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R&D and Promotion Path of Multi-source Data Fusion Technology in Smart Classroom Construction

Bei Zhang[1] *and Lin Zhang*[2,*]

[1] College of Teacher Education, Xingtai University, Xingtai, Hebei, 054000, China
[2] Research and Development Center, Hebei Institute of Machinery & Electricity, Xingtai, Hebei, 054000, China

SUMMARY: *In this paper, we propose a learning input assessment model based on multi-source data fusion, which analyzes students' expression features with VGG16 network, acquires mouse track data corresponding to students' expressions based on deep neural network, and then deeply fuses students' log data and interaction data based on the data conversion algorithm in the event window. The model is utilized to establish a smart classroom, based on which the multidimensional learning characteristics of 50 students are studied, thereby promoting the application of multi-source data fusion technology in the education sector. The multi-source data fusion model can effectively recognize the emotional changes of students in the smart classroom, and the accuracy of multi-emotion recognition is more than 95%. In the smart classroom, the students' mouse browsing trajectories focused on the web pages of "Teaching and Learning" and "Teaching Tools and Resources", with a total click frequency of 1959 and 2005, respectively. Based on the above characteristics, the model classified the 50 students into five categories: focused students, persistent students, persistent students, occasional students and abandoned students, and the average learning input values of each category of students were 4.55, 3.57, 2.48, 1.48, and 0.54, respectively. The construction of the smart classroom is helpful for the wide dissemination of the model.*

KEYWORDS: *Multi-source data fusion; Learning engagement assessment model; VGG16 network; Deep neural network; Smart classroom*

1 Introduction

With the continuous development of information technology, the construction of learning environments has become increasingly important. Since the advent of multimedia technology, multimedia classrooms, with "computers + screen projection" as the main infrastructure, have been widely and extensively applied in primary and secondary schools as well as universities in China. They once attracted the attention of educational researchers, teachers, and students, providing convenience for teachers' teaching and stimulating students' interest in learning, becoming the mainstream teaching environment for college teachers to carry out teaching activities [1-3]. However, with the development of informationization construction, as well as student learning and teacher teaching for teaching resources, teaching and learning interaction, information technology and education integration and other needs constantly put forward, multimedia classrooms for teaching activities to support the elasticity of the drawbacks are increasingly apparent [4, 5]. The smart classroom, on the other hand, is the result of the

*zhanglin1992401@163.com
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development of information technology to a certain stage, and is a typical learning space [6]. Many technologies provide support for its development, including big data, Internet of Things, mobile devices, multimodal analysis and other technologies.

Regarding the concept of smart classroom, based on the study of existing literature, it is found that smart classrooms are mainly defined from the following two perspectives. Discussing the meaning of smart classroom from the perspective of learning environment, Saini and Goel describe a typical smart classroom from the perspective of functional structure, which needs to be equipped with good content presentation tools, support good teacher-student interactions and learning inputs, have a suitable physical environment, and also contain instructional management tools for attendance, feedback, and assessment [7]. Through a systematic review, Ren found that the current construction of smart classrooms in China has made significant progress at the system and facility levels, but lacks uniform evaluation standards; while at the application level, although there is an increasing focus on the appropriateness of technology and teaching needs, there is insufficient research on the design of teaching and learning activities in the smart classroom [8]. Song et al. defined the concept of "smart classroom" and constructed the "iSMART" system model based on it, and through the case of the smart classroom construction project of Wudaokou Finance School of Tsinghua University, they systematically elaborated its construction idea and integration scheme. In addition, through the case of Wudaokou School of Finance of Tsinghua University, the construction idea and integration program are systematically elaborated, and the operation mechanism of the smart classroom is further explored, in order to provide practical reference for the construction and operation of the smart classroom [9]. Ma et al. proposed a hierarchical evaluation model containing four first-level dimensions of operational interaction, behavioral interaction, cognitive interaction and creative interaction. The hierarchical nature of the model, which indicates that the lower-order interaction provides the basic support for the higher-order interaction, while the higher-order interaction extends and expands the depth of the lower-order interaction, reflects the dynamic structure of the teacher-student interaction that is progressing step-by-step and promoting each other in the smart classroom [10].

Discussing the connotation of smart classroom from the perspective of information technology, Zhang and Li designed and implemented a smart classroom system based on Internet of Things (IoT) technology, which collects real-time classroom temperature and light data through environmental sensors, and ensures the stable operation of the system by combining the dual-machine backup and clustered server architecture to realize the low-latency and high-reliability intelligent regulation of the teaching environment [11]. Wang designed a system integrating real-time monitoring and intelligent analysis around the demand for quantitative assessment of teaching effect in smart classrooms, realizing dynamic monitoring of students' behaviors through improved target detection and target tracking algorithms, and combining real-time face recognition technology based on visual tracking to quantitatively assess students' classroom attentiveness based on the three-dimensional learning state space and emotional dimensions [12]. Huang et al. proposed a set of three-layer architecture for realizing the construction and operation of context-aware smart classrooms in smart campuses, which simplifies the development process of upper-layer context-aware applications by integrating IoT devices at the bottom layer through the Raspberry Pi and providing unified application interfaces, and verifies the feasibility and validity of the scheme at the technical level [13]. Through the above literature combing, it is found that the academic research on smart classrooms mainly focuses on the connotation and characteristics research, the research on the components of smart classrooms, the research on the design of smart classrooms, and the application of smart classrooms.

