Evaluation Method of Basketball Teaching and Training Effect Based on Wearable Device

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To reduce errors in the evaluation of basketball players' training effect and facilitate the coaches to make reasonable training plans, this study proposes an evaluation method of the basketball player training effect based on wearable devices and machine learning algorithms. Wearable devices in social physics are intelligent, and their main components are integrated into clothing and other accessories. They collect data, track activities, and customize the experience to the needs and desires of users. In this study, physiological indicators such as heart rate and hemoglobin are selected as input vectors of the support vector machine (SVM), and the expected value of basketball player training effect evaluation is taken as the output to construct training samples. The parameters of the SVM are set to minimize the evaluation error as the learning objective. The SVM learns training samples and constructs an evaluation model for the training effect of basketball players. We use the method proposed in this study to evaluate the training effect of basketball players through computer simulation of dribble, pass, rebound, layup, and shooting. The experimental results show that the training effect evaluation of basketball players with the proposed method has a low relative error, high classification accuracy, and high practical application value.

Keywords: human-behavior, social physics, basketball, wearable device, training effect, support vector machine, classification accuracy

1 INTRODUCTION

As a comprehensive and strong sports event, basketball has a high requirement on the coordination, flexibility, stability, and explosive force of the players and requires high-strength training to achieve the abovementioned skills and levels [1, 2]. However, traditional basketball training cannot meet the requirements of basketball players in the new era, and especially in the basic physical quality training of athletes, there are many shortcomings [3–5]. In recent years, basketball teaching and training based on wearable devices have been gradually introduced into the basketball training system. Relevant research shows that after the introduction of basketball teaching and training based on wearable devices, the shooting accuracy is significantly higher than that of traditional training [6]. Therefore, it is of great significance to apply basketball teaching and training based on wearable devices.

Against the backdrop of science and technology, sports training is also developing new ideas, new technology, new equipment, and other aspects [7]. Wearable devices based on mobile Internet and a cloud platform with functions of wireless transmission and fast real-time feedback are increasingly, widely, and deeply used in sports training, providing a more convenient and scientific way to explore the biological significance of sports training [8–10]. Due to the needs of competitive sports, athletes

FIGURE 1 | Training effect evaluation of basketball players.
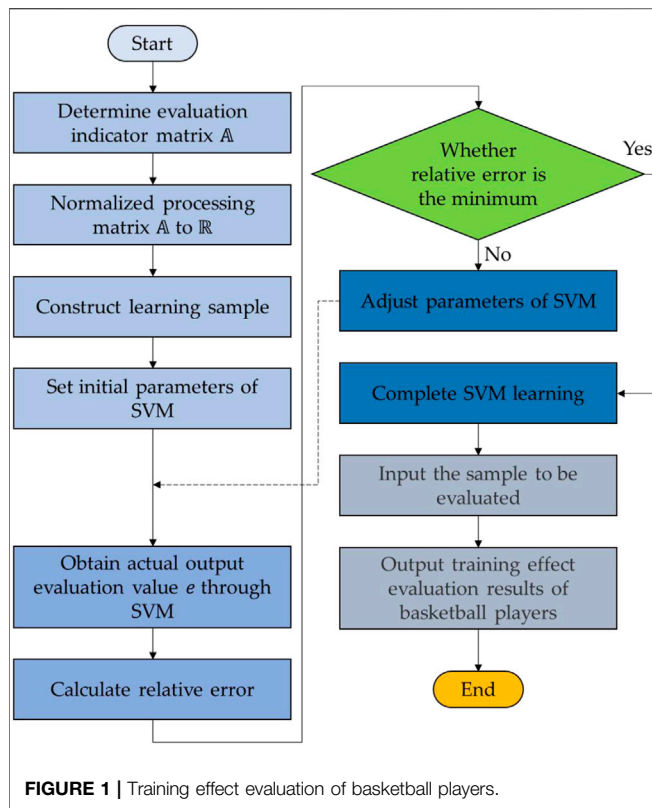
should complete physical activities under extreme conditions such as high speed and high confrontation, and any external factors may interfere with their normal performance. Therefore, wearable devices must collect data without affecting their normal performance, and integration of sensor functions and miniaturization of appearance are particularly important [11, 12].

