

Research Article

Smart System Design for College Physical Education Class Based on Abnormal Audio Detection Algorithm

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Based on dual-core technology and the theory of nontransmission and noninterference of information flow, this paper conducts a detailed system trust environment investigation on key issues such as trust routing design and reliability analysis in the embedded structure. At the same time, we will study the method of extracting features from speech data. When dealing with abnormal audio detection, firstly, the preprocessed valid audio clips are framed and windowed and have stable short-term characteristics; after the feature is stable, the frequency feature and time domain feature of audio data are analyzed and compared. And then combined with specific applications, a detailed demand analysis is carried out, and the development plan and implementation method of the college physical education network auxiliary system are proposed. The teaching system follows a three-tier system structure. In order to expand the existing functions, this paper uses the principle of modularity, starting from the following four aspects: educational resources, online question and answer, coursework, and test-related modules. We choose object-oriented and easy-to-expandable modules, such as the development and implementation of programming language environments and database systems. By applying the abnormal audio detection technology to the embedded system of college P.E. classroom, it can effectively optimize the traditional P.E. teaching mode and promote the teaching efficiency and the new development of P.E. teaching in the information age.

1. Introduction

This article explains how to use a bootloader and a stable kernel to create a root of trust for embedded systems. The article starts the FLASH accelerator program and test, verifies the trusted kernel, and protects the FLASH boot program by preventing users and advanced software from writing [1]. Through the combination of the two, the reliable root of trust security function can be guaranteed; the trusted kernel is integrated in the trusted platform in the component (vTPM), and a unified system interface is provided for users to realize the easy configuration and compatible storage of different FLASH domain installation platforms and regions [2]. Compared with a reliable computing organization structure, this method does not require additional equipment and can avoid cost overruns, power consumption, and volume, and make it more versatile [3]. In this article, a prototype system has been built to implement this method.

Experimental results show that this method can provide the trusted platform module (TPM) cryptographic service-related functions and effectively improve system security. Then, we will study the classification method of abnormal audio detection [4, 5]. This article uses deep feedforward neural network as the classifier to analyze the basic unit and architecture of deep feedforward neural network and compares the advantages and disadvantages of various activation, loss, and optimization algorithms [6]. In this article, we will design two deep feedforward model architectures for neural networks, all of which are suitable for high-performance servers with powerful computing power and energysaving embedded devices [7]. Comparison experiments with traditional algorithms show that the algorithm has good performance classification effect. Taking the development of online sports as the theme and the establishment of a sports network auxiliary system as the content, the research on the auxiliary role of network technology in physical education is

studied [8]. In the designed college sports system, physical education teachers can learn the online environment through the Internet, and they can prepare courses and PPT and use online technology to upload videos, post homework, and post test standards and results [9, 10]. Students can access the course materials on the server at any time, avoiding the problem of lack of knowledge due to the difficulty of certain technical movements in physical education [11]. The teaching system breaks the time and space boundaries of the traditional physical education model and realizes online learning and answering students' questions, and uploading and downloading data and other functions. The system interface is simple, easy to use, and easy for teachers and students to use, realizes the educational resource information management and educational resource sharing between teachers, and helps contemporary students to better study physical education, not to just focus on the knowledge of books, and let its morality, intelligence, physical, beauty, and labor get all-round development [12, 13].

2. Related Work

The literature introduces deep feedforward neural networks, analyzes the basic units and architecture of deep feedforward neural networks in detail, compares and analyzes the advantages and disadvantages of different activation functions, loss functions, and optimization algorithms, and uses Adam optimization algorithms for deep learning training the optimizer in the process, and two deep feedforward neural network model architectures are designed [14]. The literature introduces the audio event detection algorithm, introduces the framework and process of the audio event detection algorithm, and specifically states the audio preprocessing process (framing, windowing, etc.) and some classic features commonly used in audio; the basic knowledge of deep learning is related to event detection, including some commonly used networks, such as convolutional neural networks [15]. The literature introduces the CRNN abnormal audio event detection algorithm of spectrogram, extracts the spectrogram of abnormal audio event, and converts the abnormal audio into the form of spectrogram. This time-frequency representation of audio is very suitable and can be effectively input into the deep learning audio recognition model to perform further feature learning and classification; select a hybrid CRNN model as the basic recognition model, learn the features in the spectrogram, and finally give the classification results; conduct experimental training of the model, and test the accuracy of the model. With generalization ability, verify the performance of the algorithm. The literature introduces the neural network abnormal audio event CRDNN, which exists as an enhancement module of audio data [16]. The CRDNN performs a series of data enhancement calculations on the input abnormal audio data such as encoding, translation, and decoding [17]. It is experimentally proved that the CRDNN data enhancement module makes the model have stronger anti-noise performance, which proves that the addition of the module effectively suppresses environmental noise and

