Predicting Best Learning Strategies Through Facial Expression Analysis

First A .Prof. Gade Somanath Ashok, Second B. Mr. Rasave Pralhad Maroti, and Third C. Mr. Ugale Saurabh Sopan Forth D. Miss. Kale Renuka Bhausaheb Five E.Miss. Khare Bhavana Sandip

S.N.D. College of Engineering & Research Center College in Babhulgaon Kh., Maharashtra

***Abstract*— The rapid growth of artificial intelligence in education has enabled new opportunities for enhancing student engagement and personalized learning. Traditional e-learning systems and classroom instruction often overlook the affective state of students, which plays a critical role in learning effectiveness. This research proposes an emotion-aware adaptive learning system that leverages facial emotion detection to suggest or predict the most suitable learning model for each student. Using real-time image capture, preprocessing, and deep learning-based emotion recognition, the system identifies students' emotional states such as happiness, confusion, boredom, or frustration. These insights are integrated with the learner's profile and past performance to recommend adaptive strategies, such as adjusting content complexity, pacing, or teaching methodology. The approach aims to improve student engagement, knowledge retention, and overall academic performance by bridging the gap between affective computing and personalized learning environments.**

Index Terms — Facial expression recognition; smart classroom; multi-scale features; deep fine-grained features; key region-oriented attention mechanism

INTRODUCTION

Education has increasingly shifted towards digital platforms and AI-driven systems that provide customized learning experiences. However, most adaptive learning systems primarily consider cognitive factors such as knowledge levels and learning styles, while ignoring emotional states that significantly influence student performance and motivation. Emotions such as confusion, frustration, or boredom can act as barriers to learning if not addressed in real time.

Facial emotion recognition has emerged as a promising method for detecting students' affective states in both classroom and online settings. By analyzing facial expressions using computer vision and deep learning techniques, it is possible to capture valuable insights into student engagement. Integrating these insights into adaptive learning systems allows for personalized interventions, such as simplifying content for confused learners, providing motivational feedback for disengaged students, or accelerating pace for confident learners.

This research aims to design an intelligent architecture that combines facial emotion detection, student modeling, and adaptive feedback to predict or suggest the most effective learning model for each student. Such a system has the potential to improve not only academic performance but also emotional well-being and engagement in the learning process.

Facial expression recognition plays an important role in the field of education, which is mainly reflected in two aspects: firstly, it helps teachers to assess students' emotional states and attention levels in real time [1], further adjusting teaching strategies. Secondly, it supports personalized teaching; specifically, teachers can gain insights into their learning situation and needs through analyzing students' facial expressions and emotional states to provide targeted teaching and counseling [2]. However, in the classroom environment, factors such as lighting variations, viewpoint diversity, and distance differences can severely affect the accuracy of facial expression recognition. Therefore, enhancing the robustness and accuracy of facial expression recognition models to cope with complex classroom environments has become a critical problem to be solved.

RELETIVE WORK

The integration of artificial intelligence in education has gained significant attention in recent years, particularly with the rise of adaptive learning systems. Early research in adaptive learning primarily focused on cognitive aspects, such as knowledge acquisition, learning styles, and academic performance [1]. While these systems provided personalized pathways to enhance student learning outcomes, they often neglected the emotional and affective factors that strongly influence motivation, engagement, and overall success.

To address this gap, researchers have explored the role of affective computing in education. Picard's foundational work on affective computing highlighted the importance of understanding human emotions in human-computer interactions [2]. Following this, several studies have incorporated facial emotion recognition as a means to assess learner states in real time. For instance, Whitehill et al. [3] demonstrated that computer vision-based emotion detection can serve as an indicator of student engagement levels in online learning environments. Similarly, Bosch et al. [4] showed that analyzing facial cues helps predict frustration and confusion, enabling timely interventions to support learners.