In the field of data-driven learning behavior research, multi-source data covers structured data, semi-structured data and unstructured data, etc [14]. By fusing data from different channels and formats through multi-source data, mining and analyzing users' interests, behaviors, characteristics, etc., provides richer and more three-dimensional information for the construction of smart classrooms in order to provide more accurate and personalized services [15-17]. Academically, research on multi-source data fusion in smart classroom construction has also achieved fruitful results. Li and Guo discussed the development strategy of blended teaching mode supported by knowledge graph, and focused on the key role of teachers' data literacy in the construction of smart classrooms, and proposed a path to build smart classrooms based on data literacy [18]. Jing proposed a multi-source data fusion method based on set-pair analysis linkage degree, which utilizes the advantages of set-pair analysis feature function, mines the relationship between opposites, sameness and differences among measurement data, dynamically adjusts the linkage degree among data, and rationally allocates the data weights by combining the signal-to-noise ratio weighting method to realize the weighted fusion of multi-source data [19]. Based on combing the current status of data fusion research, Ma et al. analyzed the smart classroom system from the two dimensions of data source and data fusion, constructed a process model of multi-source data fusion analysis, and further carried out practical application exploration from the data fusion dimension to provide support for the construction of smart classrooms [20]. Zhang et al. proposed a smart classroom effect analysis system based on multimodal data fusion, and the real-time feedback and analysis functions of the system showed application potential in classroom mood recognition, student engagement assessment and teaching interaction optimization, providing technical support for data-driven smart education [21]. Fang et al. constructed an intelligent classroom interaction analysis system based on behaviorism theory, which integrates multi-source classroom interaction behavior data collection technology and multi-dimensional analysis model, quantitatively analyzes teacher-student interaction behaviors through multi-modal fusion algorithms, and generates teaching portraits covering classroom environment, teaching structure, execution effect and comprehensive performance [22].

The smart campus integrates these dispersed data into a comprehensive data warehouse through multi-source data fusion to provide a unified information base for the whole campus [23, 24]. Based on the smart classroom and multimodal learning analytics, Tang et al. constructed a multimodal learning analytics model centered on the six-step cycle of "goal setting-data collection-data processing-data analysis-feedback provision-intervention implementation" [25]. Li proposed a student learning behavior analysis and optimization system (LSIF) based on multi-source sensor data, which integrates multi-source sensor data from online and offline classrooms, this system achieves dynamic prediction and personalized feedback on academic performance by integrating parameters such as learning engagement, frequency of interactions, behavioral patterns, and degree of distraction [26]. Sun and Ren proposed an innovative method for multi-source heterogeneous data fusion based on IoT technology, which optimizes the data integration process by analyzing the correlation between different data types and adopting a hybrid information gain strategy, which makes full use of the system's computational and storage capabilities to achieve seamless fusion of multi-source dynamic data and enhance the availability and analytical efficacy of the data in the intelligent system [27]. Ji et al. conducted feature extraction and analysis of multimodal data with the help of natural language processing, speech recognition, computer vision, and physiological information recognition technologies to deeply mine learners' personalized implicit information and realize data-driven quantitative assessment of learning status [28].

This research focuses on the development and promotion of multi-source data fusion technology in the field of education, and for this purpose, a learning engagement assessment strategy that fuses features from multi-source data is designed using VGG16 network and deep neural network. The strategy takes students' picture data, mouse track data, and students' learning log data as inputs, and the features of each dimension are fused into a comprehensive feature for assessing students' learning engagement level. Based on this strategy, a smart classroom with multi-source data fusion is constructed from the infrastructure layer, network layer, and application layer, and a related teaching implementation strategy is designed to verify the feasibility of this strategy in the field of education.

2 Learning Input Measurement Model

This section describes the multi-source data fusion strategy for online learning inputs and builds a multi-source data fusion assessment model applicable to smart classroom learning.

2.1 Multi-source data fusion techniques

In this study, a hybrid fusion strategy was used to combine data from different sources for comprehensive analysis and assessment. Among them, facial expression data and mouse trajectory data are acquired synchronously during the learning process, and since they are temporally synchronized, it is more appropriate to fuse these temporally synchronized data. However, log data are usually recorded in a state-triggered manner, and different logging indicators are not synchronized with each other in terms of timing, so these data are only suitable for coarse-grained analysis of inputs over a period of time. Therefore, the fusion strategy of the study is divided into two steps. In the first step, the learning facial data and mouse track data are fused with features to derive the affective and cognitive inputs, while in the second step, the results of the first step are fused with the results of the learning input assessment based on the logged interaction data by means of feature fusion to finally obtain the level of the student's learning input status. The fusion assessment strategy based on multi-source data is shown in Figure 1.

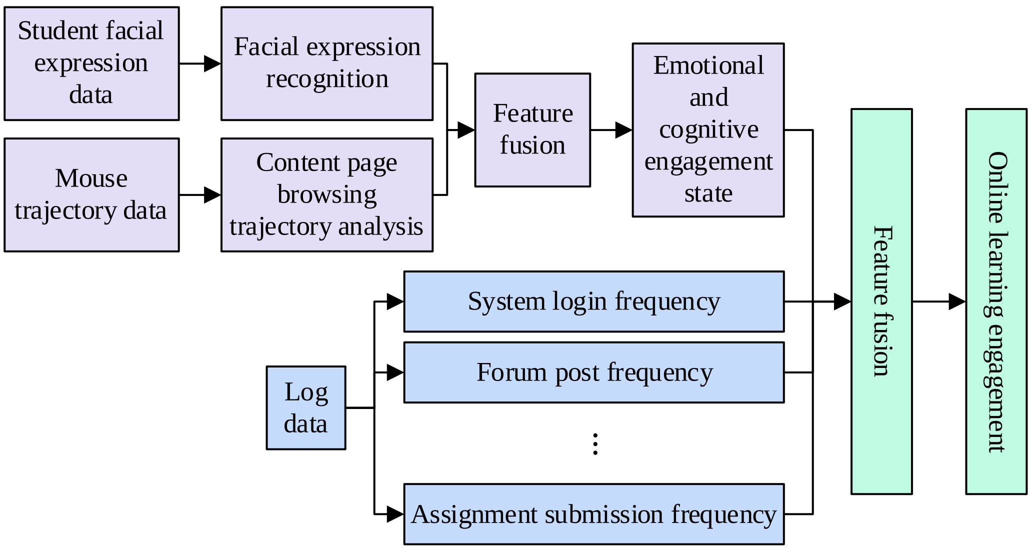

Figure 1: The fusion measurement strategy of multi-source data

2.2 Learning input measurement model construction by integrating multi-source data

This study is based on feature fusion for learning input measurement, where feature data from each dimension are fused into comprehensive feature data for unified processing. It circumvents the requirement that the data of each dimension must be independent, and also reduces the influence of weight settings on the results. The learning input assessment model of multi-source data fusion is shown in Figure 2, and the whole method process takes picture data and mouse track data as input, and finally outputs the level value of students' learning input ranging from 0 to 5 after the model processing.