Daily training of athletes is an important way to improve their performance in competitions. Daily training of athletes helps coaches to clarify the status and competitive level of athletes [13]. Training programs are formulated according to the training situation of athletes, and accurate evaluation of training effects is an important part of improving the performance of athletes. The evaluation is affected by many factors such as athlete psychological state and training environment, which is mainly divided into linear evaluation and nonlinear evaluation. The evaluation of the athlete training effect is characterized by nonlinear variation [14]. The linear evaluation method cannot guarantee the accuracy of training effect evaluation, while the nonlinear evaluation method can fully consider the impact factors of athlete training and has become the main research direction in the evaluation field. Machine learning (ML) is an efficient algorithm among nonlinear evaluation methods, among which the support vector machine (SVM) has a good evaluation effect [15, 16]. The kernel function and parameters of the SVM can effectively improve the evaluation accuracy of the athlete training effect. In view of the instability and randomness of athlete training effect evaluation, it is of great practical significance to study efficient evaluation methods.

Applying physiological-state indexes to the evaluation of an athlete's training effect can improve the scientific nature of the athlete's training process [17]. The physical function state of athletes determines the performance of the physical function of athletes. We can ascertain the physical state of athletes through wearable sensors, and it is scientific to evaluate the training effect of athletes based on the physical function state of athletes. The training tasks of athletes are adjusted through the physical state of athletes, and the whole training process is formulated scientifically. The SVM method of the ML algorithm is applied to evaluate the training effect of basketball players, which is helpful in analyzing the training effect of basketball players and improving the performance of basketball players through scientific and reasonable training plans.

The main contribution of this study is that an evaluation method of the training effect of basketball players based on wearable devices and the ML algorithm is proposed. The rest of the study is organized as follows: **Section 2** summarizes the related works; **Section 3** proposes the evaluation method of the training effect of basketball players based on wearable devices and the SVM; experimental results are reported in **Section 4**; finally, **section 5** concludes this study.

2 RELATED WORKS

Powered by advanced computer technology, the appearance and performance of wearable devices are changing more and more rapidly. Devices including GPS, accelerometer, gyroscopes, and so on have collected a large amount of original data, which increasingly relies on methods such as the support vector machine (SVM), k-means, and deep neural network (DNN) to deep mine and process the data [18]. Data mining technology can make a clear processing and display of the correlation of various factors between various data, thus discovering some sports laws of great value, achieving effective control over the process of sports training and constantly promoting wide and profound changes in competitive sports. By combining the extraction and processing methods of the abovementioned basic data of sports training, we can conclude that the accuracy and calculation methods of data operation in various sports modes may become the core elements of the future development of wearable devices. In [19], the authors combined the basic knowledge of human body posture measurement and human body model to build a parametric and variable human body posture model. Using wireless wearable devices, in [20], the authors studied the physical quality, psychological state, and training environment of the athletes and constructed the indicators for monitoring their development in routine training. In [21], the authors designed a wearable device that used acceleration sensors to obtain the acceleration information generated by the user's muscles in the process of movement. In [22], the authors provided a comprehensive overview of the application of wearable technology in evaluating biomechanical and physiological parameters of athletes. In [23], the authors designed a wearable device that accurately calculated and monitored energy consumption for exercise.

ML is a new data processing method with the rapid development of computer technology, which can ensure that
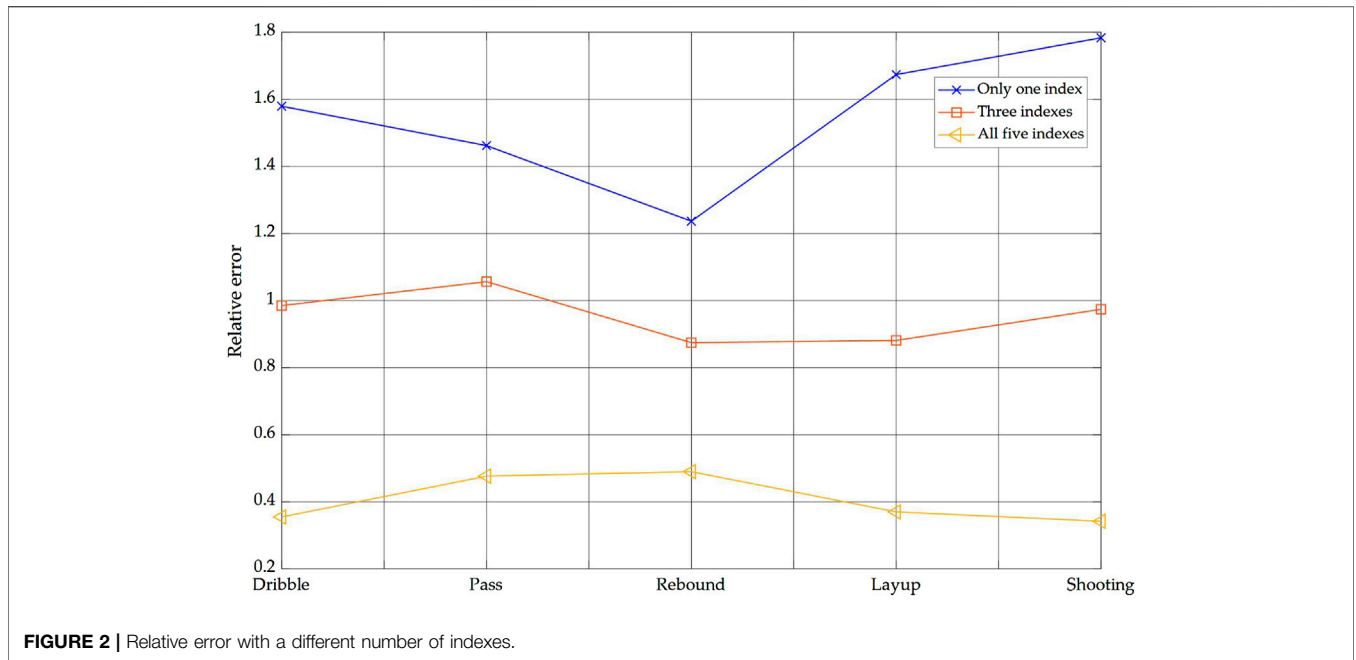
FIGURE 2 | Relative error with a different number of indexes.