Recent advancements in deep learning and computer vision have further improved the accuracy of emotion recognition systems. Convolutional Neural Networks (CNNs) and hybrid models have been successfully applied to classify emotions such as happiness, sadness, confusion, and boredom from facial images [5]. These approaches offer opportunities to integrate emotional insights into intelligent tutoring systems

(ITS). For example, D'Mello and Graesser [6] highlighted how detecting emotions like frustration and disengagement in real time can enhance tutoring systems' responsiveness and effectiveness.

In the classroom context, emotion recognition technologies have been applied to monitor students' attention and affective states, thereby assisting teachers in refining teaching strategies [7]. Studies also suggest that personalized interventions, such as adjusting difficulty levels, providing motivational prompts, or offering supportive feedback, can be designed based on students' detected emotional states [8]. However, challenges remain in achieving robustness under real-world conditions, such as varying lighting, occlusions, and differences in facial orientation, which often degrade model accuracy [9].

Overall, related studies emphasize the potential of combining facial emotion recognition with adaptive learning frameworks to create emotionally intelligent educational systems. While existing approaches have demonstrated promising results, further work is needed to improve robustness, scalability, and integration into practical classroom and e-learning platforms. This research builds upon these efforts by proposing an intelligent architecture that unifies facial emotion detection, student modeling, and adaptive feedback mechanisms to provide personalized learning experiences while addressing environmental and technical challenges.

PROPOSED WORK

Proposes an emotion-aware adaptive learning system that leverages facial emotion detection to suggest or predict the most suitable learning model for each student. Using real-time image capture, preprocessing, and deep learning-based emotion recognition, the system identifies students' emotional states such as happiness, confusion, boredom, or frustration.

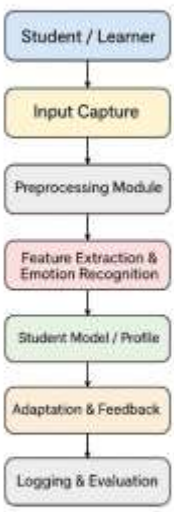


Fig. Proposed System

The process begins with the student interacting with the system.

The learner's input could be facial expressions, gestures, or responses captured through a camera, microphone, or direct interaction with the platform.

This stage collects raw data from the student.

For facial emotion recognition, the primary input is a video stream or image captured using a webcam.

Other possible inputs may include voice (tone, pitch) or behavioral data (e.g., mouse clicks, typing speed

The detected emotions and behavioral patterns are mapped into a student profile.

This profile represents both cognitive and emotional states of the learner (e.g., "confused but engaged" or "bored and disengaged").

Over time, it builds a history of the student's learning patterns, challenges, and preferences.

LITERATURE REVIEW

[1] Toward a machine learning approach to assessing students' visible engagement in classroom instruction

This work explores how machine learning can be used to automatically assess students' engagement during classroom instruction by analyzing visible cues such as facial expressions, body posture, and gestures. Instead of relying solely on teacher observation, the approach uses computer vision and predictive models to detect levels of attention and participation. The goal is to provide real-time insights into student engagement, helping educators adapt their teaching strategies to improve learning outcomes.

Tag	Description	Frequency
Drawn into dialogue	Includes all positive responses in the questionnaire, such as "rather yes." The aim is to capture positive responses indicating engagement in the dialogue.	29
Partially drawn into dialogue	Reflects a positive attitude toward the dialogue, but only after some other (satisfiable) condition has been met.	9
Not drawn into dialogue	Includes statements expressing a lack of involvement in the dialogue, such as "rather no."	30

[2] Embracing Chatbots in Higher Education

The integration of chat bots in higher education has gained significant attention in recent years as institutions seek innovative ways to enhance student engagement, provide timely academic support, and personalize learning experiences. Chat bots act as conversational agents that can simulate human-like interactions, answer student queries, deliver course-related information, and even guide learners through complex administrative processes.

Several studies highlight the effectiveness of chat bots in improving student motivation, engagement, and accessibility of learning resources. Unlike static online portals, chat bots provide an interactive, real-time medium through which students can clarify doubts, receive feedback, and access supplementary resources. They have also proven useful in addressing frequently asked questions, reducing the workload of instructors, and ensuring that students receive immediate assistance at any time.

