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Real-Time Emotion Recognition in Online Learning Using Google Teachable

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Abstract:

Understanding learners' emotional engagement in e-learning environments remains challenging due to the limited availability of non-verbal cues, despite its importance for motivation and participation. This paper proposes a facial emotion recognition approach using Google's Teachable Machine to support real-time emotion detection within online learning environments. The system analyzes facial expressions captured through a standard webcam to classify four basic emotional states: happy, sad, neutral, and angry. An experimental design was employed using simulated emotional expressions collected under controlled conditions, including adequate lighting and front-facing facial images. The results indicate that the system can provide instructors with additional affective cues to support formative assessment and instructional awareness in synchronous online learning. The proposed approach emphasizes practical instructional feasibility and accessibility compared to more complex emotion recognition models, as it does not require specialized hardware or advanced programming skills.

Keywords: *Affective Computing, Emotion Recognition, Facial Expression Analysis, Online Learning, Teachable Machine*

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Introduction

Online learning has significantly transformed teaching and learning practices. Despite its flexibility, online learning presents new difficulties for teachers, especially when it comes to comprehending the conditions and engagement of students during virtual instruction. The students' emotional experiences have a big influence on their learning motivation, concentration, engagement, and overall success. Students in online learning environments experience diverse emotional states, such as boredom, confusion, frustration, and satisfaction, which may emerge at different stages of the learning process. Because they are dynamic and change throughout the learning process, these emotional states influence students' cognitive engagement and knowledge construction (D'Mello & Graesser, 2012). Since the number of non-verbal communication signs that the lecturers use in the online learning process is limited, the lecturers might experience difficulties when interpreting the emotions that are shown by the students. Estimating the students' shown emotions might not be accurate since the access to the non-verbal communication signs used during the online learning process, especially when the students are passive, might not be easy.

When the teacher cannot recognize the emotions of the student, it becomes quite difficult to develop the required teaching styles for the particular student. This becomes more challenging when the teacher has to deliver highly complicated concepts while also motivating the student to be more proactive in the discussion and communicate effectively with the teacher as well as the rest of the class. In light of the challenges, the application of Artificial Intelligence (AI) has emerged as a feasible approach to understanding students' emotional responses in online learning environments. One of the growing research areas that marry AI and education involves the use of computer-based methods to determine the emotional state of students. The area of affective computing has become a significant domain in education, as reported by the latest studies that involve the use of systematic reviews. There is a growing need to use AI and ML to determine the emotions of students (Yuvaraj et al., 2025). Affect detection, which enables adaptive instructional responses based on learners' emotional states, has been established as a fundamental component of intelligent educational systems by early foundational work (Calvo & D'Mello, 2010). As per educational psychology, one of the major aspects influenced by emotions is learning experiences as well as learning outcomes. For instance, achievement emotions like happiness, boredom, confusion, as well as frustration with learning outcomes, would be immensely influenced in case of engagement with learning activities (Pekrun, 2024). When it comes to online learning, it would be difficult for the teacher to express their emotions because of the limited information presented to them.

Building upon these theoretical foundations, recent empirical studies have explored the practical application of AI-based emotion recognition in online learning environments. Findings from recent research indicate that teachers are able to use the webcam-based facial expression method in order to detect real-time emotional states of the learners without interrupting teaching and learning practices, thereby promoting teacher-student awareness in an online class (Llurba & Palau, 2024; Zhou, 2023). The effectiveness of AI-assisted emotion analysis in online learning has been demonstrated in previous studies. These studies included multimodal emotion detection analysis, which analyzed students' body expressions, eye movements, and facial movements to detect emotions during online courses (Qi et al., 2024). The application of instructor-assisted online course modifications has been evaluated in the context of CNN-assisted emotion detection, as demonstrated in a study (Ye, 2022). The analysis of this technology has been evaluated in order to analyze the students' online course as it will help the instructors understand the emotions of the learners, as demonstrated in the comprehensive study analysis conducted in the study (Mangaras Yanu Florestiyanto, 2024).