improves the accuracy of abnormal audio event detection in different situations and real environments with different signal-to-noise ratios [18]. The literature introduces the related technologies used to construct the physical education network auxiliary system, such as the three-tier model, database access technology, and programming technology [19, 20].

3. Embedded System and Abnormal Audio Detection

3.1. Embedded System. The original purpose of trusted computing is to solve the hidden dangers of computer systems, and most of the existing researches are also carried out on computer systems. Embedded systems and computer systems are very different in their technical roots and application fields. Therefore, research results applicable to computer systems cannot be directly transferred to the embedded field. Building an integrated trusted computing environment faces many new scientific problems.

Embedded computer, as a computer designed for specific applications, not only has some common characteristics of computers, but also has its own obvious characteristics. Embedded devices have a special technical environment, such as significant differences between different architectures and systems. These attributes prevent embedded devices from using the security protection that was originally applicable to traditional IT devices. The reliability research of embedded computing environment can learn from the results of computer reliability collaborative research, but the unique attributes and requirements of embedded systems must also be considered.

The main body of embedded system computing is the application software running on it. Building a reliable embedded computer environment includes providing reliable operating media and related technical mechanisms for the application software, such as computer hardware and software environments.

Establish a comprehensive trust route, that is, how to design a trusted route according to the requirements of the embedded system. The core concept of DRTM dynamic trust routing technology is to introduce new CPU commands and use the commands and related mechanisms provided by the processor to achieve a dynamic structured and reliable measurement environment. We can use new instructions to create a controllable and verifiable execution environment that is not affected by the components loaded by the system, ensuring that the program is loaded under the instructions and not manipulated by other components, forming reliable dynamic execution surroundings.

3.2. Abnormal Audio Feature Extraction. For different shortterm analysis methods, in order to obtain different audio data characteristic parameters, different window functions need to be selected according to the analysis method. The process of framing and windowing audio data requires multiplying the audio waveform by the time domain window function. This process should make the gradient at both ends of the time frame as small as possible to avoid sudden changes at both ends of the time frame. The intercepted audio waveform is slowly reduced to zero, which weakens the interception effect of the audio frame. The window function should increase the bandwidth of 3 dB in the frequency range, and the maximum sideband should be small.

The formula for the rectangular window is

$$h(n) = \begin{cases} 1, 0 \le n \le (N-1), \\ 0, n = other. \end{cases}$$
(1)

The frequency response of the digital filter is

$$H\left(e^{j\omega T}\right) = \sum_{n=0}^{N-1} e^{-j\omega T} = \frac{\sin\left(N\omega T/2\right)}{\sin\left(\omega T/2\right)} e^{-\frac{j\omega T\left(N-1\right)}{2}}.$$
 (2)

The rectangular window has a linear frequency response, and the frequency corresponding to the first zero value of the frequency response is

$$f_{01} = \frac{f_s}{N} = \frac{1}{NT_s}.$$
 (3)

The Hamming window function is as follows:

$$h(n) = \begin{cases} 0.54 - 0.46 \cos\left[\frac{2\pi n}{N-1}\right], 0 \le n \le N-1, \\ 0, & n = ft. \end{cases}$$
(4)

The rectangular window has better spectral smoothness, but it damages high-frequency information greatly, causing loss of waveform details. The Hamming window protects high-frequency information better and preserves the details of audio signal data. Therefore, the Hamming window is in the audio; the performance in classification is better than rectangular windows.

The choice of window shape is very important in audio signal data analysis. The choice of different window functions will affect the short-term characteristics of time domain analysis parameters. Choosing a suitable window function is the basis of audio signal analysis.

