MACHINE LEARNING AND EMOTION RECOGNITION: VALIDATION OF AN ALGORITHM AND PERSPECTIVES OF USE

MACHINE LEARNING E RICONOSCIMENTO DELLE EMOZIONI: VALIDAZIONE DI UN ALGORITMO E PROSPETTIVE D'USO

Emanuele Marsico
Pegaso Telematic University (UNIPEGASO)
emanuele.marisco@unipegaso.it

Umberto Barbieri
Niccolò Cusano University
umberto.barbieri03@gmail.com

Luigi Piceci
Niccolò Cusano University
luigi.piceci@unicusano.it

Double Blind Peer Review

Citazione

Marsico E., Barbieri U., Piceci L (2023), Machine learning and emotion recognition: validation of an algorithm and perspectives of use, Giornale Italiano di Educazione alla Salute, Sport e Didattica Inclusiva - Italian Journal of Health Education, Sports and Inclusive Didactics. Anno 7, V 2. Supplemento Edizioni Universitarie Romane

Doi:
https://doi.org/10.32043/gsd.v7i2.967

gsdjournal.it
ISSN: 2532-3296
ISBN: 978-88-6022-479-8

ABSTRACT

The literature emphasises the role of emotional regulation in determining optimal educational trajectories. Therefore, we propose to validate a useful algorithm for the identification of subjective emotional state through the recognition of facial expressions. Such an Artificial Intelligence (AI) algorithm is based on the two-dimensional Arousal-Valence model. The aim will be achieved through a careful analysis of the correlation between the output of the algorithm and the complementary neurophysiological monitoring performed by means of biofeedback.

La letteratura sottolinea il ruolo della regolazione emotiva nel determinare traiettorie educative ottimali. Pertanto, si propone di validare un algoritmo utile per l'identificazione dello stato emotivo soggettivo attraverso il riconoscimento delle espressioni facciali. Tale algoritmo di Intelligenza Artificiale (AI) si basa sul modello bidimensionale di Arousal-Valence. Lo scopo sarà raggiunto attraverso un'attenta analisi della correlazione tra l'output dell'algoritmo e il monitoraggio neurofisiologico complementare effettuato tramite biofeedback.

KEYWORDS

Emotion Recogniton, Machine Learning, Biofeedback, Artificial Intelligence

Riconoscimento delle emozioni, Apprendimento automatico, Biofeedback, Intelligenza Artificiale

Received 11/09/2023
Accepted 26/09/2023
Published 26/09/2023

Introduction[1]

Emotions are psychophysiological and relational processes that influence individuals' cognitive and behavioral functions. In academic settings, emotions are involved in modulating attention, motivation, memory, and the transfer of acquired knowledge (Mayer, 2019). Furthermore, they can either facilitate or hinder learning depending on how they are recognized, managed, and integrated with thinking processes (Jerath R, Beveridge C. Respiratory Rhythm, 2020; Usán Supervía, P., & Quílez Robres, A., 2021). For example, Pekrun (2021) explored emotions related to reading and learning from texts, which are primary sources of information and knowledge. The author emphasized the importance of emotions in text comprehension, memory formation, as well as in generating new ideas and problem-solving. Particularly, by activating various brain areas involved in cognitive processes such as the amygdala, hippocampus, prefrontal cortex, and dopaminergic system, emotions modulate the encoding, consolidation, and retrieval of information in long-term memory (Tyng, C.M., Amin, H.U., Saad, M.N., & Malik, A.S., 2017). Moreover, the literature highlights a positive correlation between experiencing adaptive emotions and students' academic performance.

