

Emotion Recognition by Deep Learning to Support Mathematics Learning and Reduce Math Anxiety: A Review of Pedagogical Approaches

Vikas Jangra * and Sumeet Gill 

Department of Mathematics, Maharshi Dayanand University Rohtak-124001, Haryana, India

vikasjangra96.rs.maths@mdurohtak.ac.in

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Abstract

Mathematics learning is affected by various achievement emotions such as enjoyment, boredom, frustration, and anxiety. Math anxiety can decrease motivation, perseverance, working-memory capacity, and performance while the teacher struggles to watch each individual student. This conceptual review consolidates research on mathematics-related emotions, emotion recognition based on deep learning, affective tutoring, and anxiety reduction with the help of artificial intelligence. This paper tries to answer two questions: (1) How can emotion recognition based on deep learning be used in math education to support learning and decrease anxiety? (2) What kind of technical, pedagogical, and ethical guidelines are necessary for using it? On the basis of the literature reviewed, a human-centric approach with three layers: sensing, interpretation, and pedagogical response is proposed. The visual, vocal, physiological, and interaction signals are processed into probability-based affect estimates which could be used for adjusting the pace, providing hints, scaffolding, and supportive feedback. Although it is possible to recognize emotions in a classroom, the performance of existing solutions depends on the task, dataset, emotion labels, and context and does not show any evidence of anxiety reduction. Thus, the role of emotion-aware artificial intelligence should be complementary to teacher's judgments.

Keywords: affective computing, deep learning, emotion recognition, mathematics education, math anxiety, intelligent tutoring systems

1. Introduction

Mathematics is an emotion-laden discipline in which positive emotions such as enjoyment and negative emotions like boredom and anxiety play a role in the motivation, engagement, and performance of students. Math anxiety is significant because the worry associated with number-related or mathematical activities may foster avoidance, lower self-efficacy, and reduce the cognitive capacity needed for solving problems (Schukajlow et al., 2023).

Nonetheless, teachers encounter constraints while trying to measure the affective state continuously, especially in large, hybrid, and online classes. Self-report questionnaires and interviews continue to be useful tools in measuring valid data; however, these measures may not assist with immediate instructional intervention. New developments in computer vision, speech processing, physiological measurement, and interaction analysis provide an opportunity to estimate the learner's affect in relation to learning during instruction (Liu & Wang, 2022; Yuan, 2022). The estimation is probabilistic and context-dependent since a particular facial expression or physiological change does not imply math anxiety in learners.

The present conceptual review draws parallels between mathematics education literature and deep learning-based emotion recognition and affect-aware tutoring. Two main research questions drive this discussion:

- (1) How can deep learning-based emotion recognition be incorporated into mathematics teaching practices to facilitate learning and alleviate math anxiety?
- (2) What technical, pedagogical and ethical considerations should guide its integration?

This paper introduces the topics of emotion and math anxiety, analyzes existing emotion recognition approaches and affect-aware tutoring systems, summarizes the literature in Table 1, proposes a pedagogical approach consisting of three layers, and formulates implementation recommendations and research directions.

2. Emotions, Math Anxiety and Learning

All theories – control-value, expectancy-value, self-determination, and self-efficacy – view emotion and motivation as crucial components of students' engagement in mathematical activities and persistence despite increasing difficulties. Positive activating emotions may facilitate engagement while boredom and anxiety are linked with maladaptive forms of motivation and poor achievement patterns (Schukajlow et al., 2023). This is not a deterministic relationship: the meaning and influence of the particular emotional state depend on the intensity of the experience, time period, task requirements, existing knowledge base, and control/value appraisals.

