[1]Mangaras Yanu Florestiyanto

[2]Herman Dwi Surjono,

[3]Handaru Jati

Emotion Recognition for Improving Online Learning Environments: A Systematic Review of the Literature

Abstract: - The increased intervention of computer vision in enhancing learning environments has intrigued modern literature on educational research. Affective tutoring system (ATS), student emotion recognition system (SERS), sentiment analysis, and multi-agent system (MAS) have significantly enhanced the online learning environment. Without preceding technologies, online learning environment growth was found to be redundant due to a lack of a corrective mechanism in marginalized viewpoints of tutor in noting facts for their learning environment. As a result, computer vision was found to enhance the online learning environment by providing tutors with enhanced monitoring ability and assistive measures. The following study incorporated a systematic review of 33 papers, efficiently reflecting technology usage in education. The study examined methods for extracting and analyzing emotional data, machine learning algorithms, flexibility to individual learners, camera quality, and ethical issues. This study sought to illuminate these systems' pros and cons. This research shows that emotion recognition systems can improve online learning. These technologies quantify and analyze students' emotional responses, helping educators improve teaching techniques and material. With real-time input on students' emotions, teachers can adjust their methods to keep students engaged and increase academic performance.

Keywords: Online learning, Affective-Adaptive-Intelligent Tutoring System, Emotion recognition.

I. INTRODUCTION

The transformation of learning to online platforms has readily disrupted students' attention spans and instructors' conventional methods to turn them in favour of the learning environment [1]. Emotion recognition system in computer vision is a breakthrough technology that scans digital images and quantifies students' attention span [2],[3]. The inclination of students' attention powers the learning environment. Multiple teachers have presided over ways of experiential learning to maintain students' interest and propose methodologies that strengthen students' attention spans. However, anxiety, boredom, cluelessness, and overwhelming response to the learning environment can significantly deter the progress of the learning environment [4]. Practitioners efficiently detected students in physical classrooms by noticing their lack of ability to discuss in class. Contrarily, in online courses, the dependence on technological and external factors has significantly reduced teachers' capabilities to determine students' willingness to participate in class.

Kohonen neural mapping is readily incorporated into an affective tutoring system (ATS) for online education as it analyzes clustering trends and self-organizing maps [5]. Its ability to grow in an unsupervised environment using artificial intelligence (AI) can extensively enable it to develop ATS. The modernized requirement of ATS incorporates the issue of students' attention span [6]. It was noticed that the concept of retention of students was directly related to their ability to maintain attention in class [7]. However, there was a significant need to quantify students' attention span as the traditional research determined the aspect to be qualitative and to be determined using the students' physical responses, including their response rate, body language, and facial expressions. For online learning, only facial expressions can be incorporated by the tutor. Yet, their ability to view students on a smaller screen of their devices readily neglects their attention towards students, limiting their ability to improve the learning environment.

This research aims to investigate the effectiveness of emotion recognition systems in online learning environments, focusing on feature extraction, feature selection, emotion analysis, the types of emotions assessed

[1] Student, Engineering Science, State University of Yogyakarta, D.I. Yogyakarta, Indonesia, 55281,

[2]Professor, Engineering Science, State University of Yogyakarta, D.I. Yogyakarta, Indonesia, 55281,

[3]Assoc. Professor, Engineering Science, State University of Yogyakarta, D.I. Yogyakarta, Indonesia, 55281

[1] mangarasyanu.2023@student.uny.ac.id, [2] hermansurjono@uny.ac.id, [3] handaru@uny.ac.id

(surprise, interest, confusion, and awe), and the effects of individual differences, camera quality, and ethical considerations. This study examines how these systems improve student and teacher learning and engagement while addressing their implementation issues in education.

II. METHODOLOGY

A. Research Questions

The research questions (RQ) were delineated to maintain the review's focus. The design of these entities was facilitated by utilizing the Population, Intervention, Comparison, Outcomes, and Context (PICOC) criteria, as outlined by Kitchenham and Charters [8]. Table I presents the structure of the research questions using the PICOC framework.

Table I. PICOC

Population	Online learning, Intelligent Tutoring Systems, Affective Tutoring Systems.
Intervention	Emotion recognition using computer vision, Computer vision algorithms, and datasets.
Comparison	Compared to standard online learning settings without emotion recognition.
Outcomes	Better online learning, student enthusiasm, increased engagement, enhanced academic performance, improved instructor performance, increased emotional well-being of online students, and user satisfaction with online learning platforms.
Context	Various online learning platforms and environments (e.g., MOOCs, LMS), different academic subjects and courses, ethical considerations related to privacy and data security, technical feasibility, and limitations of implementing computer vision systems in online learning.

