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Research Article

Video Visualization Technology and Its Application in Health Statistics Teaching for College Students

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In view of the present situation of "learning difficulty" in health statistics, this paper proposes a video visualization technology based on the convolutional neural network, which updates parameters by calculating the gradient of loss function to obtain accurate or nearly accurate loss function. Taking the students from 2014 to 2017 in a university in Henan as the research object, this paper analyzes the video visualization technology and its application effect on the teaching of college students' health statistics from the aspects of students' course awareness, learning behavior, communication between teachers and students, knowledge mastery, and course satisfaction. The results show that the external model load difference between each explicit variable and latent variable is statistically significant. Learning behavior and communication between teachers and students have a direct impact on the mastery of knowledge, and the degree of influence from high to low is as follows: learning behavior and communication between teachers and students. The teaching effect model of health statistics based on video visualization technology of the convolutional neural network has certain practicability.

1. Introduction

Health statistics is a science of applying the principles and methods of mathematical statistics to study the health status of residents and collecting, sorting, and analyzing data from the field of health services [1, 2]. It is a discipline aiming at practical application and an important tool for medical research. With the increasing attention paid to scientific research work in our country, it not only is a required course of preventive medicine but has become a popular learning course for students and medical personnel of other medical majors such as clinical medicine [3, 4]. Health statistics plays an important role in training scientific research thinking of medical talents [5].

Health statistics is a subject that uses the principles and methods of mathematical statistics and probability theory to collect, sort out, and analyze medical data. With the development of medical research, in order to meet the needs of medical research, in the current medical colleges and universities, medical statistics has become a required course. The content of health statistics is rigorous and abstract, with strong logic and a large number of complex mathematical formulas and abstract concepts. According to previous studies, although students have a positive learning attitude and strong learning needs for health statistics, they think that health statistics is difficult to learn and their application ability is poor. It is difficult for some students to fully understand the important statistical knowledge such as normal distribution and hypothesis testing [6]. It is difficult for them to correctly distinguish the difference and connection between standard deviation and standard error, reference value range and confidence interval, correlation and regression, etc. Many students cannot choose appropriate statistical methods according to the type of data [7]. A survey of graduate students majoring in health statistics and epidemiology in a university also shows that how to correctly choose and use statistical methods is the biggest trouble that students face in the process of learning. Students do not have a thorough understanding and solid grasp of health statistics knowledge, which will lead to unsatisfactory statistical practice in the future work. The reason why it is difficult to study in detail is not only the difficulty of understanding the knowledge but also the difficulty of obtaining high-quality resources. At present, the existing network resources of health statistics are simply listed and lack of logic and some learners find it difficult to find learning materials suitable for their own level [8]. In sharp contrast, health statistics teachers have accumulated a large number of high-quality teaching resources in the long-term teaching; but limited by the teaching method of face-to-face teaching, these contents are only used in the class or within the college and the high-quality resources are not effectively promoted and fully utilized [9, 10].

In addition, as an important applied discipline, health statistics needs to form a systematic and high-quality knowledge system, so that medical workers can quickly acquire corresponding knowledge according to their work needs. Therefore, it is urgent to build an intelligent learning tool of health statistics by means of video visualization technology in close combination with the subject characteristics of health statistics, so as to achieve the following effects: to help learners to independently learn health statistics knowledge in fragmented time and improve their practical application ability of health statistics methods.

Section 2 introduces the video visualization technology and its related research status in the teaching of health statistics for college students. In Section 3, the construction of the key technologies of video visualization based on the convolutional neural network is studied. Section 4 is the research object and research method of this paper. Section 5 is the result and discussion, and Section 6 contains the conclusions.

2. Related Work

With the rapid popularization of the Internet and the accelerated promotion of educational informatization, the scale of online education expands rapidly, which is expected to promote educational fairness and improve the quality of learning [11]. However, the common form of traditional online education is to move offline classroom to online, providing homogeneous and template learning resources for students with different characteristics, which also weakens students' interaction in the learning process, resulting in an unsatisfactory learning completion rate and learning satisfaction.

In recent years, the concept of "student-centered" education has been widely accepted, from "teaching" to "learning," from educators to learners, and from lifelong education to lifelong learning. But this kind of change has put forward brand-new challenge and request to the learning way [12]. At the same time, just as "there are no two identical leaves in the world," each student's knowledge level and learning attitude are different and their perceived knowledge difficulty will also be different. If we treat all learners only in a mode of "one size fits all", and provide the same learning guidance and help for them, which may cause learners who have high study ability feel bored because of small study challenges while learners whose study ability is low feel confused without help, leading to low learning engagement. To solve these problems, it is necessary to provide help according to the actual needs of learners [13, 14], that is, to provide personalized help and guidance. Under this background, the video visualization technology system emerges as The Times require. Video visualization technology is committed to understanding the personalized characteristics of learners through the mining of student education data and pushing learning resources to meet the needs of personalized learning, breaking the traditional group learning structure. The professional reports "2017 Horizon Report (Basic Education Edition)" and "2018 Horizon Report (Higher Education Edition)" both point out that video visualization technology plays a key role in promoting the development of online education, helping to achieve efficient and meaningful personalized learning.

The video visualization technology system is to provide learners with appropriate learning activities and the best video visualization system according to their learning characteristics such as knowledge and skill level and learning style. Through the real-time analysis of the learning process, it is constantly revised and improved to achieve personalized learning. The video visualization technology system needs a powerful knowledge model as a support. From the knowledge characteristics of health statistics, health statistics has strong logic and clear knowledge relationship in each chapter, which is conducive to the construction of knowledge model, which is the basis of knowledge visualization push [15–17]. Some scholars have explored the construction of knowledge models and learning systems by taking mathematics and mathematics subjects such as high school mathematics [18], calculus [19], and high school physics [20] as the research subjects, which has a reference value for this study.