Table 1. Summary of the Main Studies Covered in this Review

Study	Context and sample	Input / Method	Reported Outcome	Pedagogical Relevance
Barrón Estrada et al. (2014)	Third-grade mathematics; school deployment	Facial landmarks, neural network, affective ITS	Favourable implementation results; no single accuracy reported	Emotion-responsive feedback in elementary mathematics
Whitehill et al. (2014)	Students completing learning tasks	Facial expressions and machine learning	Binary automated engagement detection comparable with human judgments; no single accuracy reported	Engagement monitoring linked with performance
Mastorodimos & Chatzichristofis (2019)	Survey of mathematics ATSS	Review of recognition methods and response strategies	Not applicable—survey paper	Maps emotions to tutoring interventions
Liu & Wang (2022)	200 university volunteers	Physiological feature fusion; CNN-LSTM; ACO optimization	84.52% binary; 66.21% three-class; 38.14% five-class accuracy	Stress and mental-health monitoring
Yuan (2022)	Classroom facial-expression video	MTCNN, attention/loss design, visual feature fusion	93.53% classroom emotion accuracy	Real-time classroom affect estimation
Etcuban (2025)	320 college algebra students	ChatGPT-supported algebra learning	Confidence/anxiety and performance associations; no model accuracy	Low-stakes explanations and confidence support
Dimaunahan et al. (2026)	30 Grade 11 non-STEM students	ChatGPT; quasi-experimental pre/post design	Reduced anxiety and improved algebra performance; no model accuracy	AI-supported algebra intervention
Sudhandradevi & Bhuvaneswari (2025)	FER2013 + EmoFace; presentation context	CNN-RF and CNN-LSTM hybrid	Approximately 60% average; class F1 up to 0.81	Stress, frustration, and confidence estimation
Zhang & Leong (2025)	Classroom trials and public datasets	Multimodal CNNs with dynamic attention	85.3% emotion-recognition accuracy	Personalized interventions in smart learning
Wang et al. (2026)	Real classroom facial-emotion dataset	Attention-ResNet	F1-score = 0.861	Robust real-time classroom recognition

Note. Only where reported in the original studies, the accuracy is provided. Qualitative or non-accuracy results are retained as is without converting to invented values.

There is also evidence that emotions of students engaged in mathematics online are connected with their achievement. For instance, using the Assessment Online Emotions Questionnaire with 406 Grade 10 students, Polydoros et al. (2025) established that the dimensions of emotions predict performance of students when demographic variables are controlled. This justifies the use of affect as one of the factors to consider when designing lessons; however, this does not mean that automatic categorizations of emotions replace students' self-reports.

Mathematics anxiety can be seen as tension, apprehension, or fear that impedes participation in mathematics-related activities. The nascent attempts of AI-based approaches try to offer

immediate clarification, low-pressure practice, and affective encouragement. According to Etcuban (2025), ChatGPT usage was linked to algebra self-efficacy and performance, whereas according to Dimaunahan et al. (2026), the same group of participants experienced reduced anxiety and better algebra performance in a quasi-experimental conference study involving 30 Grade 11 students who were not STEM-oriented. Moreover, Kaur (2025) created a chatbot to help with math anxiety based on AI that incorporates both cognitive scaffolding and affective encouragement.

3. Deep Learning in Educational Emotion Recognition

The emotional recognition in education uses facial images or videos, audio, physiological information, and behavioral information. The CNN architecture is usually employed in the case of spatial information; recurrent neural network models such as LSTM are employed in the case of temporal patterns, while attention or fusion of information is carried out through time or through modalities. Generally speaking, the output of such models can be classified into states like confusion or boredom, continuous valence-arousal, or engagement and stress.