Existing systems for emotion recognition are mostly based on deep learning models, which are impractical to fully integrate within the educational environment, as they require substantial amounts of data, computational power, and technical knowledge (Rathod et al., 2022; Savchenko, 2021). Certain writers have suggested that browser versions of Teachable Machine offered easier development, implementation, and teacher confidence in using AI software in the classroom (Kurz et al., 2024). Although emotion recognition within the context of online learning has been extensively addressed by research, to date, research largely centers on more complex architectures of deep learning, and Google Teachable Machine remains an unexamined tool. Such architectures could potentially be extremely successful, but they could also prove to be of little use and are quite hard to implement in an online learning process. At the current stage, it can be said that there has been inadequate research conducted by models such as Google Teachable Machine, leading to a lack of hard facts related to the use, adaptability, and usability of browser-based software.

In addition to technical feasibility, the implementation of emotion recognition tools in real-world classrooms is also influenced by pedagogical, environmental, and contextual factors. The benefits contributed by such advanced technology, which can allow learning effortlessly for everyone in the class, make a tremendous contribution towards the integration of efficient techniques of algorithms in the class learning environment. The technology tools, as studied in this research, have immense significance and are considered both technology and society because of their non-technological role in the outer boundaries of technology (Chen & He, 2022; Salloum et al., 2025). The virtual-class contains varying levels of challenging factors, which have features such as light, cameras, as well as models of the face expressed in the natural-class environment, which exist in the outer boundaries/components of the world. The technology itself varies according to the levels of learning (Hakim et al., 2024; Li et al., 2024). Previous studies have shown a strong correlation between lower learning outcomes and participation, particularly in technology-mediated learning environments, and emotional conditions like boredom and inactivity (Bosch, 2016).

In recent years, there has been a significant amount of research that endorses the role of some emotional states, such as boredom and confusion, in the processes related to the acquisition of knowledge acquisition processes, including Self-Regulated Learning (SRL), Experiential Learning (EL), and Participatory Learning (Ding & Xing, 2022; Zhou, 2023). Although SRL, EL, and Participatory Learning techniques have been gaining acceptance in the literature as effective methods for supporting and assisting in the learning process, very few have employed next-generation Affective Computing methods for the same in computer science education.

This study investigates the extent to which Google Teachable Machine (TM), a browser-based machine learning platform, can be utilised to identify learners' emotional states in online learning environments. Google Teachable Machine employs facial image analysis to classify emotional states based on key facial features captured through a webcam. It looks at the key facial features that determine if a person indicates a particular emotion, such as joy, sadness, or anger. Previous studies have highlighted the influence of environmental factors, such as lighting conditions, on the accuracy of facial emotion recognition, which is therefore considered in the design and evaluation of the proposed system in this study. In this research, an attempt has been made to examine how feasible it is to use Google Teachable Machine as a browser-based tool for conducting real-time facial emotion recognition in an online learning context. This paper will aim to find the viability of using Google's Teachable Machine software for real-time facial recognition of emotions in an online learning space. This research has significant contributions to existing literature in three forms. (1) it establishes the viability of a light-weight software for the detection of emotions. (2) it establishes the software in terms of its usability by educators who do not possess programming skills. (3) it establishes its relevance to learning processes.

Research Method

This study employed an experimental design to examine the feasibility of using Google Teachable Machine for real-time facial emotion recognition in a simulated online learning context, with an emphasis on instructional applicability rather than algorithmic optimization. The system focuses on four emotional expressions, happy, sad, neutral, and angry, which commonly occur in virtual classrooms and are closely associated with students' engagement levels. The study is positioned as a feasibility-focused investigation rather than a performance benchmarking study.

Figure 1 illustrates the entire process for emotion detection, from sequentially collecting facial images to evaluating the finished model after validation. This gives a clear picture of both the development and the validation process concerning the Emotion Detection System.