If the sampling period is T_s , the window length is N, and the frequency resolution is Δf , that is,

$$\Delta f = \frac{1}{NT_s}.$$
(5)

It can be seen from the above formula that the time resolution decreases as the frequency resolution increases, and the frequency resolution also decreases as the window length decreases, which improves the time resolution. In the time domain analysis of audio data, if the window length N is large, the window function corresponds to a low-pass filter, which shields the high-frequency part of the audio signal, the waveform of the high-frequency part of the audio is lost, short-term energy fluctuations occur, and the change with time is too small to accurately reproduce the change of the audio signal amplitude; if the window length N is too small, the passband of the filter becomes wider, the short-term

energy changes greatly, and the energy function oscillates greatly. Generally speaking, the window length is usually 80–160 points when the sampling rate is 8000 Hz.

The time domain analysis of the audio signal refers to the separation and analysis of the time domain parameters of the audio signal. The best understood audio visualization model is the delay time line waveform. The audio signal is in the time domain because the essence of the audio signal is time. Domain signal and time domain analysis is one of the most widely used audio analysis methods. Time domain analysis is usually applied to the most basic parameter analysis and feature extraction. The time domain analysis method has several notable characteristics. The time domain signal of the speech signal is relatively intuitive, and the physical meaning is relatively clear. The time domain signal analysis algorithm is easier to implement, and the calculation is complicated. Degree is low. The characteristic parameters of the audio signal in the time domain include short-term energy, shortterm zero crossing, etc., which will be further analyzed below.

Assuming that the audio signal in the time domain is x(l), and the *n*-th frame audio signal obtained after frame and window processing is $x_n(m)$, then $x_n(m)$ has the following relationship:

$$x_n(m) = \omega(m)x(n+m)n \le m \le N-1, \tag{6}$$

$$\omega(m) = \begin{cases} 1, & m = 0 \sim (N-1), \\ 0, & m = others. \end{cases}$$
(7)

Use E_n to represent the short-term energy of the *n*-th frame audio signal, namely,

$$E_n = \sum_{m=0}^{N-1} x_n^2(m).$$
 (8)

Since E_n is the square sum of the amplitude of the audio signal, the high-level audio signal with larger amplitude has a great influence on the function value. It can be improved to the short-term average amplitude function M_n , which can weaken its effect on high voltage; the sensitivity of the flat signal is defined as follows:

$$M_n = \sum_{m=0}^{N-1} |x_n(m)|.$$
 (9)

If the short-time zero-crossing rate of the *n*-th frame audio signal $x_n(m)$ is Z, that is,

$$Z_n = \frac{1}{2} \sum_{m=0}^{N-1} |sgn[x_n(m)] - sgn[x_n(m-1)]|.$$
(10)

When calculating short-term over-limit parameters, if the input audio signal passes through the converter, its operating point is shifted, or it contains 50 Hz mains frequency interference, the calculation process will cause larger errors. In the audio signal input process, the cut-off frequency of the anti-aliasing bandpass filter is usually set higher than 50 Hz to prevent influence. Therefore, it does not work for the operating point of the cheap converter, and the DC component of each frame is usually calculated and excluded.

In the field of speech classification, Mel frequency cepstral coefficient (MFCC) is a commonly used speech function. The Mel scale is the frequency scale corresponding to the characteristics of the human ear, which roughly corresponds to the log-normal distribution of the actual frequency. The specific corresponding relationship is given by the following formula:

$$Mel\ (f) = 2595lg\left(1 + \frac{f}{700}\right). \tag{11}$$

If the critical frequency bandwidth is less than 1000 Hz, the bandwidth is about 100 Hz, which is almost linearly distributed. If the critical frequency bandwidth is higher than 1000 Hz, the critical frequency bandwidth is log-normal.

The lower, center, and upper limit frequency of adjacent triangular bandpass filters has the following relationship:

$$C(l) = h(1-1) = l(l+1).$$
(12)

According to the amplitude spectrum of the audio signal, the output of each triangular bandpass filter is

$$m(\mathbf{l}) = \sum_{k=l(l)}^{h(l)} W_l(k) | X_n(k) | l = 1, 2, 3, \dots, L.$$
(13)

Calculate the logarithm of all filter outputs obtained by the above formula, and perform the discrete cosine transform shown in the following formula to obtain the Mel frequency cepstral coefficient.

$$c_{mfcc}(i) = \sqrt{\frac{2}{N}} \sum_{l=1}^{l} lgm(l) \cos\left\{ \left(l - \frac{1}{2} \right) \frac{i\pi}{L} \right\}.$$
 (14)

The process of calculating the frequency coefficients of the Mel cepstrum requires fast Fourier transform, but the fast Fourier transform has a great impact on the system. If the number of fast, there are too few Fourier transform points, and the frequency resolution is too low, which will cause large errors and reduce the accuracy; if the number of fast Fourier transform points is too small, the calculation of the system will be complicated and cannot meet the requirements of real-time processing. For hardware with different processing capabilities, the parameters of the MFCC calculation process need to be adjusted to find a balance between accuracy and efficiency.