With the rapid development of wireless communication technology, video visualization technology has become a beautiful scenery in university health statistics. The communication mode of "video visualization technology + university education" has promoted the fashion communication of health statistics. It "has helped the fashion communication of nonlegacy culture. According to the survey, if students can solve health statistics problems through extracurricular resources, it will be of great help to improve the learning effect. We can summarize and extract the key points of health statistics, carry out a visual display of difficulties of knowledge, analyze the vital cases, differentiate the concept and classification in different materials and build a diversified, multi-level and systematic knowledge system according to the degree of learners' demand for health statistics. It is helpful to consolidate students' basic knowledge of health statistics and improve students' practical application ability of statistical methods. Especially in the context of "Internet+," it is a very positive attempt to apply "video visualization technology + platform education" to health statistics. This study hopes to use information technology to share excellent resources and promote the learning of health statistics through video visualization technology software.

Therefore, whether the matching use of the video visualization technology system has a positive impact on students, teachers, and the interaction between teachers and students, how to correctly use the wireless network communication technology in enterprises, and how to improve the quality of health statistics teaching for college students are all problems worth exploring and studying.

3. Analysis of Key Techniques of Video Visualization Based on the Convolutional Neural Network

By learning and training the intrinsic nature and representation features of the sample data, the neural network obtains the important information such as the voice, text, and image, which has the explanatory function, so that the machine has the same analysis and learning ability as human, and can carry out activities such as voice and text recognition and object detection. At present, neural networks have achieved remarkable results in speech and image recognition [21, 22].

If the neural network structure is regarded as a network, its core ideas are as follows:

(1) Each layer of the network uses unsupervised learning

(2) An unsupervised learning only trains one layer of the network and takes its training results as the input of its higher layer

(3) All network layers can be adjusted by supervised learning

Among the neural networks, the common networks with good performance include AlexNet, VGGNet, ResNet, SqueezelNet, and DarkNet. The reason why this paper chooses to use the neural network is to use its powerful learning and training function to analyze the clipped airport video images including visual features such as color, texture, shape, and statistical features and combine with real-time visibility data to realize the detection of airport visibility. However, with the increase of user needs and the development of computer technology, the disadvantages of high cost and heavy computation workload of general neural networks are becoming more and more prominent. In addition, the processing objects of this paper are mainly images. If there is no convolution operation in the deep neural network model, the number of learning parameters will explode catastrophically.

3.1. Properties of Convolutional Neural Networks. The convolution neural network consists of one or more of the convolution and the whole connection at the top of the layer (the layer can be 1×1 convolution as the final output) composed of a feedforward neural network, consisting of partial correlation of neurons in the hidden layer of the local small area which can be used as the underlying input data, make the network have the characteristics of local awareness, and can obtain the edge information [23–25]. In addition, the network shares the same convolution kernel in all images through weight sharing and retains the original position relationship. Meanwhile, the network automatically trains and extracts the features of each layer for many times, so that the network can fully explore the local features of the image while effectively limiting the number of parameters and preventing overfitting [26].

No matter what kind of convolutional neural network, there must be five layers of input, convolution, activation, and pooling and fully connected in the structure, as shown in Figure 1. And each layer has a specific role [27, 28]. Among them, the input layer can input the data within the three-dimensional dimension. The airport image data processed in this paper belongs to 3D, because generally color images contain R, G, and B channels.

Generally speaking, for a model with the same level of accuracy, the smaller the architecture, the more advantages it has: ① smaller communication requirements, ② less parameters and data, and ③ easier to be applied on devices with limited memory, such as the field-programmable gate array (FPGA). The lightweight convolutional neural network (LCNN) can greatly reduce the operating parameters and improve the computational efficiency under the condition of keeping the performance unchanged after changing the convolution mode. At present, the common lightweight convolutional neural network models include SqueezeNet, MobileNet, ShuffleNet, and Xception.

3.2. Structure of Convolutional Neural Networks

3.2.1. Analysis of the Convolution Layer Structure. Convolution operation is the most critical technology in the structure of the convolutional neural network. By this operation, the convolution layer can extract various features of the input signal. For example, the shallow convolution layer can obtain the low-order features of the target, while the deep convolution layer can extract the high-order features of the target. The convolution operation passes through a series of fixed-size convolution kernels and performs sliding and inner product operations on the input signal of the convolution layer according to the set step size, resulting in a brand-new feature map. The convolution layer is the core of the network, and feature extraction is realized in the process of translation on the original image. It consists of many filters, including the size and depth. There are usually odd-sized windows such as 3×3, 5×5, and 11×11, and the depth is the number of convolution kernels [29, 30]. The specific operation process is shown in Figure 2.

In the specific convolution operation, there are two situations: the first one is as shown in Figure 2. Due to the convolution kernel window and sliding step size, the generated feature map is inconsistent with the size of the input signal. The second method can make the output characteristic map keep the same size as the input signal by filling 0 at the boundary of the input signal.

After the convolution operation, a nonlinear activation function is usually adopted. The main reason is that the introduction of nonlinear factors can make the output of the network no longer just a linear combination of inputs but can approximate any complex function and effectively improve the ability of the network to learn complex things [31–33]. At present, commonly used nonlinear activation functions include saturated nonlinear functions sigmoid,

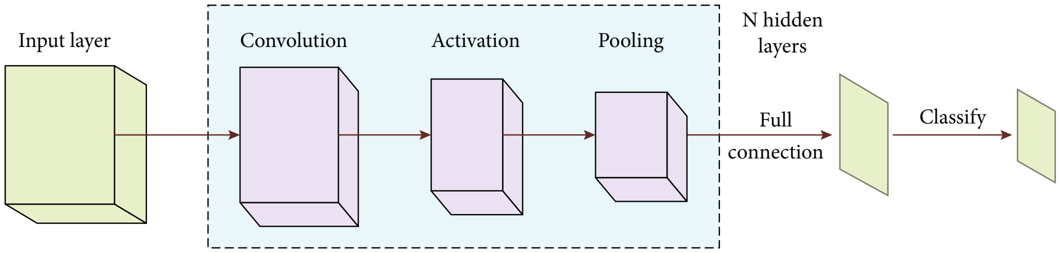

Figure. 1: Convolutional neural network structure diagram.

