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A Bayesian Classification Network-based Learning Status Management System in an Intelligent Classroom

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ABSTRACT: Awareness of students' learning status, and maintaining students' focus and attention during class are important issues in classroom management. Several observation instruments have been designed for human observers to document students' engagement in class, but the processes are time-consuming and laborious. Recently, with the development of artificial intelligent technologies, artificial intelligence in education (AIED) has become an important research topic. Several studies have applied image recognition technologies to determine students' learning status. However, little research has employed both sensor technology and image recognition technology in learning status analysis. Moreover, it remains unknown if learning status analysis is accurate enough to substitute for human observers. Furthermore, no feedback has been provided individually to students to manage their learning status by maintaining their attention in class. In this paper, a learning status management system in an intelligent classroom is proposed. Several types of information about students were detected and collected by both sensor technology and image recognition technology, and a Bayesian classification network was employed to inference the students' learning status. Moreover, the system includes a feedback mechanism, which not only provides the results of the just-in-time learning status analysis to teachers, but also notifies students who are detected as being unfocused in class. Two experiments were conducted to verify the accuracy and effectiveness of the proposed system. Results showed that the learning status analysis highly corresponded to the observation of human beings, and the students were more attentive in class.

Keywords: Classroom management, Intelligent classroom, Learning status analysis, Bayesian classification network

1. Introduction

In traditional classrooms, learning efficiency is usually influenced by students' learning status. If students are inattentive, drowsy, or even fall asleep, they are not able to absorb the content taught by teachers. Teachers usually use a wide variety of classroom management strategies to keep students focused and attentive during class (Kounin, 1970; Evertson, 1994; Kyriacou, 1997). However, since teachers must pay attention to their own instruction, it is challenging for them to also be aware of the individual learning status of each student (Yang, Cheng, & Shih, 2011) and to provide suitable feedback in a timely manner. It is also impossible for teachers to record students' individual learning status all the time in-class for further evaluation and/or analysis. While several classroom observation instruments have been designed for human observers to document students' engagement in class (O'Malley et al., 2003; Dockrell, Bakopoulou, Law, Spencer, & Lindsay, 2012; Eddy, Converse, & Wenderoth, 2015), the observation and documentation processes mainly depend on human labor. It is not only time-consuming, but also laborious. Moreover, since the learning status is recognized by observers rather than teachers, teachers are not able to learn the just-in-time results of the observation and change their instructional strategies accordingly to achieve better classroom management.

Recently, with the development of artificial intelligent (AI) technologies, artificial intelligence in education (AIED) has become an important research topic (Hwang, Xie, Wah, & Gašević, 2020; Chen, Xie, Zou, & Hwang, 2020; Chen, Xie, & Hwang, 2020; Tang, Chang, & Hwang, 2021; Yang, Ogata, Matsui, & Chen, 2021). Chen et al. (2020) attempted to investigate the gap between application and theory during the rise of AIED; one of their findings was that "*most influential AIEd studies are concerned about the application of AI technologies in the contexts of online or web learning, while few concerned about the promotion of learning and teaching in physical contexts with the help of AI technologies*" (p. 16). Their finding reveals that applying AI technologies in physical classroom settings for enhancing the learning and teaching process is a potential research issue. In view of this, research on intelligent classrooms which employ AI technologies, such as sensor technology and image recognition technology, has arisen (Zhu, Xu, & Gao, 2020; Li, Tan, & Hu, 2021; Li, 2021). Generally, the term "Intelligent classroom" refers to a physical classroom that integrates advanced educational technology to improve teachers' abilities to promote student learning and students' abilities (Winer & Cooperstock, 2002; Ramadan, Hagras, Nawito, El Faham, & Eldesouky, 2010).

To address the problem of learning status management in class, some research has employed image recognition technologies to analyze the videos/images of students, using facial actions and expressions to determine students' learning status in real time (Hwang & Yang, 2009; Yang, Cheng, & Shih, 2011; Huang, Li, Qiu, Jiang, Wu, & Liu, 2020; Yang, Yao, Lu, Zhou, & Xu, 2020). However, students' learning status is not only reflected in their facial actions and expressions. Although sensor technology is useful for detecting students' behaviors in the classroom (Chang & Chen, 2010), little research has employed sensor technology in learning status analysis. Moreover, most studies did not evaluate the accuracy of the learning status analysis by comparing it with judgements by classroom observers. It is therefore uncertain whether the results of learning status analysis are sufficiently accurate to substitute for human observers. On the other hand, to keep students attentive in class, feedback should be provided to both students and teachers according to the learning status detected. However, only some research has provided feedback to teachers, while little research has provided feedback individually to the students themselves to maintain their attention in class.

