



A Data-Driven Study on Assessing the Effectiveness of Ideological and Political Education Based on Learning Analytics and Behavioral Tracking

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SUMMARY: *The paper implements a target detection and tracking method to record students behavior in the classroom and constructs a behavioral database to be applied to ideological and political education classes. Following the preprocessing of the behavioral data, enhancement of the representation of the learning behavior characteristics of the students, and incorporation of the TELF-HC model, a TELF-PSPOC model on the basis of a three-layer integrated learning framework is proposed. A number of public video datasets are chosen and the best accuracy of the dataset built in this work is compared with those of the chosen public datasets. The TELF-PSPOC model is then employed to evaluate and classify the online classroom learning behaviors of the students, track the presence of the activities like listening, taking notes, discussion and imitation, and determine the level of participation of the students in ideological and political education courses. The levels of achievement of the students in these courses could also be obtained by combining various types of learning behavior. On the dataset of this paper, the SlowFast model and the Swin Transformer model achieve a prediction accuracy of 78.79% and 81.06 respectively, which indicates that the dataset built is both reasonable and practical. Students 3, 7, 8, 9, 24, 28, 34, and 36 have low values of overall individual engagement in the classroom of ideological and political education. Student 4 has the highest engagement during teacher instruction, whereas student 3 has the lowest.*

KEYWORDS: *TELF-PSPOC model; TELF-HC model; learning behavior; goal detection and tracking; engagement; ideological and political education*

1 Introduction

Due to the accelerated development of information technology and the ever-increasing growth of social intelligence, data has become one of the important productive resources in today's society. One of the most notable methods of enhancing the identification of people with the road, theory, and system of socialism with Chinese characteristics is data-driven ideological and political education which is also seen as a means to ensure long-term political stability [1, 2]. Ideological and political education is an essential part of training high-quality socialist builders and successors, and data-driven learning analysis and behavior tracking provide new insights and effective solutions to improve its effectiveness [3-5].

Learning analysis is a form of big data technology to build student learning profiles by collecting data on learning environments, interests, reading habits, and other important factors to have a better insight into the personality traits, academic results, and ideological and political literacy of students [6-9]. Based on it, the teachers are able to provide more specific instruction,

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create educational programs that are appropriate for students at various stages, and enhance the level of ideological and political education even more [10, 11]. In contrast, behavioral tracking is a more holistic assessment of student quality and developmental potential as assessed by data on academic performance, social practice outcomes, innovation and entrepreneurial activity, and other related dimensions [12-14]. It will be possible to identify the issues and deficiencies of students on time with such data analysis, which would allow providing targeted assistance to ensure personalized, differentiated, and comprehensive development of students in ideological and political education, with an increased number of high-quality socialist builders and successors with high ideological and political competence [15-18].

The current research uses student behavior as the main data that are derived by the data system created in the course of delivering an online open course in ideological and political education. Utilizing the target detection and tracking algorithms it records behavioral data and creates a student behavior database of ideological and political education classrooms. The TELF-PSPOC model is built upon the idea of a three-layer integrated learning framework and the overall architecture of TELF-PSPOC along with the elements of TELF-HC model are analyzed. The dataset that has been created in this study is subsequently checked using two popular neural network architectures, SlowFast and Swin Transformer. Using this foundation, the TELF-PSPOC model is used to determine the learning behaviour of the students in ideological and political education classes, their total and average participation, and deduce their academic performance in ideological and political education.

2 Access to classroom videos and target detection and tracking

This chapter proposes a method for acquiring student classroom behavior data based on target detection and tracking to provide a data base for the training of subsequent behavioral evaluation models, as well as for testing.

2.1 Data-driven classroom-based learning analytics

(1) Teaching Structure Flow of Online Open Courses

Empowered by information technology, online open courses have undergone fundamental changes in teaching mode, interaction mode, evaluation method and other aspects compared with traditional classrooms. The teaching structure process of online open courses usually includes three stages: pre-course orientation, in-course study, and post-course extension.

(2) Data System Generated by the Teaching Process of Online Open Courses

The teaching implementation process of online open courses generates a large amount of multimodal data, which contains learning process and learning result data, providing a data basis for evaluation.

The online open course hybrid teaching structure process and data system are shown in Figure 1.

The vast amount of multimodal information that can be generated throughout the teaching process is divided into various classes in this paper, such as teacher-student behavioral data, teacher-student emotional data, assessment data, and classroom management data.

Teaching and learning activities of both teachers and students contain explicit and implicit behavioral features. Teachers have the offline behavioral information that encompasses the organization of classes and interactive sessions, and online behavioral information which includes online tutoring and examination of the learning conditions of students. The behavior of students also involves listening performance in a traditional classroom setting, interactive

tasks and online behaviour such as logging into the learning system, accessing learning materials, engaging in forum talk and so forth. With these information, the current study is mostly based on the online classroom behaviors of the students in order to evaluate the effectiveness of ideological and political education.