3.3. Abnormal Audio Detection Algorithm. Due to the strong feature self-learning ability of deep learning and the continuous development of the strong classifier of neural network, it has successfully been widely used in various audio-related tasks. This paper conducts research on the abnormal audio event detection algorithm related to deep learning. Two different features are used as the input data of the deep learning model: the first is the original sampling point of the abnormal audio is directly used without any feature engineering,

and they are arranged in chronological order into two dimensions. The graph structure is used as the input of the deep learning model to form an end-to-end algorithm mode; the second is to extract the spectrogram of the abnormal audio signal as the input of the deep learning model. Both features are graph structures, and the same hybrid neural network model of convolutional neural network and cyclic neural network is used to calculate and fit them; finally, the abnormal sound classification and results are obtained through the Softmax function.

The above two abnormal sound recognition algorithms use the same neural network model. The difference is the input features, which are the folded map of the original audio sampling points and the audio spectrogram. The flowchart of the abnormal sound recognition algorithm based on deep learning is shown in Figure 1.

Since this article studies an abnormal audio event detection algorithm based on deep learning, and the CNN part of the CRNN model used next is a two-dimensional convolutional layer, the input features must be data with a twodimensional structure. The audio original sampling point folded map refers to the original waveform; sampling point of the audio signal is expanded by frames, and each frame is arranged in a row. All the frames are arranged in chronological order to form a two-dimensional data structure, which is called folded image of the original audio sampling points.

Figure 2 shows the conversion of an abnormal sound into a spectrogram. The time-frequency representation of this audio is very suitable and can be efficiently input into the subsequent deep learning audio recognition model for further feature learning and classification, and the specific transformation details are as follows.

First, each independent abnormal audio is divided into frames to obtain L frame audio, where i is the frame number, sequence number, and n is the sequence mark of the data point in a frame of audio. The specific calculation formula is

$$S_{i}(k) = \left| \sum_{n=0}^{N-1} s_{i}(n) \cdot w(n) \cdot e^{-j2\pi n k/N} \right|.$$
(15)

After stacking all the frames after FFT transformation, the audio spectrogram is obtained. Because the dimensionality of FFT is too high, and audio monitoring requires strong real-time performance, it needs to be reduced in dimensionality. Studies have shown that human hearing is not linear. It is logarithmic at high frequencies and more linear at low frequencies. Therefore, the Mel scale is designed as a method of bending the linear frequency domain to make it more in line with natural perception:

mel
$$(f) = 1125 \cdot \ln\left(\frac{1+f}{700}\right)$$
. (16)

The core of the CNN is convolution and max pooling (Max Pooling), and the other network layers are just some nonlinear components. When CNN is working, the convolution window (convolution kernel) is used as a local feature classifier to learn high-level features. By obtaining



FIGURE 1: General block diagram of abnormal sound recognition algorithm based on deep learning.

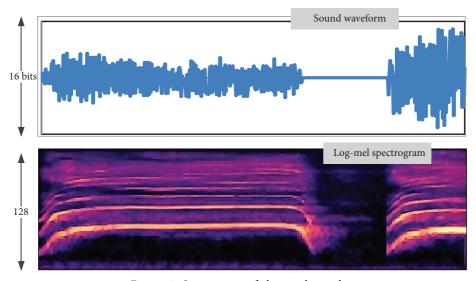


FIGURE 2: Spectrogram of abnormal sound.

these weights, the product combination between the two is obtained, and a relatively high-level value and corresponding feature map are given, so first-order local features are obtained from the original image, and then higher-order features are obtained. When putting all of this into GPUs, CNN can be optimized very fast. The specific formula is as follows:

$$a'_{j} = f\left(\sum_{i=1}^{M_{j}} a_{j}^{l-1} \cdot k_{ij}^{l} + b_{j}^{l}\right).$$
(17)

Excluding some discrete points and noise, the data provided for the same problem all have the same distribution and characteristics. The model learns this distribution characteristic of the data in the training data and is applied in the test data. However, in deep learning, with the deepening of the network layer and the superposition of nonlinear transformations, the data distribution often faces the problem of internal changes in sample points and gradually becomes unstable. The role of the batch normalization layer is to maintain this data distribution and the stability of the characteristics, after the data of each layer are passed through the batch normalization layer, and the original distribution that is about to be deformed is fixed back, so as to avoid the problem, as shown in Figure 3.