computers can have the same learning ability as human beings, and it also provides technical support for effectively processing large-scale data. As a typical intelligent classification model, the SVM has excellent classification ability and has been widely used in data classification. In [24], the authors proposed an SVM kernel function that could classify data without spatial transformation. In [25], the authors proposed an unbalanced data classification algorithm based on clustering and SVM. In [26], the authors proposed an improved cost-sensitive SVM (ICS-SVM) algorithm to solve the imbalance problem in network traffic recognition. In [27], the authors proposed a fast classification method of the SVM (FC-SVM) based on data reconstruction. Marking a sufficient number of training samples is time-consuming and laborious; as for this, in [28], the authors proposed a large-scale data classification strategy and then used the selected instances to train a multi-kernel SVM to obtain the classifier model to predict the subsequent new instances (LSDC-MKSVM).

3 MACHINE LEARNING–BASED TRAINING EFFECT EVALUATION OF BASKETBALL PLAYERS

3.1 The Machine Learning–Based Algorithm

Let $\mathbb{P}(s)$ be the probability measure existing in space s and the set of existing functions be, respectively, $\mathbb{C}(s, A)$ and $a \in \varnothing$, then, the minimum risk functional can be achieved [29], which is defined as follows:

$$r(a) = \int \mathbb{C}(s, A) \mathrm{d}\mathbb{P}(s), \tag{1}$$

where the probability measure $\mathbb{P}(s)$ is unknown, but there is a fixed independent distribution sample. Let y be the output of the trainer, which can be 0 or 1. Existing $L(x, A)$, where $A \in \varnothing$ represents the set of indicator functions and the cost function is defined as follows.

