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Student Engagement Analysis Using Facial Expression in Online Course

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***Abstract*— Due to the COVID-19 outbreak in recent years, long distance learning has been prevalent. The increasing need of online learning calls for the effectiveness of the learning evaluation method in digital learning through human-computer interaction (HCI) to be strengthened. Therefore, this study collects bigdata images through computer vision, collects data on the students' emotional and behavioral dimensions under multi-dimensionality, and analyzes these data through deep learning (DL) with the student engagement model. This proposes an online student learning engagement analysis system based on biometrics image processing applied to artificial intelligence (AI). In the prediction of student participation, emotional and behavioral dimension data obtained from different students will be used to find out the weight relations between these two engagement dimensions and engagement value through the regression model of DL and evaluate participants' engagement status in online learning.**

Keywords— Facial expressions, Student engagement, Online learning.

I. Introduction

In recent years, the prevalence of COVID-19 urged governments around the world to recommend people to social distance. Whereas, schools are public places where many people gather, so distance teaching can be expected to become a future trend. The education method under the traditional teaching environment prioritizes instilling knowledge into students and arranging frequent examinations in a short period of time to stimulate students to study and achieve the goal of improving their grades. Nonetheless, compared with online teaching, traditional teaching still has its irreplaceable role. For example, teachers can adjust their teaching style according to his or her students' participation in class as feedback; students can also discuss the material that is too difficult to understand interactively with the teachers in class. Students can discuss with teachers instantly and with the interactive freedom without the constraints of asynchronous learning. If the teaching environment is altered to a long distance synchronous/asynchronous teaching, teachers will not be able to confirm the students' attentiveness in the classroom, whether they are present in front of the screen at all times, etc.

Student engagement is considered to be synonymous with educational quality and is positively correlated with a student's perseverance, satisfaction, learning efficiency, and degree completion [1]. Kahu [2] mentioned that student engagement is a reflection of a student's internal psychological state, which includes behavior, cognition and emotion. Krause *et al.* [3] found that student engagement is related to the student's psychological participation in activities, and the quality and frequency of participation in the process can further predict learning outcomes.

In this paper, we utilize the concept of student engagement as a measurement of students' learning outcomes and proposes an analysis system for student participation in online courses based on facial expressions. It will use the detection of macro expression and micro expression of human face in biometric image recognition, as well as the participation detection and evaluation of students' learning by recording class notes, to give teachers an objective standard to measure students' learning outcomes.

II. Proposed Method

In recent years, online teaching has become popular, as the pandemic has forced many teachers into online teaching. As a result, many online paid teaching platforms have gradually emerged. Therefore, this paper proposes an online course platform as a reference for teachers' teaching feedback and also presents the system in the form of a web page for a student's convenience. The web server used in this study uses Apache server combined with PHP and MySQL databases, and uses HTML, CSS, and JavaScript as web development tools. The website is divided into student and teacher access portals. Students can watch videos through the student web page and pay to unlock them to view their learning results. Teachers can upload classroom videos through the teacher terminal page and view the students' progress in their classrooms to adjust their teaching policies. The system will also provide an area for the student to take notes on. A student notetaking section is shown in Fig. 1.

The engagement detection process architecture proposed in this paper uses facial expressions as the input data of the model architecture to detect the two engagement dimensions of emotional and behavioral engagement [4]. In the emotion dimension detection process, the architecture used for macro-expression detection is ResNet-18 [5]. In the detection process, the image will first be detected, and when a face is detected in the image, the facial information will be extracted. A face alignment is performed, and the aligned image crops the face to obtain the entire face area as input. In the training process of the macro-expression detection model, an attention mechanism [6-7] is added to allow the model to focus only on the facial regions that are helpful for the emotion classification results and enhance the generalization ability of the model. Micro-expression detection is composed of two model architectures, CNN and long short-term memory (LSTM) [8], as shown in Fig. 2. Because each micro-expression is composed of localized subtle movements that may appear in responses in all regions or in a single region. Ekman *et al*. [9], most of the facial emotions from muscle movements are directly or indirectly affected by these two regions, so the extracted facial information will be used in the micro-expression detection framework. Cropping is performed to obtain two regions of interest (ROI), the eye and eyebrow regions and the mouth region. Then, the CNN model is individually trained to extract the spatial features of the ROI, and the extracted spatial features will be used as the input data of the LSTM model. The LSTM model will extract temporal features from the sorted spatial features, and finally obtain temporal and spatial features. The CNN model of each ROI will be connected to an LSTM model, and the results of the LSTM will be merged together, and then two fully connected layers will be used to classify the features and obtain the prediction result of the sample. During model training, the public datasets used are CASME II, SAMM, and SMIC, respectively, and the database containing emotion is classified into positive emotions and negative emotions according to the definition of emotion dimension in [4].

