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Design of Intelligent Assisted Teaching System for Civics and Political Science Classes in Colleges and Universities Based on Image Processing Algorithms and Methods of Analyzing Students' Interactive Behavior

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Abstract In traditional teaching, it is time-consuming and labor-intensive to ensure the teaching quality only through teachers' observation of students' behavioral status. Therefore, deep learning algorithms and image processing algorithms are used to construct an intelligent assisted teaching system, so as to realize classroom target detection, interactive behavior recognition and classification. By analyzing students' interactive behaviors and monitoring the classroom status in real time, the quality of education and teaching is further improved. Taking 14 examples of Civics and Political Science classes in a university as research samples for empirical analysis, it can be seen that the accuracy rate of the algorithm proposed in this paper for detecting standing behavior reaches 84%, and the accuracy rate of the overall behavior detection system is 81.4%, which is a good effect. Teacher-student interaction behavior is most often characterized by "instruction-passive response". Student-teacher interaction behavior "Passive Response-Lecture" appeared most frequently. The student-student interaction behavior is most often "debriefing-debriefing".

Index Terms interactive behavior, deep learning, image processing, target detection, intelligent assisted teaching system

I. Introduction

In the context of the era of rapid development of science and technology, artificial intelligence (AI), as a cutting-edge technology, is profoundly changing all areas of social life, including the education industry [1]. Especially in the stage of higher education, especially in ideological and political education, which is a key field concerning the future of the country and the hope of the nation, the application of AI shows its incomparable value and potential [2]. Ideological and political education in colleges and universities shoulders the important mission of guiding college students to establish a correct worldview, outlook on life and values, how to use artificial intelligence technology to optimize the intelligent teaching aid system for ideological and political courses in colleges and universities, and to improve the quality and effect of education, which is a new topic facing colleges and universities [3].

Teaching assistance systems are generally categorized into three types, one is a system that directly assists teachers or students in their daily work or study, and the second is an application in a specific aspect, such as the use of portable devices to enhance classroom interaction. The third type incorporates intelligent assistants to introduce artificial intelligence to make the system more intelligent to assist teaching and learning [4].

In the first type of assisted teaching system, Mohanty, A et al [5] proposed a classroom management system where student attendance will be recorded using face recognition, in addition the system will help the teacher to recognize the students who are lecturing by using voice differentiation algorithms.Heffernan, N. T and Heffernan, C. L [6] developed the ASSISTments platform system that provides better instructional feedback to student users for better learning outcomes.Patikorn, T et al [7] designed and deployed a pedagogical assistance system called TeacherASSIST that allows teachers to provide on-demand help services to students on the ASSISTments online learning platform which is effective in improving student learning outcomes.

In the second category of assistive teaching systems, Almusawi, H. A et al [8] attitudes to the use of wearable devices in the physical education classroom and demonstrated that these technologies hold educational promise in the areas of teacher-student interaction, participation, assessment and feedback, providing innovative and practical solutions for teaching and learning in physical education.Goh, F et al [9] reviewed the current use of portable technology as a pedagogical aid in the classroom and found that the technology can be used to monitor student activity, posture, movement, proximity, and relationships, augmenting traditional methods of classroom observation, especially to provide feedback in terms of real-time quantitative data for instruction. In addition to student observation, teachers can use portable devices to improve the effectiveness of their teaching practices.Tham, J. C. K[10] used Google Glass in his study to record events, students can submit real-time queries, and teachers can provide important learning objectives or thought processes during time-sensitive activities for students to review at a later date.

The third type of intelligent assistants are usually deployed as part of an online teaching platform to help online students with functions such as completing assignments and answering questions.Paiva, R and Bittencourt, I. I [11] used virtual assistants to find scenarios from a large amount of data that are similar to the teacher's current situation, and they predefined solutions for each scenario to help the teacher to understand the situation and solve the problem. Zhang, X et al [12] developed and deployed an intelligent teaching assistant system called I-assistant, which combines artificial intelligence algorithms to analyze student data to assist teachers in instructional design, and combines intelligent algorithms with classroom teaching to help teachers teach accurately and effectively.Liu, J et al [13] proposed a system that consists of a teaching material service (TMS), a dynamic Symbol Store Service (dSPS) and Assignment Management Service (AMS) as three key modules of an enhanced Intelligent Instructional Support System (e-ITSS) to collaborate with teachers for efficient classroom production, as well as for the implementation of personalized learning. Robles, D and Quintero M, C. G [14] used fuzzy logic and case-based reasoning to develop an Intelligent Assisted Teaching System that enabled student performance assessment and provided feedback for personalized instruction, deployed on a web platform using information and communication technology.

It is foreseeable that in the current and a long period of time afterward, teachers are still the main object of classroom teaching, and the main goal of the intelligent teaching aid system is still to assist teachers in teaching, not to replace them. Therefore, it is necessary to design a more comprehensive intelligent teaching aid system to assist teachers. At the same time, in the existing teaching assistance system, many methods only do the information exchange through online or use mobile or portable devices to enhance classroom interaction, i.e., only build some specialized and separated applications, failing to build an integrated information system to deal with the comprehensive challenges of the Civics and Political Science classroom teaching in colleges and universities.

