17) with respect to w, b, ε_i is 0, yielding

$$\begin{cases} w = \sum\limits_{i=1}^{m} \alpha_i y_i x_i \\[2mm] \sum\limits_{i=1}^{m} \alpha_i y_i = 0 \\[2mm] \alpha_i = C - \beta_i \end{cases} \tag{18}$$

Substituting Equation (18) into its dyadic problem calculation yields

$$L(w, b, \varepsilon, \alpha, \beta) = \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \alpha_i \alpha_j y_i y_j x_i^T x_j. \tag{19}$$

Since $\beta_i \geq 0$, then having $0 \leq \alpha_i \leq C$, so the model representation of Equation (16) is transformed into

$$\begin{cases} \min\limits_{\alpha} \dfrac{1}{2} \sum\limits_{i=1}^{m} \sum\limits_{j=1}^{m} \alpha_i \alpha_j y_i y_j x_i^T x_j - \sum\limits_{i=1}^{m} \alpha_i \\[2mm] \text{s.t.} \sum\limits_{i=1}^{m} \alpha_i y_i = 0, \quad 0 \leq \alpha_i \leq C. \end{cases} \tag{20}$$

After simplification, only the variable α remains in Equation (21), so it is only necessary to find the value of α when the constraints are satisfied and the equation takes on a very small value. This paper uses the SMO algorithm to solve for the value of α: fix the parameters other than α, and then solve for the extreme values on α. The SMO algorithm is a very simple algorithm. However, due to the constraint $\sum_{i=1}^{m} \alpha_i y_i = 0$, α can be derived from other variables if other variables than α are fixed. Therefore, the SMO algorithm selects two variables α_p and α_q in α at a time and fixes the other parameters. In this way, after the initialization of the parameters, SMO can keep performing the following two steps until convergence.

(1) Select two variables α_p and α_q to be updated.

(2) Fix the parameters other than α_p and α_q, and solve Equation (21) to obtain the updated α_p and α_q.

Finally, the optimal solution for fatigue detection in track and field training can be obtained after solving the value of α by the SMO algorithm.

5. Experiments and analysis of results.

5.1. Feature selection result analysis.
In this paper, 1419 EEG data of 85 track and field athletes collected in literature [21] were used as data sets, of which 60% were training sets, 30% were test sets, and 10% were verification sets. After the EEG artifacts were removed, the awake state and fatigue state corresponding to the EEG data were labeled. To prevent training errors, ten-fold cross-validation is used to partition and verify the data set. The average of ten-round results is the average accuracy rate (mAP) of the model, which makes the model more reliable. The experiment used a PC desktop with Inter (R) i9-9820 CPU and NVIDIA GeForce RTX 2080 SUPER GPU to train and test the built model. Adam was adopted to optimize the model parameters, the learning rate was set to 0.0001, and the batch size of each iteration was 64.

To estimate the importance of characteristic selection, this article compares the maps of 10 track and field athletes (marked 1–10) under various characteristic ratios, and the outcome are implied in Table 1. The highest mAP of each athlete under characteristic ratios is bolded. As can be seen from Table 1, there are 6 athletes with the highest mAP when the characteristic proportion is 80% or 100%, and only 2 athletes with the highest mAP when the characteristic proportion is 40% or 60%. For athletes No. 4 and No. 10, mAP showed a downward trend as the characteristic of preserved characteristics increased, because these athletes had invalid or redundant features. Furthermore, for athletes Nos. 3, 5, 8, and 10, the mAP fluctuated between 5% and 10% as the proportion of preserved characteristics increased.

As shown in Figure 4, when the model contains 80% features, it can achieve the highest classification accuracy, mAP is 93.05%, and standard deviation is 4.12. When it contains 100% specific column features, the classification accuracy is the second highest, mAP is 92.4%, and standard deviation is 2.03, followed by 60%, 40% and 20%. FSA algorithm has the best classification performance when 80% of the features are retained. Therefore, the suggested RF feature importance and ranking importance methods are used to score the importance of features, and deleting low correlation invalid characteristics and high redundancy features can reduce the training cost of the model and improve the classification efficiency.