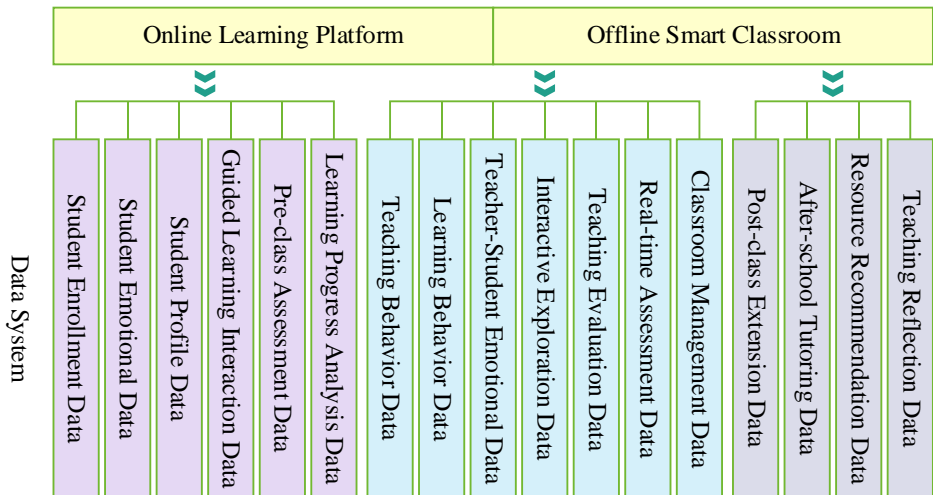


Figure 1: Online open course mixed teaching structure process and data system

2.2 Student Behavior Data Acquisition Based on Target Detection and Tracking

Fig. 2 provides an illustration of how to collect classroom teaching video data. Web-crawling methods and manual downloads are applied to get video materials that contain keywords related to classroom teaching. All of the teaching videos are then subjected to target tracking in order to derive sequential images of individual students. The image sequences are then tagged manually, which generates a student classroom behavior video dataset as well as a student classroom behavior image dataset.

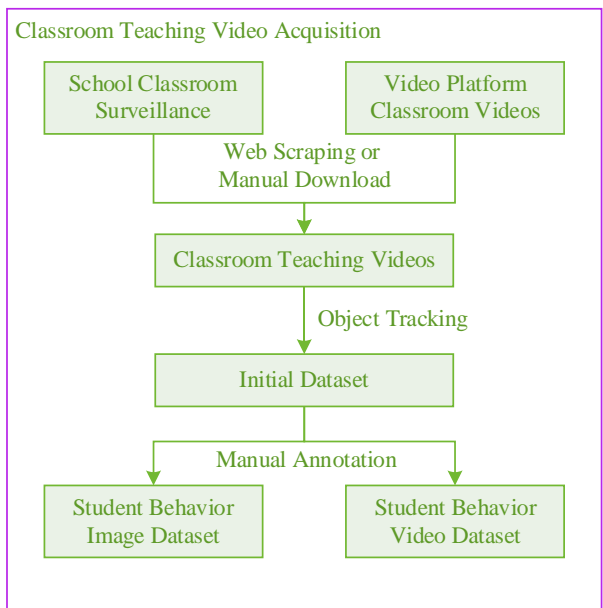


Figure 2: Classroom teaching video data acquisition process

2.3 Deep Learning-based Classroom Student Goal Detection and Tracking

To determine the actions of each student in classroom teaching videos, it is necessary to start with identifying and following each learner instance in the video and subsequently extract its spatio-temporal properties. Precise detection and location of students in classroom videos are important conditions before detecting their behavior. The study applies a target detection system based on a cross-stage localization network and pyramid attention network to do real-time recognition of students in classroom scenes. Thereafter, a combination of deep neural networks, Kalman filtering and the Hungarian algorithm is used to track student images across the next adjacent frames and thus finish the continuous detection and tracking of students in the classroom teaching videos.

2.3.1 Real-time detection of student targets

The paper presents a solution to the problem of identifying the student targets in a video that demonstrates teaching in a classroom with the help of a video-object-detection approach based on deep learning to achieve a real-time detection of students. Equation (1) shows the convolution operation at every stage of the cross-stage local network, which is intended to be used as part of the feature extraction and target detection process in the deep learning architecture that will receive the frames of the classroom videos:

$$h_l(X) = (X * W + b) \otimes \sigma(X * V + c) \quad (1)$$

where $X \in R^{N \times m}$ is the input to each layer, $W \in R^{k \times m \times n}$ represents the weights of each layer, $b \in R^n$ represents the bias value of each layer, $\sigma(X * V + c)$ represents the convolution operation, $V \in R^{k \times m \times n}$ represents the weights of the convolution kernel, $c \in R^n$ represents the bias of the convolution layer, N represents the total number of convolution layers, k represents the number of the current convolution layer, m represents the dimensionality of the picture, and n represents the number of neurons in the convolution layer.

Once the target characteristics of classroom teaching video frames are identified, the high-level representations trained by the convolutional neural network are combined using a feature fusion network. These fused representations will be used to feed a convolutional detection network and calculate the confidence score of one of the classes as described in Equation (2):

$$C_i^j = P_r(\text{Object}) * IOU \quad (2)$$

where C_i^j represents the confidence of the j th prediction frame of the i th square, $P_r(\text{Object})$ represents the probability of whether the current prediction frame has an object or not, and IOU represents the ratio of the intersection and concatenation of predicted edges to the real edges as shown in Eqs. (3) to (5):

$$IOU = \frac{S_1}{S_2} \quad (3)$$

$$S_1 = \left(\min(x_{p2}, x_{l2}) - \max(x_{p1}, x_{l1}) \right) * \left(\min(y_{p2}, y_{l2}) - \max(y_{p1}, y_{l1}) \right) \quad (4)$$

$$S_2 = (x_{p2} - x_{p1}) * (y_{p2} - y_{p1}) + (x_{l2} - x_{l1}) * (y_{l2} - y_{l1}) - S_1 \quad (5)$$

where $(x_{p1}, y_{p1}, x_{p2}, y_{p2})$ is the coordinates of the upper-left and lower-right points of the true target box, $(x_{l1}, y_{l1}, x_{l2}, y_{l2})$ are the coordinates of the two points on the upper left and lower right of the predicted target frame, S_1 is the area of the intersection part of the real target frame and the predicted target frame, and S_2 is the area of the juxtaposition of the predicted target frame and the real target frame.