In this paper, based on students' classroom information, we design an intelligent assisted teaching system including classroom module, data module and learning state detection module by utilizing data acquisition, face recognition, gesture recognition and data storage technologies. Among them, the classroom module incorporates deep learning-based behavior classification algorithm, image processing and enhancement algorithm. After accurately and individually marking individual students using the image processing and enhancement algorithm, the interactive behaviors of each student are then classified using SVM and mean selection, so as to analyze the interactive behaviors of the detected students and derive the overall situation of the students' performance in the classroom. In order to verify the feasibility and validity of the methods involved in this paper, five different classroom interaction behaviors and the accuracy on the dataset were verified. Fourteen classroom examples of Civics in a university were selected for the study to analyze in detail the main modes of interaction behavior between teacher-student, student-teacher, and student-student.

II. Overall design of the intelligent auxiliary teaching system

II. A.Requirements analysis and framework design

Student classroom information data is crucial for teaching analysis, so it can not only identify individual students, but also integrate and summarize the data of multiple students to evaluate the teaching process in all aspects.

Although on the basis of the intelligent classroom, some predecessors have realized the work of emotional state recognition and somatosensory detection, but the student's seat number and student identity binding, and can not be in multiple classes, free access to the situation, real-time dynamic response to the classroom learning situation [15].

Therefore, the measurement of the system is recorded by the students in the classroom, and the analyzer is the teacher or teaching evaluator. According to the above research phenomenon, in order to solve the shortcomings of the traditional classroom, the proposed requirements are as follows:

1. Multiple data sources to collect classroom and student data, and record any valuable information of students in the teaching process.
2. Multiple devices to collect data. Because of the limited scope of a single device collection, multiple devices to collect more student information data on the entire smart classroom.
3. The system is a multi-data source, but also involves a lot of equipment, many functions, the need for equipment management.

4. The original single front data source processing, student identification, and scalability, in order to have the subsequent functions added.
5. Fusion processing of multiple data sources, student behavior detection, and scalability, in order to have subsequent features added.
6. Teacher console to display statistical identification and detection results.
7. Database storage of multiple data sources.

II. B.Hardware architecture design

The hardware architecture used in the assisted teaching system developed in this thesis follows the same general principle of icing on the cake, i.e., maximizing the use of existing network and teaching devices. Classroom desktop computers, projectors or LCD screens were used as existing equipment, to which student and teacher personal terminals were added.

Teachers' terminal devices and students' terminal devices are connected to a cloud server on the Internet through campus or classroom wireless routers. The teacher's terminal can be an existing desktop PC in the classroom or some mobile communication device. The student terminal should be consistent with the teacher's terminal.

The functional framework of the intelligent assisted teaching system is shown in Figure 1, in which the classroom module is mainly responsible for recording the whole teaching process of the teacher, generating teaching video streams through the video recording sub-module and transmitting them to the students' terminals in real time, and at the same time helping students to ask questions through the pop-up interactive sub-module to promote classroom interactions between the teacher and the students, so as to ensure the synchronization of teaching and learning. During non-lecture hours, teachers and students can ask questions, answer questions, discuss, assign and collect homework, conduct classroom tests, transfer files, etc. through the group communication submodule, and at the same time, it can also count the usual grades and homework, attendance, etc. All teaching videos and group communication data can be uploaded to the cloud server through the data upload submodule. The connection between students' and teachers' terminals and the cloud server is realized through the login sub-module; the files and homework data in the teaching videos and group communication can be downloaded locally through the data download sub-module. The learning status monitoring module is mainly responsible for real-time monitoring of students' learning status in the classroom, and consists of face orientation-based learning status monitoring submodule and deep learning-based learning behavior monitoring submodule. The learning status monitoring submodule based on face orientation captures photos of students' faces in the classroom, and calculates the rotation angle of the faces through feature analysis, so as to determine whether the students are listening to the lectures attentively or not. The learning behavior monitoring sub-module based on deep learning intercepts a short video of students in the classroom, and determines whether the students in this short video are sleeping, eating, looking around, talking with others and other non-serious learning actions through deep learning neural network, so as to achieve the purpose of judging the learning status of students. These judgment results are uploaded to the teacher so that the teacher can know the students' learning status in real time and warn the students who do not study seriously. The data module is responsible for managing the data generated by the classroom module and the learning status detection module.