To create an intelligent classroom with a more effective classroom management facility, a learning status management system is proposed in this study. Various types of sensors were used to obtain students' physiological signals, and a small camera was installed in front of each desk to capture the image or take videos of each student. Several features that could be used to infer students' learning status were detected and collected by sensor technology and image recognition technology. To infer students' learning status from the collected features, a Bayesian classification network was employed. A Bayesian classification network is a probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph (DAG) (Jensen, 1996). It is ideal and versatile for a wide range of tasks including prediction, diagnostics, reasoning, and decision making in situations of uncertainty (Pourret, Naïm, & Marcot, 2008). The learning status of students inferred by the proposed system could be recorded for further analysis. Moreover, a feedback mechanism was also included in the system to notify students who had become inattentive, drowsy or had fallen asleep so as to regain their attention. It also provided a dashboard for teachers to visualize the real-time learning status of each student; teachers could then adjust their instructional strategies in a timely fashion so as to achieve better classroom management.

To evaluate the performance of the proposed system in classroom management, system validation was performed to verify the accuracy of the learning status management system. The correlation between the students' learning status determined by the proposed system and that determined by human observers was analyzed in the system validation. Moreover, a quasi-experiment was conducted to evaluate the efficacy of the learning status management system. Two classes of students taking the course "Introduction to Computer Science" participated in the experiment. One class was assigned to the experimental group, which studied in the intelligent classroom with the learning status management system enabled. Another class was assigned to the control group, which also studied in the same classroom with the learning status management system disabled. The degrees of students' attention of the two classes were analyzed and compared. Thus, there were two research questions to be investigated in this study:
Q1. Does the learning status determined by the proposed system correspond to that determined by human observers?
Q2. Can students' attention in class be promoted when the proposed system is enabled?

2. Literature review

2.1. Classroom management

Classroom management, also known as class management, covers a very wide range of activities (Evertson, 1994). Doyle (1986) defined classroom management as the necessary preparation and procedures for establishing and maintaining an environment in which teaching and learning take place. He believed that classroom management is a prerequisite for successful teaching. Froyen (1988) defined classroom management as including content management, covenant management and conduct management. Content management refers to the management of classroom space, teaching materials, equipment, the movement of students, and the process of instruction. Covenant management focuses on the classroom group as a social system; teachers should pay attention to managing interpersonal relationships in the classroom. Conduct management refers to dealing with discipline problems in the classroom. Emmer and Stough (2001) defined classroom management as "*actions taken by the teacher to establish order, engage students, or elicit their cooperation*" (p. 103) The Glossary of Education Reform provided a versatile concrete definition of classroom management as "the wide variety of skills and techniques that teachers and schools use to keep students organized, orderly, focused, attentive, on task, and academically productive during a class" (Great Schools Partnership, 2014)

Evertson and Weinstein (2006) believed that in order to attain high quality classroom management, five actions are indispensable for teachers: (1) establish a caring and supportive relationship with students; (2) organize and implement teaching to optimize students' learning opportunities; (3) encourage students to participate in academic tasks; (4) promote students' social skills and self-regulation ability; and (5) use appropriate interventions to help students solve their behavior problems. Kyriacou (1997) identified that the most common and destructive problem behaviors were talking with classmates, followed by inattention, wandering, and idleness. The findings indicated that relatively minor forms of student misbehaviors are a common concern for teachers, and that teachers spend a considerable amount of time on behavior management issues (Clunies-Ross, Little, & Kienhuis, 2008).

From the literature above, it can be seen that how to improve the effectiveness and efficiency of classroom management, which involves identifying students' learning behaviors to determine their learning status and taking suitable actions to help them concentrate on learning, has become an important research topic. In this study, the term *learning behavior* refers to students' behaviors that occur during the learning process. The term *learning status* refers to an individual's mental state during the learning process, which can be determined by the individual's learning behaviors. For example, a student with the learning behavior of "talking with classmates" while the teacher lectures would be considered as having the learning status of "inattention."

2.2. Learning behavior identification to assist classroom management

Delgado et al. (2011) indicated that concentration during learning is the key factor influencing learning effect. If a student cannot concentrate on learning, it will affect the learning mood, resulting in lower learning concentration and lower learning effect. Schmidt (1990) also pointed out that attention plays an important role in traditional classroom learning. When students start to lose concentration or feel tired or even start to fall asleep, the learning content will be ignored and the learning efficacy will be decreased. To help students concentrate on learning, teachers should pay attention to classroom management, especially to the management of students' learning status, which can be determined by identifying their external learning behaviors.