At the same time, the coordinate position of the target frame is obtained by calculation, then the loss function is shown in Eq. (6) to Eq. (10):

$$loss = 1 - IOU + \frac{\rho^2}{c^2} + \alpha v \quad (6)$$

$$\rho^2 = (x_p - x_l)^2 + (y_p - y_l)^2 \quad (7)$$

$$c^2 = \left(\max(x_{p2}, x_{l2}) - \min(x_{p1}, x_{l1}) \right)^2 + \left(\max(y_{p2}, y_{l2}) - \min(y_{p1}, y_{l1}) \right)^2 \quad (8)$$

$$v = \frac{4}{\pi^2} \left(\arctan \frac{w_l}{h_l} - \arctan \frac{w_p}{h_p} \right)^2 = \frac{4}{\pi^2} \left(\arctan \frac{x_{l2} - x_{l1}}{y_{l2} - y_{l1}} - \arctan \frac{x_{p2} - x_{p1}}{y_{p2} - y_{p1}} \right)^2 \quad (9)$$

$$\alpha = \frac{v}{1 - IOU + v} \quad (10)$$

In this case, ρ stands for the distance between the centroid of the predicted bounding box and the target box; c means the diagonal length of the smallest enclosing rectangle containing both the predicted box and the ground-truth box; v is the measure of similarity in aspect ratios of the predicted box and the ground-truth box; and α is the weight associated with v .

2.3.2 Real-time tracking of student goals

To get images of all student instances, the target detector method is initially applied, followed by putting every detected instance into a lightweight appearance embedding model to extract its visual properties. The Kalman filter is then utilized to predict the feature state of all learners in the next frame. When the scale and location of the student instance in the next frame are determined, the Hungarian matching method is used to match the matched instances between the frames, allowing tracking of the students in a classroom scene. The process of the classroom student tracker algorithm is shown in Fig. 3.

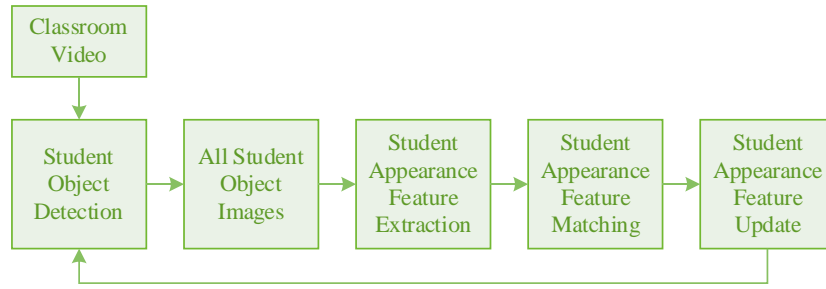


Figure 3: The classroom student target tracking algorithm process

3 Framework for evaluating student performance in online ideological and political education courses

In order to solve the problem of sparse features of students' learning behaviors in online courses of ideological and political education, a model framework for evaluating students' performance in online courses based on a three-layer integrated learning framework (TELF-PSPOC) is proposed, which contains feature enhancement for students' learning behaviors in online courses and heterogeneous classifiers with three-layer integrated feature learning (TELF-HC).

3.1 Overall structure

The framework of TELF-PSPOC model is shown in Figure 4. This chapter proposes a three-layer integrated learning framework based on the two-layer STACKING integration framework, which has four main parts:

- (1) Data preprocessing to form preprocessing files.
- (2) XGBoost processes the preprocessing file to obtain preprocessed attribute values.
- (3) Feature construction of student performance behavioral features for online courses to form an interpretable student behavioral feature matrix.
- (4) TEFL-HC processes the student behavior feature matrix to obtain evaluation results.

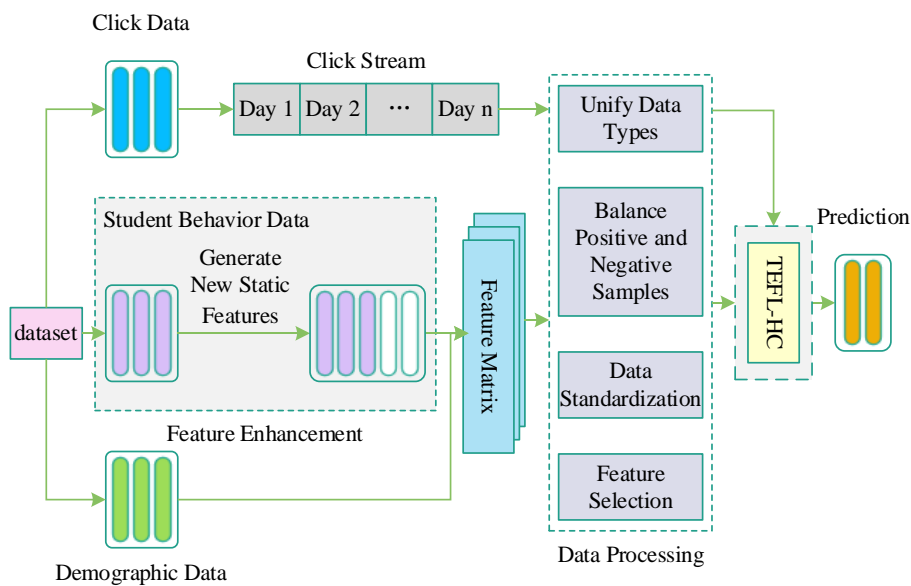


Figure 4: TELF-PSPOC framework

3.2 Modeling approach

3.2.1 Data pre-processing

The network preprocesses data to reduce data noise based on the characteristics of student performance in online courses.