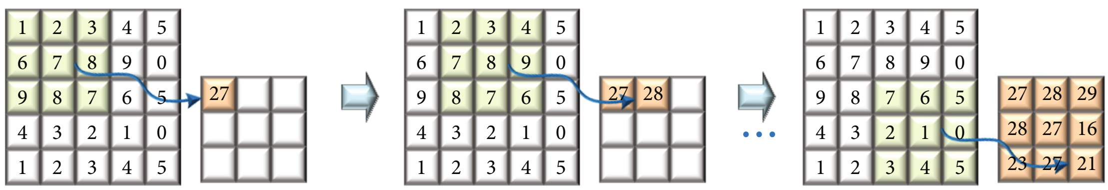

Figure. 2: Schematic diagram of the convolution process.

tan h, etc. and unsaturated nonlinear functions ReLU, etc., shown as follows:

$$\begin{aligned}\mathrm{Sigmoid}(x) &= \frac{1}{1+e^{x}},\\ \tan h(x) &= \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}},\\ \mathrm{ReLU}(x) &= \max\,(0, x).\end{aligned} \tag{1}$$

The main difference of the above activation functions lies in that the unsaturated nonlinear functions can effectively avoid the problem of vanishing gradient or explosion in the network because there is no saturated smooth region in the saturated nonlinear functions, so that the network can converge more quickly and stably. To sum up, the operation carried out by the convolutional layer can be described as follows:

$$\mathbf{X}_{\mathrm{out}} = f(\mathbf{X}_{\mathrm{in}} \otimes \mathbf{W} + \mathbf{b}). \tag{2}$$

$\mathbf{X}_{\mathrm{in}}$ and $\mathbf{X}_{\mathrm{out}}$ are the input and output of the convolution layer, respectively, f is nonlinear activation function, and $\mathbf{W}$ and $\mathbf{b}$ represent convolution kernel weight and bias, respectively. This symbol of $\otimes$ is the basic symbol for mathematical operations and represents the tensor product. This can be applied in different contexts such as vectors, matrices, tensors, vector spaces, algebras, topological vector spaces, and modules. The meaning of this sign is the same in all cases: the most general bilinear operation, also called an external product in some contexts.

3.2.2. Structural Analysis of the Pooling Layer. The pooling layer is usually connected in series after the convolution layer, which is essentially a downsampling operation, and the main purpose is to make the features have certain spatial invariance. At present, the commonly used pooling operations include maximum pooling and average pooling, which obtain results by calculating the maximum and average values of local areas, respectively. Maximum pooling can retain the most important feature information in a local area [34], especially for very sparse features. The calculation process is shown in Figure 3. The average pooling can well summarize the overall spatial information of the local area.

In that pool process of the input image, the pool cores are moved according to the pool step size. Common pooling methods include average pooling and maximum pooling. The maximum value is used to represent the local area for maximum pooling, which makes the overall characteristics of the image more significant. The average pooling method uses the average value to represent the local area, which makes the overall characteristic information of the image smoother. When training the model, the pooling layer can help the network to focus on learning the pixel features of the image, help improve the generalization and robustness of the network, and avoid the overfitting of the network.

3.2.3. Batch Standardized Analysis. As the network becomes deeper and deeper, there will be a very obvious gradient dispersion problem, which will change the distribution of input signals and affect the learning ability and performance of the network. In order to effectively alleviate this problem, Sabanci et al. proposed **BN** to overcome the internal covariate offset problem and the main process can be divided into the following two steps [35–39].

(1) To calculate the mean and variance of input signals for data standardization processing, the calculation expression is as follows:

$$x_i' = \frac{(x_i - \mu)}{\sqrt{\delta^2 + \theta}}, \tag{3}$$

where μ and δ^2 represent the mean and variance of the input signal, respectively, and θ is a constant that ensures numerical stability

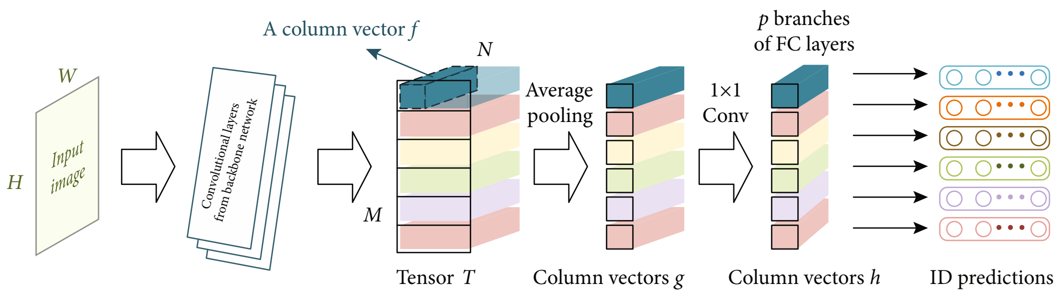

FIGURE. 3: Schematic diagram of the pool layer structure.

(2) A linear transformation is used to recover the normalized data, and its calculation expression is shown as follows:

$$y_i = \alpha x_i' + \beta, \tag{4}$$

where α and β represent learnable parameters of two networks.