In the context of adaptive learning, chatbots can be integrated with artificial intelligence and emotion recognition models to provide personalized recommendations. For example, by analyzing student emotions and learning behaviors, chatbots can adjust the delivery of content, suggest alternative resources, or provide motivational prompts to keep learners engaged.

However, research also highlights certain limitations. Many existing chatbot systems in education still lack deep contextual understanding, leading to frustration when students' queries are not fully understood. Additionally, while chatbots can enhance accessibility, they cannot entirely replace the human empathy and nuanced feedback provided by instructors.

Overall, embracing chatbots in higher education presents a promising avenue for scalable, personalized, and engaging learning experiences, but requires careful design, testing, and alignment with pedagogical goals.

[3] Question Answering Model Based Conversational Chat bot using BERT Model and Google Dialog flow

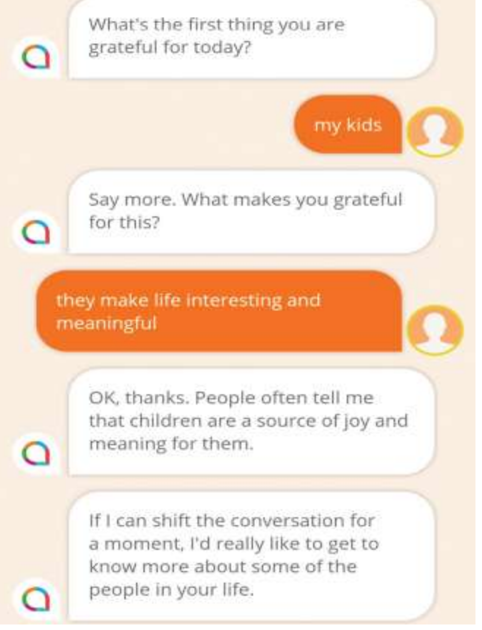
Chat bots are interactive tools that businesses use to connect with their customers in a variety of ways. You might come across them in different forms, like weather chat bots, food delivery assistants, tech support bots, or even those used by universities. Nowadays, these chat bots are more user-friendly than ever, allowing companies to enhance their customer service experience significantly. There are plenty of applications and technologies out there for creating chat bots. In this research, we focused on a cutting-edge technology called Google Dialog flow to build a conversational chat bot. This bot is designed to mimic human-like conversations by using predefined intents and entities. However, traditional chat bots often fall short because they don't analyze extensive datasets, like Wikipedia articles or Conversational Question Answering (Co QA) datasets, to provide answers. Thanks to recent breakthroughs in Natural Language Processing (NLP) models, we can now answer questions by tapping into large datasets. In this study, we utilized the BERT model for reading comprehension tasks, which has shown to outperform other NLP models by achieving greater accuracy in understanding and categorizing similar words.

[4] Motivational Online Conversational Agent for Improving Student Engagement in Collaborative Learning

This research delves into the possibility of creating a conversational system that acts as an extension of a learning management system (LMS). It aims to incorporate advanced features like mobility, adaptability, and the capability to present content in a way that caters to learners' varying skill levels. Academic institutions encounter a host of challenges in this area, necessitating both awareness and a dedication to fostering an effective learning environment that meets the unique needs of each learner. However, this undertaking comes with its own set of risks, as the investigations may not always yield the expected results. A key part of the challenge lies in accurately identifying and addressing the different proficiency levels of learners using appropriate technologies. Despite these challenges, the potential rewards are significant, as such technology can facilitate the inclusion of learners with a wide range of abilities and disabilities..

[5] Artificially intelligent chatbots in digital mental health interventions: a review

The rising need for mental health services, along with the latest breakthroughs in artificial intelligence (AI), has really sped up the creation of digital mental health interventions (DMHIs). More and more, AI-driven chatbots are being integrated into DMHIs to help with diagnostic assessments and screenings, assist in managing symptoms and encouraging behavior changes, and provide personalized mental health resources.