In the first step, the data types are unified.

In the second step, positive and negative samples are equalized.

The third step, data normalization. The z-score method is used to normalize the data and convert the data of different magnitudes into a uniform magnitude to ensure the comparability between the data. The specific method is shown in equation (11):

$$X^* = \frac{x - \mu}{\delta} \quad (11)$$

where μ is the data mean and δ is the standard deviation of the data.

The fourth step is feature screening.

3.2.2 Feature enhancement

Pass rates, grades on full-stage tests, and daily hits on online resources are used to describe students' learning behavior in an ideological and political education class. Define

$F = [f_1, f_2, \dots, f_n]^T$, where f_i is the i th feature vector ($1 \leq i \leq n$). Define $f_i = [x_{i1}, x_{i2}, \dots, x_{ik}]$, where x_{ia} is the a th sample in the i th feature vector ($1 \leq a \leq k$).

The pass rate reflects the percentage of students passing the stage test, as shown in equation (12):

$$passRate_i = \frac{passAss_i}{totalAss} \quad (12)$$

where $passRate_i$ is the pass rate of the i student in all the stage tests, $passAss_i$ is the number of times the i student passed the stage tests, and $totalAss$ is the total number of times the stage tests were taken.

The average grade reflects the average performance of students during the course as shown in equation (13):

$$scoreAvg_i = \frac{\sum_{k=1}^n score_{ik}}{n} \quad (13)$$

where $score_{ik}$ is the staged test score of the i student at the k stage of learning and n is the total number of stages of learning.

The standard deviation of the stage test scores reflects the stability of the students' performance over the course of the program, as shown in equation (14):

$$scoreSdev_i = \sqrt{\frac{\sum_{k=1}^n (score_{ik} - scoreAvg_i)^2}{n}} \quad (14)$$

The average number of clicks is a resource used to describe the learning behavior of students,

which operationally reflects the intensity of their learning during the study period, as shown in equation (15):

$$avgClicks_i = \frac{\sum_{d=1}^m click_{id}}{m} \quad (15)$$

where $click_{id}$ is the number of clicks of the i th student on the d th day and m is the total number of days of the course.

The standard deviation of the number of clicks reflects the balance of clicks generated by students' learning behaviors during the course, as shown in equation (16):

$$sdevClicks_i = \sqrt{\frac{\sum_{d=1}^m (click_{id} - avgClicks_i)^2}{m}} \quad (16)$$

The standardized score of hits is defined as the relative position of the raw score among the scores of the batch to which it belongs, reflecting the relative position of the student's intensity of learning among the set of students studying the same course to which it belongs. This is shown in equations (17) to (19):

$$avgClicks = \frac{\sum_{i=1}^a avgClicks_i}{a} \quad (17)$$

$$sdevClicks = \sqrt{\frac{\sum_{i=1}^a (sdevClicks_i - avgClicks)^2}{a}} \quad (18)$$

$$sscoreClicks_i = \frac{avgClicks_i - avgClicks}{sdevClicks} \quad (19)$$

where $avgClicks$ is the average number of clicks for students taking the course, and $sdevClicks$ is the standard deviation of the number of clicks for students taking the course.

3.2.3 TEFL-HC

The TEFL-HC model consists of a pre-training layer, a base learner layer and a meta-learner layer. The features of the i th student are composed of demographic data (D_i), students' learning behaviors in online courses (B_i), and click-through data (C_i).

(1) Pre-training layer

The demographic data D_i and the learning behaviors B_i of the students in the online course are connected into vectors F_i^S with m -dimensional features, $F_i^S = [x_{i1}, x_{i2}, \dots, x_{im}]$, $i = 1, 2, \dots, u$, where m is the number of columns and u is the number of feature vectors.

XGBoost is based on GBDT, which supports linear classifiers compared to GBDT, and Taylor expansion of the cost function by introducing second order derivatives.

The decision tree DART with dropout is used as a weak classifier in XGBoost, which can effectively prevent overfitting when converting high-dimensional features to one-dimensional features using nonlinear regression. Finally, the prediction results are combined with the original data as $F_i^S = [x_{i1}, x_{i2}, \dots, x_{im}, x_{(im+1)}]$.

(2) Base Learner Layer

In this layer, BRF, ET and CatBoost are used as base learners.

(3) Meta-learner layer

For each base learner, training and test data are generated using 5-fold cross validation. CatBoost belongs to the balanced tree model and can overcome overfitting using ordered Boosting. CatBoost evaluates the results of students' performance in an online course by learning the feature vectors input to the meta-learner layer F_i (0 or 1).