To identify and record students' learning behaviors in a physical classroom for learning status analysis, several tools have been developed in the literature, such as classroom observation instruments, classroom teaching video analysis software, and/or observation scales (O'Malley et al., 2003; Dockrell, Bakopoulou, Law, Spencer, & Lindsay, 2012; Eddy, Converse, & Wenderoth, 2015; Flanders, 1961; Rich & Hannafin, 2009). For instance, the Flanders Interaction Analysis System (FIAS) is an observational tool used to observe verbal communication in the classroom (Flanders, 1961). It uses a system of categories to encode the classroom behavior of both teacher and students. However, non-verbal gestures are not taken into account (Amatari, 2015). Classroom Video Analysis (CVA) is another well-known method in which the entire teaching process is recorded and then analyzed (Kersting, 2008; Kersting et al., 2012). CVA measures "usable teacher knowledge" by scoring their written analyses of classroom video clips.

These traditional methods of learning behavior identification for learning status analysis rely heavily on the manpower of the classroom observers, so the process is rather time-consuming, laborious and inefficient. Moreover, since the analytical results cannot be provided to the teachers in a timely manner while they are instructing students in the classroom, they are not able to adjust their instruction strategies immediately to achieve better classroom management.

2.3. AI and Sensor technology for learning status analysis

With the development of Artificial Intelligence (AI), various AI technologies, such as sensor technology, image recognition technology, Bayesian classification networks, fuzzy logic, decision trees, neural networks, genetic algorithms, and Hidden Markov Models (HMM), have been employed in the education domain (Tang, Chang, & Hwang, 2021). To eliminate the timely constraint and relieve the burden of manpower in traditional learning status analysis, some studies have applied AI technologies to develop systems for learning status analysis (Hwang & Yang, 2009; Yang, Cheng, & Shih, 2011; Huang, Li, Qiu, Jiang, Wu, & Liu, 2020; Yang, Yao, Lu, Zhou, & Xu, 2020).

Hwang and Yang (2009) proposed an auto-detection and reinforcement mechanism for learning status analysis in distance education. They employed image recognition and detection techniques to recognize the inattention and fatigue status of learners. A Bayesian network assessment was employed in their reinforcement mechanism to reduce detection misjudgment and enhance accuracy. Yang et al. (2011) proposed a computer vision system to automatically analyze learners' videos to recognize nonverbal facial expressions to discover the learning status of students in distance education. Adaboost classifiers were applied to extract facial parts from students' videos, and specific emotional expressions were recognized by HMM. To recognize students' typical classroom behaviors, Huang et al. (2020) applied a deep convolutional neural network (D-CNN) to analyze students' images of head poses and facial expressions. Yang et al. (2020) identified students' concentration degrees during classroom learning by detecting their head motions, such as raising and lowering their heads, from in-classroom videos. The concentration degrees are linked to the teacher's teaching characteristics, including audio features, the course topics taught in different time periods, and the speed of the teacher's speech when explaining the topics.

As we can see from the literature, most of the studies that have used AI technologies in learning status analysis employed image recognition technologies to determine students' learning status in real time. However, students' learning status can not only be reflected in their facial actions and expressions, but can also be revealed by their physiological signals, such as body movement, and pulse. Although sensor technology is useful in detecting students' behaviors in the classroom (Chang & Chen, 2010), little research has employed sensor technology in learning status analysis. Moreover, most studies did not evaluate the accuracy of the learning status analysis. While some studies have evaluated the accuracy, the evaluations were only based on testing examples of facial recognition. No comparison with human judgements using real images captured in the physical classroom has been made. It still remains unknown if learning status analysis is sufficiently accurate to substitute for human observers. On the other hand, to manage students' learning status to maintain their attention in class, feedback should be provided to both students and teachers according to the learning status detected. However, only some research has provided feedback to teachers to allow them to consider changing their instructional strategies. Little research has provided feedback individually to students to manage their learning status, keeping them attentive in class.

To fill the research gap, a learning status management system is proposed in this paper. Both sensor technology and image recognition technology are employed for learning status analysis. To validate the accuracy of learning status analysis, the correlation between the students' learning status determined by the proposed system and those determined by human observers was analyzed. A feedback mechanism, which will provide feedback to both the teachers and the students, is also included to keep the students attentive. With the help of the proposed system, it is hoped that better classroom management can be achieved.

3. Method

3.1. Bayesian classification network-based learning status management system

The proposed learning status management system included a learning status inference engine and a feedback mechanism. The learning status inference engine was responsible for analyzing students' learning status. The determined learning status was recorded in a database. The feedback mechanism was responsible for giving suitable feedback to both teachers and students according to the students' learning status. When students received feedback, they would be aware of their learning status and adjust it so as to be attentive. When teachers received feedback, they could change their instruction strategies to maintain students' attentiveness.

A four-layer Bayesian inference network is employed in the learning status inference engine. A Bayesian network is a type of probabilistic graphical model that uses Bayesian inferencing for probability computations. A set of variables and their conditional dependencies are represented via a directed acyclic graph in the Bayesian network. Bayesian network assessment can reduce detection misjudgment and enhance accuracy. It was found that Bayesian networks could also be used to evaluate or predict the learning behavior of students in a distance learning environment (Xenos, 2004; Hwang & Yang, 2009).