BN has many advantages: (1) it allows us to use a higher learning rate to improve network training speed without the risk of gradient dispersion, (2) it is not necessary to consider the initialization of network parameters too much, which reduces the dependence of gradient on parameters, (3) the dropout operation can be removed from the network in some cases, (4) it reduces the risk that the network will fall into a saturated state when the saturated nonlinear activation function is used, and (5) it effectively improves the generalization ability of the network.

3.3. Loss Function and Parameter Learning. At present, the parameter learning methods adopted by convolutional neural networks are all based on the gradient descent algorithm, which is an algorithm that updates parameters by calculating the gradient of the loss function. The specific process is shown as follows [40–42]:

(Step 1) Forward propagation process

Assuming that the input signal is x and the output value of its input layer is a^l, then, the corresponding outputs of the subsequent layers ($l = 2, 3, \cdots, L$) can be calculated as follows:

$$z^l = w^l a^{l-1} + b^l, \tag{5}$$

$$a^l = \sigma\left(z^l\right), \tag{6}$$

where w^l and b^l are the corresponding parameters of each layer, that is, the parameters to be updated by the network, and σ is the activation function adopted by each layer of the network.

(Step 2) Calculate the error of the output layer

According to the definition, the output layer L error can be calculated as follows:

$$\delta_j^L = \frac{\partial C}{\partial z_j^L}, \tag{7}$$

where C is the loss function adopted by the network. In order to establish a connection between it and the activation value of the output layer $a^L{}_j$, equation (7) is simplified to (8) according to the chain rule.

$$\delta_j^L = \frac{\partial C}{\partial a_k^L}\frac{\partial a_k^L}{\partial z_j^L}. \tag{8}$$

Since, when $k \neq j$, $\partial a_k^L / \partial z_j^L = 0$, equation (8) is simplified to the following:

$$\delta_j^L = \frac{\partial C}{\partial a_j^L}\frac{\partial a_j^L}{\partial z_j^L}. \tag{9}$$

According to equation (6), the final calculation formula of output layer error can be obtained as follows:

$$\delta_j^L = \frac{\partial C}{\partial a_j^L}\sigma'\left(z_j^L\right). \tag{10}$$

(Step 3) Backpropagation error

Similarly, the calculation expression of errors in other layers except the output layer is as follows:

$$\delta_j^l = \frac{\partial C}{\partial z_j^l}. \tag{11}$$

In order to establish a relationship between it and the output layer error, equation (12) can be obtained by using the chain derivative rule for equation (11).

$$\delta_j^l = \sum_k \frac{\partial C}{\partial z_k^{l+1}}\frac{\partial z_k^{l+1}}{\partial z_j^l} = \sum_k \frac{\partial z_k^{l+1}}{\partial z_j^l}\delta_k^{l+1}. \tag{12}$$

According to the calculation expression (13) between adjacent layers of the network, the calculation expression (14) for all layer errors except the output layer can be derived.

$$z_k^{l+1} = \sum_j w_{kj}^{l+1}\sigma\left(z_j^l\right) + b_k^{l+1}, \tag{13}$$

$$\delta_j^l = \sum_k w_{kj}^{l+1} \delta_k^{l+1} \sigma' \left(z_j^l \right). \tag{14}$$

(Step 4) Update parameters

Since the main purpose of the network is to update parameters w^l and b^l at each layer, the expression of the parameter update value can be derived as equation (15) by using the error of backpropagation at each layer.

$$\begin{aligned} \frac{\partial C}{\partial w_{jk}^l} &= \frac{\partial C}{\partial z_j^l} \frac{\partial z_j^l}{\partial w_{jk}^l} = a_k^{l-1} \delta_j^l, \\ \frac{\partial C}{\partial b_j^l} &= \frac{\partial C}{\partial z_j^l} \frac{\partial z_j^l}{\partial b_j^l} = \delta_j^l. \end{aligned} \tag{15}$$

Finally, the parameters are updated according to the rules of the gradient descent algorithm and the formulas are as follows:

$$\begin{aligned} w' l &= w^l - \eta \frac{\partial C}{\partial w_{jk}^l}, \\ b' l &= b^l - \eta \frac{\partial C}{\partial b_j^l}. \end{aligned} \tag{16}$$

The loss functions widely used in the target semantic segmentation algorithms include the mean square error and cross-entropy. The mean square error reflects the difference between the prediction result a and the label data y at each pixel, as shown in (17).

$$C(w, b) = \frac{1}{2n} \sum_x \|y - a\|^2. \tag{17}$$

When this function is used for back propagation, its parameter update expression is as follows:

$$\begin{aligned} \frac{\partial C}{\partial w} &= \frac{1}{n} \sum_x (a - y) \sigma'(z) \frac{\partial z}{\partial w}, \\ \frac{\partial C}{\partial b} &= \frac{1}{n} \sum_x (a - y) \sigma'(z). \end{aligned} \tag{18}$$

It can be found that the above parameter updates are closely related to $\sigma'(z)$. If the activation function is sigmoid, it will appear when the network is trained to a certain period and the neuronal output approaches 1 [43, 44]. When $\sigma'(z)$ is close to 0, it will lead to the slow update of network parameters, which is not conducive to the overall network learning process. To solve this problem, more and more networks adopt cross-entropy instead of the mean square error and the expression of cross-entropy is shown as follows:

$$C(w, b) = -\frac{1}{n} \sum_x [y \ln a + (1 - y) \ln (1 - a)]. \tag{19}$$

Similarly, the expression of its parameter update value can be derived as follows:

$$\begin{aligned} \frac{\partial C}{\partial w} &= \frac{1}{n} \sum_x (a - y) \frac{\partial z}{\partial w}, \\ \frac{\partial C}{\partial b} &= \frac{1}{n} \sum_x (a - y). \end{aligned} \tag{20}$$

In this case, the parameter update is related to the error between the network output and the label. The larger the error, the faster the update speed will be, and it will not be affected by the activation function, which can well avoid the problem caused by the smaller gradient in the mean square error.