4 Evaluation of the effectiveness of ideological and political education in response to student behavior in the classroom

4.1 Results of constructing a video dataset of student classroom behavior

4.1.1 Experimental Design and Performance Analysis

Benchmark datasets used in the comparison include four open-access video datasets, that is, Kinetics-400, Kinetics-600, Something-Something v2 and UCF-101, which are utilized as benchmark datasets to compare with the student classroom behavior video data created in this paper. Before being experimented on, every dataset is divided into training, validation and testing subsets in 6:2:2 ratio. Training subset is used to train the neural network, validation subset is introduced in order to evaluate errors and tune parameters to enhance the generalization ability of the model and the test subset is used to measure the recognition accuracy.

Each of the model training steps has been conducted on the Ubuntu 18.04 operating system with the help of the PyTorch deep learning framework and Nvidia Quadro RTX 6000 GPUs. The complete hardware and software configuration to be used in training and evaluation are given in Table 1. The hyperparameters of the neural network models used in the experiments were all set as follows: BatchSizes of 32, Learning rate of 0.003, and Epochs of 200.

Table 1: Model training and test configuration

Device name	Concrete parameter
Operating system	Ubuntu18.04
Processor	Intel(R) Xeon(R) Gold 5218 × 2
GPU	Nvidia Quadro RTX 6000 × 2
CUDA version number	12.1
Cudnn version number	8.9.2
Depth learning framework	Pytorch 2.1.1

4.1.2 Comparison of experimental results

In order to verify the reasonableness of the number of productions of this dataset, the average number of videos per category was counted for the four video datasets Kinetics-400, Kinetics-600, Something-Something v2, UCF-101, and the student classroom behavior dataset of this paper.

The average number of videos per category for the datasets Kinetics-400, Kinetics-600, Something-Something v2, UCF-101, and Student Classroom Behavior of this paper are about 400, 600, 1300, 150, and 200. The dataset of this paper has already exceeded the amount of data in a single category than that of the UCF-101 dataset, which proves that it can be used for deep learning training. However compared to recent large video datasets such as Kinetics-400,

Kinetics-600, and Something-Something v2, the dataset produced in this paper still needs to be expanded in terms of the number of videos per category.

In this section, two mainstream neural network models SlowFast and Swin Transformer are used to predict several datasets.

The comparison of the test top-1 accuracy between this paper's dataset and the public dataset is shown in Fig. 5, the training and prediction of this paper's dataset achieves an accuracy that has exceeded that of Something-Something v2. This paper's dataset has achieved a recognition rate of more than 70% with 78.79% and 81.06%, which is verified by the prediction results of the neural network model, which verifies that the structure of this paper's dataset is Rationality.

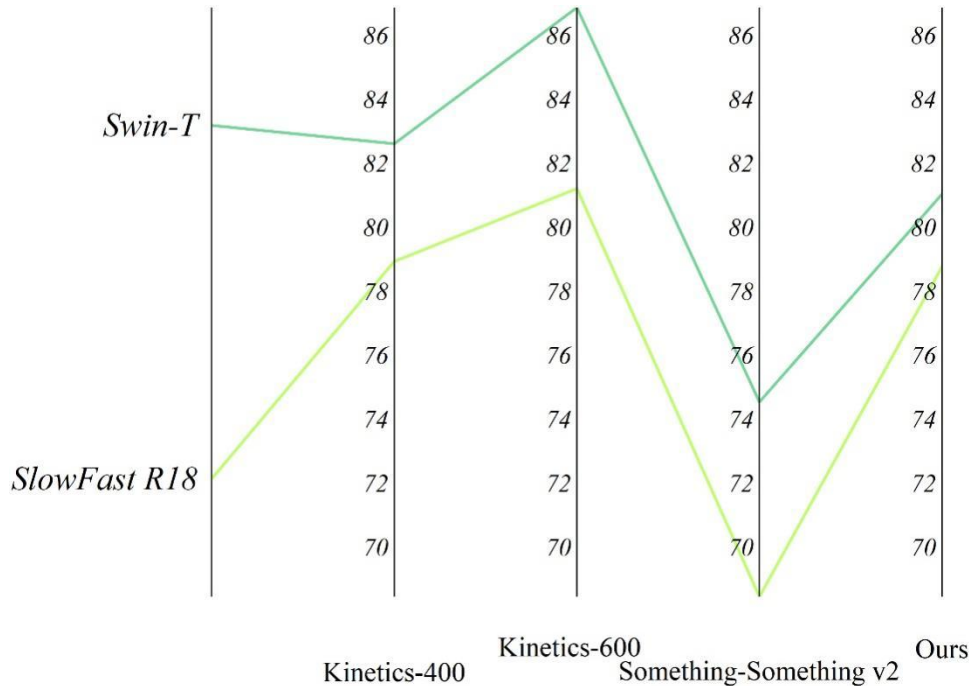


Figure 5: This article compares the test of the data set with the public data set

By predicting the accuracy of each category using different deep learning algorithms, the strengths and weaknesses of each category recognition can be judged intuitively, which helps to analyze and improve the dataset. The comparison of the test top-1 accuracies for each category in this paper's dataset is shown in Figure 6. The recognition rate of the behavior of playing cell phone and sleeping is higher, and the behavior of playing cell phone reaches more than 90% recognition rate, while the recognition rate of the behavior of reading and writing only reaches 56.32% and 62.44%, and the reason for this may be due to the fact that there are fewer reading and writing in the classroom, and there is a category imbalance problem in the dataset, so the accuracy of the recognition of the data of the fewer samples is not high enough, which is one of the directions of the enrichment of the dataset to be carried out afterward.