5.2. Comparative experimental analysis of performance.
To better evaluate the performance of the proposed model (OURS), mAP, mean accuracy (mPR), mean F1 value (mF1), MAE, mean specificity (mSP), and mean sensitivity (mSE) were comprehensively used to compare the classification performance. For the convenience of analysis, the model

Table 1. Categorization performance of 10 athletes retaining various proportions of characteristics

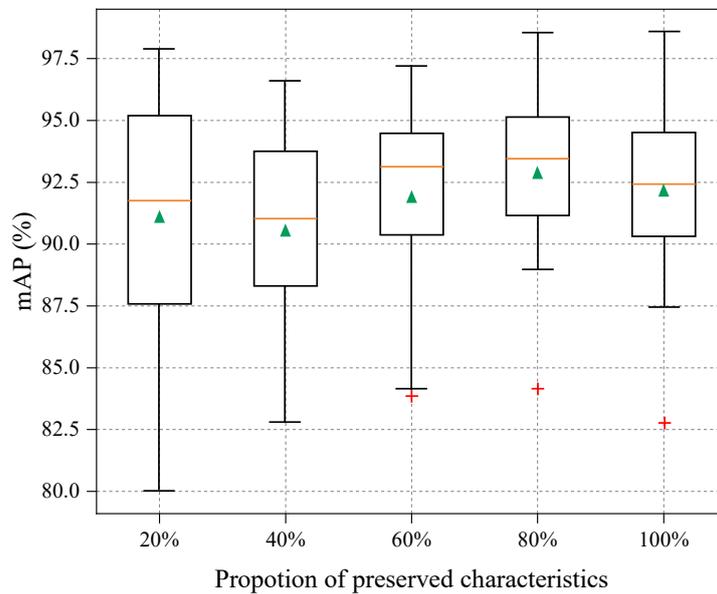| No.	20%	40%	60%	80%	100%
1	94.15%	90.12%	91.48%	94.88%	**95.24%**
2	95.28%	93.59%	95.35%	96.77%	**98.56%**
3	81.25%	84.96%	86.24%	**94.56%**	92.61%
4	**95.23%**	93.15%	91.26%	89.02%	86.14%
5	90.82%	94.21%	95.59%	96.29%	**97.31%**
6	94.06%	**95.44%**	92.69%	95.02%	91.56%
7	**92.14%**	89.39%	94.21%	85.27%	89.34%
8	87.19%	88.55%	92.68%	**94.75%**	92.14%
9	91.45%	87.11%	93.17%	94.20%	**95.27%**
10	87.25%	86.39%	83.65%	83.27%	**81.05%**

Figure 4. Accuracy comparison under various proportion of preserved characteristics

in this paper is denoted as OURS, the model in reference [16] is denoted as M1, the model in reference [18] is denoted as M2, the model in reference [19] is denoted as M3, the model in reference [20] is denoted as M4, and the model in reference [22] is denoted as M5. The comparison of mAP, mPR and F1 of different models is shown in Figure 5.