As shown in Figure 1, the four-layer Bayesian classification network is composed of a sensor layer, a feature layer, a behavior layer and a status layer. The sensor layer consists of several types of sensing devices, such as microphone, camera, body temperature, and so on. The features of a learner can be captured and recognized via these sensors. Differing from past studies, the Bayesian classification network proposed here not only uses image recognition technology to incorporate the features that can be recognized from the images/video captured by camera, but also considers the information captured from sensors embedded in the classroom and worn by students. According to the features obtained, the students' behaviors are inferred and determined. Misbehavior refers to the behaviors that would distract other students from their learning, such as chatting with classmates, bad posture or leaving their seats. For instance, the frequencies of a learner's eyes being half-closed and head nodding can be obtained by facial feature recognition from the image/video captured by camera. The drowsy behavior of a learner can then be inferenced by integrating the two frequencies. If the behavior of a student is predicted as misbehavior or fatigue, the learning status of this student is recorded as inattentive, and the degree of inattention is determined by the frequency of the misbehavior or fatigue. The sensors used for detecting the conditions of students and the learning behaviors determined are listed in Table 1. The behavior layer currently includes two behaviors, misbehavior and fatigue behavior, but can be extended to meet requirements in the future.

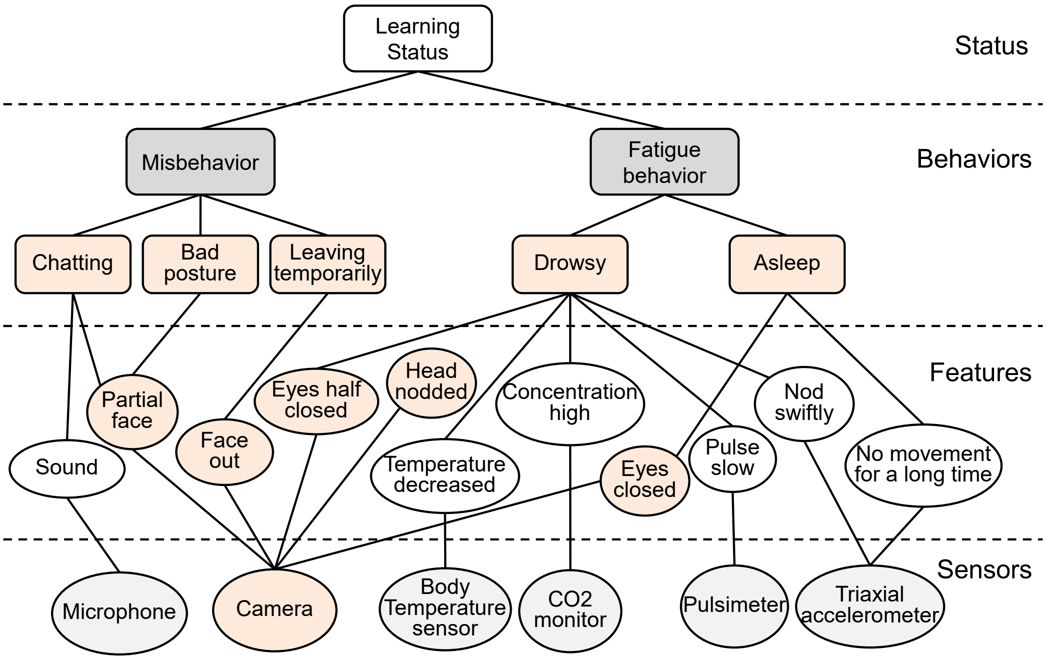

Figure 1. Bayesian classification network for learning status analysis

Table 1. The features of learning behaviors

Sensor	Condition	Behavior
Microphone	chatting	misbehavior
Camera	winking frequency and the face is not in the right place	bad posture, leaving temporarily, drowsy or asleep
Body temperature	temperature decreasing	drowsy
CO_2 monitor	high concentration	drowsy
Pulsimeter	pulse getting slow	drowsy
Triaxial accelerometer	head is nodding swiftly	drowsy or asleep

When a student is determined to be inattentive by the inference engine, the degree of inattentiveness is recorded in a database. The feedback mechanism gives feedback to both the teacher and the students accordingly. For inattentive students, the feedback could be a blinking LED installed in front of the student's desk, or a mild shake of the student's seat or smart bracelet, to remind him/her to be attentive. The feedback mechanism for students could be determined by the equipment installed in the intelligent classroom. In this study, we used LED lights as the feedback mechanism. For the teacher, a dashboard presenting the learning status of each student was displayed in the interface of the proposed learning status management system, as shown in Figure 2. The color of the status block for each student shows the degree of inattentiveness. A red block means very inattentive, a yellow block means inattentive, and a green block means attentive. Additionally, if the face is not detected all the time, it means the student is absent from class, and the status block is displayed as black. With the dashboard, the teacher can learn the status of all the students at a glance. If most students are inattentive, the teacher could change his/her instruction strategy to regain the students' attention. When the class is finished, lists of absent students and inattentive students are also provided. The teacher can use this information to provide special care to individual students after class.