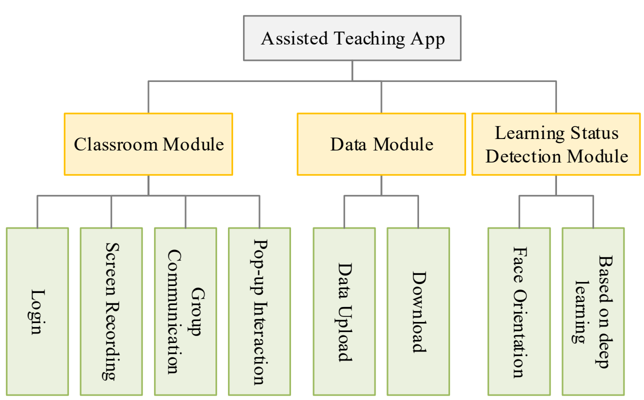

Figure 1: intelligent auxiliary teaching system function framework

III. Research on algorithms for detecting interactive behavior in classroom modules

III. A. Behavioral classification algorithms for deep learning

The two-stream convolutional neural network is composed of a spatial streaming network. The input data for the temporal streaming network is the sequence of optical flow between coherent frames, and the input data for the spatial streaming network is the still picture frames. For the video to be detected, the image frames are sampled at the same time intervals. The image frames obtained after sampling are then randomly flipped and cropped to obtain 10 inputs to the network. For the spatial streaming network, an RGB image (size 224×224×3) is used as input; for the temporal streaming network, a dense sequence of optical streams (size 2L×224×224) between consecutive L frames is used as input. Finally, the feature information in the temporal and spatial streams are fused using SVM and mean selection to classify the behaviors [16].

III. B. Image Processing and Enhancement Research

Student images obtained through target detection may have unstable quality due to lighting, angle, position, etc., and fail to highlight the desired features. Whereas, proper image processing can highlight the desired features in the image and reduce the influence of irrelevant features, so the methods of image processing need to be investigated.

III. B. 1) Image processing

Image processing has methods such as grayscale processing and binarization, through which certain features of an image are enhanced to facilitate algorithms for feature extraction [17].

Grayscale processing: the RGB color image defines the color of the pixel points in the image by the three color components R, G, and B. Because there are three color components, the RGB image has a large range of color variations. In order to reduce the amount of computation of the image during training and to highlight the effective features, the RGB image can be converted into grayscale image for processing, which can be converted into grayscale image by weighted average method, component method, maximum value method, and average value method.

Binarization is also a way to reduce the amount of image computation to deal with the image, through the selection of the threshold value, the pixel points of the image are differentiated by black and white, to reduce the influence of the complex color on the effective features in the image, so as to make the contour of the target in the image more obvious, there are mainly double-peak thresholding, P parameter thresholding, OTSU algorithms, through which the image segmentation threshold can be divided.

Twin-peak thresholding method: the principle of the twin-peak thresholding method is to analyze the gray-scale image by analyzing the gray-scale histogram of the gray-scale image, and if the shape of the gray-scale histogram is in the form of a twin-peak, the value at the bottom of the gray-scale peaks between these two gray-scale peaks will be selected as the threshold value, and then the image will be processed using binarization.

P Parametric Thresholding: P Parametric Thresholding is also a method applied to grayscale images with the following steps:

1, set the proportion of the target object to the image as $P\%$ by a priori condition.

2, Then set the threshold as Th.

3, Calculate the number of pixel points N of the target object in this case.

4, Calculate the proportion of N to the overall image (let the length of the image be a, the width be b, and the overall pixel points be $a \times b$):

$$scale = \frac{N}{a \times b} \tag{1}$$

See if the ratio is close to $P\%$, and set the threshold to Th if it is, or Th_{new} if it is not:

$$Th_{new} = Th_{old} + \Delta g \tag{2}$$

Then repeat 3 to 4 steps until a suitable threshold is found.

OTSU Algorithm: OTSU (maximum between class variance) is an adaptive way to determine the image segmentation threshold, which divides the specified image into two parts: the target (also called foreground) and the background. Then the two parts are classified by calculating the threshold value and selecting the threshold with the highest degree of differentiation as the optimal threshold, the process is shown below:

Let the segmentation threshold between the target and the background be set to T, the proportion of target pixel points to the overall image be S_{obj}, the average gray level be $Gray_{obj}$, and the background pixel points account for S_{back} of the overall image, the average gray level be $Gray_{back}$. The average gray scale of the overall image is $Gray_{pic}$, and the variance between the target and the background is Var_{class}, the specific steps are as follows:

1. Select the gray threshold T_i of the image, calculate the number of pixels in the image with gray value less than T_i as N_{obj}, and calculate the number of pixels greater than the threshold T_i as N_{back}.

2. Compute Grayobj and Grayback.

3. Compute S_{obj} and S_{back}:

$$S_{obj} = \frac{N_{obj}}{a \times b}, S_{back} = \frac{N_{back}}{a \times b} \tag{3}$$

4. Calculate the average gray scale:

$$Gray_{pic} = S_{obj} \times Gray_{obj} + S_{back} \times Gray_{back} \tag{4}$$

5. Calculate the interclass variance:

$$Var_{class} = S_{obj}\left(Gray_{obj} - Gray_{pic}\right)^2 + S_{back}\left(Gray_{back} - Gray_{pic}\right)^2 \tag{5}$$

By selecting the grayscale thresholds $T_1, T_2, \ldots, T_n$ of the image and then repeating the above steps, the threshold T_i which makes the maximum variance is selected as the best threshold by which segmentation is performed.

III. B. 2) Image enhancement

For a relatively small number of behavioral images in the dataset, image enhancement can be used to increase the number of images, image enhancement specific ways are image offset, rotation, flip scaling [18].

Image Offset: Image offset refers to moving all pixels in an image in the horizontal direction (x axis direction) or vertical direction (y axis direction) by a specified offset.