Yuan (2022) proposed a new method for detecting emotions using face detection, visual feature fusion, and attention-based learning achieving 93.53% accuracy in the classroom data set used in the research. On the other hand, Whitehill et al. (2014) found out that the use of facial information allowed automatically discriminating student engagement, and the engagement information provided was correlated with the task performance. Wang et al. (2026) found an F1 score of 0.861 of an Attention-ResNet algorithm on a real-classroom facial-emotion data set. It is not possible to compare such metrics because they have been obtained under different conditions. Multimodal approaches attempt to minimize the ambiguity of individual cues. Liu & Wang (2022) used multimodal modeling by combining physiological cues with CNN-LSTM and obtained 84.52% accuracy for two, 66.21% for three and 38.14% for five class classification of university students. Zhang and Leong (2025) employed facial expressions, heart rhythms, and digital behaviors using modality-based CNN models and dynamic attention and achieved emotion recognition accuracy of 85.3%. On the other hand, Sudhandradevi & Bhuvaneswari (2025) achieved an average performance of about 60% for seven-class facial emotion recognition, showing how the performance of algorithms could fall with finer labels and difficult contexts.

4. Pedagogical Challenges in Mathematics Classrooms

Large classroom size, pressure from the curriculum, and learner differences complicate the detection of all instances of confusion, boredom, and anxiety. Quiet students do not ask for

help, and expressive behaviour varies from one individual to another and from one culture to another. Thus, a classifier that is technically accurate is likely to come up with an educationally wrong conclusion if it disregards task context, prior knowledge, self-report, and the teacher's judgment.

The core instructional challenge, thus, is not only emotion recognition but rather the decision regarding the appropriate action. Confusion may be indicative of effective learning and scaffolding needs, whereas high arousal could be an indication of excitement or stress. It is, therefore, important to take into consideration the persistence of the emotion over time, mathematics achievement, help-seeking behaviour, and feedback from students (Mastorodimos & Chatzichristofis, 2019).

Math anxiety is acquired through repeated experience over time as a result of failure, public embarrassment, time constraints, and negative evaluation. The use of emotion-aware technology is pedagogically justifiable only if it is integrated into supportive teaching practices such as low-pressure practice, explicit instruction, autonomy-supportive feedback, and corrective opportunities.

5. Conceptual Framework for Emotion-Aware Mathematics Pedagogy

This framework consists of three interconnected layers: sensing, interpretation, and pedagogical action. As depicted in Figure 1, this is a human-in-the-loop cycle rather than an autonomous surveillance pipeline. Consent, data minimisation, fairness assessment, uncertainty communication, and feedback from teachers and students exist in all three layers.

5.1. Sensing Layer

The sensing layer collects only the data needed for an explicitly stated pedagogical question. Sources can be facial expressions and body posture collected through video, prosodic information from speech, heart rate variability or skin conductance collected from wearables, as well as behavioral cues such as response time, repeated mistakes, hints, and typing behavior. School districts must select the least intrusive sensing modality combination that answers the instructional question and offer alternative means for students who do not agree to be observed via video, audio or wearable sensors.

5.2. Interpretation Layer

The interpretation layer translates the signals into probabilistic estimates within specific time windows. Convolutional neural networks could capture visual information, while LSTM and

transformers could capture temporal dynamics. Multimodal fusion can combine different prediction modalities. Outputs should provide confidence or uncertainty but not latent information. Training and evaluation should be done using classroom-related data and reporting class-wise precision, recall, F1 score, calibration, subgroup performance, and external validation metrics rather than accuracy.

5.3. Pedagogical Response Layer

This layer interprets persistent patterns into appropriate responses. The teacher's dashboard could show trends and uncertainty at the classroom level but not rank individual students. The intelligent tutor could provide a hint after multiple wrong answers and frustration, simplify the task temporarily, suggest a model problem, or give a brief regulation message. Critical decisions including referrals or punishment should not be based only on the emotion classifier's results.