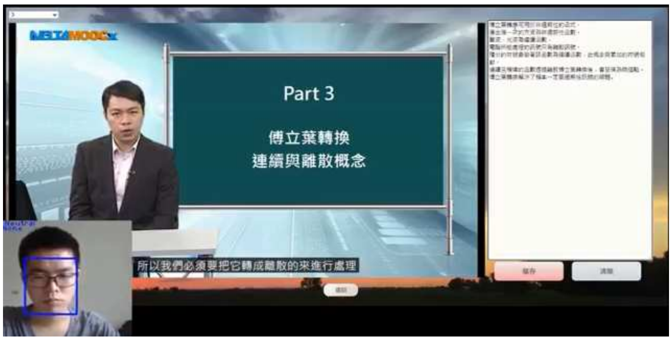

Figure 1. Students participating in distance courses.

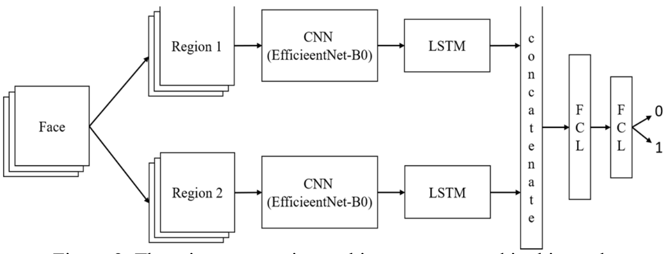

Figure 2. The micro-expression architecture proposed in this work.

III. Experimental Results and Discussion

This study uses two methods to conduct experiments on emotional participation. The first is to use only macro-expression detection to identify facial emotions, and to use the shortest duration of macro-expressions as the time interval for emotion recognition. The second is to use macro-expression detection and micro-expression detection and use frame-by-frame detection to identify facial emotions. The deep regression model is trained on these two cases, and the obtained weights are [0.0205, -0.0227], [0.1001, -0.0180], where the first dimension is the weight value of the emotion dimension, and the second dimension is the value of the behavior dimension. According to the weight of the regression model, it can be known that participation is positively correlated with the number of positive emotions, but negatively correlated with notetaking. It can be seen from the experiment that taking notes while watching the course video may affect the student' absorption of the course content, and further lead to poor learning effect. It can be seen that the emotional dimension has a greater impact on the experimental results than the behavioral dimension. Additionally, the weight of the emotional dimension after adding micro-expression detection is higher than that of the macro-expression detection. The importance of the emotional dimension also increases correspondingly, so the use of micro-expression detection on the emotional dimension can effectively improve the accuracy of engagement detection.

IV. Conclusion

This study will collect the students' face image big data through computer vision from their psychological and behavioral characteristics and use these data through DL and combining the student engagement model to analyze and propose an artificial intelligence online learning feedback system based on biometrics image technology. Evaluating a student's engagement, the data of emotional and behavioral dimensions will be obtained from various students through the regression model of deep learning to find out the weight relationship between these two dimensions of participation and the level of participation. The participation status of online teaching is assessed. The proposed method can be used for statistical analysis and evaluation of the online teaching status of emerging digital learning in the future. On the other hand, the feedback information through the system can provide teachers with an objective and statistical reference to student engagement.

References

[1] G. D. Kuh, "What student affairs professionals need to know about student engagement," *Journal of College Student Development*, vol. 50, no. 6, pp. 683-706, 2009.

[2] E. R. Kahu, "Framing student engagement in higher education," *Studies in Higher Education*, vol. 38, no. 5, pp. 758-773, 2013.

[3] K. L. Krause and H. Coates, "Students' engagement in first-year university," *Assessment and Evaluation in Higher Education*, vol. 33, no. 5, pp. 493-505, 2008.

[4] L. Wang and Y. He, "Online learning engagement assessment based on multimodal behavioral data," *Transactions on Edutainment XVI*, vol. 11782, pp 256-265, 2020.

[5] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 770-778, 2016.

[6] P.-Y. Yang, S.-Y. Jhong, and C.-H. Hsia, "Green coffee beans classification using attention-based features and knowledge transfer," *IEEE Int. Conference on Consumer Electronics- Taiwan*, pp. 1-2, 2021.

[7] P. Wang, H.-W. Tseng, T.-C. Chen, and C.-H. Hsia, "Deep convolutional neural network for coffee bean inspection," *Sensors and Materials*, vol. 33, no. 7(1), pp. 2299-2310, 2021.

[8] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735-1780, 1997.

[9] P. Ekman and W. V. Friesen, "Facial action coding system (FACS): a technique for the measurement of facial actions," *Rivista Di Psichiatria*, vol. 47, no. 2, pp. 126-138, 1978.