$$h_\theta\left(y, L(x, A)\right) = \begin{cases} 0, & y = L(x, A) \\ 1, & y \neq L(x, A) \end{cases}, \tag{2}$$
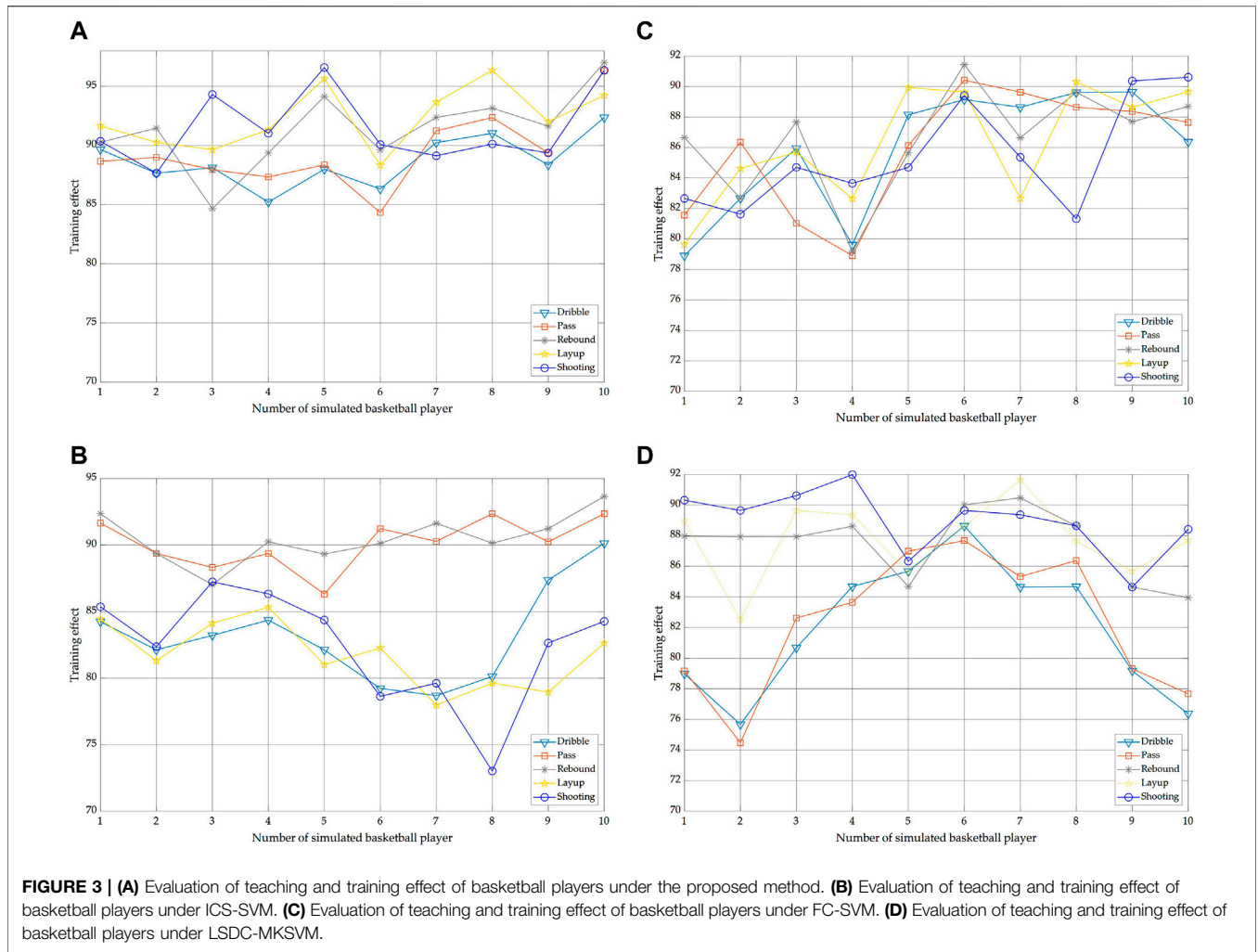
where θ is the parameter. By specifying the indicator function $L(x, A)$ and the output probability of the trainer, the function of the lowest probability of the classification error must be obtained on the basis of the known training set.

The SVM has a high promotion level [30, 31], which seeks the final results of models with the best learning ability and low complexity based on limited sample information. It is suitable for high-dimension, small sample, and nonlinear data space, and its generalization level is high. Selecting the SVM as the evaluation method of the training effect of basketball players can make full use of the advantages of the SVM in data processing of small samples and obtain the best classification surface [32] through a small number of samples. The obtained classification surface evaluates the training effect of basketball players who pay the lowest price and has the highest popularization.

Training data are represented by (x_k, y_k) and satisfy $k = 1, 2, \cdots, n$, $x_k \in R^d$, and $y_k \in \{-1, 1\}$, and n is the number of samples. If there is a hyperplane $\mathbb{H}$, we have

$$wx + b = 0, \tag{3}$$

where w and b represent the normal line of the superplane and the orthogonal distance from the superplane to the origin,

FIGURE 3 | (A) Evaluation of teaching and training effect of basketball players under the proposed method. **(B)** Evaluation of teaching and training effect of basketball players under ICS-SVM. **(C)** Evaluation of teaching and training effect of basketball players under FC-SVM. **(D)** Evaluation of teaching and training effect of basketball players under LSDC-MKSVM.

respectively. The positive and negative data are separated by the hyperplane $\mathbb{H}$. The hyperplane interval is defined as follows:

$$\frac{2}{w} = d_1 + d_2, \tag{4}$$

where w, d_1, and d_2 represent the Euclidean norm [33] of w and the two samples closest to $\mathbb{H}$.