As can be seen from Figure 5, mAP of OURS is 93.61%, which increases 21.96%, 16.42%, 11.97%, 8.5% and 5.46% respectively compared with M1, M2, M3, M4 and M5, achieving the highest classification accuracy. In addition, mPR and mF1 of OURS are 90.14% and 92.57%, respectively, which are also higher than the other five models. The fatigue detection of M1 and M2 is based on DT and SVM respectively, and the time-frequency domain features of the original EEG are directly used for classification, and the feature extraction is insufficient, resulting in poor classification effect. Both M3 and M4 are based on CNN for fatigue classification. Although CNN has strong feature extraction capability, it is a classifier with high computational complexity and redundant features, resulting in lower classification performance than M5 and OURS. M5 uses PCA to select the optimal feature subset, and the classification accuracy reaches 88.15%, but the feature extraction
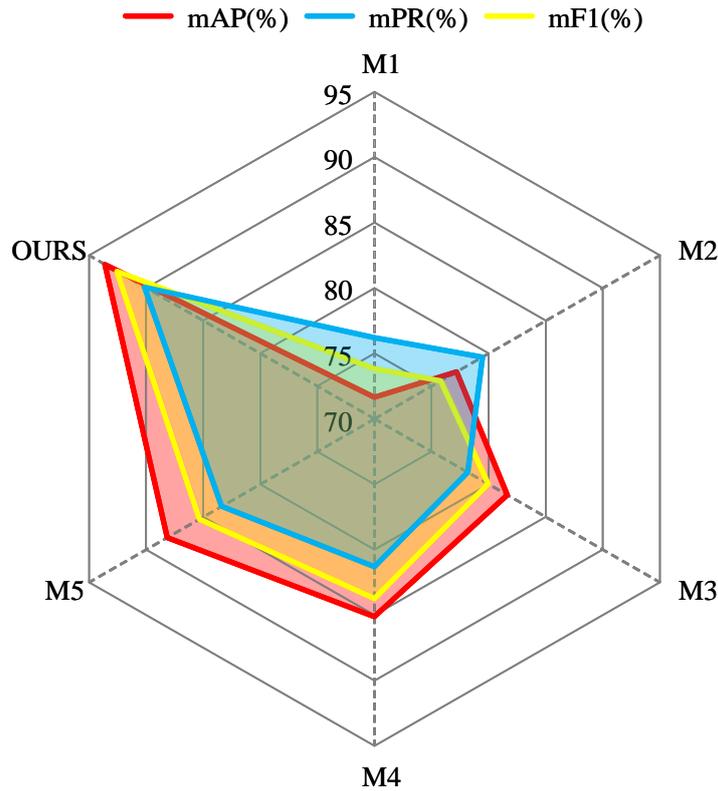
Figure 5. Comparison of classification performance of different detection models

is insufficient, and the SVM optimization is not combined with the characteristics of athlete training. To sum up, OURS has good detection performance.

The MAE, mSP and mSE pairs of the six models are shown in Table 2. mSP and mSE are the gold standard to measure the validity of the model, and the larger the value, the better the classification effect. The mSP and mSE of OURS are 97.62% and 98.28% respectively, both higher than the other five models, which verifies the effectiveness of OURS. In addition, the MAE of OURS is 0.61, which is 0.36–4.75 lower than that of the other five models, indicating that OURS has a high detection accuracy. OURS not only uses CNN for full feature extraction, but also deletes redundant features through RF and realizes fatigue detection by using optimized SVM classifier, which greatly improves the detection efficiency and verifies the effectiveness and efficiency of OURS.

Table 2. Fatigue testing performance of different models

Indicators	M1	M2	M3	M4	M5	OURS
MAE	5.36	3.57	2.91	1.59	0.97	0.61
mSP/%	72.05	79.17	84.93	89.56	93.19	97.62
mSE/%	78.52	83.35	88.94	91.74	95.33	98.28

6. **Conclusion.** In view of the issues of irrelevant features and unsatisfactory results in the current track and field training fatigue detection methods, this paper proposes a track and field training fatigue detection model based on FSA and ML. Firstly, the eye artifact contained in EEG was removed by ICA method, and the remaining component signals were decomposed and reconstructed to obtain pure EEG. Nextly, the EEG is transformed into two-dimensional image by continuous wavelet transform, and feature

extraction is carried out by multi-channel CNN. Then, RF is used to score and select important features and construct important feature vector space. Finally, the important features are input into the SVM classifier, which is used to judge the fatigue state and obtain the final fatigue detection classification result. The experimental results show that the classification accuracy of the proposed model is high, which proves that the proposed model is feasible and has practical application value.

Although the proposed model has achieved some results, the ICA method used for EEG artifact removal relies on prior knowledge. In the next step, the automatic artifact removal algorithm will be studied to further improve the efficiency of fatigue detection.