Image Rotation: Image Rotation is to rotate the coordinates of the pixels in an image with the center of the image S as the origin of rotation without changing the RGB pixels of the original image, and the distance between the pixels after rotation and the center of the image S remains unchanged, which is usually realized by means of matrix transformation.

Image Flip: Image Flip refers to flipping an image with horizontal (x, y -axis direction) or vertical (y -axis direction) as the axis of symmetry.

Image scaling: Image scaling refers to the process of resizing an image, which consists of two ways: downsampling (image reduction), and upsampling (image enlargement).

Downsampling (sampling by a factor of $k \times k$ times) is the process of reducing the size of an image of size $m \times n$, resulting in a new image of size $(m/k) \times (n/k)$, the pixel regions of size $k \times k$ of the original image are averaged to take the average pixel values of the pixel regions, which are taken as the pixel values of the corresponding pixel points in the new image.

Up-sampling is mainly achieved by interpolation, and the commonly used interpolation methods are nearest neighbor interpolation and bilinear interpolation:

Nearest Neighbor Interpolation is a simpler form of interpolation, where the grayscale of the pixel closest to the requested pixel is assigned to the requested pixel.

It is known that $A_{11} = \left(x_1, y_1\right)$, $A_{12} = \left(x_1, y_2\right)$, $A_{21} = \left(x_2, y_1\right)$, $A_{22} = \left(x_2, y_2\right)$ The coordinates of these four points are needed for the $P = (x, y)$ points are interpolated as follows:

First interpolate linearly in the x direction:

$$\begin{aligned} f\left(B_1\right) &\approx \frac{x_2 - x}{x_2 - x_1} f\left(A_{11}\right) + \frac{x - x_1}{x_2 - x_1} f\left(A_{21}\right) B_1 = \left(x, y_1\right) \\ f\left(B_2\right) &\approx \frac{x_2 - x}{x_2 - x_1} f\left(A_{12}\right) + \frac{x - x_1}{x_2 - x_1} f\left(A_{22}\right) B_2 = \left(x, y_2\right) \end{aligned} \tag{6}$$

The coordinates of the P point are then obtained by linear interpolation in the y direction:

$$f(P) \approx \frac{y_2 - y}{y_2 - y_1} f\left(B_1\right) + \frac{y - y_1}{y_2 - y_1} f\left(B_2\right) \tag{7}$$

IV. Detection accuracy of five types of behaviors

Although many algorithms perform well in datasets or other scenarios, algorithms for student behavior detection in classroom scenarios are difficult to apply directly to existing algorithms. The difficulties are: 1) For student behavior detection in classroom scenarios, a specific dataset is required and the dataset for training neural networks is large. 2) Deep learning models are generally large, and the application will face the problem of insufficient computational power of the model-bearing devices (embedded development boards, etc.). 3) There is a certain ambiguity in determining the behavior of the students in the classroom, and it is difficult to achieve the classification of the behaviors.

The accuracy of this paper's algorithm to detect five different behaviors is given as shown in Figure 2. From the figure, it can be seen that the algorithm of this paper has a higher accuracy of 84% in detecting the standing behavior and a lower accuracy of 78% in detecting the writing behavior. It is clear from the analysis that the standing posture is not easily obscured and has less leakage rate, so the detection accuracy is higher. The sleeping posture is not easily detected and has a lower accuracy rate. Overall, the accuracy rate of the behavior detection system is 81.4%, which is more satisfactory.

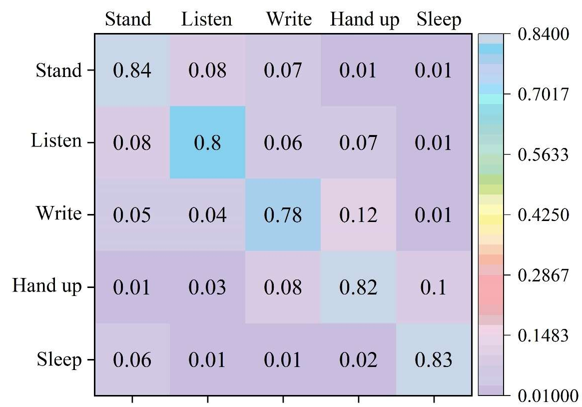

Figure 2: Detection accuracy of five kinds of behaviors

The accuracy of each algorithm on the dataset and on the JetsonTX2 under the condition of detecting videos of the same classroom scene is shown in Figure 3. As can be seen from the figure, SSD performs the best on the dataset, achieving an accuracy of 80.4%. The accuracy of this paper's algorithm is 79.1%, which is slightly lower than SSD but higher than the other algorithms, and has a large advantage over the two lightweight networks. On Jetson TX2, compared to on the dataset, the accuracy of the algorithms are reduced, the accuracy reduction of this paper's algorithm is the smallest, and the accuracy of all the algorithms are higher than the other algorithms.