The SVM method is used to search the hyperplane with maximum interval.

$$\min_{(w,b)} \frac{1}{2}w^2. \tag{5}$$

subject to

$$y_k(wx_k + b) - 1 \geq 0, \ k = 1, 2, \cdots, n. \tag{6}$$

The optimal classification surface problem is transformed into its duality problem by the Lagrange optimization method, which is defined as follows:

$$O(\lambda) = \frac{1}{2}\sum_{k,p=1}^{n} \lambda_k \lambda_p x_k x_p y_k y_p - \sum_{k=1}^{n} \lambda_k. \tag{7}$$

Taking $\sum_{k=1}^{n} \lambda_k y_k = 0$ and $\lambda_k \geq 0, k = 1, 2, \cdots, n$ as constraints, the minimum value of **Eq. (7)** is solved by using the Lagrange multiplier λ_k corresponding to the sample. The samples corresponding to nonzero λ_k in the obtained results are support vectors.

The final optimal classification function is defined as follows:

$$D = \text{sgn}(wx + b) = \text{sgn}\left(\sum_{k=1}^{n} \lambda_k x_k x y_k + b'\right), \tag{8}$$

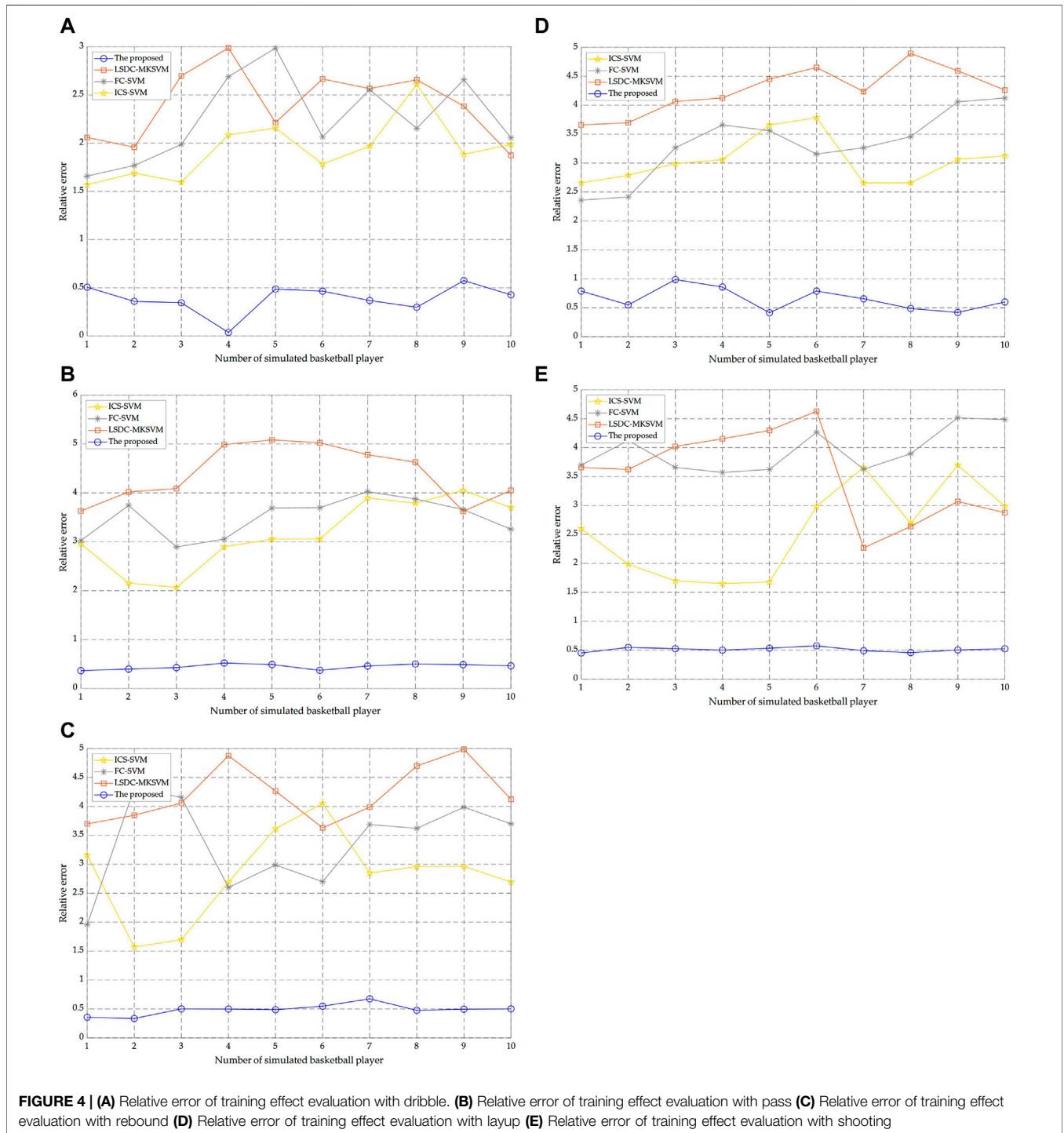where b' is the classification threshold.