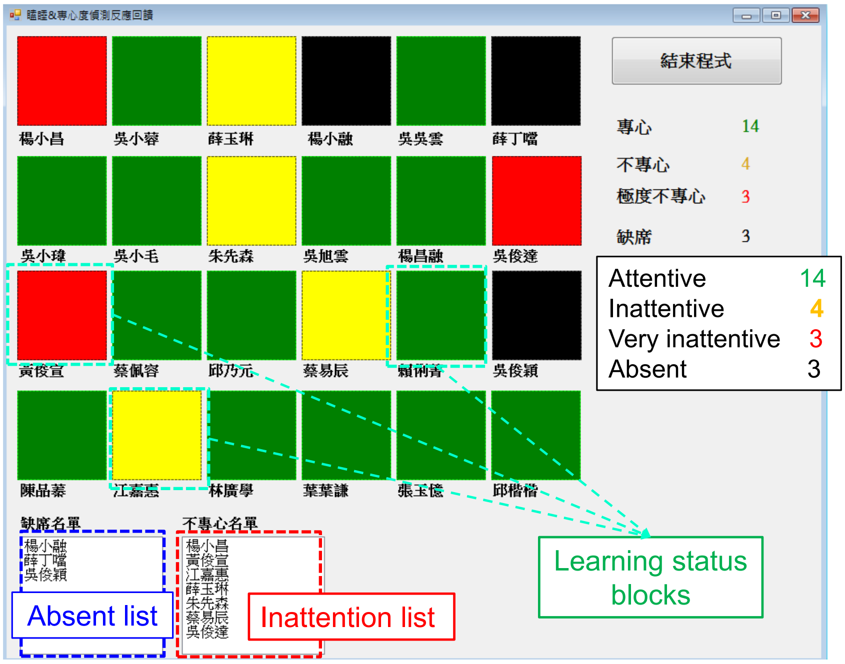

Figure 2. The interface of the learning status management system

3.2. Experiment design

The four-layer Bayesian inference network-based learning status management system was implemented in a context-aware classroom (Figure 3). The classroom is equipped with several sensors and feedback devices in the intelligent classroom, and Zigbee technology was employed to drive the equipment. Cameras were used to collect the features of students for learning status management, and a CO_2 monitor and three complex sensors were installed for collecting the context information (CO_2 concentration, temperature, humidity and illumination). Two experiments were conducted: one for accuracy and the other for effectiveness. The two experiments investigated two research questions, *Q1: Does the learning status determined by the proposed system correspond to that determined by human observers?* and *Q2: Can students' attention in class be promoted when the proposed system is enabled?*" All participants involved in the experiment were informed in advance that their facial information would be collected and recorded during the experiment.