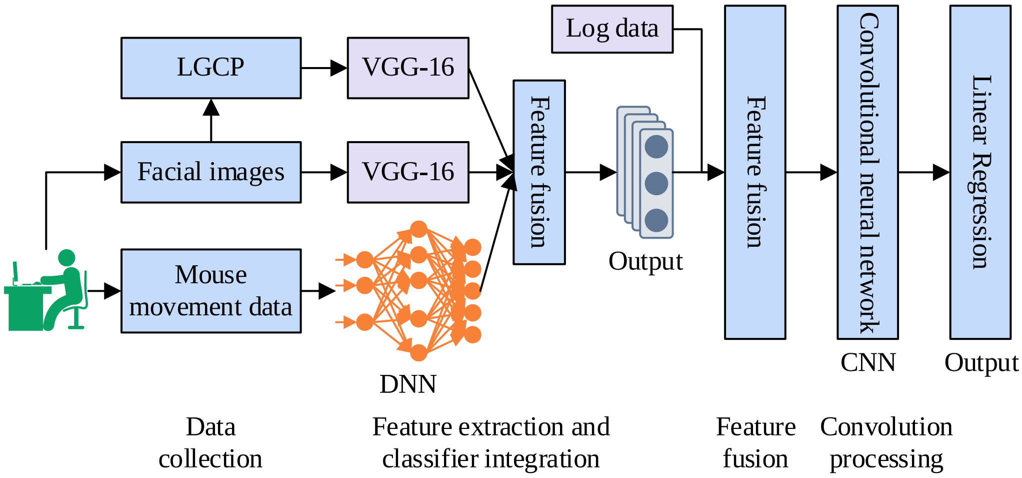

Figure 2: The study input evaluation model of multi-source data fusion

2.2.1 Characterization of the emotional dimension

The face expression recognition part is carried out in two parts, one part uses the face source image data as input and the other part uses an adaptive weighted local Gray code pattern (LGCP) based feature extraction method to extract features from the face source image as input. In addition, a VGG16 network is used for expression recognition on the input data of the two parts, which mainly consists of convolutional, fully connected and softmax output layers, and a pooling layer is connected to the different types of convolutional layers to perform pooling operations to reduce the risk of overfitting.

The hidden layer of the model uses a linear rectifier function (ReLU) as an activation function, which can be represented using the max function:

$$f(x) = \max(0, x) \tag{1}$$

Neuron node a_j^l in the convolutional layer feature map:

$$a_j^l = f\left(\sum_{i \in M_j} w_{ji}^l a_i^{l-1} + b_j^l\right) \tag{2}$$

where w_{ji}^l denotes the weight of the j rd neuron node in layer l connected to the i th node in layer $l-1$. M_j denotes the set of all feature node nodes connected to the j th neuron node in layer l. The model uses cross entropy as the cost function:

$$Loss = -\left[\sum_{i=1}^{n} \sum_{k=1}^{3} \hat{y}_k^{(i)} \log\left(y_k^{(i)}\right)\right] \tag{3}$$

where n denotes the number of training instances and $\hat{y}_k^{(i)}$ denotes the k th output value corresponding to the i rd training instance, which is calculated as:

$$y_k^{(i)} = \frac{e^{\theta^{(k)T} x^{(i)}}}{\sum_{j=1}^{3} e^{\theta^{(j)T} x^{(i)}}} \tag{4}$$

The fully connected layer portion of each of the two VGG16 models yielded 2048-dimensional feature vectors to represent the features of the images in their respective channels, which were then fused and further processed by means of stitching.

2.2.2 Mouse track characteristics

The deep neural network model is used in the processing part of the mouse trajectory data, and the mouse trajectory data within the 15-second time period before the timestamp of the expression image to be analyzed is selected as input. The coordinate position information of the mouse C can be represented as:

$$C = \{l_x, l_y, t\} \tag{5}$$

l_x and l_y denote the pixel size of the mouse cursor from the top and left end of the page, respectively, and t denotes the timestamp at the time of acquisition. The sub-model calculates the node taking probability size by softmax function. Finally, the three sub-modules are integrated by the voting method to get the combined input level value, which is calculated by the formula:

$$\begin{gathered} p\left(a_j \middle| x_l, E_1, \cdots, E_k\right) = \sum_{k=1}^{K} \omega_k p\left(a_j \middle| x_l, E_k\right) \\ j = 1, 2, \cdots, m; l = 1, 2, \cdots, n. \end{gathered} \tag{6}$$

where j denotes 3 learning input levels, x_l denotes the training sample, E_k denotes the k th classifier, and ω_k is the weight of the k th classifier. The weights of the classifiers are calculated using voting with the formula:

$$\omega_k = R_k \bigg/ \sum_{k=1}^{K} R_k ; k = 1, 2, \cdots, K \tag{7}$$

2.2.3 Log Behavioral Characteristics

In the study, since the time when the study course starts and the time when the final course ends are fixed, the log data and the interaction data are consistent in timeframe and can be further two-dimensionalized in order to facilitate cross-sectional comparisons among students. Log data is the learning behavior data generated by students while learning in the smart classroom, including resource learning behavior, interaction learning behavior, and homework quiz behavior. The study converts the log data through the event window based data conversion algorithm, which is as follows:

Inputs: set of students S, set of event types EC, set of events E, learning input levels predicting event cycles t