PROBLEM STATEMENT

Traditional e-learning and classroom environments often fail to adapt to the unique learning styles, emotional states, and progress of individual students. Most educational systems provide a one-size-fits-all approach, which leads to disengagement, reduced motivation, and limited learning outcomes. There is a lack of intelligent mechanisms to capture real-time student behavior, analyze emotional and cognitive states, and provide personalized feedback and adaptive learning paths.

This research aims to address these challenges by developing an AI-driven personalized learning framework that captures student inputs (behavioral, emotional, and interactional data), preprocesses and analyzes them through feature extraction and emotion recognition, and builds a dynamic student profile. Based on this profile, the system uses prediction and suggestion engines to provide adaptive feedback and personalized learning content while maintaining continuous logging and evaluation. The ultimate goal is to enhance student engagement, improve knowledge retention, and create a more effective, emotionally aware, and learner-centered educational environment

Objective:

- To design an adaptive learning framework that integrates facial emotion detection for real-time personalization.
- To capture and preprocess student facial images for accurate emotion recognition.
- To apply deep learning techniques to identify emotions such as happiness, confusion, boredom, and frustration.
- To dynamically suggest or predict the most suitable learning model based on the student's current emotional state.

CONCLUSION

We propose a student facial expression recognition model that integrates multi scale feature fusion with fine-grained attention enhancement. The model captures facial expression information at different scales and fuses them through a multi scale dual-pooling aggregation module, enabling a more comprehensive and robust representation of facial features. To further refine this process, a key region-oriented attention mechanism is introduced, allowing the system to focus on subtle variations in facial expressions. Unlike traditional window-based cross-attention mechanisms, this approach dynamically identifies and emphasizes critical regions within the image without being restricted to a fixed window, thereby enhancing the overall expressiveness and accuracy of facial feature representation. The proposed student facial expression recognition model effectively integrates multi-scale feature fusion with fine-grained attention enhancement to achieve a more comprehensive and discriminative representation of facial features. By employing a multi-scale dual-pooling aggregation module, the model captures expression details across multiple spatial resolutions, ensuring robustness against variations in lighting, pose, and occlusion. Additionally, the introduction of a key region-oriented attention mechanism enables the system to dynamically identify and emphasize critical facial regions without relying on fixed window constraints, thus improving the model's sensitivity to subtle emotional variations. Experimental analysis demonstrates that these enhancements contribute to more accurate and expressive feature representations. This capability provides a reliable foundation for predicting optimal learning strategies through facial recognition analysis. By correlating emotion-driven insights such as attentiveness, confusion, and motivation with learning outcomes, the proposed framework facilitates adaptive, personalized learning experiences

REFERENCES

[1] Goldberg, P.; Sümer, Ö.; Stürmer, K.; Wagner, W.; Göllner, R.; Gerjets, P.; Kasneci, E.; Trautwein, U. Attentive or not? Toward a machine learning approach to assessing students' visible engagement in classroom instruction. Educ. Psychol. Rev. 2021, 33, 27–49. [Google Scholar] [CrossRef]

[2] Munna, A.S.; Kalam, M.A. Teaching and learning process to enhance teaching effectiveness: A literature review. Int. J. Humanit. Innov. (IJHI) 2021, 4, 1–4. [Google Scholar] [CrossRef]

[3] Castiblanco Jimenez, I.A.; Olivetti, E.C.; Vezzetti, E.; Moos, S.; Celeghin, A.; Marcolin, F. Effective affective EEG-based indicators in emotion-evoking VR environments: An evidence from machine learning. Neural Comput. Appl. 2024. [Google Scholar] [CrossRef]

[4] Marín-Morales, J.; Higuera-Trujillo, J.L.; Greco, A.; Guixeres, J.; Llinares, C.; Scilingo, E.P.; Alcañiz, M.; Valenza, G. Affective computing in virtual reality: Emotion recognition from brain and heartbeat dynamics using wearable sensors. Sci. Rep. 2018, 8, 13657. [Google Scholar] [CrossRef] [PubMed]