BN can reduce this negative impact. Through the normalized calculation method, the output value of each intermediate layer is pulled back to a standard normal distribution with a mean of 0 and a variance of 1. When this standard after the distributed data enters the activation layer, the activation value gradually stabilizes, the gradient back propagation becomes larger, and the convergence speed becomes faster, thereby avoiding the problem of gradient disappearance. The specific operating formulas of BN are shown in formulas (18)–(20):

$$\mu_B \leftarrow \frac{1}{m} \sum_{i=1}^m x_i, \tag{18}$$

$$\sigma_B^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_B)^2, \qquad (19)$$

$$\widehat{x}_i \xleftarrow{x_i - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}},\tag{20}$$

$$y_i \leftarrow \gamma \hat{x}_i + \beta \equiv BN_{\gamma,\beta}(x_i). \tag{21}$$

Since the algorithm in this article uses maximum pooling, we will mainly introduce the schematic diagram of the maximum pooling layer and the maximum pooling. The specific formula is shown

$$T_j^1 = f\left(down\left(T_j^{l-1}\right) + b_j^l\right). \tag{22}$$

The parameters of the maximum pooling are the pooling area and stride. The pooling area is a matrix that represents the range involved in the pooling operation. The stride is the amplitude of the matrix moving up and down. Once the

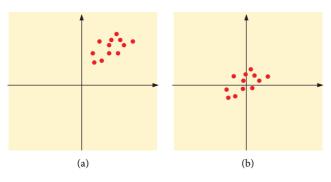


FIGURE 3: Batch normalization effect diagram. (a) Before batch normalization. (b) After batch normalization.

maximum pooling area and stride are determined, the maximum pooling operation is also fixed, there are no parameters that need to be iteratively optimized, and gradient descent does not need to change any values. The idea of maximum pooling is based on the consideration of the redundancy of the extracted features. It is simple to think that when the maximum feature of a certain adjacent region is extracted, it is often enough to represent all the characteristics of the region; that is, the maximum value is retained. The maximum value often means that certain specific features may have been detected.

3.4. Analysis of Simulation Results. In the GRU part of the cyclic network in the CRNN model, setting different time steps affects the performance of abnormal sound recognition. The abnormal sound data set used in the experiment is the pure data set A, and the test recognition rate is shown in Figure 4.

The CRNN model convolves the input Log-Mel spectrogram in the frequency domain and the time domain, and then performs Max Pooling. Max Pooling achieves the purpose of data dimensionality reduction by selecting the local maximum eigenvalues and pooling in the frequency domain. For audio, it is clear that the class task is effective. The only controversy is that the frequency domain pooling will discard some pitch changes, but all these depend on the data type and are not important for abnormal sound recognition. The key question is whether pooling in the time domain is a good idea, and whether the time domain pooling operation will lose the timing information that is important for the sound. This is still open.

Whether the time domain pooling affects the feature size input to the recurring layer after the CNN is over, a rigorous understanding, time domain pooling will reduce the time scale of the features extracted from the spectrogram. The number of cycles in the final cycle layer decreases; that is, the number of time steps decreases. Of course, the feature dimension of each time step remains unchanged, which is still the number of convolution kernels in the last convolution layer. In order to test the impact of time domain pooling on network performance, by not adding pooling in the time domain and gradually adding large pooling, the characteristics of different time scale dimensions are input to the loop layer and the recognition effect is obtained. From the

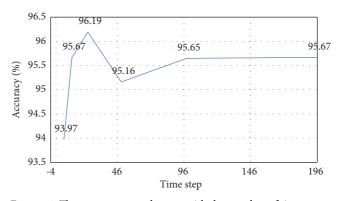


FIGURE 4: The accuracy rate changes with the number of time steps.

experimental result graph, it can be seen that pooling in the time domain does not significantly reduce the recognition effect, but the performance is better at 24 steps. Secondly, the fewer time steps represent the faster running speed.