Output: dataset of 2D features D
1. set $D=\varnothing$.
2. get course start time T_{start}, end time T_{end}
3. for $i:=0; i\le\left(T_{start}-T_{end}\right)/t; i++$ do
4. $StartTime_i=T_{start}+i*t$
5. $EndTime_i=\min\left(StartTime_i+t,T_{end}\right)$
6. $W_i=W_i\cup\left\{\left(StartTime_i,EndTime_i\right)\right\}$
7. end
8. get student set S, event set E
9. foreach $s_k\in S$ do
10. get event set $E_k\in E$ for student k
11.foreach $e_{kj}\in E_k$ do
12. get e_{kj} time window w_{kj}, event type ec_{kj}
13. set $SE_{e_{kj},ec_{kj}}=0$
14. set $EC_k=\varnothing$
15. if w_{kj} in W and ec_{kj} in E_k then
16. $SE_{e_{kj},ec_{kj}}=SE_{e_{kj},ec_{kj}}+1$
17.end if
18. $EC_k=EC_k\cup\left\{\left(w_{kj},ec_{kj},SE_{e_{kj},ec_{kj}}\right)\right\}$
19.end
20. $D=D\cup\left\{\left(s_k,EC_k\right)\right\}$
21.end

The obtained two-dimensionalized data was processed using a convolutional neural network with two fully connected layers immediately following the convolutional and pooling layers, and the output layer was output using linear regression to represent the value of the level of student learning inputs.

During the model training process, the parameters of the model were tuned using the back propagation algorithm. Batch Gradient Descent (BGD) is used for the optimal solution of the model. Its cost function can be expressed as:

$$J\left(W,b\right)=\frac{1}{m}\sum_{i=1}^{m}J\left(W,b;x^{(i)},y^{(i)}\right)=\frac{1}{m}\sum_{i=1}^{m}\left(\frac{1}{2}\left\|h_{W,b}\left(x^{(i)}\right)-y^{(i)}\right\|_2^2\right) \tag{8}$$

where W,b is the parameter to be optimized, the optimization method is to find the partial derivation of each parameter through the loss function, combined with the chain rule to adjust the parameter one layer at a time from the output layer of the neural network to the opposite direction of the input layer. The specific adjustment law can be expressed as:

$$
\begin{aligned}
W_{ij}^{(l)'} &:= W_{ij}^{(l)} - \eta \frac{\partial}{\partial W_{ij}^{(l)}} J(W,b) \\
b_i^{(l)'} &:= b_i^{(l)} - \eta \frac{\partial}{\partial b_i^{(l)}} J(W,b)
\end{aligned} \tag{9}
$$

where η is the learning rate or iterative step size during gradient descent.

3 Smart classroom design based on multi-source data fusion

3.1 Smart Classroom Hierarchy Model

Through the study of related literature on the construction model of smart classroom, it is found that the current construction of smart environment is mainly researched in several aspects, such as the selection of technology, intelligent management of classroom, space design, and the construction of software and hardware platforms. This paper analyzes and researches the positioning of the smart classroom construction, and through exchanging and discussing with experts in the field of smart classroom construction, the construction of the smart classroom is divided into 4 levels, and the concept of constructivism should be carried through the construction content of each level.

The hierarchical model of the smart classroom system is shown in Figure 3. From the hierarchical model, it can be seen that the design of the entire smart classroom, the construction of the first three levels need to be designed from the perspective of being able to realize the design of teaching contexts, promote collaborative communication among students, and from the perspective of the students, to provide students with a comfortable learning space, and to provide teaching tools for the teaching interactions to take place. The top layer is the interaction layer, and the purpose of the construction of smart classrooms is to provide students with a variety of cognitive tools and learning resources through the support of the other three levels, so that students will be interested in learning, and this interest should be maintained for a long period of time, and through continuous learning and progress, to enhance the ability of self-solving real-world problems, that is, the application of knowledge, and to realize the meaningful construction of students' knowledge.

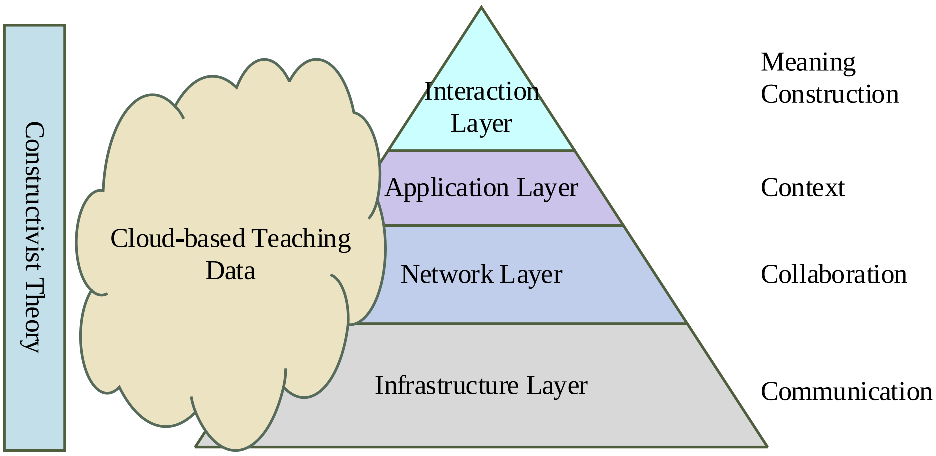

Figure 3: Intelligent classroom system level model

3.2 Specific design

The smart classroom system architecture is shown in Figure 4. The study starts from the perspective of teachers and students carrying out teaching activities, and refers to the smart classroom design plans of several universities to design the three layers of infrastructure layer, network layer and application layer of a university's smart classroom in order to promote the application of multi-source data fusion technology in the field of education.