The following research questions have been crafted from the research aim:

1) How do alternative feature extraction and selection methods affect emotion analysis accuracy in online learners of different ages and education levels?

2) Which machine learning or artificial intelligence algorithms identify surprise, fascination, perplexity, and wonder best in online learning environments as part of emotion recognition systems?

3) How do online emotional recognition systems account for student variability and adjust to individual learners' needs and abilities? How does this compare to regular online learning without emotion recognition?

B. Inclusion and Exclusion Criteria

The following table shows the inclusion and exclusion criteria incorporated in this research:

Table II. Inclusion and Exclusion Criteria

Criteria	**Inclusion**	**Exclusion**
Type of Course	Emotional recognition system in the learning environment, improvement in learning environment	Traditional learning systems, conventional classroom management techniques
Student Performance	Objective tests and assessment	Self-analysis and ratings
Language	English	Any language other than English
Study design	Contains relationship between dependent and independent variable	There is no significant display of testing relationship between the discussed variables
Statistical information	Studies using concrete statistical information to prove their points	Studies using insufficient statistical information
Publication date	2017 – present	Earlier than 2016 or 2016
Publication Type	Accredited research journals	Grey literature
Study context	Higher educational framework	Primary or secondary education without online learning platforms
Subject	All subjects	-
Intervention duration	At least a single term of study duration	Selected courses only incorporated in a study
Keywords	Student Emotion Recognition System, Learning Environment, Concept Retention, Online Learning Environment, and Technology	Other keywords that are not included in inclusion criteria.

C. Data Source and Literature Research

The data source and literature search for this study was extensive which resulted in the achievement of over 500 studies from accredited sources, including the Journal of Education, Teaching in Higher Education, Journal of Learning Sciences, Review of Educational Research, Academy of Management Learning, and Educational Researcher among several others. Each preceding journal was explored for research covering emotion recognition systems in virtual learning environments.

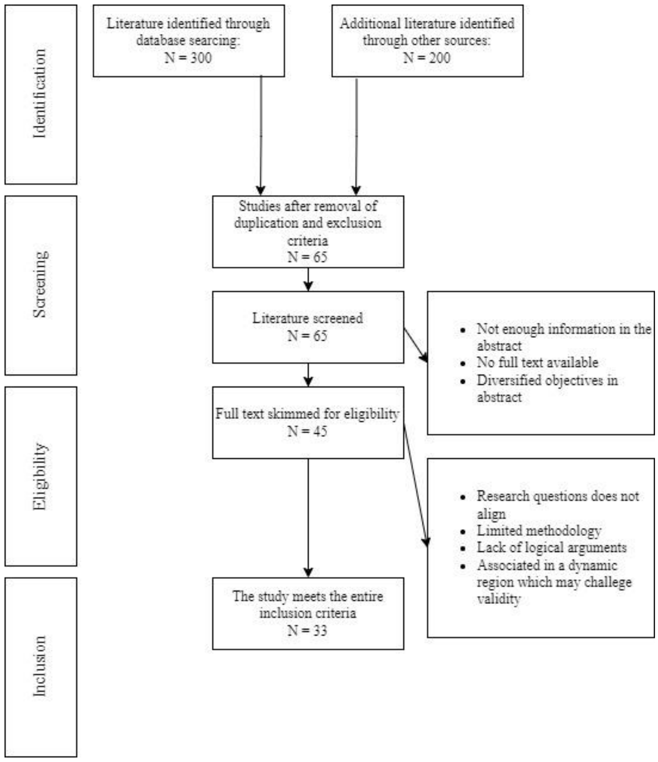

Fig. 1. PRISMA Guidelines

III. Research Results

A. Diversity of Student Emotion in Online Learning Environment

Student emotions in learning are defined by four distinct reflections on the learning environment: surprise, interest, confusion, and awe [9]. Each of the preceding reflections on the learning environment determines its effectiveness. Teachers in online learning environments try to develop students' interest and not forward towards confusion due to the dynamic abilities of the students to clear out their confusion [10]. Moreover, it was noticed that students' distinct characteristics in the classroom are the prime reason for teachers' inability to standardize an affective learning environment. As a result, this study was designed to exterminate the possibility of a lower attention span and a counterproductive learning environment by understanding student emotions in the online learning environment. A multi-agent system (MAS), affective computing, and sentiment analysis are standard methods to understand the diversity of student emotions in a learning environment.