4. Application of College Physical Education System Based on Related Technology

4.1. System Requirement Analysis. As the basis of online sports teaching support, the business needs of the system are mainly analyzed from the perspective of education design. When designing online education, we must adhere to the following teaching design principles: focus on the analysis of educational objectives and content, focus on the creation of situations in the design of educational activities, and emphasize and value the important role of educational activities. At the same time of learning, it pays attention to the design of information resources to assist "learning," emphasizes the use of various information resources, and emphasizes student-centered autonomous learning design and "collaboration," and collaborative learning environment design and network design are the main educational strategies.

First of all, we need to clarify the goal of network technology to support physical education. When deciding educational goals, we must carefully consider the technical characteristics of computers and networks, and combine them with the characteristics of sports itself. In actual physical education courses, network technology can only play an auxiliary role, because only through actual operations and practical exercises can the expected effects of the courses be achieved.

The educational goal of the system is to enable students to use the network-supported education system for physical education, which will greatly increase students' interest in learning, help understand and master the curriculum, teaching points and difficulties of this article, and give students enough room for maneuver. Promote students' learning initiative. The exchange and communication between students and teachers can strengthen teachers' understanding of students' learning through online question and answer, and quickly and accurately understand students' learning and knowledge. Through video and multimedia, it is possible to reproduce the content of the physical education class, learn the difficult content repeatedly, and put it into practice in theory.

Due to the diversity of student groups, a single classroom teaching is far from meeting the diverse learning needs of students. Establish a sports network auxiliary system to create an environment for students to learn knowledge outside of sports. Through this system, students can make up for their shortcomings in physical education. At the same time, teachers can also use the teaching assistant system to organize and control their courses to guide them in learning.

We hope that we can use the interactive network education model to design sports network auxiliary systems, use the networked education environment to support physical education, and achieve the following goals:

- (1) The system design must fully demonstrate the benefits of online education: give full play to the leading role of students, consciously carry out independent learning, teacher-student interaction is no longer restricted by the time and place of traditional education, and the networked education environment becomes teachers and elective students. The communication channels between each other provide space for information exchange between each other.
- (2) Fully demonstrate the benefits of physical education in the classroom: fully demonstrate the leadership role of teachers, guide students to set learning goals according to the curriculum requirements, and understand the main points and difficulties of education.
- (3) Utilize the network education environment to give full play to the advantages of multimedia education: if information media such as symbols, sounds, graphics, animations, and videos are integrated to create a human-computer with a graphical interactive interface and interactive window controls, the interactive capabilities will be greatly improved.
- (4) Convenient for teachers and students: physical education teachers prepare online lessons in a networked learning environment, upload PPT and technical videos, publish assignments and grade exams, and announce final evaluation standards and results through the Internet. In physical education,

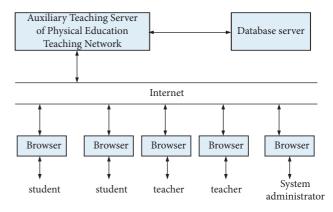


FIGURE 5: A brief description of the physical education network auxiliary system.

to avoid performance problems such as technical difficulty, you can refer to the teaching materials on the server at any time to listen to the lessons more carefully.

4.2. System Structure Design. Online education mainly chooses Internet-based application systems, and all functions are completed through the interaction between the application server and the user's browser. System-related data are maintained and organized by the database server. Figure 5 shows brief description of the system.

The educational resource module contains five submodules. This module is an open module. Students only need to enter the system URL in the address bar of the browser to directly access the educational resource module. Therefore, when designing this module, the response speed of students' questions should be considered, making the entire page as simple and generous as possible, making each sub-module easy to access, and complying with the design rules of today's major Web applications.

Links in the system navigation bar point to each submodule and other modules. The structure of each submodule corresponds to this figure, and two methods are needed to achieve this effect: one is how to use the framework, how to customize the framework, and how to insert different parts into the framework; the other is to call the ASP statement and use table methods where appropriate to complete this operation. This system uses a table format, which makes the entire system more uniform and the overall effect more coordinated.

4.3. System Function Module Design. There are three tables in the database of the online Q&A subsystem: teachers, students, and teaching management. Table 1 shows the main structure of the teacher table.

Table 2 shows the main structure of the student table.