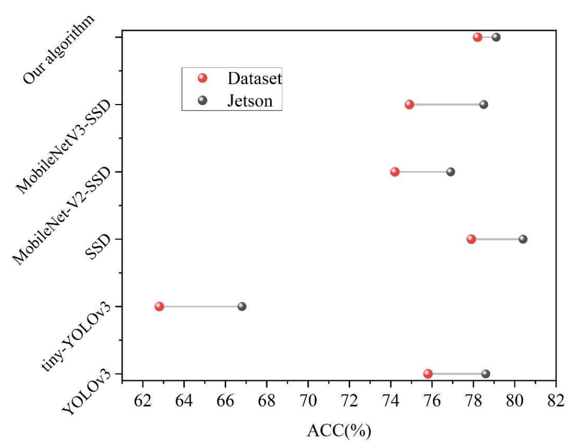

Figure 3: Accuracy of each algorithm

V. Empirical studies

V. A. Classroom teaching structure

After establishing the final Intelligent Tutoring Civics Teaching System, this chapter will then carry out practical applications with the help of the Intelligent Tutoring Civics Teaching System and its interactive behavior detection algorithms to analyze the classroom teaching interactive behaviors with the example of college Civics classes as the research object. In this study, 14 classroom transcripts of excellent teachers nationwide using tablet PCs to carry out Civics teaching in colleges and universities were selected.

The data can show characteristics as shown in Table 1.

First, the ratio of teacher's language to the total is between 19.1% and 48.17%, which can reflect that teacher's speech is not occupying most of the classroom time, and the proportion of the time it occupies has declined significantly, implying that the teacher may be more likely to use non-verbal behaviors.

Second, among the selected lesson examples, there were eight lesson examples in which the ratio of student speech to total was greater than 20% of the student speech norm, indicating that the classroom time for students to speak, communicate, and present had increased, and there were six lesson examples in which the ratio of student speech to total was less than 20% of the student speech activities, indicating that the students' verbal behavioral activities were fewer, which implied that the students might have had more chances to carry out nonverbal behavioral activities.

Third, there were 11 classroom examples where the ratio of classroom silence to total was more than 2%, which accounted for a certain portion of the classroom time, suggesting that there were some temporary pauses in the classroom to think about problems and behaviors that did not contribute to instructional disruption.

Table 1: classroom teaching structure analysis table (%)

Class	The ratio of teacher language to total	The ratio of student language to total	[teacher language + teacher media usage] ratio of total	[student language + student media use behavior] ratio to total	The ratio of silence to total
1	45.06	28.59	46.96	48.3	4.84
2	41.12	27.79	44.63	53.05	2.42
3	35.18	26.85	45.11	50.91	4.08
4	31.75	29.13	44.72	49.99	5.39
5	41.97	14.87	52.25	45.86	1.99
6	32.26	19.18	43.65	53.08	3.37
7	24.48	12.01	55.78	42.05	2.27
8	19.1	21.08	30.76	63.05	6.29
9	24.6	3.93	47.39	51.67	1.04
10	47.19	16.79	54.28	44.51	1.31
11	32.09	9.96	44.54	52.49	3.07
12	48.17	25.72	64.18	32.36	2.56
13	21.8	20.53	31.6	62.05	6.45
14	32.55	28.23	38.27	57.28	4.55

V. B. Teacher behavior

Teachers' behaviors, as shown in Table 2, were greater than 100% for both direct and indirect influence language in the 14 lesson examples, and more time was spent on direct influence speech than on indirect influence discourse, suggesting that teachers tended to adopt direct discourse to have a direct influence on students' behaviors.

Table 2: The teaching style statistics table (%)

Class	The ratio of direct influence to indirect impact	The ratio of negative reinforcement to positive reinforcement
1	458.37	132.76
2	208.53	152.49
3	520.45	557.17
4	188.68	122.06
5	140.61	62.35
6	488.93	792.34
7	318.22	46.33
8	168.04	236.39
9	437.97	120.96
10	440.04	90.35
11	426.13	271.46
12	446.62	95.19
13	476.71	184.24
14	262.3	167.14

V. C. Gray-scale diagram analysis

V. C. 1) Teacher-Student Interaction Behavior

In order to analyze the main interactive behaviors between teachers and students in the Civics classroom, the five types of interactive behaviors that appeared with stronger grayscale in the grayscale diagram of the frequency of teacher-student interactive behaviors in all the lesson examples were counted separately. In the grayscale diagram, the stronger the grayscale, the greater the frequency of the interaction behavior, the higher the frequency; the weaker the grayscale, the smaller the frequency, the lower the frequency; white means that the frequency and the frequency are 0, that is, there is no such interaction behavior. Taking example 1 and example 2 as an example, the teacher-student interaction behavior in example 1 is shown in Figure 4, and the five types of interaction in example 1 from strong to weak grayscale are as follows: ① Instruction - passive response. ② Instruction-reporting display. ③ Instruction-temporary pause. ④ Instruction-reading learning materials such as e-textbooks and e-books. ⑤ Questioning closed questions-passive response.