Students who exhibit behaviors of engagement, persistence, and intrinsic motivation demonstrate greater ability to regulate their affective and motivational sphere, leading to significantly better outcomes compared to those who do not possess such skills (MacCann et al., 2019; Linnenbrink-Garcia, L., Patall, E.A., & Pekrun, R., 2016). For these reasons, the present study falls within the broad field of affective computing - the study and development of systems and devices that can recognize, interpret, process, and simulate human affects (Mejbri, N., Essalmi, F., Jemni, M., & Alyoubi, B.A., 2021) - with the aim of developing a tool capable of enhancing students' learning experience. Over time, Emotion-Based Adaptive Learning Systems (EBALS) have been developed to adapt the teaching-learning process to students' emotions. These systems detect students' emotions through biometric sensors, artificial intelligence algorithms, or natural language analysis techniques and adjust content, difficulty, and feedback based on students' emotional state. The goal of EBALS is to create a more engaging, motivating, and personalized learning environment that takes into account individual differences and student preferences (Taurah, S.P., Bhoyedhur, J., & Sungkur, R.K., 2019).

[1] The manuscript is the result of a collective work of the authors, whose specific contribution is to be referred to as follows: Emanuele Marsico paragraph: 2; Umberto Barbieri paragraphs: 1, 3; Luigi Piceci coordinator and paragraph: 4

For example, Fatahi (2019) conducted an experimental study to assess the impact of an adaptive e-learning environment based on students' personality and emotion on various learning indicators such as engagement, satisfaction, and academic success. The study involved a sample of 60 Iranian university students enrolled in a four-week online English language course. The students were randomly assigned to two conditions: an experimental condition, where they used the adaptive e-learning system, and a control condition, where they used the traditional system. The results showed that the experimental condition yielded significantly higher values than the control condition for all considered indicators. However, to design effective learning environments, it is essential to collect affective data that can reflect the student's emotional state while minimizing the intrusiveness of measurement techniques (Denervaud, S., Mumenthaler, C., Gentaz, E., & Sander, D.; 2020). Consequently, the application of an artificial intelligence algorithm to detect and categorize facial movements is the appropriate solution, as facial expression conveys a higher percentage of communicative information in humans compared to any other nonverbal means such as hand gestures, body gestures, and text (Zhao, et al.; 2022). Charles Darwin (1872) was one of the first to systematically study this topic, arguing that emotions are innate and universal, and they manifest through facial and behavioral signals. Darwin also proposed that emotions are correlated with the activity of the autonomic nervous system, which regulates involuntary physiological functions.

However, the nature and number of human emotions are still subject to debate. Some authors have proposed and hypothesized the existence of basic emotions such as joy, sadness, fear, anger, disgust, and surprise, which are distinct and recognizable across cultures (Ekman et al.; 1983). Other authors have suggested that emotions are better described by continuous and bipolar dimensions such as pleasure-displeasure, activation-relaxation, and dominance-submissiveness (Russell & Mehrabian; 1977). This project aims to propose a validation protocol for an Artificial Intelligence (AI) algorithm—a convolutional neural network (CNN) trained through deep learning methods—based on the construction of a training dataset structured according to the two-dimensional Arousal-Valence model. The emotions will be distributed in a circular two-dimensional space, encompassing the dimensions of arousal and valence (Magdin, et al.; 2021). The predefined objective will be achieved through a careful analysis of subjective responses to emotion-inducing stimuli (Gur, et al.; 2002) to extract the parameters necessary for creating an initial dataset of normative values.

These values will be derived from the correlation between the algorithm's output and complementary neurophysiological monitoring conducted through biofeedback (A. Albraikan, B. Hafidh, and A. El Saddik; 2018).