B. Affective Computing

Technology in education is ubiquitous in today's fast-paced digital society. The introduction of affective computing in education represents a significant change. Human-machine connection across digital platforms helps affective computing understand and respond to human emotions [11]. In this education paradigm shift, the teacher-student relationship becomes digital machine-student. With affective computing technologies that use artificial intelligence to evaluate students' performance and attention, modern learning environments are more efficient [12]. This section examines the pros and cons of using emotional computing in teaching.

Digital learning settings are more efficient thanks to affective computing. The ability to assess pupils' emotions and alter educational content is a significant benefit. Emotion detection algorithms in affective computing systems can detect dissatisfaction, engagement, boredom, and perplexity [11]. These systems use this data to dynamically change learning content pace and complexity in real-time, keeping students challenged and engaged.

This adaptability is especially useful in remote or online learning, where real teachers may need more empathy and a personal touch. By analyzing students' emotions and behaviors, affective computing technologies help digital teachers respond empathetically and effectively [12]. This personalized approach improves student satisfaction and motivation by connecting them to the digital learning environment. This adaptability is a benefit, but it raises worries about technology overuse. Teachers have continuously assessed pupils' moods and adjusted their teaching approaches. Affective computing may replace human intuition and knowledge with computational decision-making.

Affective computing addresses traditional and digital learning pedagogical issues. Conventional teaching approaches can be monotonous. Affective computing makes learning more flexible and engaging. The system can smoothly switch to multimedia, interactive exercises, or gamified content when a learner becomes bored [11]. Dynamic adjustments prevent boredom and interest pupils in learning.

Affective computing addresses limited student-teacher contact, especially in big classes. Affective computing uses sentiment analysis and emotional detection to personalize and respond. This lets the system detect struggling pupils and help them quickly [13]. The result is a more inclusive and supportive learning environment where no kid is left behind.

However, using technology to improve pedagogy has downsides. Affective computing systems capture and analyze sensitive student emotional data, raising privacy and data security concerns. Handling and protecting this data has severe ethical consequences.

Integrating affective computing into education improves student attention and engagement, a significant problem for educators in the digital age. In the age of digital distractions, keeping students focused is difficult. Real-time student emotion monitoring with affective computing is a unique solution. The system can identify when students' attention wanes and refresh them with explanations or interactive activities [12].

Through historical evaluations of students' emotional responses and performance, affective computing can reveal learning trends. With this knowledge, the system can suggest study strategies and resources. If a student struggles with a concept, the system can deliver further information or practice tasks [11]. This personalized support increases engagement and fosters growth by valuing effort and improvement.

Finally, emotional computing has improved efficiency, adaptability, and pedagogy in education. However, this technology's limitations and ethical issues must be critically examined. Affective computing could transform learning and engage students, but it raises worries about teaching, privacy, and data security. Managing the pros and cons of emotional computing in education will be vital as this technology shapes learning.

C. Student Emotion Recognition System

1) **Analysis of SERS in Digital Education**

Student emotion recognition system (SERS) is among the breakthrough technologies to quantify the efficiency of the learning environment [4]. Conventionally, qualitative remarks on the learning platform and checking it against the end-of-year marks achieved by students portrayed a skewed measurement of the efficiency of the learning environment and students' emotional responses. Contrarily, developing SERS using computer vision sufficiently empowered the digital learning environment as tutors were busy focusing on concepts in class. It was noticed that tutors devoted their time explaining the concepts while reflecting on the students participating in class. However, introverted students and marginalized attention failed to achieve the attention of tutors. Thus, the incorporation of SERS sufficiently empowered online learning. The stages of SERS implementation incorporate the system's design, eye detection, and head rotation [14]. The following points covered each of the preceding modules distinctively:

a) Design of the system: The system is designed on the local binary pattern (LBP), which is an extensive program that determines students' participation in class by incorporating eye detection and head rotation [15]. It was noticed that involuntary or voluntary movements of the head and eye can efficiently enable the system to determine students' level of understanding.
b) Eye detection module: For eye detection, the facial recognition system can be incorporated [16]. However, it is dependent on users' camera quality to include their face and eye rotation in the design, which may hinder its results' effectiveness. Therefore, the learning environment should standardize the use of devices among students for efficient SERS.
c) Head rotation module: The head rotation module detects head movement by angle of eyes and their visibility. SERS triggers a notification to the practitioner regarding the lack of concentration from students in attending the lecture, in which they can determine their behavior according to the conversation. Furthermore, the following model was proposed to implement SERS in educational settings.