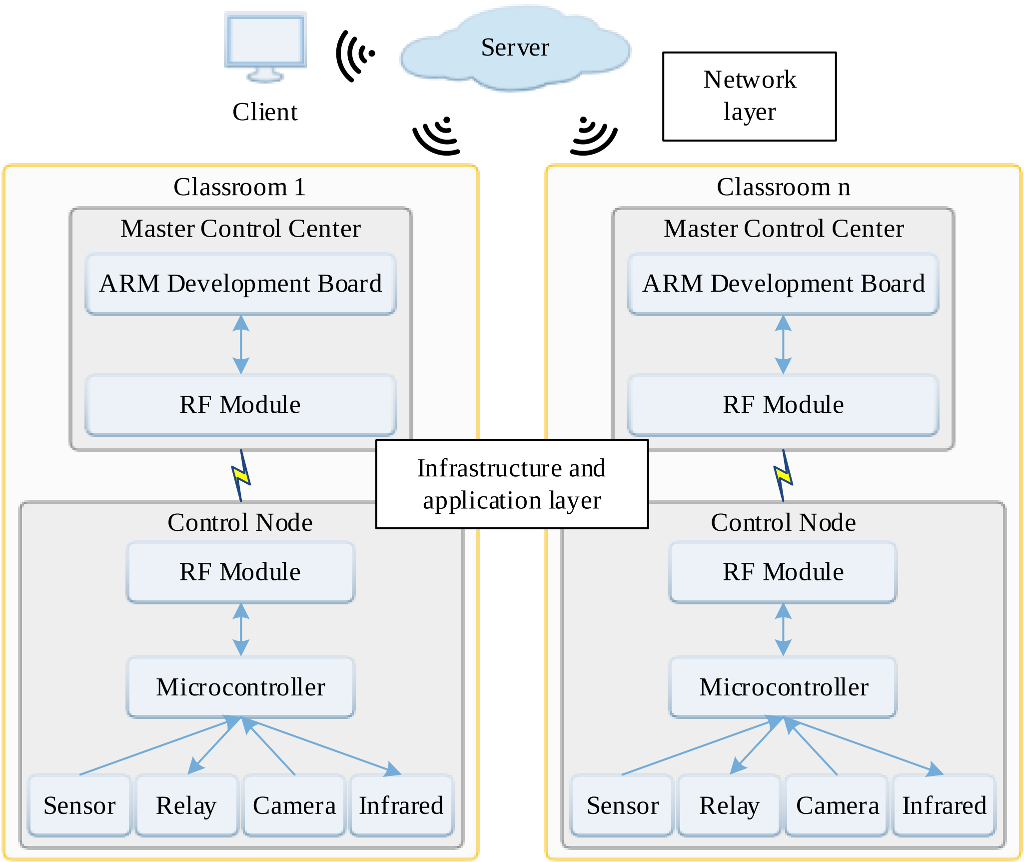

Figure 4: Intelligent classroom system architecture

3.2.1 Infrastructure layer

The design of the learning environment should first be student-centered, so that students like and want to stay in the designed teaching environment for learning. In the smart classroom, seats that are comfortable, easy to move, and easy to put together in various combinations are introduced to accommodate all kinds of teaching activities. The use of multi-screen displays enables the content to be presented on multiple displays at the same time, and even the content on the whiteboard can be presented on the device. Smart classroom construction, will join the remote interactive system to carry out remote teaching, first of all, to realize the quality of teaching resources can be utilized to a greater extent, so that more students can choose their favorite courses.

3.2.2 Network layer

The application of smart classroom requires a good network environment as a support, the construction of the network environment, including wired, wireless network, wireless sensor network, need to consider the application of wireless sensor network will be the above various types of teaching facilities to realize the connection between each other, to achieve the intelligent control of the classroom. In addition, teaching in the smart classroom will generate a large amount of teaching data, including student learning statistics, interactive data, video resources generated by the remote interactive system, etc. At the same time, teachers and students need a stable wired and wireless network environment to support the access to information, off-site interaction.

3.2.3 Application layer

In the smart classroom, an online learning input assessment model that integrates multi-source data is introduced. The data of the whole teaching process before, during and after class, including students' attendance data and classroom interaction data, can be used to form a data report for teachers to visualize students' learning status. In addition, by mobilizing camera information, the online learning input assessment model integrates multi-source data to obtain students' expression data and mouse track data, which is convenient for teachers to understand the students' smart classroom application layer is designed to record the teaching data generated in the process of students' learning through technical support, forming educational big data. Through long-term data accumulation and analysis, it realizes intelligent education, improves students' learning efficiency, and promotes the development of students' higher-order thinking skills.

4 Research and analysis of learning inputs in smart classrooms

4.1 Instructional Design for Smart Classrooms

The study designed a research experiment on student learning engagement based on the designed smart classroom. The purpose of the experiment is to investigate the impact of smart classrooms based on multi-source data fusion technology on student learning engagement and how multi-source data fusion technology can be generalized.

The experimental subjects recruited were from college students of a university mentioned above, and the recruitment notice was posted through an online platform, with students enrolling themselves to participate. Based on the enrollment information provided by the students, the study screened out 50 students with distinctive characteristics whose average age was 20 years old. As the data of students' expression images, mouse tracks and log behaviors in the smart classroom may violate students' privacy, the study has obtained students' privacy authorization before the start of the teaching. 50 students will start a public course in the smart classroom constructed above, in which the online learning platform is borrowed from the Learning Channel software, and the teacher imports all the video learning resources and courseware used in the classroom into the Learning Channel for students' online learning. The online learning platform is borrowed from the Learning Channel software. The class time for students to participate in a public course in the smart classroom is 90 minutes, and the hardware facilities, such as cameras, are adjusted before the start of the course in order to obtain multi-source characteristic data of students. The log data and interaction data obtained from the smart classroom are analyzed by the multi-source data fusion assessment method.

4.2 Multidimensional characterization based on learning inputs

4.2.1 Multidimensional emotion recognition

In the smart classroom, the camera captures seven emotions presented by students' facial expressions including happiness, sadness, surprise, fear, disgust, anger, and depression. The study intercepts some of the camera-captured images of students' facial expressions as the emotion recognition dataset for the model, and the emotion embodiments in the dataset are labeled by the students themselves.