1. Materials and Methods

Facial emotion recognition

Deep learning is a branch of machine learning that relies on deep artificial neural networks, composed of multiple layers of computational units that can learn complex data representations (Paszke, et al.; 2019). Deep learning has proven to be effective in recognizing complex and nonlinear patterns in data, such as images, sound, and natural language. Facial emotion recognition (FER) using deep learning involves creating a model that can take an input image of a person's face and output their emotion from a predefined set of categories (Mellouk & Handouzi; 2020). To do this, the model must be able to extract relevant facial features, such as mouth shape, eye shape, and eyebrow position, and associate them with the corresponding emotion. The method used in this study is based on a convolutional neural network (CNN) (Arriaga, O., Valdenegro-Toro, M., & Plöger, P.; 2017) trained on a dataset of 35,685 images annotated with seven classes of emotions: happiness, surprise, anger, sadness, fear, disgust, neutral. The CNN has a four-level structure: an input layer, two hidden layers, and an output layer. The input to the network is a grayscale image resized to 48x48 pixels. The network has two hidden layers that use convolutional filters and ReLU activation functions to extract features from the image. After each hidden layer, max-pooling is applied to reduce the data size, and dropout is used to prevent overfitting. Finally, the output layer uses fully connected layers to classify the emotions of the input image. In the preprocessing stage, for face and landmark localization (eyes, nose, mouth, etc.) in a single processing phase, the "RetinaFace" algorithm (Deng et al.; 2019) was employed. This algorithm uses a multi-task CNN that simultaneously performs regression and classification of face bounding boxes and regression of landmarks. In addition, RetinaFace implements a face normalization mechanism based on facial geometry, which enhances the quality of the input images provided to the network.

The limitations of the presented model mainly concern occlusion and variations in pose or lighting (Ekundayo, O.S., & Viriri, S.; 2021). The first condition refers to elements that hinder the recognition of a person's distinctive facial features, such as mustaches, beards, glasses, hair, or veils. In the second condition, non-frontal view and variations in light intensity can contribute to distorting the background or hiding crucial landmarks for classification. Furthermore, the training databases of the algorithm show poor ethnic diversity, which can lead to biases and errors in emotion recognition for individuals belonging to minority ethnic groups, such as African Americans, Latinos, or Asians (Dominguez-Catena, I., Paternain, D., & Galar, M.; 2023).

Biofeedback

Emotion, understood as a multi-component response triggered by emotionally significant events, is the subject of investigation in this study. In particular, the focus is on the relationship between emotion and activation of the autonomic nervous system (ANS), without assuming a one-to-one connection between the two phenomena (Pei, W., Lo, T.T., & Guo, X.; 2020). The specificity of ANS responses in different emotions and the internal consistency of these responses constitute the core of this investigation. To achieve these objectives, an approach based on biofeedback has been adopted, using specific measurement domains. The biofeedback tool used in this research is a device that allows for the measurement and monitoring of physiological responses of the autonomic nervous system (ANS) in relation to emotions, using electrodes and sensors (Semerci, Y.C., Akgün, G., Toprak, E., & Barkana, D.E.; 2022). This tool is based on the acquisition and analysis of relevant physiological data to provide real-time visual or auditory feedback to the subject undergoing the experiment. Heart rate variability (HRV) has been selected as it represents an indicator of autonomic arousal (Mendes, W.B., Major, B., Mccoy, S.K., & Blascovich, J.; 2008). The biofeedback tool allows for the recording of cardiac activity by focusing on the measurement of intervals between heartbeats. HRV analysis focuses on two fundamental components: high frequency (HF-HRV) and low frequency (LF-HRV). HF-HRV reflects parasympathetic nervous system activity, while LF-HRV can be influenced by both the sympathetic and parasympathetic nervous systems. Additionally, the ratio of LF to HF is examined as an indicator of the balance between sympathetic and parasympathetic activities. To assess electrodermal activity, specific parameters have been identified to measure skin conductance, considering the amount of sweat present in the eccrine glands as an indicator of such activity. In particular, the level of skin conductance (SCL) has been adopted as a measure of mental stress, cognitive load, and autonomic arousal (Boucsein, W., Koglbauer, I.V., Braunstingl, R., & Kallus, K.W.; 2010). Attention has also been given to skin conductance responses (SCR), representing electrodermal changes of a specific amplitude occurring within a specific time interval. Finally, skin conductance amplitude (SCA) has been considered as a measure of the variation in skin conductance, observing the transition from the pre-stimulus level to the peak level reached after the stimulus (Rimm-Kaufman, S.E., & Kagan, J.; 1996).