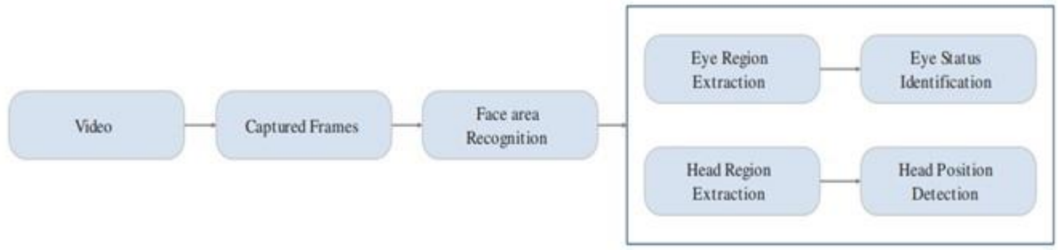

Fig. 2. Head and Eye Rotation Module in SERS [17]

2) Implementation Methodology

Viola-Jones algorithm is an ML technique for object detection published in "Rapid object detection using a boosted cascade of simple features" [18]. The system's inclination was developed for facial recognition, which evolved towards educational platforms using LBP [19]. The following pointers were designed to analyze the power of the Viola-Jones algorithm and LBP to determine the high, medium, and low concentrations among the students in the online learning environment.

a) High Concentration: Students analyze High concentration by the fixed position of the head and eye on the screen [20]. If not facing the screen, it is analyzed that the background activities are consuming space in the students' minds, which may deter their ability to concentrate on teaching material taught by the instructor fully.
b) Medium Concentration: The medium concentration detection is skeptical through LBP and Viola-Jones algorithm [21]. The reason for skewness in the decisive approach towards determining concentration level is its strategy of analyzing a single eye facing the screen. In contrast, the other eye is not visible in a fixed head position.
c) Low Concentration: Low concentration is determined by periodic movement of the head and eye for longer [22]. The determination of low concentration using the Viola-Jones algorithm is concrete as it readily determines that students concentrate more on the background activities than lectures.

It was argued that simplifying head and eye responses in class can sufficiently undermine the effectiveness of SERS [23]. However, studies have shown that the primary engagement attributes displayed by students for attention are their heads and eyes despite their characteristics, which may be introverted or extroverted [22]. Therefore, the efficiency of the Viola-Jones algorithm and LBP should be extensively accredited in the modern education system.

D. Benefits of Emotion Recognition System for Online Learning Environment

1) **Enhanced Learning Environment**

The traditional classroom learning environment was enhanced by teachers' ability to communicate with students [24]. Teachers reflected on students' behavior to enhance the learning environment. However, developing online learning platforms increased communication barriers between students and teachers. As a result, there was an improved need for technology to maintain transparency between the two stakeholders [25]. Emotional recognition system work in online platforms enabled the learning environment to be productive by quantifying student response ratings [26]. Furthermore, it allowed the practitioner to diversify their teaching methods approach to grasp students' desired level of attention.

2) **Better Decision-Making Strategies for Teachers**

Conventionally, teachers' decision-making was made through on-spot judgments on the problem, contributing to misaligned decisions that further deteriorated the learning environment [27]. In the emotional recognition system, the AI and ML-trained model creates an accurate result from student expression and action in the digital learning environment, enabling the teacher to follow a standardized approach towards enhancing the learning environment [28].

3) **Engagement of Students and Teachers**

Engagement of students and teachers in online learning environments was significantly tampered with increased barriers in communication. However, the emotional recognition system especially empowered the affective computing method to enhance engagement among students and teachers [22]. Teachers were increasingly aware of their student's behavior, which enabled them to extensively finalize their approach toward the learning environment.

E. Challenges of Computer Vision for Education Technology

Computer vision technology in education creates a conflict between data privacy and security and fairness and prejudice. Institutions must critically navigate these contradictory forces to employ technology ethically and fairly. Data privacy and security are crucial in the digital age, especially for sensitive student, teacher, and staff data [29]. Data breaches, unauthorized access, and visual data exploitation have serious repercussions, requiring solid protections. To protect data, encryption, access controls, and permissions are recommended [29].