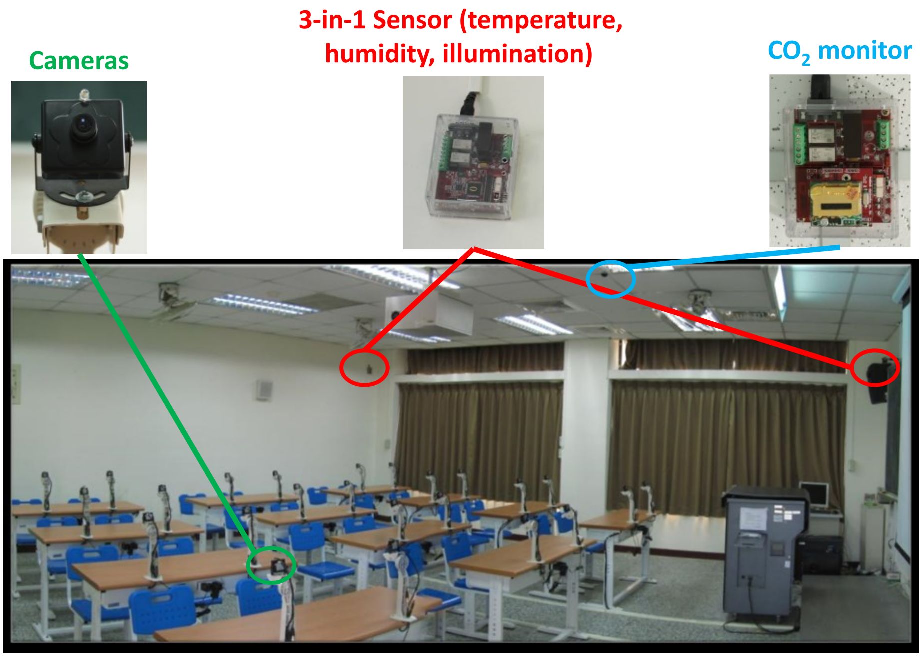

Figure 3. Intelligent classroom and embedded sensors and controllers

In order to verify the accuracy of the learning status inference engine, compared to human observers (raters), the first experiment was conducted as shown in Figure 4. There were 20 students who participated in this experiment. While they learned in the intelligent classroom with the proposed learning status management system enabled, the face of each learner was captured by the camera set before each of them. During the class, both the video clips and the learning status determined by the system were recorded. After class, each video clip of each student was manually examined by three raters, and the frequency of the fatigue state of each student was rated. The rating results were then compared with the results determined by the system.

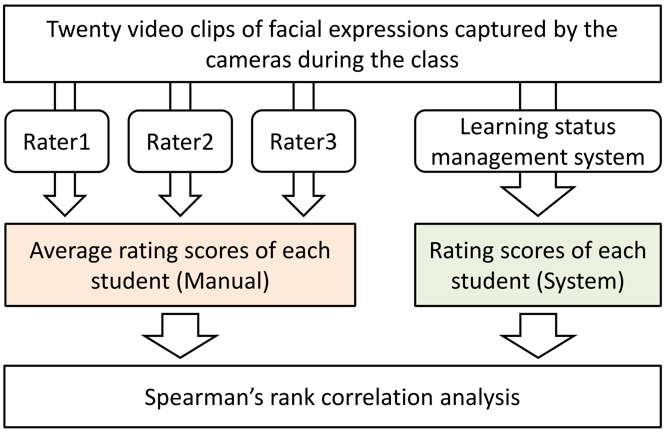

Figure 4. Accuracy evaluation procedure

On the other hand, in order to verify the effectiveness of the learning status management system, a 2-week field experiment was conducted in the intelligent classroom. Sixty-four students in two classes were involved in the experiment. The learning subject was "Introduction to computer science" and each class was 45 minutes in length. In week 1, both classes learned in the same classroom and the learning status management system was disabled during class. After class, a pre-questionnaire was administered for the students to complete. In week 2, one class was assigned to be the experimental group, and the other was assigned to be the control group. When the experimental group was learning in the classroom, the learning status management system was enabled. Conversely, the system was disabled when the control group was learning in the same classroom. Similar to the process in week 1, a post-questionnaire was administered after class for the students to complete. The experiment process is shown as Figure 5.

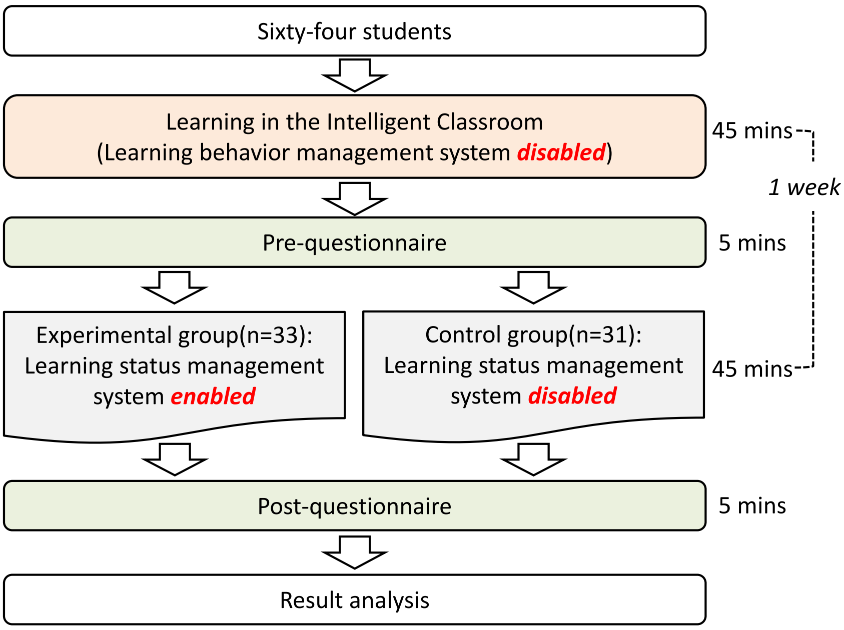

Figure 5. Effectiveness evaluation procedure

There are three question items in the pre-questionnaire and post-questionnaire for the students to self-evaluate their learning status during class, as listed in Table 2. The questionnaire used a 5-point Likert scale. Students were asked to self-evaluate their degree of conformity with "completely agree (5)," "agree (4)," "no opinion (3)," "disagree (2)" and "completely disagree (1)." Since the purpose of this experiment was to verify whether the learning status management system could keep students attentive during learning, which is the major purpose of classroom management, the effectiveness of the proposed system was evaluated by measurements that reflected the students' degree of attentiveness.