REFERENCES

[1] T. J. Abitante, S. B. Rutkove, K. R. Duda, and D. J. Newman, "Effect of athletic training on fatigue during Neuromuscular Electrical Stimulation," *Frontiers in Sports and Active Living*, vol. 4, 894395, 2022.

[2] B. T. Saragiotto, C. Di Pierro, and A. D. Lopes, "Risk factors and injury prevention in elite athletes: a descriptive study of the opinions of physical therapists, doctors and trainers," *Brazilian Journal of Physical Therapy*, vol. 18, no. 02, pp. 137–143, 2014.

[3] L. W. Oglesby, A. R. Gallucci, and C. J. Wynveen, "Athletic trainer burnout: a systematic review of the literature," *Journal of Athletic Training*, vol. 55, no. 4, pp. 416–430, 2020.

[4] N. R. Adão Martins, S. Annaheim, C. M. Spengler, and R. M. Rossi, "Fatigue monitoring through wearables: A state-of-the-art review," *Frontiers in Physiology*, vol. 12, 790292, 2021.

[5] K. Kaida, M. Takahashi, T. Åkerstedt, A. Nakata, Y. Otsuka, T. Haratani, and K. Fukasawa, "Validation of the Karolinska sleepiness scale against performance and EEG variables," *Clinical Neurophysiology*, vol. 117, no. 7, pp. 1574–1581, 2006.

[6] C. Zhang, C.-X. Zheng, and X.-L. Yu, "Automatic recognition of cognitive fatigue from physiological indices by using wavelet packet transform and kernel learning algorithms," *Expert Systems with Applications*, vol. 36, no. 3, pp. 4664–4671, 2009.

[7] A. Penson, S. van Deuren, M. Worm-Smeitink, E. Bronkhorst, F. H. van den Hoogen, B. G. van Engelen, M. Peters, G. Bleijenberg, J. H. Vercoulen, and N. Blijlevens, "Short fatigue questionnaire: Screening for severe fatigue," *Journal of Psychosomatic Research*, vol. 137, 110229, 2020.

[8] S. Rasa, Z. Nora-Krukle, N. Henning, E. Eliassen, E. Shikova, T. Harrer, C. Scheibenbogen, M. Murovska, B. K. Prusty, and E. N. o. ME/CFS, "Chronic viral infections in myalgic encephalomyelitis/chronic fatigue syndrome (ME/CFS)," *Journal of Translational Medicine*, vol. 16, pp. 1–25, 2018.

[9] F. Bjørheim, S. C. Siriwardane, and D. Pavlou, "A review of fatigue damage detection and measurement techniques," *International Journal of Fatigue*, vol. 154, 106556, 2022.

[10] G. Theofilidis, G. C. Bogdanis, Y. Koutedakis, and C. Karatzaferi, "Monitoring exercise-induced muscle fatigue and adaptations: making sense of popular or emerging indices and biomarkers," *Sports*, vol. 6, no. 4, 153, 2018.

[11] T. Bestwick-Stevenson, R. Toone, E. Neupert, K. Edwards, and S. Kluzek, "Assessment of fatigue and recovery in sport: narrative review," *International Journal of Sports Medicine*, vol. 43, no. 14, pp. 1151–1162, 2022.

[12] B. T. Jap, S. Lal, P. Fischer, and E. Bekiaris, "Using EEG spectral components to assess algorithms for detecting fatigue," *Expert Systems with Applications*, vol. 36, no. 2, pp. 2352–2359, 2009.

[13] Z. Yang and H. Ren, "Feature extraction and simulation of EEG signals during exercise-induced fatigue," *IEEE Access*, vol. 7, pp. 46389–46398, 2019.

[14] H. R. Al Ghayab, Y. Li, S. Siuly, and S. Abdulla, "Epileptic EEG signal classification using optimum allocation based power spectral density estimation," *IET Signal Processing*, vol. 12, no. 6, pp. 738–747, 2018.