After training, the model was used to recognize the emotions of students in the smart classroom, and Figure 5 shows the confusion matrix of the model's emotion recognition results. The model recognizes surprise, disgust and anger with 100% accuracy, but occasionally misjudgment occurs. For example, there is a 1.85% probability of recognizing happy emotion as surprise emotion and a 2.42% probability of misjudging sad emotion as fear. In addition, the model's recognition accuracy of repressed emotions is relatively the lowest, only 95.77%, and this type of emotion is easy to be recognized by the model as sadness, fear, and disgust, which may be due to the fact that students show less repressed emotions in the smart classroom classroom, which leads to the model's poor learning of this type of emotion. The accuracy of the model in recognizing students' emotions is more than 95%, which is sufficient to accomplish the task of acquiring the characteristics of students' emotional dimensions in the smart classroom.

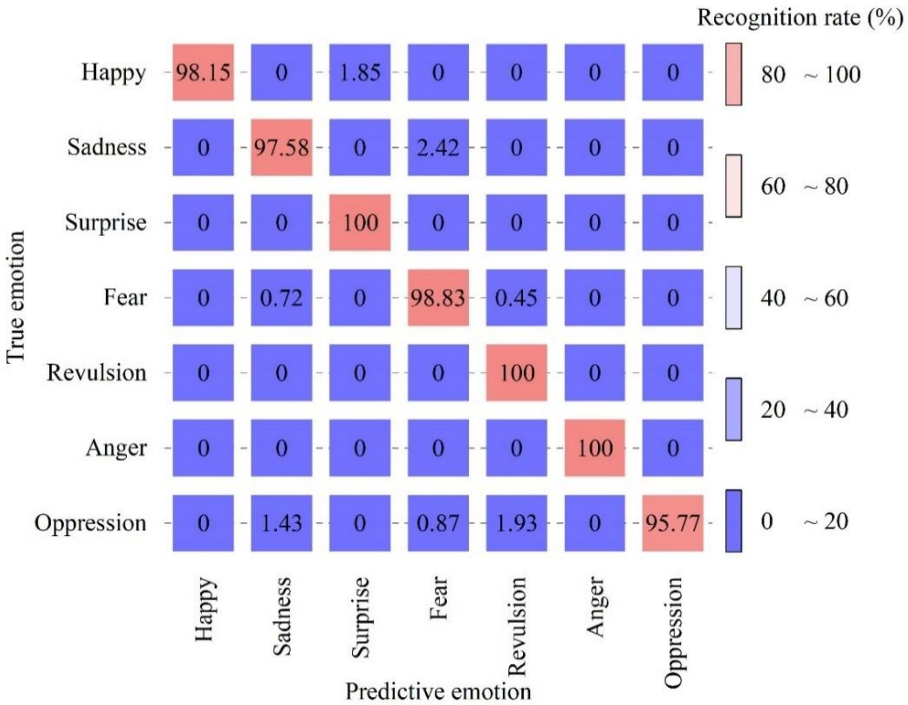

Figure 5: Confusion matrix of cognitive recognition results

4.2.2 Mouse track

The mouse trajectory data in the smart classroom records the types of web pages that students visit and the corresponding timestamps. Web pages can be roughly classified into six categories, namely: "Teaching and Learning", "Collaboration and Communication", "Teaching Tools and Resources", "Creation and Expression", "Assessment and Feedback", and "Games and Entertainment". To ensure the temporal correspondence with the online learning behavior dataset, the network log contents during the semester when the course started were selected as the second dataset. This dataset contains a total of 1.5 million records from 50 students.

Figure 6 compares the cumulative frequencies of 50 students' web browsing activities across various web pages. In the statistics of students' web browsing information, the categories "Teaching and Learning" and "Teaching Tools and Resources" are the ones that most students frequently click on with their mice in the smart classroom. The cumulative frequencies of the 50 students reached 1,959 times and 2,005 times respectively. Additionally, the mouse click frequency for "Games and Entertainment" was the lowest, with a cumulative frequency of only 825 times. For example, student No. 50 clicked on "Teaching and Learning", "Collaboration and Communication", "Teaching Tools and Resources", "Creation and Expression", "Assessment and Feedback", and "Games and Entertainment" respectively, with frequencies of 19, 15, 46, 28, 54, and 68. Among them, the frequency of clicking on "Games and Entertainment" was much higher than that of other students. These types of web pages are very likely to have nothing to do with learning, and may have some impact on his academic performance. Undeniably, the smart classroom provides great convenience for students' online learning, but for some students, their self-control becomes the main factor affecting their learning outcomes.

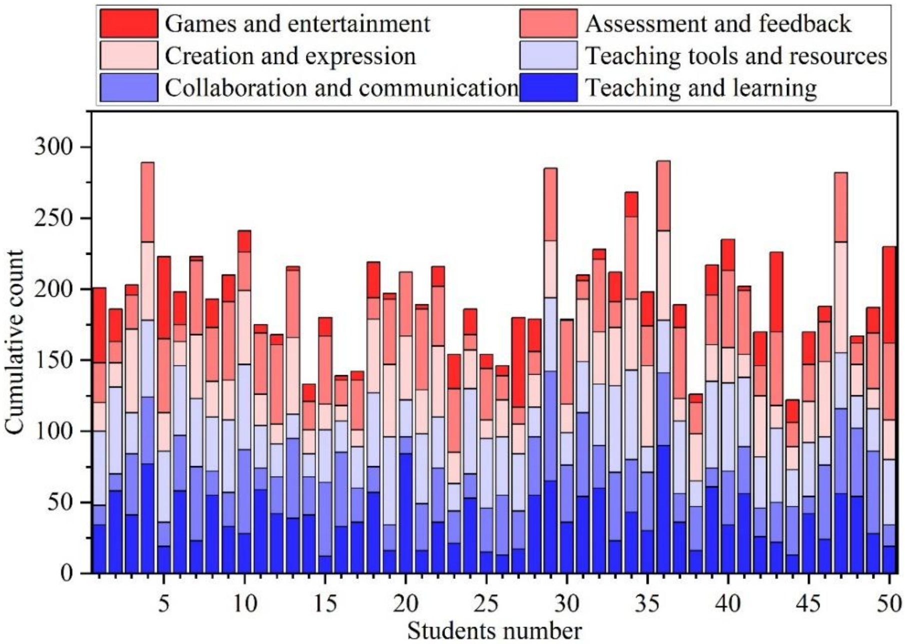

Figure 6: Browse through the cumulative frequency of all kinds of web pages

4.2.3 Learning Log Behavioral Statistics

This section of the study deals with the activities of students' independent learning in the smart classroom. The study classifies students' learning behaviors in the smart classroom into three categories: resource learning behaviors, interactive learning behaviors, and homework quiz behaviors. Among them, resource learning behaviors mainly include watching videos, recording notes and online check-in, interactive learning behaviors mainly include posting and replying to posts, and homework quiz behaviors mainly include submitting homework and completing quizzes. Using the model in this paper, the logs of students' learning behaviors in the smart classroom are analyzed.