Table 2. Learning status questionnaire

	Question items
I1	I was mostly attentive during the class
I2	I seldom remained fatigued during the class
I3	I didn't doze off during the class

4. Experiment results

4.1. Accuracy evaluation of the learning status inference engine

In order to evaluate the correlation between human-rated ranks and computer-rated ranks of students' degrees of inattention, Spearman's rank-order correlation was determined. It is a nonparametric version of the Pearson product-moment correlation. Spearman's correlation coefficient (rs) measures the strength and direction of association between two ranked variables. The coefficient is computed by formula (1), where r_s represents the Spearman's rank correlation coefficient, n represents the number of observations, and di represents the difference between the two ranks of each observation. The result of Spearman's rank-order correlation is listed in Table 3.

$$r_s = 1 - \frac{6\sum di^2}{n(n^2-1)} \tag{1}$$

Table 3. Correlation between system rating and manual rating

			Ranker
Spearman's rho (ρ)	System rating	Correlation Coefficient	.787***
		Sig.(2-tailed)	.000
		N	20

Note. ***Correlation is significant at the 0.001 level (2-tailed).

Table 4. Explanation of the value range of the rank correlation

Range of coefficient	Correlation degree
$\rho \le 0.3$	Low
$0.3 < \rho \le 0.7$	Medium
$\rho > 0.7$	High

From Table 3 and Table 4, we can find that the Spearman coefficient (r_s) is 0.787, which is larger than 0.7. The test of correlation significancy shows that probability Sig. (2-tailed) is 0.000 (< .05). This implies that there is a significant positive correlation between the system ratings and human ratings, and the correlation degree is high. From the analytical result, we can find that the rating results from the system can be treated as similar to the human rating results. In other words, the prediction of learning status by the proposed inference engine is highly accurate. We can therefore answer research question Q1: the learning status determined by the proposed system highly corresponds to that determined by human observers.

4.2. Effectiveness evaluation of the learning status management system

In order to investigate the effectiveness of the learning status management system, the learning status questionnaire shown in Table 2 was conducted after class in week 1 and week 2. The questionnaire results collected in week 1 were regarded as the pre-questionnaire results and those in week 2 as the post-questionnaire results. An independent sample t-test was applied to evaluate the results. The analysis results of the pre-questionnaire showed that there was no significant difference in I1, $t(62) = -0.800$, $p = .427$, $d = 0.20$, between the experimental group ($M = 3.48$, $SD = 1.00$) and the control group ($M = 3.29$, $SD = 0.94$). Moreover, there was also no significant difference in I2, $t(62) = -0.604$, $p = .548$, $d = 0.15$, between the experimental group ($M = 3.24$, $SD = 1.12$) and the control group ($M = 3.06$, $SD = 1.237$). Similarly, there was also no significant difference in I3, $t(62) = -0.934$, $p = .354$, $d = 0.35$, between the experimental group ($M = 3.58$, $SD = 1.06$) and the control group ($M = 3.23$, $SD = 0.96$).

After different treatments, the post-questionnaire was collected. The independent sample *t*-test result of the post-questionnaire between the two groups is listed in Table 5.

Table 5. Independent sample *t*-test result of the post-questionnaire between the two groups

Question items	Mean (Std.)		*df*	*t*	Effect size(d)
	System enabled (N = 33)	System disabled (N = 31)			
I1. I was mostly attentive during the class	3.70 (0.73)	3.23 (0.85)	62	-2.394^{*}	0.59
I2. I seldom remained fatigued during the class	3.79 (0.74)	3.00 (1.32)	46.59	-2.926^{**}	0.74
I3. I didn't doze off during the class	4.12 (0.74)	3.45 (1.18)	49.91	-2.702^{**}	0.68
Average score	3.87 (0.53)	3.23 (0.96)	46.16	-3.273^{**}	0.83

Note. $^{*}p < .05$; $^{**}p < .01$.