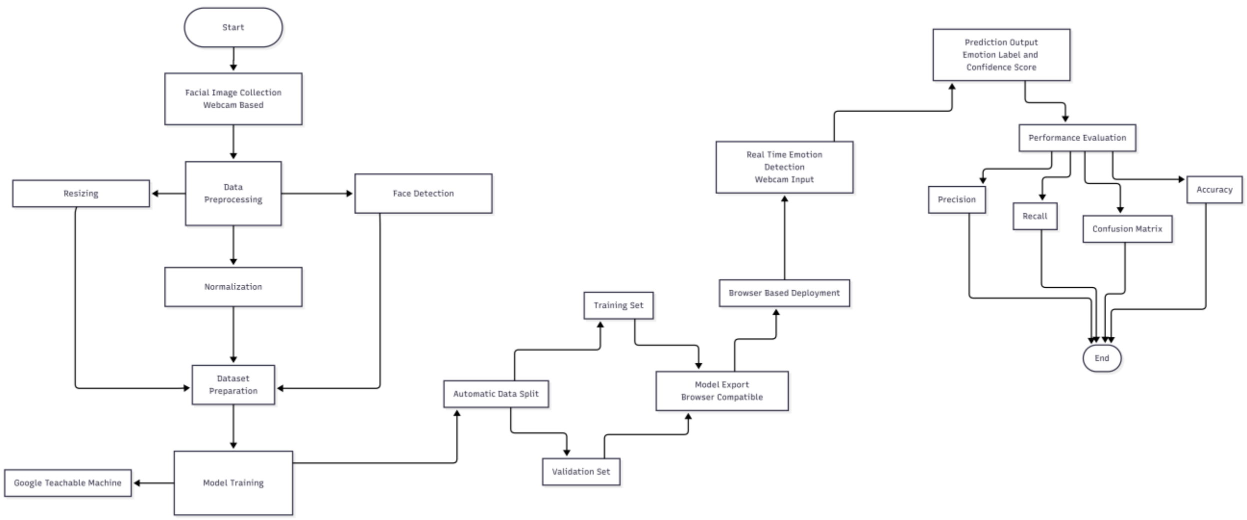

Figure 1. Workflow of the proposed real-time emotion recognition system

The previous workflow outlines the steps taken, which include facial image collection, data preprocessing, model training through Google Teachable Machine, implementation via web browser, live emotion detection, and assessing the performance of the four emotional reactions: happy, sad, neutral, and angry.

Participant and Ethical Considerations

The subjects who participated in this study were undergraduate students majoring in informatics. The participation of the subjects was voluntary, and they were asked to give their consent before collecting any data. No personal identifier was used, and all the facial images were used only for the purpose of this research. In Table 1, all emotional expressions in this study were simulated under controlled conditions to ensure participant comfort and ethical compliance. There were 8 undergraduate students who participated in this study.

Table 1. Participant and Dataset Description

Emotion Class	Description
Number of participants	8 undergraduate students
Emotion categories	Happy, Sad, Neutral, Angry
Images per emotion	40 images per emotion
Total images	160 images
Data collection	Webcam (simulated expressions)
Environment	Controlled lighting, front-facing camera

Data Collection

A total of eight undergraduate students participated in the data collection process, resulting in approximately 40 facial images for each emotion category. The facial images were captured using the participants' webcams as they intentionally expressed simulated emotions related to online learning activities. The subjects were required to display their facial expressions of happiness, sadness, anger, and neutrality. In order to ensure that only the frontal face of the subject is considered, these tasks were executed in environments that were controlled and properly lit. Images with improper facial alignment or insufficient lighting were excluded from the dataset.

Data Preprocessing

Using Google Teachable Machine's built-in features, all facial images are automatically processed. This includes resizing and normalization to ensure consistent input dimensions throughout training. The facial image processing features provided in Google Teachable Machine were automatically utilized in the facial image processing. To ensure the images are of the same size during training of the Google Teachable Machine model, each photo was resized.

Model Training Using Teachable Machine

The collected data would then be used by the Google Teachable Machine in developing the image-classification machine learning model. The methodology behind the development of the CNN model in Google Teachable Machine includes the use of transfer learning, which is beneficial in training data effectively when the data volume is low. Further, it can also be obtained that splitting of data into training as well as validation data would also be done by the Google Teachable Machine. All the training and validation were done automatically on the site. Model training is carried out iteratively until stable classification results are obtained in all emotion categories. The use of Google Teachable Machine emphasizes accessibility and ease of use for educators without programming backgrounds in Table 2.