Self-Assessment Manikin

The Self-Assessment Manikin (SAM) represents an emotional assessment tool based on images, designed to objectively and standardizedly probe and measure human emotional responses (Bradley and Lang, 1994). The approach is based on the premise that emotions can be characterized by three fundamental dimensions: valence/pleasure, perceived arousal, and dominance/control (Xie, T., Cao, M., & Pan, Z.; 2020). In SAM, these three dimensions are evaluated through a series of unique scales composed of individual rating items. For valence/pleasure, a scale ranging from positive to negative ratings is used. Perceived arousal is measured using a scale that varies from high levels to low levels. Lastly, dominance/control is assessed on a scale ranging from low levels to high levels. The stylized figure is used as a reference point for identifying emotional responses. Questionnaire participants are asked to select the position that best represents their emotional experience in relation to the specified dimensions (Sainz-de-Baranda Andujar, C., Gutiérrez-Martín, L., Miranda–Calero, J.Á., Blanco-Ruiz, M., & López-Ongil, C.; 2022). This allows for obtaining a subjective assessment of emotional responses from individuals, providing an immediate visual representation of their perceptions. The use of SAM within the present study enables reliable and comparable measurement of participants' emotional responses. As an image-based method, SAM reduces reliance on subjective verbal descriptions, offering a more universal and consistent approach in evaluating emotions (Geethanjali, B., Adalarasu, K., Hemapraba, A., Kumar, S.P., & Rajasekeran, R.; 2017).

Dataset

The datasets used in the present study are widely employed in research on emotions and the perception of facial, vocal, and behavioral expressions.

- International Affective Picture System (IAPS) (Lang, P.J., Bradley, M., & Cuthbert, B.N.; 1999): a collection of images with standardized affective values on a two-dimensional scale of valence (pleasantness-unpleasantness) and arousal (activation-arousal). The images were selected to represent different semantic categories such as people, animals, objects, and scenes. The database was created to provide a visual stimulation tool for research on emotions and their psychophysiological correlations.

- Cohn-Kanade (CK) (Lucey, P., Cohn, J.F., Kanade, T., Saragih, J.M., Ambadar, Z., & Matthews, I.; 2010): a collection of facial expression images acquired from subjects who displayed controlled emotions through a sequence of facial movements. The database was created to provide an automatic facial expression recognition tool and for research on emotions and their non-verbal communication.
- International Affective Digitized Sounds (IADS) (Yang, et al.; 2018): a collection of sound recordings with standardized affective values on a two-dimensional scale of valence and arousal. The recordings were selected to represent different semantic categories such as human voices, environmental sounds, and non-verbal sounds. The database was created to provide an auditory stimulation tool for research on emotions and their psychophysiological correlations.
- Berlin Database of Emotional Speech (Emo-DB) (dan Zbancioc, M., & Feraru, S.M.; 2015): a collection of vocal recordings with standardized affective values on a two-dimensional scale of valence and arousal. The recordings were acquired from subjects who spoke sentences in German with different vocal emotions, such as happiness, sadness, anger, disgust, fear, and boredom. The database was created to provide an automatic recognition tool for vocal emotions and for research on emotions and their non-verbal communication.
- The Chieti Affective Action Videos database (CAAV) (Di Crosta, et al.; 2020): a collection of videos of human actions with standardized affective values on a two-dimensional scale of valence and arousal. The videos were acquired from subjects performing different actions, such as hugging, kissing, crying, laughing, greeting, and walking. The database was created to provide a visual and auditory stimulation tool for research on emotions and their psychophysiological correlations.