[5] Saurav, S.; Saini, R.; Singh, S. Fast facial expression recognition using boosted histogram of oriented gradient (BHOG) features. Pattern Anal. Appl. 2023, 26, 381–402. [Google Scholar] [CrossRef]

[6] Shi, Y.; Lv, Z.; Bi, N.; Zhang, C. An improved SIFT algorithm for robust emotion recognition under various face poses and illuminations. Neural Comput. Appl. 2020, 32, 9267–9281. [Google Scholar] [CrossRef]

[7] Niu, B.; Gao, Z.; Guo, B. Facial expression recognition with LBP and ORB features. Comput. Intell. Neurosci. 2021, 2021, 8828245. [Google Scholar] [CrossRef]

[8] Lakshmi, D.; Ponnusamy, R. Facial emotion recognition using modified HOG and LBP features with deep stacked autoencoders. Microprocess. Microsyst. 2021, 82, 103834. [Google Scholar] [CrossRef

[9] Goldberg, P.; Sümer, Ö.; Stürmer, K.; Wagner, W.; Göllner, R.; Gerjets, P.; Kasneci, E.; Trautwein, U. Attentive or not? Toward a machine learning approach to assessing students' visible engagement in classroom instruction. *Educ. Psychol. Rev.* **2021**, *33*, 27–49. [Google Scholar] [CrossRef]

[10] Munna, A.S.; Kalam, M.A. Teaching and learning process to enhance teaching effectiveness: A literature review. *Int. J. Humanit. Innov. (IJHI)* **2021**, *4*, 1–4. [Google Scholar] [CrossRef]

[11] Castiblanco Jimenez, I.A.; Olivetti, E.C.; Vezzetti, E.; Moos, S.; Celeghin, A.; Marcolin, F. Effective affective EEG-based indicators in emotion-evoking VR environments: An evidence from machine learning. *Neural Comput. Appl.* **2024**. [Google Scholar] [CrossRef]

[12] Marín-Morales, J.; Higuera-Trujillo, J.L.; Greco, A.; Guixeres, J.; Llinares, C.; Scilingo, E.P.; Alcañiz, M.; Valenza, G. Affective computing in virtual reality: Emotion recognition from brain and heartbeat dynamics

using wearable sensors. *Sci. Rep.* **2018**, *8*, 13657. [Google Scholar] [CrossRef] [PubMed]

[13] Saurav, S.; Saini, R.; Singh, S. Fast facial expression recognition using boosted histogram of oriented gradient (BHOG) features. *Pattern Anal. Appl.* **2023**, *26*, 381–402. [Google Scholar] [CrossRef]

[14] Shi, Y.; Lv, Z.; Bi, N.; Zhang, C. An improved SIFT algorithm for robust emotion recognition under various face poses and illuminations. *Neural Comput. Appl.* **2020**, *32*, 9267–9281. [Google Scholar] [CrossRef]

[15] Niu, B.; Gao, Z.; Guo, B. Facial expression recognition with LBP and ORB features. *Comput. Intell. Neurosci.* 2021, *2021*, 8828245. [Google Scholar] [CrossRef]

[16] Lakshmi, D.; Ponnusamy, R. Facial emotion recognition using modified HOG and LBP features with deep stacked autoencoders. *Microprocess. Microsyst.* **2021**, *82*, 103834. [Google Scholar] [CrossRef]

[17] Shou, Z.; Zhu, N.; Wen, H.; Liu, J.; Mo, J.; Zhang, H. A Method for Analyzing Learning Sentiment Based on Classroom Time-Series Images. *Math. Probl. Eng.* **2023**, *2023*, 6955772. [Google Scholar] [CrossRef]

[18] Xue, F.; Tan, Z.; Zhu, Y.; Ma, Z.; Guo, G. Coarse-to-fine cascaded networks with smooth predicting for video facial expression recognition. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, New Orleans, LA, USA, 18–24 June 2022; pp. 2412–2418. [Google Scholar]