When the experimental sample is linearly indivisible, the relaxation term γ_k is introduced to **Eq. 7** and **Eq. (8)**, and the acquisition method is defined as follows:

$$\min_{(w,b)} \frac{1}{2}w^2 + C\gamma_k, \tag{9}$$

subject to

$$y_k(wx_k + b) - 1 \geq 0, \ k = 1, 2, \cdots, n. \tag{10}$$

When the penalty term $C > 0$ is a constant, then the duality problem condition is converted to $0 \leq \lambda_k \leq C$

FIGURE 4 | (A) Relative error of training effect evaluation with dribble. **(B)** Relative error of training effect evaluation with pass **(C)** Relative error of training effect evaluation with rebound **(D)** Relative error of training effect evaluation with layup **(E)** Relative error of training effect evaluation with shooting

When the evaluation is a nonlinear problem, the input feature x is transformed into the high-dimensional feature space according to the constructed nonlinear mapping, and the optimal classification hyperplane [34] is constructed from the high-dimensional feature space of the mapping.

The kernel function $Ker(x_k, x_p)$ which meets the Mercer condition, can transform the nonlinear classification problem

into a linear classification problem in the optimal classification plane [35]. The objective function is defined as follows:

$$O(\lambda) = \frac{1}{2} \sum_{k,p=1}^{n} \lambda_k \lambda_p Ker(x_k, y_n) y_k y_p - \sum_{k=1}^{n} \lambda_k. \quad (11)$$

In this case, the optimal classification function is defined as follows:
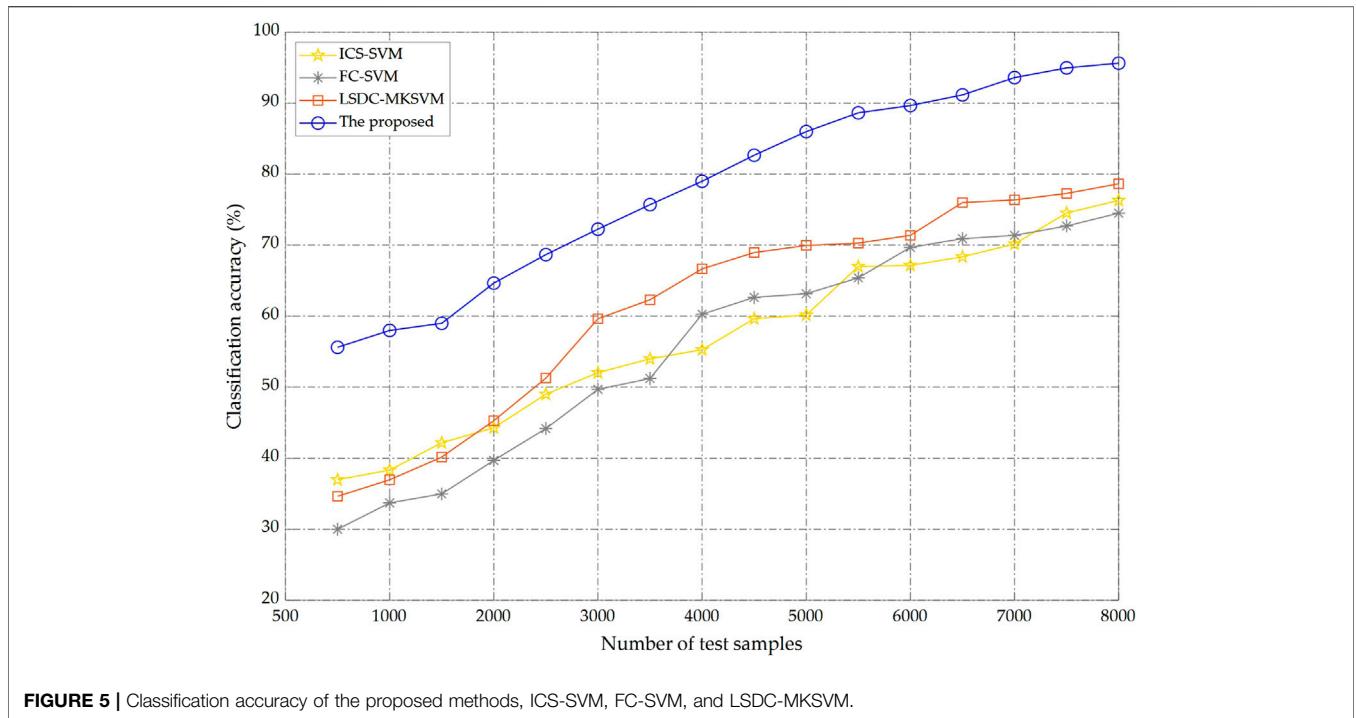
FIGURE 5 | Classification accuracy of the proposed methods, ICS-SVM, FC-SVM, and LSDC-MKSVM.