Table 2. Model Training and Evaluation Setup

Aspect	Description
Platform	Google Teachable Machine
Model type	Transfer learning (CNN-based)
Total images	160 images
Evaluation mode	Live webcam testing
Metrics	Accuracy, Prediction

Model Evaluation

The trained model was evaluated using live webcam input under controlled lighting conditions. For every facial expression that it was able to identify, it made predictions about emotions along with the level of confidence for every emotion. The webcam images were tested on the model for performance. The model's capacity to discriminate between simulated emotional expressions was evaluated using standard classification metrics, such as accuracy, precision, recall, and confusion matrix. In this case, however, the experiment aimed at finding out how well it was able to differentiate between the four emotions in normal conditions, a case that included appropriate lighting. The results are presented in the results and discussion part.

Result and Discussion

Result

Using the Google Teachable Machine, an emotion recognition system was developed with four different emotional categories: happy, sad, neutral, and angry. These four emotion categories were selected based due to their frequent occurrence in online learning settings and to maintain a consistent experimental setup.

Table 3. Performance metrics for the four classes of emotions

Emotion Class	Accuracy (%)	Precision (%)	Recall (%)
Happy	94.6	95.2	93.8
Sad	88.1	86.9	89.4
Neutral	91.7	90.8	92.6
Angry	89.9	90.3	88.7

An emotion recognition model could perform a process through a website that could take real-time inputs from the webcam after being tuned by the training procedure. The output that was derived from the assessment of the Emotion

Recognition Process includes, but is not limited to the labels that recognized the emotions and, more precisely, the confidence level of each facial expression identified. Among the usual assessment criteria that could be applied to classification models were accuracy, precision, and confusion matrix assessments. Table 3 presents the classification performance obtained under simulated conditions with controlled lighting and a limited dataset.

The results of the assessment showed that the model achieved an overall accuracy of 91.1% under controlled experimental conditions, indicating its feasibility for recognizing simulated facial emotions in an online learning scenario. The higher recognition accuracy for the happy emotion may be attributed to more distinctive facial features compared to other emotion classes. However, accuracy for 'sad' and 'angry' emotions was marginally affected, which might be because these two have quite similar features, along with being quite subtly expressed. In order to further evaluate the classification trend of the model, a confusion matrix has also been created in Table 4. The confusion matrix was generated from repeated live testing sessions and reflects aggregated predictions rather than a fixed offline test split.

Table 4. Confusion matrix for four-class emotion recognition

Actual \ Predicted	Happy	Sad	Neutral	Angry
Happy	47	1	2	0
Sad	2	44	3	1
Neutral	1	2	46	1
Angry	0	2	3	45

As it can be seen from Table 4, the results of predictions are concentrated around the diagonal elements of the confusion matrix, which means that they are correct for the four emotional classes. The off-diagonal errors in classification are limited to small errors between the classes of neutral, negative emotions representing similar displays of low-intensity emotions on the face, such as sad and angry. These results suggest that the developed model is capable of distinguishing between simulated facial emotions under controlled illumination conditions.

Discussion

The results of this study show that, under simulated online learning conditions, a browser-based facial emotion recognition system created using Google Teachable Machine can identify four basic emotional states, happy, sad, neutral, and angry, with an overall accuracy of 91.1%.

The results indicate several concrete instructional applications for synchronous online learning environments. For example, if students exhibit negative or non-expressive responses during the learning process, it may be considered a non-participative behaviour. When negative or neutral emotional states are identified, teachers can modify their teaching methods by introducing interactive questions, brief discussions, or pacing changes. In the online formative assessment component, the affective feedback strategy may help the teacher in understanding how students have been reacting to the online learning process.