2. Experimental protocol

The sample will consist of 100 participants randomly selected from individuals aged between 18 and 30 years, with a predominance of Caucasian origin. This choice reflects the distribution of the reference population and takes into account the bias present in the algorithm's training dataset. To minimize sources of error in facial expression analysis, participants with psychological, neurological, or morphological conditions that could alter expression or perception of emotions will be excluded from the sample. Participants with face occlusions such as facial hair, glasses, veils, or other elements that could hinder the functioning of the algorithm will also be excluded. Before undergoing the test, participants will need to complete a questionnaire to verify inclusion and exclusion criteria. Participants will also receive information about the purpose and procedures of the study and will be required to provide their written informed consent. The sample size has been calculated to ensure sufficient statistical power to test the study hypotheses. Additionally, all necessary precautions will be taken to protect the confidentiality and privacy of the participants during the experimental process.

The stimuli used are divided into three categories: images, sounds, and videos. The images are sourced from the IAPS database and the CK face database, which collects photographs of faces with six emotional expressions: happiness, sadness, surprise, anger, disgust, and fear. Sixty faces (ten per expression) and sixty IAPS images are selected and presented for 5 seconds each. Each image is presented only once. The sounds are sourced from the International Affective Digitized Sounds (IADS) and Emo-DB. Sixty sounds from various categories (e.g., nature sounds, animal sounds, mechanical sounds, human voices) and different emotional valences (positive, negative, or neutral) are selected. Each sound has a duration of approximately 5 seconds and is presented only once. The videos are sourced from the Chieti Affective Action Videos database (CAAV). Ninety videos, half of which are positive and half negative, are selected, with a total duration of 15 seconds each. Each video is presented only once. The entire set of stimuli is presented in a single session lasting approximately 30-40 minutes. During stimulus administration, participants will be seated in a quiet room with controlled lighting to minimize potential sources of external distraction. The stimuli will be presented in a predetermined order to avoid contamination effects between the different categories. Participants will rate their emotional response to each stimulus on a 5-point Likert scale, where 1 corresponds to a negative emotion, 3 to a neutral emotion, and 5 to a positive emotion. During stimulus exposure, participants' physiological parameters, such as sweating and heart rate variability, will be measured. Additionally, a webcam will record participants' facial expressions. Assessing participants' emotional state through a Likert scale after exposure to an emotional stimulus provides a measure of their subjective perception of emotion (Stöckli, S., Schulte-Mecklenbeck, M., Borer, S., & Samson, A.C.; 2018). This measure can be compared with the physiological responses measured by biofeedback to verify the consistency between perception and emotional reaction. Furthermore, the Likert scale can be used to identify any individual differences in emotion perception that may influence the accuracy of the emotion recognition algorithm. This allows for an analysis of whether certain individuals have difficulty recognizing specific emotions and whether these difficulties are correlated with individual factors such as age, gender, or past experience.

Additionally, we have decided to complement the Likert scale with the Self-Assessment Manikin (SAM) questionnaire to ensure a more comprehensive and accurate assessment of participants' expressed emotional responses. This choice is justified by our desire to capture the underlying emotional landscape of the analyzed experience in a more complete manner. Through the SAM questionnaire, it is possible to collect a subjective evaluation from individuals, while the Likert scale aims to provide a broader and comparative evaluation. The integration of these two assessment tools allows us to obtain an articulated perspective of emotional responses, leveraging both the subjective aspect expressed by participants through the SAM questionnaire and a more general and comparative assessment through the Likert scale. This integration enables us to acquire a multidimensional view of the emotional experience, contributing to a deeper understanding of the phenomenon analyzed within the context of our research.

At the end of the session, the collected recordings are analyzed using the facial expression recognition algorithm. Biofeedback utilizes the physiological data recorded during stimulus presentation to identify the emotions expressed by the participants. Arousal and valence scores are calculated for each presented image, sound, and video through the comparison and correlation of the outputs (Carretero-Dios, et al.; 2023).