$$D = \text{sgn}\left(\sum_{k=1}^{n} \lambda_k y_k Ker(x_k, x) + b'\right). \quad (12)$$

Different types of nonlinear decision surface SVMs can be realized by different kernel functions [36], and RBF is selected as the kernel function of training effect evaluation of basketball players, which is defined as follows.

$$Ker(x_k, x) = \exp\left(-\frac{\|x - x_k\|^2}{2\sigma^2}\right). \quad (13)$$

3.2 Training Effect Evaluation of Basketball Players

The physiological information generated by basketball players during training can reflect the training effect and show more information that cannot be evaluated by the previous evaluation system of the training effect of basketball players.

$X = \{x_1, x_2, \cdots, x_n\}$ and $Y = \{y_1, y_2, \cdots, y_n\}$ are used to represent the training sample set of basketball players and the test indicator set which can reflect the training effect of basketball players (such as heart rate, hemoglobin, creatine kinase, etc.), respectively. Matrix $\mathbb{A} = (a_{ij})_{n \times m}$ is used to represent the indicator matrix of basketball player training sample set X for measurement indicator set Y. The basketball player training sample x_i for measurement indicator set y_i is presented in $a_{ij} = y_j(x_i)$, $(i = 1, 2, \cdots, n, j = 1, 2, \cdots, m)$. The standardized indicator sets $\mathbb{A}$ to $\mathbb{R} = (r_{ij})_{n \times m}$ are constructed to eliminate the influence of different physical dimensions on the evaluation training effect [37].

The input of training effect evaluation of basketball players is the measured value vector $(r_{i1}, r_{i2}, \cdots, r_{im})$ of the basketball player training sample x_i under the physiological measurement indicator y_i. Taking the evaluation result e_i of basketball player training effect x_i as the output. there exists a nonlinear mapping between the normalized matrix $\mathbb{R}$ and evaluation result, which is represented by M, and its function is as follows:

$$e_i = M(r_{ij}). \quad (14)$$

The basketball player training effect sample $x_i = (r_{i1}, r_{i2}, \cdots, r_{im})$ is selected as the input vector of the SVM, and the training effect sample evaluation value is selected as the regression target value of the SVM [38]. Constructing a learning sample set by $S = \{(x_i, e_i)\}_i^n$, the regression function is defined as follows:

$$u = \sum_{k=1}^{s} (\lambda_k - \lambda_k')\kappa(x, x^k) + b, \quad (15)$$

where x^k and s represent the support vector and the number of support vectors, respectively; λ_k represents the Lagrange multiplier, and $x^k = (r_{k1}, r_{k2}, \cdots, r_{km})$, $k = 1, 2, \cdots, s$.

Given the aforementioned values, the nonlinear mapping M between the indicator measurement vector $(r_{i1}, r_{i2}, \cdots, r_{im})$ and the training effect evaluation value e_i of the basketball player training sample x_i under the measurement physiological index y_i is realized.

Applying the SVM of ML to evaluate the training effect of basketball players is shown in **Figure 1**.

1) According to the physiological indicators that affect the training effect of basketball players, the evaluation indicator matrix $\mathbb{A}$ of training effect is determined.

2) The indicator matrix $\mathbb{A}$ for evaluating the training effect of basketball players is transformed into the normalized matrix $\mathbb{R}$.

3) The basketball player training effect sample $x_i = (r_{i1}, r_{i2}, \cdots, r_{im})$ and evaluation value e_i are used to construct the learning sample set $Q = \{(x_i, e_i)\}$. We randomly select samples from the learning sample set to construct a training set and evaluation set for SVM learning.

4) RBF is selected as the kernel function of the SVM to obtain the regression function.

5) After obtaining the ideal parameters, the learning process of the SVM [39] is completed, and the training effect of basketball players is evaluated by the trained SVM. The physiological test index vector $(r_{i1}, r_{i2}, \cdots, r_{im})$ of the training effect sample x_i of basketball players is input to be evaluated, and the final evaluation result e^i_{SVM} of the basketball player training effect of the SVM can be obtained.