An analysis carried out in relation to the accuracy of classification of the emotion of the system indicates that the accuracy of classification of happiness emotion with high facial expression components was more accurate in comparison to the accuracy of classifications of other emotions related to sadness and anger emotions. This pattern is consistent with findings in effective computing literature. This research indicated that happiness can actually be related to a situation of high facial muscle expression in comparison to the anger emotion, which can actually be observed through facial muscle expression in relation to high muscle expression without any problems (Savchenko, 2021; Ye, 2022). In contrast to this situation, it could have been argued in relation to the analysis of confusion matrix. This has been indicated to state the maximum number of errors carried out between the groups in this research. This has been indicated in this research to occur between the neutral and negative emotion. In online learning environments, learners typically exhibit more subdued facial expressions than in face-to-face settings, so such misclassifications are expected (D'Mello & Graesser, 2012; Llurba & Palau, 2024).

However, even under such scenarios, generalization of these results should be approached cautiously. Model performance may vary across different student populations, lighting conditions, webcam quality, and spontaneous emotional expressions. Not to mention, natural displays that are commonly brought about under a typical online learning experience, all of these possible factors that might have an effect on these models. Thus, it can be noted that within the context of the study conducted, the experimental design will not cover the simulation of a typical learning experience scenario or, as a matter of fact, seeks to establish the efficiency that such a system can actually achieve.

Additionally, the study has a restriction related to the limited categories of emotions used. Although happy, sad, neutral, and angry emotions are commonly used in facial emotion recognition research and are technically suitable for browser-based implementation, learning-relevant emotions such as boredom and confusion were not explicitly included. These emotions are closely linked to cognitive engagement and self-regulated learning, yet they often manifest through subtle facial cues or temporal behavioral patterns that are difficult to capture using single-modality visual analysis alone (D'Mello & Graesser, 2012; Pekrun, 2024).

From a theoretical standpoint, this study contributes to affective computing by demonstrating that emotion-aware systems can be implemented using low-barrier, browser-based AI tools suitable for educational contexts. In addition, the fact that this research has succeeded in highlighting the link between affective states and online engagement in online learning communities makes it theoretically important regarding engagement. The fact that these affective states may further be differentiated or recognized with respect to their inclusion in learning analytics strongly asserts the pertinence of carried-out research work for this purpose within AI and Learning Analytics. The findings also reinforce engagement theory by highlighting the relationship between observable affective states and learner participation in online environments, and support the integration of affective signals within AI-supported learning analytics.

Future research results should extend this work by incorporating multimodal emotion recognition approaches, combining facial expressions with speech cues, eye gaze, or interaction patterns. As explained above, previous studies have noted that using multimodal affect recognition (D'Mello & Graesser, 2012; Qi et al., 2024), added more insight into the learners' affective processes in addressing tasks related to learning that are complex. In fact, other states relevant to learning in an online context, which are boredom and confusion, will enhance the affects computing also when identified.

Conclusion

This study demonstrates the feasibility of using Google Teachable Machine (TM) as a browser-based tool for real-time facial emotion recognition in a simulated online learning context. The proposed browser-enabled system is suitable for online learning environment with limited technical infrastructure, as it does not require advanced programming skills or specialized hardware. The experimental results indicate that the system can classify four basic emotional states, happy, sad, neutral, and angry, under controlled conditions, including adequate lighting and front-facing images. When students' emotional states are identified during online classes, it can provide instructors with additional affective cues to support instructional decision-making and formative assessment. Overall, this study contributes empirical evidence supporting the instructional feasibility of lightweight affective computing tools and highlights their potential role in developing more responsive, emotion-aware online learning practices.

References

Bosch, N. (2016). Detecting student engagement: Human versus machine. *Proceedings of the 2016 Conference on User Modeling Adaptation and Personalization*, 317–320. https://doi.org/10.1145/2930238.2930371

Calvo, R. A., & D'Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods, and their applications. *IEEE Transactions on Affective Computing*, *1*(1), 18–37. https://doi.org/10.1109/T-AFFC.2010.1

Chen, Y., & He, J. (2022). Deep Learning-Based Emotion Detection. *Journal of Computer and Communications*, *10*(02), 57–71. https://doi.org/10.4236/jcc.2022.102005