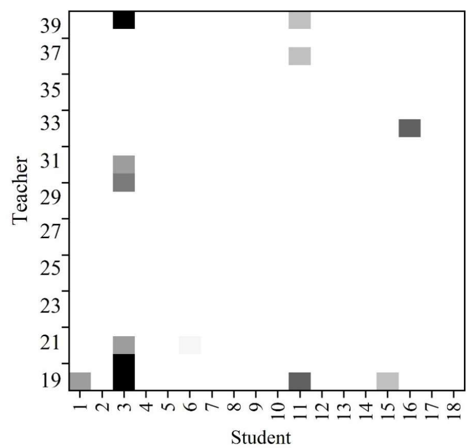

Figure 4: Class 1 teachers - students' interaction frequency number gray scale

The behavior of teacher-student interactions in the example of Civics 2 is shown in Figure 5, and the five types of interactions in the example of Civics 2 in shades of gray ranging from strong to weak are as follows: ① Instruction-passive response. ② Instruction - temporary pause. ③ Instruction-active response. ④ Asking closed questions-passive response. ⑤ Instruction-complete the exercise. Obtaining feedback results.

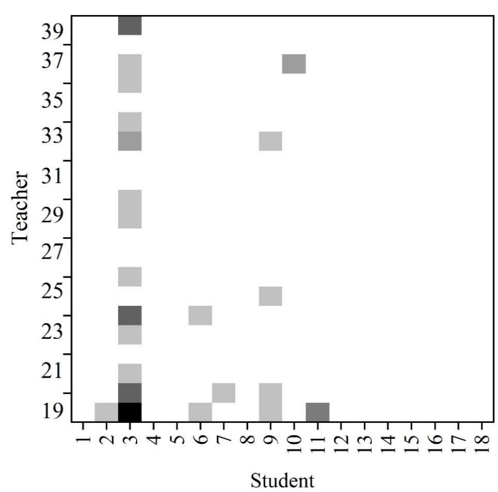

Figure 5: Class 2 teachers - students' interaction frequency number gray scale

The five kinds of gray scale from strong to weak behaviors were set as rank 1, rank 2, rank 3, rank 4, rank 5, and the interaction behaviors described in the statistical examples 1~14, and the statistical results of the teacher-student interaction behaviors are shown in Table 3. The results show that the five most frequent types of teacher-student interaction behaviors are "instruction-passive response", "closed-ended question-passive response", "instruction-temporary pause", "instruction-report display", and "instruction-active response".

Table 3: Teacher - student interactive behavior statistics

Behavior	1	2	3	4	5
Lecture - passive response	1	0	1	0	0
Lecture - the exhibition	0	0	0	1	0
Indicator - passive response	9	1	0	1	1
Directive - active response	1	0	4	0	1
Indicator - exchange show	0	2	1	1	1
Instruction - discussion with peers	0	0	0	1	0
Directive - student evaluation	1	0	0	0	0
Instruction - practice	0	0	0	0	1
Indicator - login learning platform/open software	0	0	0	0	1
Instructions - reading electronic textbooks, e-books and other learning materials	0	0	2	0	0
Instructions - complete the practice and get feedback	0	2	1	0	4
Indicator - using split screen projection software to present individual or team learning results or dynamic rendering exploration	0	1	1	4	0
Guide - exchange show	0	0	0	1	0
Question closing question - thinking problem	0	1	0	0	1
Question closing question - passive response	2	5	3	1	2
Indication - temporary pause	2	5	2	0	1

V. C. 2) Student-Teacher Interaction Behavior

In order to analyze the main ways of student-teacher interaction behaviors in the classroom, the five types of interaction ways that appeared in the grey scale diagram of the frequency of student-teacher interaction behaviors in all the examples of the Civics class with a strong grey scale were counted respectively. Take Case 1 and Case 2 as an example, Case 1 student-teacher interaction behavior is shown in Figure 6, the five types of interaction from strong to weak gray scale in Case 1 are: ① passive response - lecture. ② Reporting and displaying - adopting opinions. ③Reading e-textbooks, e-books and other learning materials - instructions. ④ Reporting and displaying - comments. ⑤ Reporting and displaying-encouragement and praise.

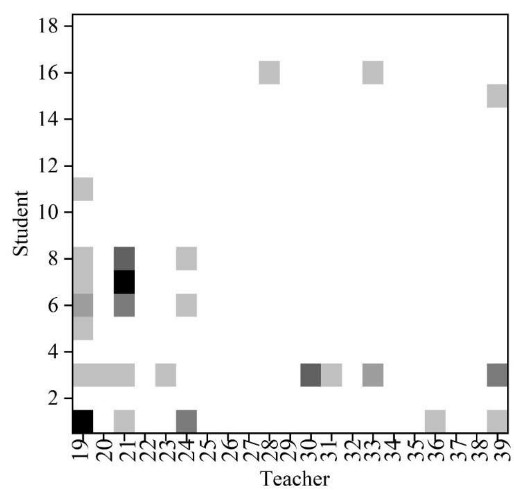

Figure 6: class 1 student - teacher interactive behavior frequency matrix

Civics Lesson Example 2 Student-Teacher Interaction Behaviors As shown in Figure 7, the five types of interactions in Lesson Example 2, ranging from strong to weak shades of gray, are. ①Passive Response-Encouragement and praise. ② Passive Response-Lecture. ③ Temporary pause - instruction. ④ Passive Response - Ask closed questions. ⑤ Passive Response - Instruction.