The descriptive statistics of resource learning behaviors are shown in Table 1. The mean value of video viewing completion was 97.95%, with the highest number of video viewing completion at 100% and only one video viewing completion at less than 50%. The distribution of the number of notes recorded by individual students while studying the online resources of the course was relatively discrete, and the study categorized the number of notes into [0, 10], (10, 20], (20, 30], and (30, +∞] or more, a total of four intervals, whose percentages were 26%, 48%, 18%, and 8%, respectively, with the majority of the students' number of notes falling between (10, 20]. In addition, the study categorized the check-in ratios into [40, 60], (60, 80], and (80, 100], totaling 3 intervals, whose percentages were 2%, 4%, and 94%, respectively. The highest percentage of sign-up rate was in (80, 100], where 20 people signed up at 100%.

Table 1: Resource learning behavior description statistics

Student number	Video viewing completion (%)	Number of notes	Check-in ratio (%)
1	83.5	2	63.29
2	100	34	100
3	100	15	100
4	100	79	100
5	67.5	4	74.85
6	98.45	38	100
…	…	…	…
48	100	22	94.05
49	100	13	100
50	43.27	0	43.71
Mean±SD	97.95±8.46	17.46±12.56	91.83±10.98

The statistical analysis of interactive learning behavior is shown in Table 2. The study divided the number of postings into [0, 5], (5, 10], (10, +∞], a total of three intervals, accounting for 32%, 44%, 24% respectively. It shows that the number of posts made by students is mainly concentrated around 5 to 10, and the number of posts is 0, accounting for 18%, which indicates that some students are not active in posting. In the case of reposting, the number of reposts between 0 and 5 is 34 students, accounting for 68%, indicating that most students lack the willingness to repost. Comparing the reposting and posting situations, students preferred posting behavior in the smart classroom.

Table 2: Statistical analysis of interactive learning behavior

Student number	Post	Reply
1	0	0
2	15	3
3	7	4
4	2	4
5	3	2
6	9	1
…	…	…
48	0	0
49	12	10
50	0	0
Mean±SD	7.26±5.52	4.32±3.91

The statistical analysis of homework quiz behavior is shown in Table 3. The instructor issued five quizzes; 10 students participated in all five quizzes, 6 participated in four, 12 participated in three, 13 participated in two, 6 participated in one, and 3 did not participate in one. Overall student quiz participation was high and students generally took the quizzes seriously. The quizzes totaled 10 points, and the study divided the quiz scores into [0, 3], (3, 7], and (7, 10], for a total of three intervals, with percentages of 16%, 64%, and 20%, respectively. The overall scores are mainly concentrated in the stage of (3, 7], and the analysis shows that the quiz scores are average, belonging to the middle level, which indicates that the students have an average mastery of the basic part of the course.

The instructor issued a total of 15 assignments successively in the course, and the assignments were submitted 15 times by 7, (10, 15) times by 20, (5, 10] by 17, and (0, 5] by 6, indicating that most of the students submitted their assignments more often. The assignments totaled 20 points, and the assignment grades were distributed in [0, 5], (5, 10], (10, 15], and (15, 20], and the percentages of the four intervals were 6%, 38%, 50%, and 6%, respectively. Most of the students' assignment scores were concentrated between (10, 15], indicating that the students' operational ability was relatively better than their mastery of basic knowledge.

Table 3: Statistical analysis of test

Student number	Test frequency	Submission number	Test score	Homework score
1	1	2	0.4	3.9
2	4	7	6.8	12.7
3	3	10	5.5	11.8
4	5	15	9.8	19.5
5	5	12	8.2	10.8
6	4	13	4.7	10.2
…	…	…	…	…
48	3	3	8.4	12.6
49	5	10	5.2	7.9
50	0	2	0.7	0
Mean±SD	2.84±1.49	10.42±3.75	5.30±2.27	10.35±3.61

4.2.4 Assessment of the level of learning engagement

For the standardized data, the k-means method is used to cluster the data, and the number of clusters ranges from 2 to 10, and the scores for the number of clusters from 2 to 10 are calculated using the variance ratio criterion method, respectively. Figure 7 shows the score of the number of clusters, the horizontal coordinate is the number of clusters, and the vertical coordinate is the corresponding score of each number. As the number of clusters increases, the cluster scores show a tendency to increase and then decrease. The highest score is 832 when the 50 students are divided into 5 categories, i.e., it is most appropriate to divide the data of students' online learning behaviors into 5 categories.