4. Objects and Methods

4.1. Respondents. From 2014 to 2017, students in a university in Henan province of China were selected as the research objects. The investigator who had received unified training conducted a questionnaire survey in an anonymous way in the extracurricular time when the subjects were learning health statistics, through actual surveys and interviews, from December 2021 to April 2022. On the questionnaire platform, we conducted a random questionnaire investigation on the application of video visualization technology in the teaching of health statistics for college students in the form of an electronic questionnaire. A total of 402 questionnaires were distributed and 366 were recovered, with a recovery rate of 91.04%. 360 questionnaires were effective, with an effective rate of 98.36%. The 360 questionnaires effectively collected this time were randomly divided into two groups, one group of data (180 copies) was used to establish the model, and the other group of data (180 copies) was used to evaluate the model and explore the influencing factors. Among the 180 random samples used in this model evaluation and influencing factor analysis, as shown in Figure 4, there were 74 boys and 104 girls, with 2 missing. There are 31 students in the class of 2014, 41 in the class of 2015, 63 in the class of 2016, and 45 in the class of 2017. The average age was (20.83 ± 0.98) years. The consent of all the surveyed students was obtained before the questionnaire was conducted.

4.2. Research Tools. The questionnaire was designed by literature and interview, and the presurvey was conducted before the formal survey. The questionnaire included 19 items from 5 dimensions including course awareness (3 observed variables, A1~A3), learning behavior (4 observed variables, B1~B4), teacher-student communication (5 observed variables, C1~C5), knowledge mastery (4 observed variables, D1~D4), and course satisfaction (3 observed variables, E1~E3). Each item was scored on the Richter 5-level scale, with scores from 1 to 5 indicating "strongly disagree" to "strongly agree." A teaching model of "health statistics"

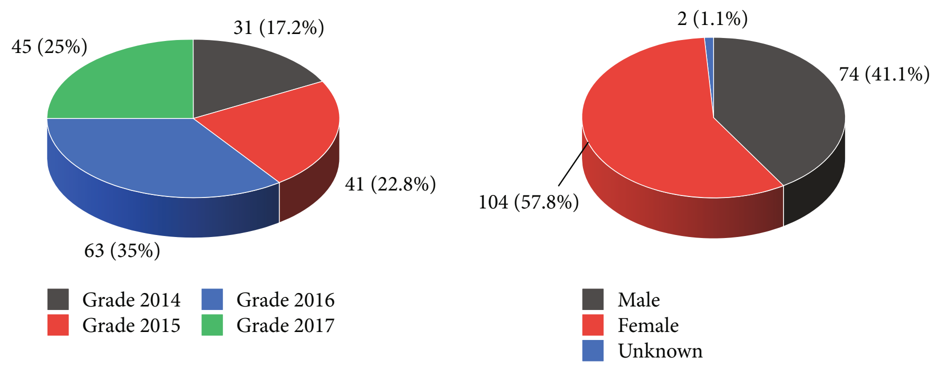

Figure. 4: The statistical analysis of samples.

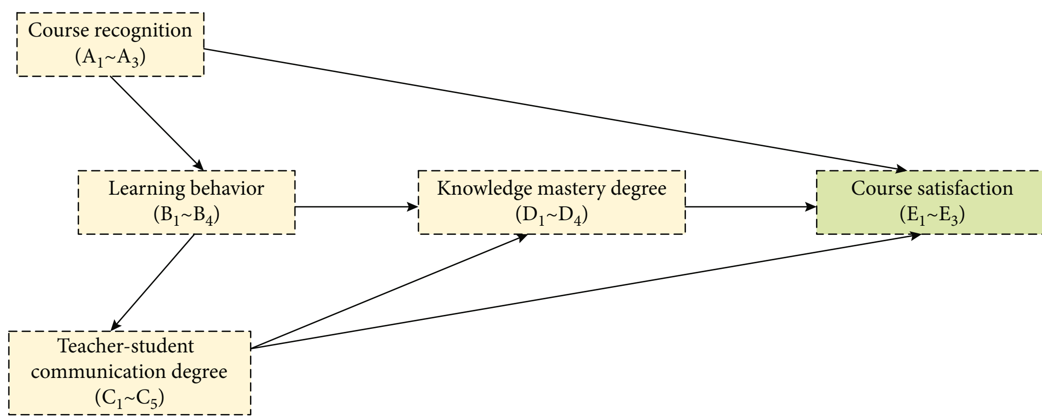

Figure. 5: Schematic diagram of the teaching model of health statistics.

was built according to the dimensions and items of the questionnaire, as shown in Figure 5. It is proved that the model has good reliability, validity, and explanatory ability.

4.3. Statistical Method. The database was established using Epidata3.1, and data entry for two people and two places was performed. SPSS21.0 was used for data collation and description of the basic situation of the survey subjects. The SmartPLS3.1.2 software developed by Ringle et al. of the University of Hamburg in Germany was used for PLS-SEM model construction, model evaluation, and influencing factor analysis.

5. Results and Discussion

5.1. Score Analysis of Each Latent Variable. For the convenience of comparison and viewing, the total score of each latent variable was linearly transformed by 0~100. After linear transformation, the average scores of each latent variable were as follows: course cognition (90.33 ± 10.34). The score of learning behavior was 70.22 ± 13.09, communication between teachers and students 54.71 ± 14.88, and knowledge mastery 65.44 ± 12.51); the score of course satisfaction was 80.22 ± 12.66.