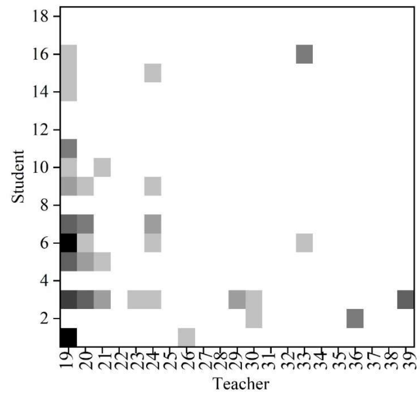

Figure 7: class 2 student - teacher interactive behavior frequency matrix

Table 4: Student - teacher interactive behavior statistics

Behavior	1	2	3	4		5
Passive response - instruction		1	4	4	0	0
Passive responsiveness - indicator		1	5	2	0	1
Passive response - acceptance of emotion		0	1	0	0	1
Passive response - encourages praise		2	0	1	1	1
Passive response - adoption of advice		2	1	1	0	1
Passive response - question closing problem		2	1	1	2	1
Active responsiveness - indicator		0	0	1	0	0
Active responsiveness - adoption		1	0	1	0	1
Exhibition - instruction		2	0	2	0	0
Exhibition indicator		0	1	1	0	0
Express - accept emotions		0	0	0	1	0
Show - encourage praise		0	0	4	0	0
Show - adopt opinions		1	0	1	0	1
Exchange show - comments		0	0	0	0	1
Students' evaluation - adoption of opinions		0	0	0	0	1
Student evaluation - review		0	1	0	0	0
Reading electronic textbooks, e-books and other learning materials - instructions		1	0	1	0	1
Finish the practice, get feedback results - teach		0	0	0	0	1
Finish the practice and get feedback results - instructions		0	1	0	1	0
Complete the practice, get feedback results - interactive rendering		1	0	1	0	0
Using split screen projection software to present individual or team learning results or dynamic rendering exploration processes - instructions		1	0	0	0	1
Thinking problem - indication		0	0	1	2	0
Temporary pause - indicator		0	2	1	1	2
Passive response - instruction		1	4	4	0	0

The five behaviors with gray scale from strong to weak were set as level 1, level 2, level 3, level 4, and level 5, respectively, and the above interactive behaviors were counted, and the statistics of student-teacher interaction behaviors are shown in Table 4. The results showed that the five most frequent types of student-teacher interaction behaviors were "passive response-teaching", "passive response-instruction", "passive response-encouragement and praise", "passive response-asking closed-ended questions", and "passive response-adopting opinions".

V. C. 3) Student-Student Interaction Behavior

In order to analyze the main ways of student-student interaction behaviors in the Civics classroom, the interaction ways that appeared in a stronger gray scale in the gray scale graph of the frequency of student-student interaction behaviors in all the lesson examples were counted separately. The grayscale diagram of student-student interaction behaviors is shown in Figure 8.

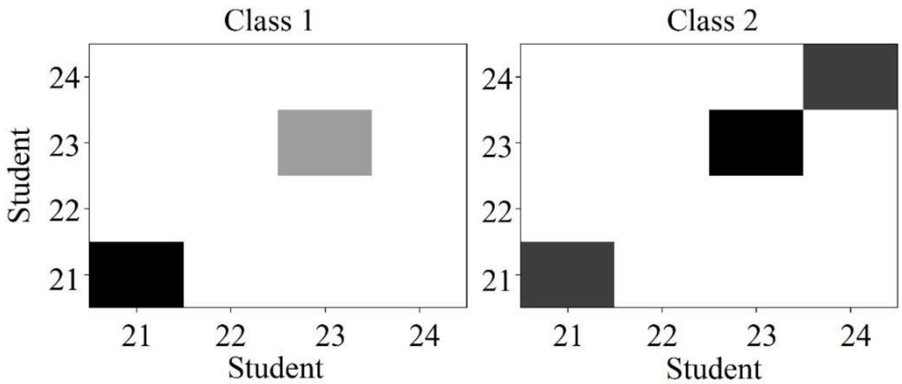

Figure 8: Student - student interaction frequency number grey scale

The three behaviors with gray scale from strong to weak were set as level 1, level 2, and level 3, and the statistical results of student-student interaction behaviors are shown in Table 5.

The results showed that the most frequent types of interaction behaviors between students and students were "report and display", followed by "discussion with peers - discussion with peers", then "student mutual evaluation - student mutual evaluation", and finally "active talking-active speaking".

Table 5: Student interaction statistics

	1	2	3
The exhibition shows the exhibition	12	0	1
Active speaking - active speaking	1	0	3
Discuss with your partner -- discuss with your partner	0	6	1
Student mutual evaluation - student evaluation	0	1	4

Table 6: Sample 1 transmission and technology ratio

Classification		Content	Ratio	Frequency
Teacher interaction	Traditional interaction directly affects	Teach	31.2%	980
		Indication		
		Criticize		
	Technical interaction	Teachers accept emotions	9.89%	284
		Teachers encourage praise		
		Adopt opinions		
		Open question		
		Closed questions		
		Multimedia		
Student interaction	Traditional interaction	Student feedback	22.83%	633
		Interactive presentation		
		Response (passive response)		
		Answer (active response)		
	Technical interaction	Active question	20.45%	567
		Discuss with your partner		
		Exhibition		
		Review changes in the pre-class online practice		
		Teach		
		Interact with school resources and see online resources		
		Interact with the intelligent mentoring system		
		Interactive presentation learning with intelligent mentoring system		