[15] R. Espinosa, J. Talero, and A. Weinstein, "Effects of tau and sampling frequency on the regularity analysis of ECG and EEG signals using ApEn and SampEn entropy estimators," *Entropy*, vol. 22, no. 11, 1298, 2020.

[16] M. M. Hasan, M. H. Mirza, and N. Sulaiman, "Fatigue state detection through multiple machine learning classifiers using EEG signal," *Applications of Modelling and Simulation*, vol. 7, pp. 178–189, 2023.

[17] M. T. Worsey, H. G. Espinosa, J. B. Shepherd, and D. V. Thiel, "One size doesn't fit all: Supervised machine learning classification in athlete-monitoring," *IEEE Sensors Letters*, vol. 5, no. 3, pp. 1–4, 2021.

[18] H. Wang, L. Zhang, and L. Yao, "Application of genetic algorithm based support vector machine in selection of new EEG rhythms for drowsiness detection," *Expert Systems with Applications*, vol. 171, 114634, 2021.

[19] W. H. Gu, Y. Zhu, X. D. Chen, L. F. He, and B. B. Zheng, "Hierarchical CNN-based real-time fatigue detection system by visual-based technologies using MSP model," *IET Image Processing*, vol. 12, no. 12, pp. 2319–2329, 2018.

[20] H. Li, Y. Wang, and Y. Nan, "Motion fatigue state detection based on neural networks," *Computational Intelligence and Neuroscience*, vol. 10, no. 1, 9602631, 2022.

[21] S. Karvekar, M. Abdollahi, and E. Rashedi, "Smartphone-based human fatigue level detection using machine learning approaches," *Ergonomics*, vol. 64, no. 5, pp. 600–612, 2021.

[22] J. Min, M. Cai, C. Gou, C. Xiong, and X. Yao, "Fusion of forehead EEG with machine vision for real-time fatigue detection in an automatic processing pipeline," *Neural Computing and Applications*, vol. 35, no. 12, pp. 8859–8872, 2023.

[23] T.-Y. Wu, H. Li, S. Kumari, and C.-M. Chen, "A Spectral Convolutional Neural Network Model Based on Adaptive Fick's Law for Hyperspectral Image Classification," *Computers, Materials & Continua*, vol. 79, no. 1, pp. 19–46, 2024.

[24] F. Zhang, T.-Y. Wu, J.-S. Pan, G. Ding, and Z. Li, "Human motion recognition based on SVM in VR art media interaction environment," *Human-centric Computing and Information Sciences*, vol. 9, 40, 2019.

[25] D. Valkenborg, A.-J. Rousseau, M. Geubbelmans, and T. Burzykowski, "Support vector machines," *American Journal of Orthodontics and Dentofacial Orthopedics*, vol. 164, no. 5, pp. 754–757, 2023.

[26] A. Kocaoğlu, "An efficient SMO algorithm for solving non-smooth problem arising in ε-insensitive support vector regression," *Neural Processing Letters*, vol. 50, no. 1, pp. 933–955, 2019.

[27] A. Tharwat, "Independent component analysis: An introduction," *Applied Computing and Informatics*, vol. 17, no. 2, pp. 222–249, 2021.

[28] M. Petrović, V. Rakočević, N. Kontrec, S. Panić, and D. Ilić, "Hybridization of accelerated gradient descent method," *Numerical Algorithms*, vol. 79, pp. 769–786, 2018.

[29] H. U. Amin, A. S. Malik, R. F. Ahmad, N. Badruddin, N. Kamel, M. Hussain, and W.-T. Chooi, "Feature extraction and classification for EEG signals using wavelet transform and machine learning techniques," *Australasian Physical & Engineering Sciences in Medicine*, vol. 38, pp. 139–149, 2015.

[30] B. P. Lovatti, M. H. Nascimento, Á. C. Neto, E. V. Castro, and P. R. Filgueiras, "Use of Random forest in the identification of important variables," *Microchemical Journal*, vol. 145, pp. 1129–1134, 2019.