Conclusions

In this project proposal, we have described an approach for validating an emotion detection algorithm from facial expressions by comparing the outputs with biofeedback. We discussed the methodology for data collection, statistical analysis, and evaluation of results. he expected outcomes of the experimental protocol are to provide an accurate and reliable assessment of the emotions expressed by participants through the analysis of their facial expressions and related physiological parameters. It is anticipated that the deep learning algorithm trained based on the data collected during the protocol can achieve high performance in emotion recognition, both in terms of accuracy and generalization to new subjects and stimuli. Particularly, the algorithm is expected to accurately recognize different emotional expressions presented during the protocol, surpassing the performance of other emotion recognition algorithms based on traditional approaches.

Furthermore, significant relationships are expected to be identified between the recorded physiological data and the detected emotions. Specifically, it is hypothesized that physiological parameters such as sweating and heart rate variability can provide valuable information for evaluating the emotions expressed by participants. Therefore, the analysis of the data collected during the protocol is expected to reveal specific physiological patterns associated with different emotional expressions. Finally, it is expected that the obtained results can be used to create an adaptive learning tool that provides support in educational and training contexts. Particularly, it is anticipated that the algorithm can be trained more effectively using the physiological data collected during the protocol, allowing the emotion recognition approach to adapt to individual subject characteristics. This way, a highly personalized emotion recognition tool could be achieved, capable of achieving high performance even in the presence of individual variations in emotional perception.

However, there are some limitations to this proposed study. For example, the sample size may not be representative of the general population, which could affect the generalizability of the results. Additionally, biofeedback presents various elements to consider, such as the considerable individual variability characterizing the study of emotional responses through biofeedback, the influence of the experimental context on obtained physiological measurements, and confounding effects that may arise. Therefore, strategies need to be adopted to control and separate these factors to isolate the desired emotional effects. In the future, it would be interesting to expand the research by including the integration of multi-modal data and exploring individual variability. One of the most promising perspectives is to integrate multi-modal data to obtain a more comprehensive and ecological understanding of emotions. Facial movement analysis represents only one of the multiple ways in which emotions manifest. The integration of vocal signals, body language, physiological data, and situational context can significantly enrich our understanding of human emotions. The use of multi-modal approaches in the context of Deep Learning can enable the creation of more complex and sophisticated models capable of capturing the diversity and complexity of human emotional experience. Another interesting perspective is to explore individual variability in the manifestation of emotions. Each individual can express and perceive emotions uniquely, and this variability represents a valuable research opportunity. Delving into the study of individual differences can enable the development of personalized models for emotion recognition, taking into account the peculiarities of each individual. Identifying distinctive traits and specific patterns could improve the accuracy of the analyses and facilitate a better understanding of individual emotional dynamics.

In conclusion, the proposed study offers an important contribution to research on emotion detection and the integration of affect-based adaptive learning tools.

References

1. Albraikan, A. A., Hafidh, B., & El Saddik, A. (2018). iAware: A Real-Time Emotional Biofeedback System Based on Physiological Signals. IEEE Access, 6, 78780–78789.
2. Arriaga, O., Valdenegro-Toro, M., & Plöger, P.-G. (2017). Real-time Convolutional Neural Networks for emotion and gender classification. ArXiv, abs/1710.07557.
3. Boucsein, W., Koglbauer, I. V., Braunstingl, R., & Kallus, K. W. (2010). The Use of Psychophysiological Measures During Complex Flight Manoeuvres – An Expert Pilot Study.
4. Bradley, M. M., & Lang, P. J. (1994). Measuring emotion: The Self-Assessment Manikin and the Semantic Differential. Journal of behavior therapy and experimental psychiatry, 25 1, 49–59.
5. Carretero-Dios, H., Delgado-Rico, E., López-Benítez, R., & Acosta, A. (2023). Differential effects of affective arousal and valence on humor appreciation in female university students. HUMOR, 36, 225–243.
6. dan Zbancioc, M., & Feraru, S. M. (2015). A study about the automatic recognition of the anxiety emotional state using Emo-DB. 2015 E-Health and Bioengineering Conference (EHB), 1–4.
7. Darwin, C. D. (2009). The Expression of the Emotions in Man and Animals.
8. Denervaud, S., Mumenthaler, C., Gentaz, E., & Sander, D. (2020). Emotion recognition development: Preliminary evidence for an effect of school pedagogical practices. Learning and Instruction, 69, 101353.
9. Deng, J., Guo, J., Zhou, Y., Yu, J., Kotsia, I., & Zafeiriou, S. (2019). RetinaFace: Single-stage Dense Face Localisation in the Wild. ArXiv, abs/1905.00641.
10. Di Crosta, A., La Malva, P., Manna, C., Marin, A., Palumbo, R., Verrocchio, M. C., Cortini, M., Mammarella, N., & Di Domenico, A. (2020). The Chieti Affective Action Videos database, a resource for the study of emotions in psychology. Scientific Data, 7.