Obtaining varied and representative training datasets to reduce bias in computer vision systems is difficult [30]. Data collection and usage rules for privacy and security may limit access to specific populations, reinforcing biases. This conflict highlights the need to balance data privacy with diversity and representation. Fairness and bias in algorithms are equally important. Biassed training data hurts computer vision systems [30]. Institutions must curate diverse training datasets and regularly test algorithms for bias [30]. This approach may violate data privacy laws since it involves sharing data from multiple sources. Bringing these competing forces together takes nuance. Institutions need a comprehensive plan that includes data anonymization, access limits, bias identification, and mitigation. Privacy and fairness must be integrated to maintain data security and algorithmic fairness.

Computer vision technology must be accessible and inclusive, but infrastructural and funding constraints make it difficult [31]. Investment in text-to-speech and speech-to-text technology is crucial to making educational resources accessible to all, including disabled students [32]. These technologies make pictures accessible by translating them into text or voice. Accessible user interfaces and programs are also necessary for inclusion [32]. Financial obstacles are significant. Budget constraints can prevent schools from buying and maintaining gear and software [31]. These costs fall disproportionately on smaller or underfunded institutions.

Balanced approaches are needed to solve these issues. Computer vision projects require careful planning and budget allocation [31]. Cloud services and technological partnerships can reduce infrastructure expenses. To ensure all kids benefit from technology, this must be balanced with accessibility initiatives. Overall, digital education must prioritize accessibility and inclusion. Strategic planning and resource allocation can overcome infrastructure and financial constraints to provide technology to all pupils.

Technical skills in educational institutions are a significant issue [33]. Many institutions need more computer vision system implementation and maintenance competence. This talent gap limits technology's potential. Significant investments in staff and educator professional development are required [33]. Computer vision training for instructors is essential. It is beneficial to seek advice and direction from AI and computer vision professionals or technology companies [33]. One must realize that not all educators are technically proficient. Educators without technical competence need user-friendly interfaces and tools to use computer vision systems.

Finally, overcoming the educational skill gap requires training, assistance, and user-friendly technology. Institutions may maximize computer vision technology by investing in employees and educators.

F. Usage of Computer Vision in the Education Sector

Computer vision, a subject of AI and computer science, has recently gained popularity for its widespread applications in numerous industries. In education, computer vision is having a significant impact. Computer vision technology is changing how kids learn, teachers teach, and institutions run.

1) **Customized Learning**

Personalized learning is a method that caters to students' needs, talents, and interests. This customized strategy uses computer vision to analyze students' behaviors and preferences. Computer vision is used in personalized learning to measure student engagement with facial recognition [34]. AI-driven systems can tell from facial expressions and body language whether a student is engaged, bored, or bewildered during a lecture. To give each student the best learning experience, teachers can change their methods by offering more support or slowing down the course. Computer vision can also detect students' eye movements to determine which parts of a digital textbook or educational film they find most interesting [34]. This data can help content authors and educators enhance educational resources by revealing which areas are most engaging and require better.

2) **Automating Administrative Work**

Many administrative duties in education are time-consuming and resource-intensive. Many managerial procedures are automated with computer vision, decreasing worker workload and enhancing efficiency [35]. Educational institutions manage many paperwork, from enrollment papers to grade reports. Scanning, digitizing, and categorizing these papers with computer vision makes information management and retrieval easier. It saves time and reduces human mistakes. Computer vision can also be used in school and university visitor management systems [35]. This system can identify and authenticate visitors, ensuring only authorized employees enter. It can also track visitor check-ins and check-outs, improving campus security.

3) **Improving Class Experience**

Computer vision can make classrooms more interactive and engaging for students. Computer-vision-enabled smart whiteboards digitize handwritten text and doodles. Teachers may quickly store and share notes, encouraging student collaboration and participation. Educational AR and VR applications use computer vision to build immersive learning environments [36]. In class, students can tour historical landmarks, dissect virtual species, and journey through the human body. Complex concepts are better understood and retained through hands-on and participatory methods.

4) **Student Feedback and Assessment**

Automated evaluation and fast student feedback depend on computer vision. Using computer vision, OMR technology scans and grades multiple-choice answer sheets rapidly and correctly [37]. This reduces instructor grading time and gives students rapid feedback. Moreover, computer vision can evaluate student writing. Automated essay scoring methods evaluate grammar, coherence, and vocabulary. While they cannot replace human review, these systems can provide preliminary ratings and feedback, saving educators time and guaranteeing grading consistency.

5) **Campus Safeguard**

Educational institutions prioritize security. Computer vision-based security systems improve campus safety. Computer vision algorithms in surveillance cameras can detect suspicious activity or people in real-time, notifying security [38]. A proactive strategy can avoid security breaches and protect students and employees. Additionally, computer vision can monitor attendance. Facial recognition technology can instantly identify pupils entering classrooms or campus buildings, eliminating manual attendance. They save time and enable universities to track student attendance more precisely.