It was found that there was a significant difference in the average scores of the three question items, $t(46.16) = -3.273$, $p = 0.002$, $d = 0.83$, and the average score for the "*System enabled group*" ($M = 3.87$, $SD = 0.53$) was significantly greater than that for the "*System disabled group*" ($M = 3.23$, $SD = 0.96$). For I1, "*I was mostly attentive during the class,*" $t(62) = -2.394$, $p = .020$, $d = 0.59$, and the average score for the "*System enabled group*" ($M = 3.70$, $SD = 0.73$) was significantly greater than that for the "*System disabled group*" ($M = 3.23$, $SD = 0.85$). For I2, "*I seldom remained fatigued during the class*", $t(46.59) = -2.926$, $p = .004$, $d = 0.74$, and the average score for the "*System enabled group*" ($M = 3.79$, $SD = 0.74$) was also significantly greater than that for the "*System disabled group*" ($M = 3.00$, $SD = 1.32$). Similarly, for I3, "I didn't doze off during the class", $t(49.91) = -2.702$, $p = .009$, $d = 0.68$, and the average score for the "*System enabled group*" ($M = 4.12$, $SD = 0.74$) was significantly greater than that for the "*System disabled group*" ($M = 3.45$, $SD = 1.18$). Hence, from Table 5, we can conclude that the proposed learning status management system was able to help students be more attentive, experience less fatigue, and doze off less often during class. We can therefore answer research question Q2: students' attention in class can be promoted when the proposed system is enabled.

5. Discussion

In this paper, two experiments were conducted to verify the accuracy and effectiveness of the proposed system. As shown in Table 3, the result of accuracy evaluation showed that the learning status determined by the system was highly correlated with the result determined by the human observers. This finding means that the proposed system can substitute human observers, and relieve the burden of manpower in traditional learning status analysis. Moreover, since the proposed system gives feedback to both teachers and students immediately after the students' learning status is determined, the time constraint of traditional learning status analysis can be eliminated.

Besides applying AI technologies to assist teachers in recognizing students' learning status, the effectiveness of the proposed system was also evaluated. The experimental results show that the proposed learning status management system was able to help students remain attentive in class. When the proposed system was enabled, the students felt more attentive, less fatigued, and were less likely to doze off. This result could be credited to the feedback mechanism of the proposed system. Since those students who are inattentive are marked in the interface of the management system (Figure 2), teachers can easily identify the students' learning status and take action to keep students attentive. For example, when most students are inattentive, the teacher can give a quiz or tell a joke to regain their attention. If only some students are inattentive, the teacher can ask a specific inattentive student to answer a question to stimulate his/her attention. On the other hand, students who are determined to be inattentive will also receive feedback from the proposed system. That will remind them to keep attentive even when the teacher does nothing in response to their learning status.

The experimental results provide evidence of the contribution of the proposed system to classroom management, but there are nevertheless some limitations to this study. Due to the limitations of equipment, not all the sensors indicated in the proposed Bayesian classification network for learning status analysis (Figure 1) were used in the experiment. The inference power of the Bayesian classification network proposed was not fully reflected in the experimental results. Moreover, the experiment was only conducted for one week. The experimental results can only represent the students' performance in this short period of time. Furthermore, only 64 students participated in the experiment. More participants would be required to obtain stronger results.

Yang et al. (2021) indicated that smart learning environments should not only focus on performance but also human feelings. Ethics and norms should also be considered, and smart learning analytics should ensure privacy by enabling students to decide whether to give their permission for capturing and using their facial features. In this study, all participants were informed and consented that their facial information would be collected and recorded during the experiment.

6. Conclusion and future work

In this study, a learning status management system based on a Bayesian classification network was proposed in an intelligent classroom. Differing from past research, both sensor technology and image recognition technology were employed in the proposed system. Two experiments were conducted to evaluate the accuracy and effectiveness of the proposed system. From the experimental results, the learning status determined by the proposed system was highly correlated to that determined by human observers. Furthermore, the degrees of students' attention in class could be promoted when the proposed system was enabled. To sum up, the proposed system is helpful to teachers for ensuring more effective classroom management. As many researchers have indicated that the concentration of students' learning is the key factor influencing the learning effect (Delgado et al., 2011; Schmidt, 1990), it can be expected that with the help of the proposed system, students' learning performance will be promoted.

In the future, we will utilize all of the sensors indicated in the proposed Bayesian classification network for learning status analysis in the experiments to fully investigate the power of the proposed system. Moreover, the experiments will be conducted for at least one semester to evaluate the impacts of the system not only on learning status management but also on learning performance. Furthermore, more students will participate in the experiments to obtain stronger results.

In the post-pandemic era of Covid-19, in order to avoid face-to-face contact, many in-class learning activities have gradually transformed into online learning, either synchronous or asynchronous. How to manage students' learning status, and keep them attentive during online learning is more challenging than in classroom learning. Currently, most learning devices used in online learning are equipped with cameras and microphones. Smart bracelets that can detect various physiological signals are also becoming increasingly versatile and popular. Excluding the sensors installed in the intelligent classroom, the proposed learning status management system can also be applied in on-line learning environments. However, to reduce the communication load of transmitting the large amount of information captured by various sensors, the learning status inference engine has to be redesigned using edge computing. Moreover, the effectiveness of the proposed system needs to be further investigated in the context of on-line learning in the future.

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