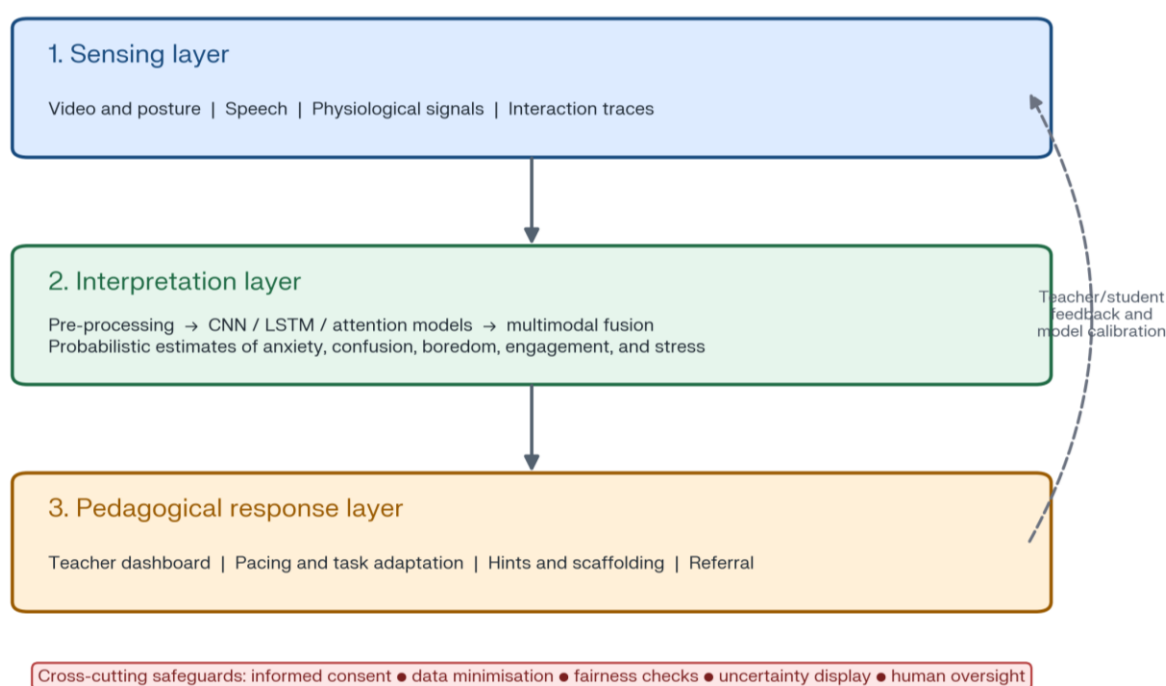


Figure 1. Human-centered three-layer architecture for emotion aware mathematics pedagogy. The framework treats model outputs as uncertain decision support and retains teacher and student oversight

6. Pedagogical Applications

6.1. Real-Time Detection and Support

Where multiple cues indicate persistent anxiety and frustration while solving problems, the instructor may stop teaching, re-explain a topic, accept mistakes, or offer a non-threatening task. Research suggests that patterns associated with emotions are identifiable in naturalistic video material, but interventions should be based on trends and triangulation instead of a single facial image (Wang et al., 2026; Yuan, 2022).

6.2. Adaptive Difficulty and Scaffolding

An affective tutoring system may utilize mastery and affective information to determine how and when hints, worked examples, motivating messages, or adjustments in task difficulty need to be given. Literature about math ATs demonstrates that sensing becomes useful for education only when the response to it is justified (Mastorodimos & Chatzichristofis, 2019).

6.3. Motivation and Engagement

Emotion-driven feedback might encourage engagement through timely and personalized assistance. Zhang and Leong (2025) found increased engagement and acceptability of personalized intervention in their tested smart-learning environment. This evidence, though, needs replicating, since initial acceptability and classifier accuracy do not guarantee sustained benefits in mathematics proficiency.

6.4. Stress and Well-Being

Physiological and multimodal models might produce additional signs of arousal and stress. Liu and Wang (2022) discovered better classification results with fusion compared to individual channels in their university population. As used in education, such signs should encourage discussion or resource provision, rather than any diagnostic conclusions, since emotion recognition systems cannot serve as diagnostic tools unless independently validated and regulated for that purpose.

6.5. Inclusive Support for Silent Students

Overall tendencies might help teachers to identify students with ongoing difficulties but unwillingness to seek assistance. At the same time, inclusivity necessitates opt-out options, accessibility considerations, culturally appropriate validation procedures, and analysis of performance differences by demographic group. The students must have an opportunity to review, challenge, and amend the interpretation.