5.2. Model Construction Analysis. The results are shown in Table 1 and Figures 6–8. Cronbach's α values of the five latent variables in Figure 6 ranged from 0.705 to 0.864, and CR values ranged from 0.828 to 0.904, all greater than 0.7. AVE values ranged from 0.551 to 0.759, all of which were greater than 0.5, and the square root of AVE was higher than the correlation coefficient of each latent variable. In Figure 7, the external model loading values of all explicit variables and latent variables showed statistically significant differences ($P < 0.001$). The path coefficients of each latent variable in Figure 8 are also statistically significant ($P < 0.05$), indicating that the model was established.

5.3. Analysis of Influencing Factors. The results of path analysis can directly reflect the direction and degree of influence of each latent variable on knowledge mastery and course satisfaction. As shown in Figures 8 and 9, it can be seen that all latent variables have a positive effect on knowledge mastery and course satisfaction. The influence degree of latent variables on knowledge mastery from large to small was as follows: learning behavior (path coefficient = 0.442, $P < 0.001$), communication degree between teachers and students (path coefficient = 0.422, $P < 0.001$). The influence degree of each latent variable on course satisfaction from large to small was as follows: teacher-student communication degree (path coefficient = 0.277, $P < 0.001$), course awareness degree (path coefficient = 0.249, $P < 0.001$), and knowledge mastery degree (path coefficient = 0.229, $P < 0.001$).

5.4. Analysis of Direct and Indirect Effects. Table 2 lists the direct and indirect effects, total effects and R^2 values of

Table 1: Correlation coefficient of latent variables in the model.

Latent variables	(1)	(2)	(3)	(4)	(5)
Course recognition (1)	0.742*				
Learning behavior (2)	0.484	0.796*			
Teacher-student communication degree (3)	0.561	0.313	0.805*		
Knowledge mastery degree (4)	0.679	0.437	0.670	0.762*	
Course satisfaction (5)	0.629	0.435	0.508	0.523	0.871*

*The square root of AVE. The data below the square root of AVE is the correlation coefficient between latent variables.

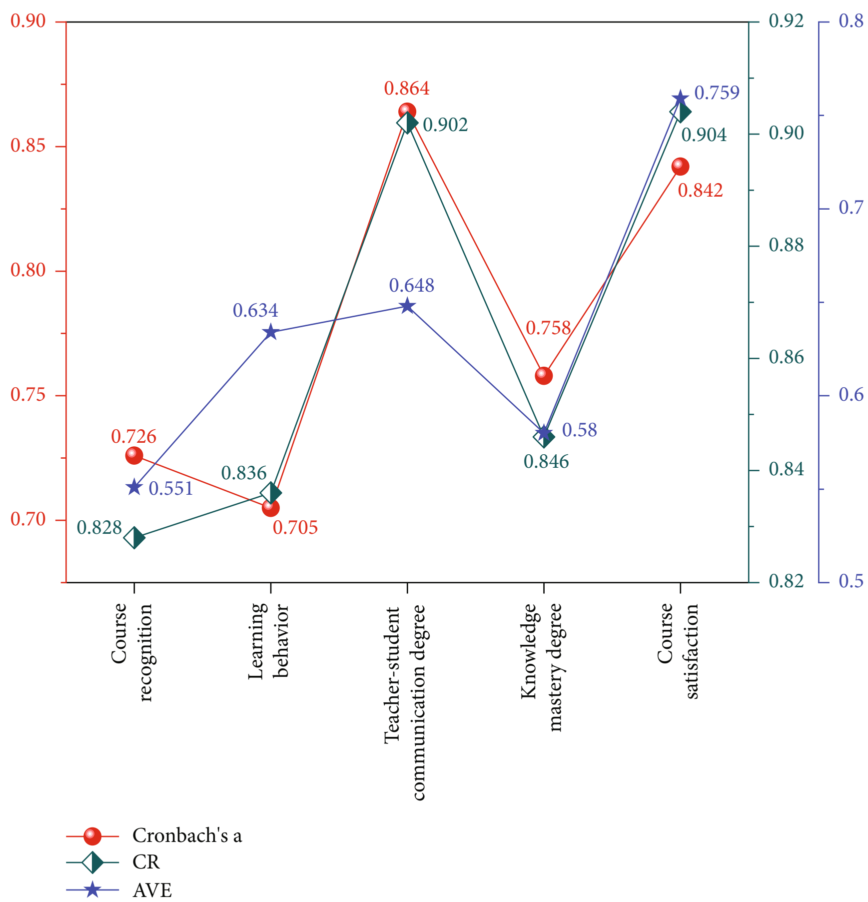

Figure 6: Correlation coefficient of latent variables in the model.

explicit variables on learning behavior, teacher-student communication, knowledge mastery, and teaching satisfaction. The differences of direct, indirect, and total effects of each predicted variable on dependent variables are statistically significant ($P < 0.05$) [45]. Curriculum cognition can explain 23.4% variation of learning behavior. Course cognition and learning behavior can explain the variation of communication between teachers and students by 31.4%. Course cognition, learning behavior, and communication between teachers and students can explain 58.3% variation of knowledge mastery. Course awareness, learning behavior, communication between teachers and students, and knowledge mastery can explain the variation of teaching satisfaction by 36.9%.