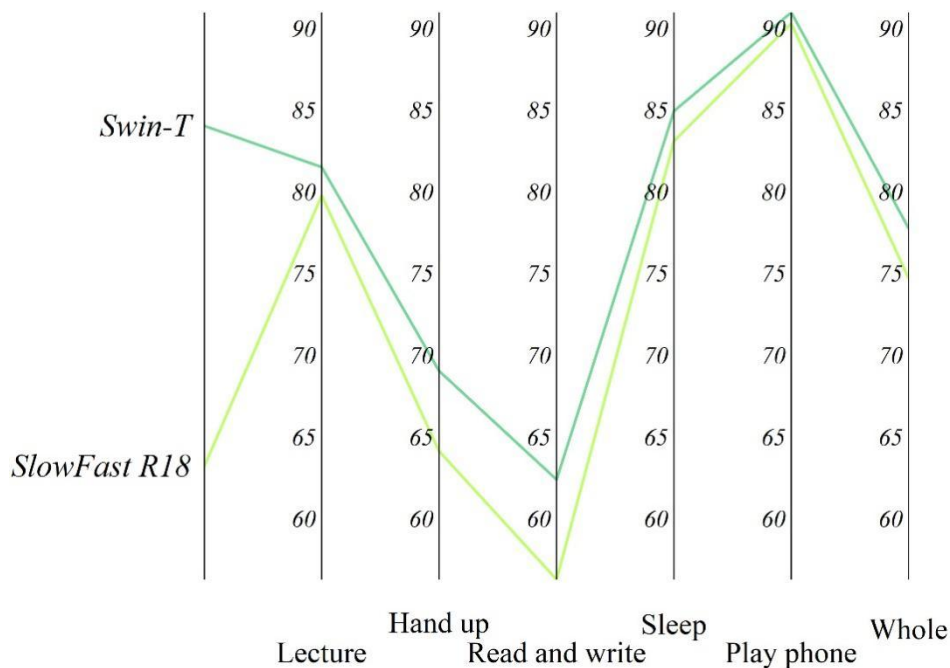


Figure 6: This paper sets the comparison of other tests

4.2 Effectiveness Assessment Based on Online Classroom Learning Behaviors

This paper randomly selects 60 complete recorded course videos, and chooses the ideological and political education class recorded in a university as a case study. There are 45 students who appear in the whole course video, excluding the students with serious blocking situation in the last two rows, this study takes the 36 complete and clear students with less blocking situation in the video as the object of the experiment.

In this paper, three indicators are defined to reflect students' learning behavior and learning engagement in the classroom, specifically including the frequency distribution of learning behaviors, individual overall engagement and individual average engagement.

4.2.1 Frequency distribution of learning behaviors

By counting the frequency of students' behavior in the ideological and political education classroom, teachers can learn information about how long students listen to lectures, how often they participate in classroom discussions, how many times they ask questions, how much time they spend taking notes, how much time they spend thinking independently, and so on. This information can help teachers understand students' learning habits and strengths and weaknesses, and then provide students with more targeted help and guidance. In addition, the frequency of specific classroom learning behavior exhibited by students can serve as an additional means of assessing the success of ideological and political instruction. Through comparisons of the frequency of occurrence of various student behaviors in the same classroom context, teachers are able to determine if their teaching methods are comprehended and appreciated by pupils and subsequently alter their instructional strategies accordingly based on the feedback provided by students.

The frequency distribution of the learning behavior of 36 students in the lecture session is presented in Figure 7. The mean percentages of the five behaviors, which include listening to lectures, taking notes, reading, discussing, and imitating are 50.07, 11.04, 12.03, 3.23, and 13.63 respectively.

The frequency of listening behavior of students 1, 2, 4, 5, 6, 11, 13, 15, 16, 17, 22, 23, 29, 31, 32, and 35 in the lecture session was more than 50%.

The frequency of note-taking behavior was more than 17% for students 6, 25, 26, 27, 30, and 33, and the frequency of reading behavior was more than 20% for students 9, 14, 18, 19, 20, and 33.

The frequency of discussion behavior was more than 17% for students 5, 7, 8, 9, 10, 20, 21, 24, 27, 28, 31, 34, 36.

The frequency of imitation behavior exceeded 15% for students 3, 7, 8, 10, 11, 12, 13, 14, 15, 19, 21, 28, and 35.