7. Challenges and Ethical Considerations

Emotion-recognition systems deduce internal states from imperfect measures. Factors such as occlusion, lighting, positioning, masking, expressive variance, neurodiversity, culture, and classroom norms can affect the link between behavior and emotion. Model confidence thus needs to be calibrated, low-confidence predictions suppressed, and uncertainty communicated to teachers.

Continuous video, audio, physiological, and interaction monitoring presents considerable privacy and security risks. The implementation process needs to define purpose, legal basis, and consent; data ownership, retention, access control, encryption, and deletion. Whenever possible, processing should happen on site, recordings should not be kept, and the smallest number of features or aggregates should be saved.

Evaluation for fairness is important, since even mean performance can obscure disproportionate error rates. Schools should test across subgroups, perform independent evaluations, conduct pilot trials, and establish an appeals process prior to implementation. Emotion-recognition systems should never be deployed to aid grading, discipline, ability grouping, or mental health diagnosis. Teachers need training in the interpretation of probabilities, detection of bias, and integration of information from system and conversation.

There are important gaps in research, including differing definitions of emotions, datasets, sample sizes, and metrics, as well as focusing on emotion recognition accuracy rather than educational effect. Future studies should preregister hypotheses, manipulate between emotion-aware and non-emotion-aware conditions, utilize math anxiety scales that have been validated, document adverse reactions and subgroup analysis, and assess achievement, anxiety, self-efficacy, and trust over time.

8. Conclusion

Deep learning approaches to affect recognition can be a means by which teachers receive additional information regarding affective factors during mathematics learning, where such signals are aggregated over time and correlated with adequate scaffolding. Technical feasibility, along with early empirical evidence of affect-aware tutoring and artificial intelligence-mediated anxiety management, is provided in current literature; however, such results are too heterogeneous to draw any conclusions on effectiveness.

In the outlined sensing-interpretation-response model, pedagogical approach and human oversight are central. Emotion predictions must be uncertain, debatable, privacy-protecting, and secondary to the judgment of the teacher and the opinion of the student. Future research should explore whether ethical design leads to sustainable improvements in mathematics learning and decreased anxiety levels in students.

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Notes on Contributors

Vikas Jangra is a Ph.D. Research Scholar in the Department of Mathematics at Maharshi Dayanand University, Rohtak, Haryana, India. He holds an M.Sc. in Mathematics and is pursuing his Ph.D. in the area of Artificial Intelligence-based mathematical modelling. His research interests include Artificial Intelligence, Machine Learning, Deep Learning, Computer Vision, Mathematical Modelling, Multimodal Emotion Recognition, Human–Computer Interaction, and Medical Image Fusion. His research focuses on developing AI-based models and computational approaches for emotion recognition and image processing applications. He has published research papers and book chapters in the areas of Artificial Intelligence, Deep Learning, Emotion Recognition, and Medical Image Fusion.

vikasjangra96.rs.maths@mdurohtak.ac.in

Sumeet Gill is a Professor and Head of the Department of Mathematics at Maharshi Dayanand University (MDU), Rohtak, Haryana, India. He holds a Ph.D. and has extensive academic and research experience in the fields of Artificial Intelligence, System Security, Computer Science, and related interdisciplinary areas. His research interests include Artificial Intelligence, Machine Learning, Neural Networks, Image Processing, and System Security. He has contributed to research through publications in reputed journals and conferences and has supervised research scholars in interdisciplinary areas. He has also undertaken various academic and administrative responsibilities at the university. His research reflects the application of computational and mathematical approaches to emerging problems in science and technology.

drsumeetgill@mdurohtak.ac.in

ORCID

Vikas Jangra  <https://orcid.org/0009-0000-5324-8358>

Sumeet Gill  <https://orcid.org/0000-0001-6471-1192>

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