D'Mello, S., & Graesser, A. (2012). Dynamics of affective states during complex learning. *Learning and Instruction*, *22*(2), 145–157. https://doi.org/10.1016/j.learninstruc.2011.10.001

Ding, Y., & Xing, W. (2022). Emotion recognition and achievement prediction for foreign language learners under the background of network teaching. *Frontiers in Psychology*, *13*, 1017570. https://doi.org/10.3389/fpsyg.2022.1017570

Hakim, G. J. P., Simangunsong, G. A., Ningrat, R. W., Rabika, J. C., Rusafni, M. R., Giri, E. P., & Mindara, G. P. (2024). Real-Time Facial Emotion Detection Application with Image Processing Based on Convolutional Neural Network (CNN). *International Journal of Electrical Engineering, Mathematics and Computer Science*, *1*(4), 27–36. https://doi.org/10.62951/ijeemcs.v1i4.123

Kurz, T. L., Jayasuriya, S., Swisher, K., Mativo, J., Pidaparti, R., & Robinson, D. T. (2024). The Impact of Teachable Machine on Middle School Teachers' Perceptions of Science Lessons after Professional Development. *Education Sciences*, *14*(4), 417. https://doi.org/10.3390/educsci14040417

Li, S., Ji, M., Chen, M., & Chen, L. (2024). Facial length and angle feature recognition for digital libraries. *PLoS ONE*, *19*(7), e0306250. https://doi.org/10.1371/journal.pone.0306250

Llurba, C., & Palau, R. (2024). Real-Time Emotion Recognition for Improving the Teaching–Learning Process: A Scoping Review. *Journal of Imaging*, *10*(12), 313. https://doi.org/10.3390/jimaging10120313

Florestiyanto, M. Y. (2024). Emotion Recognition for Improving Online Learning Environments: A Systematic Review of the Literature. *Journal of Electrical Systems*, *20*(S4), 1860–1873. https://doi.org/10.52783/jes.2255

Pekrun, R. (2024). Control-Value Theory: From Achievement Emotion to a General Theory of Human Emotions. *Educational Psychology Review*, *36*(3), 97. https://doi.org/10.1007/s10648-024-09909-7

Qi, Y., Zhuang, L., Chen, H., Han, X., & Liang, A. (2024). Evaluation of Students' Learning Engagement in Online Classes Based on Multimodal Vision Perspective. *Electronics*, *13*(1), 149. https://doi.org/10.3390/electronics13010149

Rathod, M., Dalvi, C., Kaur, K., Patil, S., Gite, S., Kamat, P., Kotecha, K., Abraham, A., & Gabralla, L. A. (2022). Kids' Emotion Recognition Using Various Deep-Learning Models with Explainable AI. *Sensors*, *22*(20), 8066. https://doi.org/10.3390/s22208066

Salloum, S. A., Alomari, K. M., Alfaisal, A. M., Aljanada, R. A., & Basiouni, A. (2025). Emotion recognition for enhanced learning: using AI to detect students' emotions and adjust teaching methods. *Smart Learning Environments*, *12*(1), 1–25. https://doi.org/10.1186/s40561-025-00374-5

Savchenko, A. V. (2021). Facial expression and attributes recognition based on multi-task learning of lightweight neural networks. *2021 IEEE 19th International Symposium on Intelligent Systems and Informatics (SISY)*, 119–124. https://doi.org/10.1109/SISY52375.2021.9582508

Ye, F. (2022). Emotion Recognition of Online Education Learners by Convolutional Neural Networks. *Computational Intelligence and Neuroscience*, *2022*, 4316812. https://doi.org/10.1155/2022/4316812

Yuvaraj, R., Mittal, R., Prince, A. A., & Huang, J. S. (2025). Affective Computing for Learning in Education: A Systematic Review and Bibliometric Analysis. *Education Sciences*, *15*(1), 65. https://doi.org/10.3390/educsci15010065

Zhou, Q. (2023). Application of AI Technology in Online Platforms Based on Cognitive Emotion Regulation. *Frontiers in Artificial Intelligence and Applications*, *378*, 262–271. https://doi.org/10.3233/FAIA231030