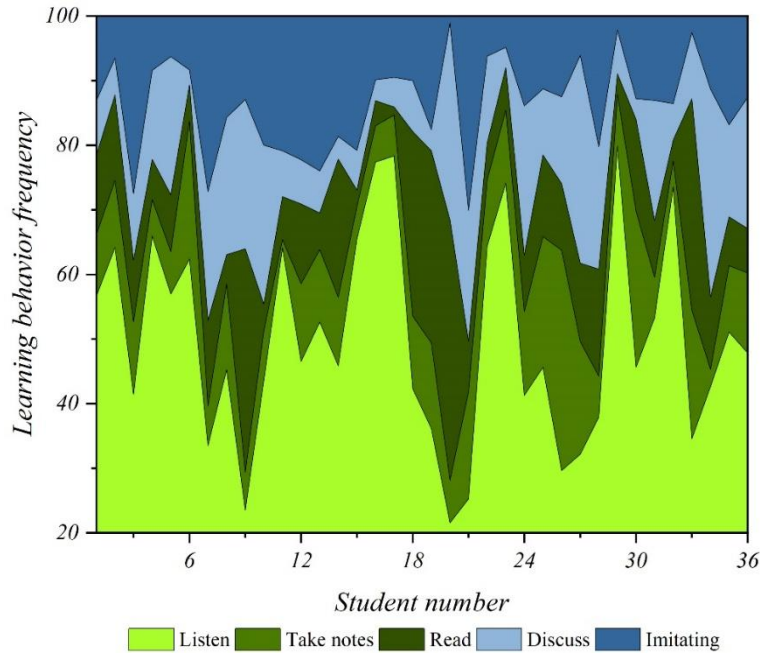


Figure 7: The learning behavior frequency distribution data of 36 students

4.2.2 Analysis of Overall Individual Commitment

On the basis of identifying learning behaviors, this paper defines individual input degree as individual overall input degree and individual average input degree. Individual overall engagement is automatically derived from the recognition algorithm for each moment, and then the average of the student's engagement value is calculated for the whole class period, which is shown in equation (20):

$$\bar{x} = \frac{\sum_{t=0}^T x}{T} \quad (20)$$

where x denotes the real-time engagement of a student at a given moment, and T denotes the sum of all moments of the course, the overall personal engagement of the 36 students is shown in Figure 8.

A negative overall personal engagement score indicates disengagement (non-engagement) and the closer it is to -1, the higher the degree of disengagement, while a positive engagement score indicates engagement and the closer it is to 1, the higher the degree of engagement.

Students 3, 7, 8, 9, 24, 28, 34, and 36 have an overall personal engagement rating of less than 0, which shows a tendency to disengage from the classroom and should be of concern to the teacher.

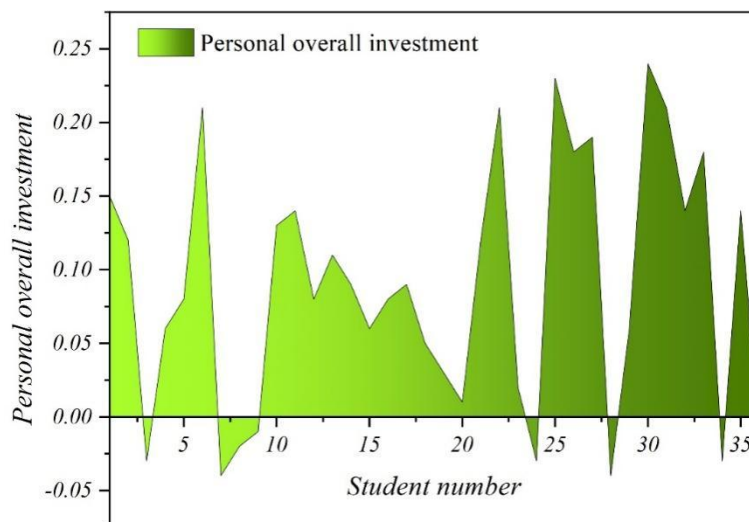


Figure 8: The overall investment of 36 students

4.2.3 Analysis of average individual inputs

Only students' learning behaviors and engagement in the whole ideological and political education class cannot intuitively reflect students' engagement in different teaching stages, so this paper proposes the concept of individual average engagement based on different teaching scenarios of ideological and political education. Individual stage input degree indicates the students' input degree in different classroom situations, and the calculation method is shown in formula (21):

$$\bar{x} = \frac{\sum_{r=0}^{T_m} x}{T_m} \quad (21)$$

where x denotes the real-time input degree of a certain student at a certain moment in the teaching scenario m , and T_m denotes the sum of moments in the teaching scenario m .

According to Equation (21), the individual stage input degrees of the top six students are calculated, and the stage-by-stage input degrees of the six students are shown in Figure 9. From the figure, it can be seen that these six students in different scenarios, learning engagement degree shows a large difference, reflecting the individual behavioral characteristics of different students.

For example, when the teacher was giving a lecture, Student 4 had the highest engagement while Student 3 had the lowest engagement, which was related to the students' looking up and listening to the lecture in these three stages.

The three students showed a high degree of variability when the teacher asked questions, with Student 1 performing significantly better than the other students, and with Student 5 and Student 6 showing negative engagement during the questioning phase, indicating that they were less motivated to raise their hands to answer questions. When the teacher asked for thinking or practicing, there was little difference in the level of engagement shown by Student 2 and Student 3, while Student 5 and Student 6 showed relatively low levels of engagement.