V. D. Analysis of classroom technology applications

In the intelligent assistive system Civics classroom, technology is a presence that cannot be ignored, and this intelligent assistive system classroom teaching interaction behavior analysis system is to speak of the traditional behaviors that are distinguished from the technology-based behaviors. As shown in Table 6, the proportion of traditional interaction in Sample 1 is 54.03%, but the proportion of teacher-student interaction using technology is 30.34%. However, the ratio of which the interaction behavior based on technology is carried out is 9.89% for teachers and 20.45% for students. It can be seen that students are more involved in interactions by operating technological devices, which is a typical feature of the classroom with intelligent assistive systems. Observing the reasons for this, it can be found that the smart assistive system classroom is equipped with digital terminal devices such as tablets for students, so that students can participate in the interaction of the subject matter through the terminal devices instead of sitting and listening to the lecture, and give feedback to the teacher in real time through the terminal devices.

The ratio of traditional and technology-based interactions in Sample 2 is shown in Table 7, where traditional interactions accounted for 46.12% of the overall teaching and learning process, and more than half of the interactions utilizing technology amounted to 52.66%. In this more than half of the interactions, the percentage of teachers is 21.58% and the percentage of students is higher than teachers is 31.08%. By comparing the data with Sample 1, we will find that the percentage of technology use is significantly higher, and observing the classroom video will show that the teacher in Sample 2 is more familiar with using the devices in the Smart Assist classroom more proficiently. The teacher will use the technology to observe the real-time learning status of students, the accuracy of the exercises, etc. Teachers use the smart devices to better grasp the teaching rhythm of the classroom, determine the students' mastery level according to their real-time status, and advance the content at the right time, so that students can better absorb and digest the knowledge they have learned, and play the role of technology assistance in the classroom of the smart assistive system. In addition, students through the client for online interaction, but also from the side of the mobilization of students' enthusiasm and enthusiasm for learning, through a novel way, so that students participate in the classroom to really become the master of learning and classroom center characters.

Table 7: Sample 2 transmission and technology ratio

<table>
<tr><th>Classification</th><th></th><th>Content</th><th>Ratio</th><th>Frequency</th></tr>
<tr><td rowspan="9">Teacher interaction</td><td rowspan="3">Traditional interaction directly affects</td><td>Teach</td><td rowspan="3">26.84%</td><td rowspan="3">742</td></tr>
<tr><td>Indication</td></tr>
<tr><td>Criticize</td></tr>
<tr><td rowspan="6">Technical interaction</td><td>Teachers accept emotions</td><td rowspan="6">21.58%</td><td rowspan="6">600</td></tr>
<tr><td>Teachers encourage praise</td></tr>
<tr><td>Adopt opinions</td></tr>
<tr><td>Open question</td></tr>
<tr><td>Closed questions</td></tr>
<tr><td>Multimedia</td></tr>
<tr><td rowspan="12">Student interaction</td><td rowspan="4">Traditional interaction</td><td>Student feedback</td><td rowspan="4">19.28%</td><td rowspan="4">536</td></tr>
<tr><td>Interactive presentation</td></tr>
<tr><td>Response (passive response)</td></tr>
<tr><td>Answer (active response)</td></tr>
<tr><td rowspan="8">Technical interaction</td><td>Active question</td><td rowspan="8">31.08%</td><td rowspan="8">864</td></tr>
<tr><td>Discuss with your partner</td></tr>
<tr><td>Exhibition</td></tr>
<tr><td>Review changes in the pre-class online practice</td></tr>
<tr><td>Teach</td></tr>
<tr><td>Interact with school resources and see online resources</td></tr>
<tr><td>Interact with the intelligent mentoring system</td></tr>
<tr><td>Interactive presentation learning with intelligent mentoring system</td></tr>
</table>

VI. Conclusion

In this paper, deep learning algorithms and image processing algorithms are integrated into the classroom module to build an intelligent assisted teaching system. It can identify, classify and analyze the interactive behaviors occurring in the classroom. Through the study of students' classroom behavior, students' performance and problems in the classroom can be analyzed in depth, providing teachers with a basis and reference for further efficient classroom teaching. Empirical studies show that the overall accuracy of the interactive behavior detection method in this paper is 81.4%, which can meet the needs of complex scenes in the classroom. Based on the 14 classroom records of ideological and political teaching in colleges and universities, it can be found that the three most frequent types of interaction behaviors between teachers-students, students-teachers and students, and students are: "instruction-passive response", "asking closed-ended questions-passive response", and "instruction-temporary pause". "Passive Response-Teaching", "Passive Response-Instruction", "Passive Response-Encouragement and Praise". "Debriefing Presentation-Debriefing Presentation", "Discussion with Peers - Discussion with Peers", "Student Mutual Evaluation-Student Mutual Evaluation".

To sum up, this thesis has some significance for students' classroom behavior detection as well as for the construction of a smart classroom.

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