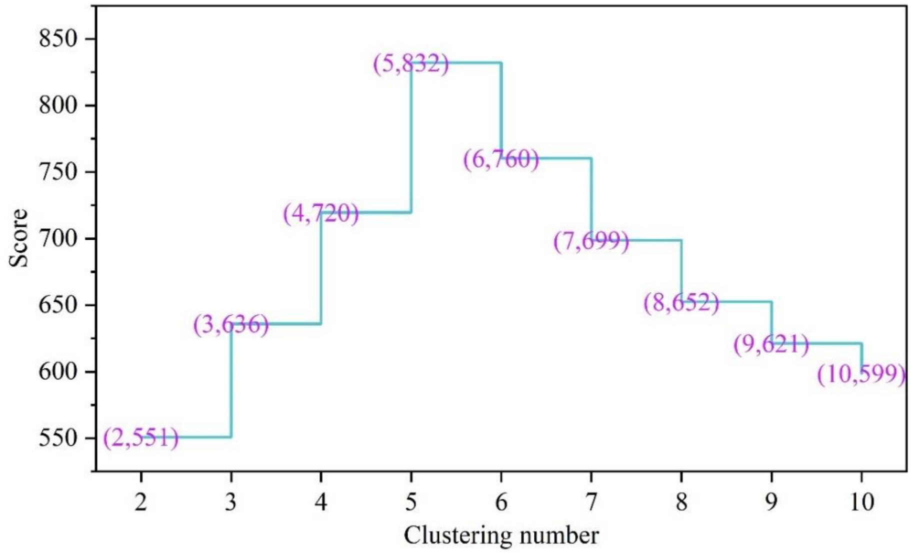

Figure 7: Clustering number scores

The k-means method was used to categorize students into five categories based on their log data and interaction data in the smart classroom, and the average score for each category was calculated. The learning categories generated from the cluster analysis are shown in Table 4. The following is a specific analysis of the behavioral characteristics of each category:

(1) Focused students, this category of students has a high duration and frequency of learning, they are usually very focused on learning and will continue to invest a lot of time and energy in the learning process.

(2) Persistent students, these students study longer and more frequently, they usually have certain learning goals, and they will try their best to maintain the continuity of learning.

(3) Persistent students, this kind of students' study duration and frequency are higher, they usually study online in their free time or when they need to study.

(4) Occasional students, whose study duration and frequency are low, usually have some learning needs but may be affected by other factors and cannot study online continuously.

(5) Abandoned students, these students have very low study hours and frequency, and have a negative emotional attitude towards learning. They usually used to engage in online learning, but have given up learning for some reasons.

Table 4: Class analysis generated by cluster analysis

Clusters	Count	Mean score				
		Resource learning	Interactive learning	Job test	Emotions	Web interaction
a	5	19.34	18.73	18.14	18.92	19.51
b	11	15.37	16.49	14.79	17.61	16.04
c	20	11.24	12.75	10.62	16.97	14.48
d	9	8.73	9.27	7.51	15.42	11.56
e	5	4.96	5.52	4.80	11.05	7.58

Figure 8 illustrates the learning engagement scores of different categories of students. The learning engagement of different categories of learners in the smart classroom varies significantly, with the average learning engagement score values of the five categories of focused students (Cluster 1), persistent students (Cluster 2), persevering students (Cluster 3), occasional students (Cluster 4), and abandoning students (Cluster 5) being 4.55, 3.57 The average scores of the five categories of learners were 4.55, 3.57, 2.48, 1.48, and 0.54, respectively.By analyzing the characteristics of students' learning behaviors and affective cognition in the smart classroom through the multi-source data fusion technology, we can provide the corresponding guidance measures for specific online learners, help teachers to formulate a reasonable teaching strategy, and provide a strong support for the promotion of the smart classroom in the future.

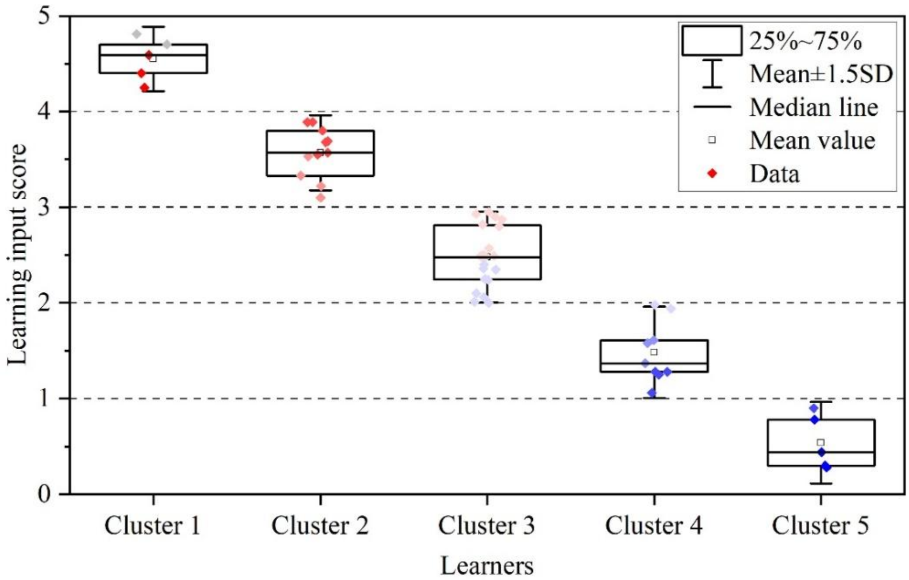

Figure 8: Student learning in different categories

5 Conclusion

The article integrates the advantages of VGG16 network and deep neural network to develop a novel multi-source data fusion technique to measure the learning input level of students based on their expression features, mouse track features, and learning behavior features when they study in the smart classroom. In order to promote this technology, a smart classroom was built using this technology and the learning input values of different categories of students were obtained.

This technology can effectively analyze students' resource learning behaviors, interactive learning behaviors, and homework quiz behaviors, and it can obtain the characteristics of students' emotional dimensions in the smart classroom, identifying a variety of emotions, including happiness, sadness, and surprise, with an accuracy of 95.77%~100%. In terms of mouse track characteristics, the web pages that students browse most are “Teaching and Learning” and “Teaching Tools and Resources”, and the least is “Games and Entertainment”, with a total frequency of 1959, 2005, and 8 times, respectively. The total frequency was 1959, 2005 and 825 times respectively. Based on this, the 50 students were categorized into five groups: dedicated students, persistent students, persevering students, occasional students, and dropout students, and the value of learning engagement level decreased step by step, with the average value between 0.54 and 4.55.

Multi-source data fusion technology can accurately obtain the multidimensional learning characteristics of students, and implement different teaching optimization strategies for different students in order to enhance their learning engagement level. As a carrier of this technology, the smart classroom can effectively promote the application of this technology in the teaching field.

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