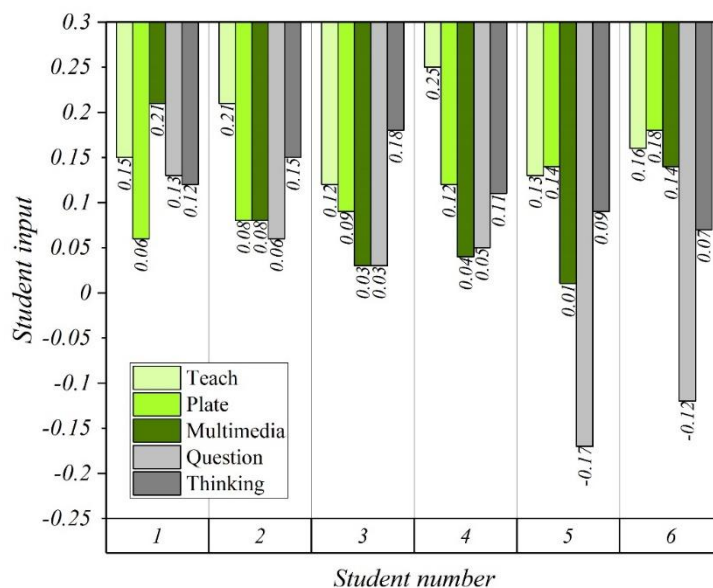


Figure 9: The investment of six students at different stages

4.3 Implementation of Learning Behavior Evaluation Model

By organizing the course data from ideological and political education (IPE) and examining the student classroom-behavior dataset developed in this study, the mining of learning-behavior data mainly focuses on four modules within the platform system: course completion rate, quiz performance, daily course visits, and forum interaction. These indicators are aligned with the dimensions of the TELF-PSPOC evaluation model, allowing the collected information to be integrated for assessing learners' achievement in IPE classes. The statistical results of students' performance based on the TELF-PSPOC model are presented in Figure 10.

For the top ten students, the daily access rate to IPE courses was not lower than 70%, and the average exceeded 90%. Students 4, 5, 6, 7, 11, 16, 17, 20, 21, 27, 28, and 31 all scored 30 points on the IPE test. Full marks of 40 were obtained by students 2, 3, 10, 13, 24, 25, 28, 31, and 34. Students 1, 2, 12, 14, 15, and 27 participated in classroom discussions 30 times, whereas students 1, 2, 3, 4, 5, 8, 9, 14, 15, 24, 29, and 36 recorded daily course visit rates above 90%.

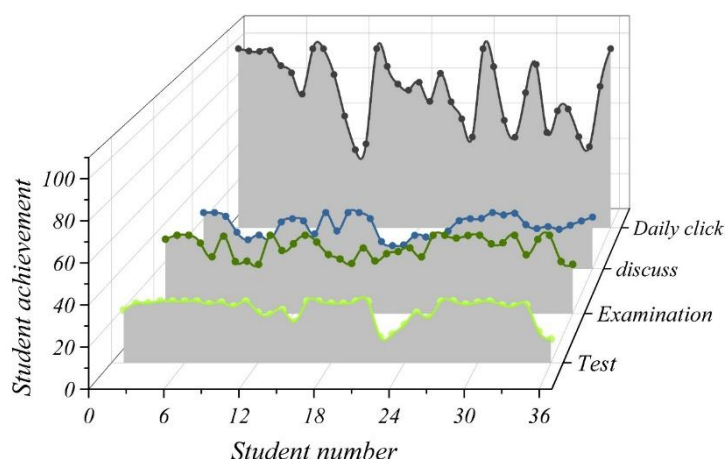


Figure 10: Student achievement statistics based on the TELF-PSPOC evaluation model

The overall performance of the entire class was summarized as indicated above, and the achievement levels of all the 36 students in the class were established and then grouped into

grades as depicted in Table 2. Of them, 4 students scored excellent in the IPE course, which are student 2, student 3, student 4, and student 14.

Table 2: 36 students' ideological and political education grades are divided

Student number	Grade	Student number	Grade	Student number	Grade
Student 1	Good	Student 13	Pass	Student 25	Good
Student 2	Excellence	Student 14	Excellence	Student 26	Pass
Student 3	Excellence	Student 15	Good	Student 27	Pass
Student 4	Excellence	Student 16	Good	Student 28	Good
Student 5	Good	Student 17	Good	Student 29	Good
Student 6	Good	Student 18	Pass	Student 30	Pass
Student 7	Good	Student 19	Pass	Student 31	Pass
Student 8	Good	Student 20	Pass	Student 32	Pass
Student 9	Good	Student 21	Pass	Student 33	Pass
Student 10	Pass	Student 22	Pass	Student 34	Pass
Student 11	Pass	Student 23	Pass	Student 35	Pass
Student 12	Pass	Student 24	Good	Student 36	Pass

5 Conclusion

The data of students classroom behavior in ideological and political education is collected in this research using target detection and tracking algorithms, and the TELF-PSPOC model is developed using the framework of the combined learning system. Using public datasets, the validity of the student classroom behavior dataset that was developed in this paper is tested by comparing it with other similar datasets to determine whether they can be used as sources of information, and students learning behaviors in ideological and political education classes are further explored together with the TELF-PSPOC model.

As regards the classroom behavior data set defined in this research and the four publicly available video data sets, namely, Kinetics-400, Kinetics-600, Something-Something v2, and UCF-101, the highest-1 test accuracy of the SlowFast model and the Swin Transformer model is over 60 percent and the respective accuracies in this paper dataset are 78.79 and 81.06 percent, respectively, which are higher than the results found in the Something-Something v2 dataset.

Based on the TELF-PSPOC model that is being used to assess the behavior of students in ideological and political education classes, the mean proportion of behaviors like listening to lectures, taking notes, reading, discussing, and imitating are 50.07%, 11.04%, 12.03%, 3.23%, and 13.63, respectively. Over 40 percent of the students could stay focused listening in the lecture portion of the ideological and political education course. The overall classroom performance in ideological and political education was arrived at by combining the performance of the various categories of students learning behaviors, which gave 4 excellent, 13 good and 19 pass students respectively.

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