6) **Special Education and Inclusion**

Computer vision technology can help students with various needs obtain the support essential to education. Computer vision can translate printed text into audio for visually impaired pupils, making instructional resources more accessible [39]. Computer vision can also help learning-disabled kids by making personalized recommendations based on educational content. If a student struggles with a topic, the system can provide more resources or change the assignment difficulty.

7) **Use in Research Work and Analysis**

In higher education and research institutes, computer vision analyzes large datasets, runs experiments, and advances research. In biology, computer vision algorithms may analyze microscopy pictures to identify cellular structures and irregularities. Social science researchers can utilize computer vision to analyze massive amounts of visual data like social media photographs and videos [40]. Researchers can better comprehend society by studying public emotion, cultural trends, and human behavior.

G. Limitation for the Study

To fully appreciate the study's scope and constraints, evaluate its limitations. Fundamental limitations are listed below:

1) **Generalizability**

The lack of generalizability is a significant area for improvement in this study. The study examines emotion recognition systems in online learning environments. However, the findings may only apply to some educational settings. Different online platforms, courses, and student groups may provide different results, making it difficult to generalize the findings.

2) **Data Privacy and Ethics**

Emotion recognition systems in education present ethical and privacy problems. This study acknowledges these concerns but may not fully address data privacy, consent, and emotional data misuse. Separate research is needed for a complete ethical appraisal.

3) **Technological Viability**

The study covers the benefits of emotion recognition systems but may not thoroughly investigate their technological viability in varied educational environments. The availability of technology infrastructure, price, and accessibility for students and institutions may hinder widespread adoption.

4) **Limited Time Frame**

The study's inclusion requirements require publication between 2017 and the present. This period may exclude works released before 2017, missing crucial insights and improvements in school emotion recognition systems.

5) **Language Bias**

The inclusion criteria exclude non-English studies. This constraint may exclude crucial studies and viewpoints from non-English-speaking places, basing the research landscape.

6) **Subject Specificity**

The study examines emotion detection systems in online learning contexts, although subject-specific differences may be overlooked. Disciplines may have different needs and obstacles when creating and using such methods.

7) **Limited Emotions**

The study assesses surprise, intrigue, bewilderment, and amazement but may not examine other feelings students and instructors may experience while online learning. Emotions and learning outcomes could be better understood with a deeper look.

CONCLUSION

Finally, computer vision-powered emotion identification technologies in online learning settings have revolutionized education. This study examined these systems' performance in feature extraction, emotion interpretation, individual differences, camera quality, and ethics. These aspects have illuminated how emotion recognition algorithms are changing online education. Emotion recognition systems in online learning environments were explored using study questions. The study examined methods for extracting and analyzing emotional data, machine learning algorithms, flexibility to individual learners, camera quality, and ethical issues. This study sought to illuminate these systems' pros and cons. This research shows that emotion recognition systems can improve online learning. These technologies quantify and analyze students' emotional responses, helping educators improve teaching techniques and material. With real-time input on students' emotions, teachers can adjust their methods to keep students engaged and increase academic performance.

Computer vision and emotion detection technologies can improve student-teacher communication in online learning. Teachers can assess student reactions and alter their teaching in a regular classroom. Virtual classrooms using emotion recognition technology allow teachers to deliver more personalized support and build closer relationships with pupils. Though beneficial, emotion recognition technologies in education bring various obstacles. Students' emotional data must be managed ethically and responsibly. Protecting sensitive data and being transparent about data usage is crucial. These systems' bias and fairness must also be addressed. Biassed algorithms may worsen student inequality by mistreating particular groups. A varied and representative training dataset and regular algorithm reviews reduce bias. Researchers must also consider accessibility and inclusion. Educational technology, including emotion detection systems, must be accessible to all pupils, including disabled ones. To avoid learning hurdles, technology should provide user-friendly interfaces and different modalities. Implementing these systems can be expensive and infrastructure-intensive, especially for low-resource schools. A thorough cost-benefit analysis is needed to justify and sustain these investments. Computer vision-powered emotion identification systems can transform online education by boosting learning environments, instructor decision-making, and student engagement. These technologies must be used responsibly, with data protection, fairness, accessibility, and cost-effectiveness in mind. As education advances to meet the requirements of all learners in the digital era, emotion detection technologies will play a key role in creating more effective and inclusive online learning environments.

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