5.5. Application Effect Analysis. As shown in Figures 8 and 9, the results show that curriculum awareness, learning behavior, and communication between teachers and students explain the variation of knowledge mastery by 58.3%. Learning behavior and communication between teachers and students have a direct impact on knowledge mastery, while curriculum awareness has an indirect impact on knowledge mastery, both of which are positive. According to the scores of each latent variable, after the linear transformation of 100 points, the scores of each latent variable are (90.33 10.339) points of curriculum cognition. Those of learning behavior are (70.22 13.094), communication between teachers and students are (54.71 14.875), and knowledge are (65.44 12.510) points. The results show that the overall score of

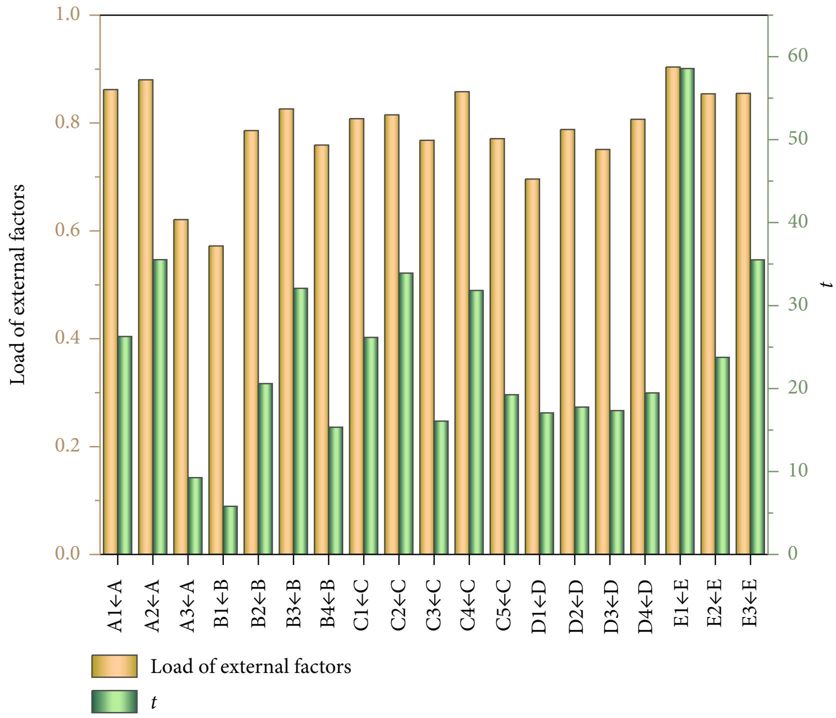

Figure 7: External model loads between explicit variables and latent variables of the model.

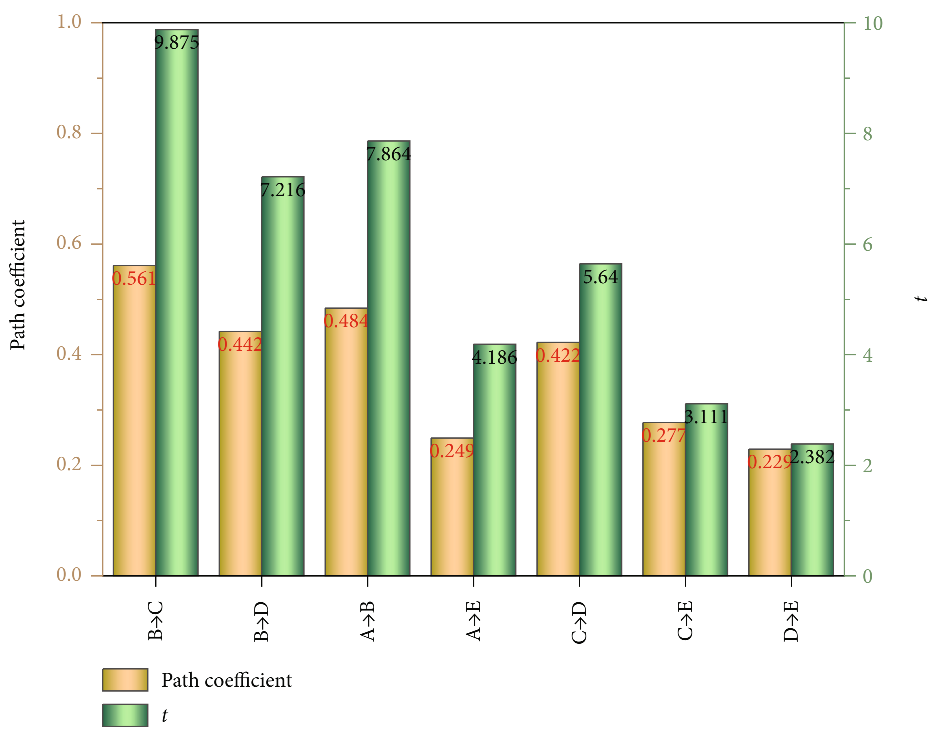

Figure 8: Path coefficient between latent variables.

students' cognition of the course of health statistics is high, indicating that students have a good understanding of the importance of this course. However, the scores of students' learning behavior, communication between teachers and students, and knowledge mastery are low, which indicates that students are not active enough in the study of health statistics, and the communication between teachers and students is lacking, which leads to poor learning effect. Among the direct latent variables that have influence on knowledge mastery, the path coefficient of learning behavior is the