4 EXPERIMENTS

4.1 Setup

We use the method proposed in this study to evaluate the training effect of 10 basketball players through computer simulation of dribble, pass, rebound, layup, and shooting. A total of 10,000 experimental samples are collected, including 2000 as learning samples and the remaining 8,000 as test samples. The radial basis function (RBF) is selected as the kernel function of the SVM, and winSVM software is used to solve the SVM. winSVM can adapt to the Windows operating system well and quickly realize the SVM classification and regression problems [40]. The learning samples are divided into 10 groups with 200 in each group. The final parameters are used to train the SVM, and the number of support vectors and parameter b of the regression function is obtained as 40 and -0.226, respectively.

4.2 Result Analysis

Data collected by wearable devices are based on the HealthData.gov dataset. The heart rate, blood oxygen, hemoglobin, creatine kinase, and blood lactate are selected as physiological test indexes to evaluate the training effect of athletes. Statistically, when only the heart rate is used as a single physiological test metric, the heart rate, blood oxygen, and hemoglobin are used as three physiological test indexes, and all five physiological test indexes are used; the relative error of training effect evaluation of basketball players is shown in **Figure 2**. As can be seen from the experimental results in **Figure 2**, with the increasing number of physiological test indexes, the relative error of the evaluation results of basketball player training effects has been reduced, indicating that adding more physiological indexes to the ML algorithm can effectively improve the accuracy of the evaluation of the training effects of

basketball players . The main reason is that multiple physiological indicators can improve the diversified effect of basketball player training effect evaluation and improve the accuracy of basketball player training effect evaluation.

The output results of evaluating the training effects of five sports for ten athletes using the method proposed in this study are shown in **Figures 3A–D**. The expert evaluation value is selected as the judgment index of the accuracy of basketball player training effect evaluation. The methods proposed in this study, ICS-SVM [26], FC-SVM [27], and LSDC-MKSVM [28], are used to evaluate the performance of basketball athletes in dribble, pass, rebound, layup, and shooting basketball movements. It can be seen from **Figures 3A–D** that the method proposed in this study has good training effects in all sports training of basketball players, and ICS-SVM has good performance in pass and rebound, while LSDC-MKSVM has high training effects in the rebound, layup, and shooting.

To intuitively show the training effect evaluation performance of the proposed method, the comparative results of the relative errors of the five sports training effects of basketball players evaluated by different methods are shown in **Figures 4A–E**. From the comparison results in **Figures 4A–E**, it can be seen that when expert evaluation values are selected as the evaluation basis for performance judgment, the relative errors of the method proposed in this study for evaluating the training effects of various sports of basketball players are all less than 1%. ICS-SVM, FC-SVM, and LSDC-MKSVM are all above 1% relative errors in evaluating the training effects of various movements for basketball players. The comparison results show that the method proposed in this study has higher performance in evaluating the training effect of basketball players. The analysis of the results of the proposed method is helpful for coaches in making training plans for the training effect of basketball players, and the method can be applied to the actual evaluation of the training effect of basketball players.

After the heart rate, blood oxygen, hemoglobin, creatine kinase, and blood lactate are collected by wearable devices from the HealthData.gov dataset, we evaluated the teaching and training effects of basketball players based on their physical function. As can be seen from **Figure 5**, with the increasing number of test samples, it is obvious that the classification accuracy of the method proposed in this study keeps the escalating trend well and reaches 95.6248%. In contrast, for the other three baselines, although the classification accuracy has been increasing with the increasing number of test samples, it has never exceeded 80%. This is because the algorithm proposed in this study constructs the optimal classification hyperplane in the high-dimensional feature space. It only needs to make the inner product sum of the new sample and all samples in the training data, which is crucial and the basic premise for nonlinear generalization using kernel later. The inner product operation is only related to the support vector, which can greatly reduce the operational complexity and improve the classification accuracy.

5 CONCLUSION

The training effect of basketball players determines the final competition results, which are affected by training methods, their quality, and other factors, so the training effect fluctuates greatly. In this study, the physiological indicators of basketball players obtained by wearable devices are used to evaluate their training effects. The training effects of basketball players are evaluated by the SVM, which has a higher evaluation performance in ML. The effectiveness of the proposed method in evaluating the training effect of basketball players is verified by pass and other movements, which has a higher guiding significance for improving the training effect of basketball players.

The SVM method has good generalization performance and simple operation. But like a neural network, it also has an inherent disadvantage, which is that it does not have a good explanatory function and does not support large samples. How to further improve the accuracy of the SVM and how to combine it with other methods (such as the neural network and rough set) to improve interpretation function and select evaluation indicators are further subjects to be studied.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

SL contributes to writing and data analysis; WZ contributes to methodology and material collection.

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