The name and message content are required, and others are optional. When students input message content, the system supports HTML editing functions, such as bolding the message content and setting it as a hyperlink. In this way,

Data item	Field name	Significance
Teacher ID	int, IDENTITY(1.1), not null	Teacher ID number automatically assigned by the system
Name	nshedbsjr(21), not null	The name of the teacher in the system
Pwd	Varchar(10), not null	Teacher's password in the system
Name	nvarchar(20), not null	Teacher's real name
Trouble	bhsdbhb(50), not null	Problems when looking for a password
Firstanswer	nvarchar(50), not null	The answer
Status	Int	Status, currently reserved
Regstatus	smallint, not null	Status at the time of registration
Code	nvarchar(10), not null	Teacher's ID number
E-mail	bxndk(50)	Teacher's e-mail

TABLE 1: The main structure of the teacher table.

TABLE 2: The main structure of the student table.

Data item	Type of data	Significance
Student ID	int, IDENTIT Y(1,1), not null	Student ID number automatically assigned by the system
Name	nvarchar(20), not null	Student's real name
Username	nvarchar(20), not null	Username in the student system
Pwd	Varchar(10), not null	Student's password in the system
Trouble	bhsdbhb(50), not null	Problems when looking for a password
Answer	hbhghsnr(50), not null	The answer
E-mail	bxndk(30)	Student's e-mail address

TABLE 3: Database structure table.

Table name	Field name	Description
Examine	Type, test questions, A, B, C, D, answer	Type: select
Exercise	Type, test questions, A, B, C, D, answer, analysis	Same as above
Account	Grade D, B, C, A	Analyze the use of statistics
Score	User, grades, multiple-choice questions, fill-in-the-blank questions, test date	User: exam ID
Admin	Username password	Administrator profile
User	Student ID, name, last reference date, application ID	Candidate form
News	Title, content, time	Related notice
Manage	Exam time, number of choices, score, number of fill-in-the-blanks, score	Score: select each
Request	Name, gender, class, contact information, e-mail	The score of the question

TABLE 4: Class table.

Data item	Type of data	Significance
Class ID	int, IDENTITY(1.1), not null	Class ID number automatically assigned by the system
Class name	nvarchar(20), not null	Class name
Teacher ID	int, not null	The ID of the teacher who created the class
Pwd	varchar(10), not null	Class password

you can enrich the information content and insert symbols and pictures.

The coursework module contains two sub-modules. This module is an open module with a physical education resource module. Students only need to enter the system URL in the browser address bar to directly enter the course module. The two sub-modules of this module are modified according to the difference in the curriculum. Therefore, in the same educational resource module, the design and implementation of these two sub-modules are electronic resources provided by these two sub-modules mainly used for the educational process. This part of the content is managed by the administrator, including adding resources and deleting resources. The tables and related fields in the database are shown in Table 3.

4.4. Database Design. The teacher ID number is the unique identification of the teacher. The system administrator is a special teacher (user name: admin), and the basic information is stored here. Regstatus is used to view teacher status information during the registration process: 0—users who can use the system; 1—the teacher is registered but not confirmed by the system administrator.

Class table structure is shown in Table 4. Student-class table is shown in Table 5.

Student #

Data item	Type of data	Significance
Student ID	int, not null	Student ID number
Class ID	int, not null	Class ID number

Varchar(20), not null

TABLE 5: Student-class table.

TABLE 6: Teacher-class table.

Student ID

Data item	Type of data	Significance
Teacher ID	int, not null	Teacher ID number
Class ID	int, not null	Class ID number
Pwd	Varchar(10), not null	Class password

The table shows that students belong to different classes and can have their own student IDs in different classes. Both the student ID number and the class ID number together identify a student in a unique class.

Teacher-class table is shown in Table 6.

This table shows that teachers can teach multiple classes, and each class has its own class password. The teacher ID number and the class ID number uniquely identify the class owned by the teacher.

5. Conclusion

This paper adopts theories and methods such as dual-core technology and uninterrupted information flow model to design trust path, trust transfer chain, reliability analysis, construction of remote authentication, and other technical methods, and apply them in the embedded trusted computing environment. Appropriate trust routing construction methods, reliability analysis models, and remote authentication methods have been experimented with, and good results have also been achieved. The network-based complementary education system is a new application field, which can overcome the limitations of time and space and provide a better educational environment for students. In this article, based on the status quo of physical education, we examine the application of network technology in sports support network systems in sports auxiliary network systems.

Data Availability

The data used to support the findings of this study can be obtained from the author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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