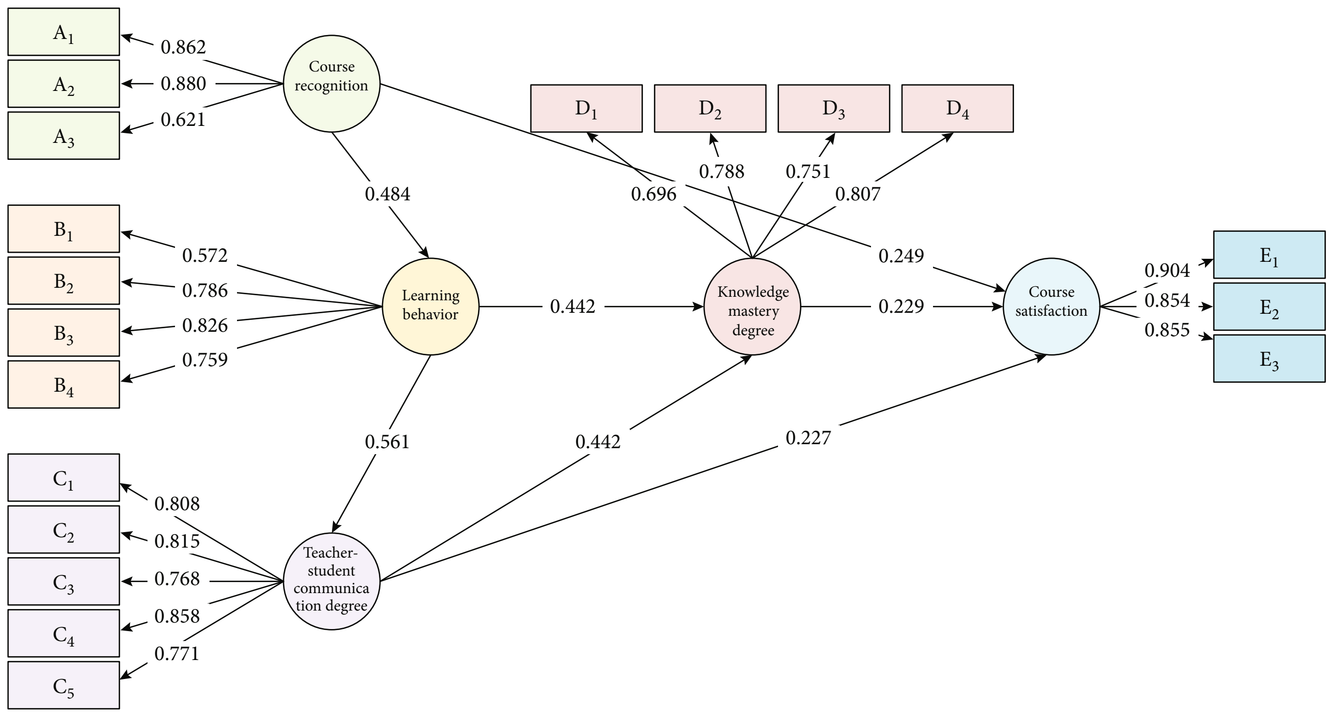

Figure. 9: Path coefficient of the teaching model of health statistics.

Table 2: Direct and indirect effects of the model.

Dependent variable	Observable variable	Direct effect	Indirect effect	Gross effect	R^2
Learning behavior	Course recognition	0.484	—	0.484	0.234
Teacher-student communication degree	Course recognition	—	0.271	0.271	0.314
	Learning behavior	0.561	—	0.561	
Knowledge mastery degree	Course recognition	—	0.328	0.328	0.583
	Learning behavior	0.442	0.237	0.679	
	Teacher-student communication degree	0.422	—	0.422	
Course satisfaction	Course recognition	0.249	0.15	0.399	0.369
	Learning behavior	—	0.311	0.311	
	Teacher-student communication degree	0.277	0.097	0.374	
	Knowledge mastery degree	0.229	—	0.229	

highest, which is 0.442, suggesting that it has the greatest influence on knowledge mastery. Secondly, the communication between teachers and students, whose path coefficient is slightly lower than that of learning behavior, is 0.422, which indicates that the degree of communication between teachers and students also has a great influence on knowledge mastery.

Therefore, in order to improve the knowledge of health statistics, students should give full play to their subjective initiative and strive to improve their learning behavior. As a teacher, we should interact and communicate with students in the teaching process and timely answer the students' confusion in the process of learning health statistics. At the same time, teachers should encourage and guide students to participate in various scientific research topics, so as to achieve the purpose of warming up the past and learning new things and applying what they have learned. Schools, colleges, etc. should continue to do a good job of guidance, enhance students' emphasis on this subject, and correct their learning attitude. The results of path analysis also show that students' awareness of subjects, communication between teachers and students, and knowledge mastery have a direct positive impact on course satisfaction, while the learning behavior has an indirect positive impact on course satisfaction. However, the four latent variables can only explain the variation of 36.9% of course satisfaction and the overall average score of course satisfaction is (80.22 12.663) after the linear transformation of 100 points, which indicates that the course satisfaction is also greatly influenced by other unknown latent variables, and further research is needed.

6. Conclusions

Based on the video visualization technology of the convolutional neural network, this paper evaluates the teaching model of health statistics and analyzes the factors that affect knowledge mastery and teaching satisfaction, so as to improve the teaching method of health statistics. This paper draws the following conclusions:

(1) Cronbach's α and Cr values of five latent variables in the model are all greater than 0.7; AVE values are all greater than 0.5. The square root of AVE is higher than the correlation coefficient of each latent variable. The differences of external model loads between explicit variables and latent variables are statistically significant ($P < 0.001$). The path coefficients of all latent variables are statistically different ($P < 0.05$)

(2) Learning behavior and communication between teachers and students have a direct impact on the mastery of knowledge, and the order of influence is as follows: learning behavior (path coefficient = 0.442, $P < 0.001$) and communication between teachers and students (path coefficient = 0.422, $P < 0.001$). Subject recognition, teacher-student communication, and knowledge mastery have a direct positive impact on course satisfaction, and the order of influence is as follows: teacher-student communication (path coefficient = 0.277, $P < 0.001$), course recognition (path coefficient = 0.249, $P < 0.001$), and knowledge mastery (path coefficient = 0.229, $P < 0.01$)

(3) For learning behavior and communication between teachers and students, the teaching effect model of health statistics based on video visualization technology of the convolutional neural network has certain practicability

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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