11. Dominguez-Catena, I., Paternain, D., & Galar, M. (2023). Metrics for Dataset Demographic Bias: A Case Study on Facial Expression Recognition. ArXiv, abs/2303.15889.
12. Ekman, P., Levenson, R. W., & Friesen, W. V. (1983). Autonomic nervous system activity distinguishes among emotions. Science, 221 4616, 1208–1210.
13. Ekundayo, O. S., & Viriri, S. (2021). Facial Expression Recognition: A Review of Trends and Techniques. IEEE Access, 9, 136944–136973.
14. Fatahi, S. (2019). An experimental study on an adaptive e-learning environment based on learner's personality and emotion. Education and Information Technologies, 1–17.
15. Geethanjali, B., Adalarasu, K., Hemapraba, A., Kumar, S. P., & Rajasekeran, R. (2017). Emotion analysis using SAM (Self-Assessment Manikin) scale. Biomedical Research-tokyo, 18–24.
16. Gur, R. C., Sára, R., Hagendoorn, M., Marom, O., Hughett, P., Macy, L., Turner, T., Bajcsy, R., Posner, A., & Gur, R. E. (2002). A method for obtaining 3-dimensional facial expressions and its standardization for use in neurocognitive studies. Journal of Neuroscience Methods, 115, 137–143.
17. Jerath, R., & Beveridge, C. (2020). Respiratory Rhythm, Autonomic Modulation, and the Spectrum of Emotions: The Future of Emotion Recognition and Modulation. Frontiers in Psychology, 11.
18. Lang, P. J., Bradley, M., & Cuthbert, B. N. (1999). International Affective Picture System (IAPS): Instruction Manual and Affective Ratings (Tech. Rep. No. A-4).
19. Linnenbrink-Garcia, L., Patall, E. A., & Pekrun, R. (2016). Adaptive Motivation and Emotion in Education. Policy Insights from the Behavioral and Brain Sciences, 3, 228–236.
20. Lucey, P., Cohn, J. F., Kanade, T., Saragih, J. M., Ambadar, Z., & Matthews, I. (2010). The Extended Cohn-Kanade Dataset (CK+): A complete dataset for action unit and emotion-specified expression. 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops, 94–101.
21. MacCann, C., Jiang, Y., Brown, L. E. R., Double, K. S., Bucich, M., & Minbashian, A. (2019). Emotional intelligence predicts academic performance: A meta-analysis. Psychological bulletin.
22. Madan, C. R., Scott, S. M. E., & Kensinger, E. A. (2019). Positive emotion enhances association-memory. Emotion, 19 4, 733–740.

23. Magdin, M., Balogh, Z., Reichel, J., Francisti, J., Koprda, Š., & György, M. (2021). Automatic detection and classification of emotional states in virtual reality and standard environments (LCD): Comparing valence and arousal of induced emotions. Virtual Reality, 25, 1029–1041.
24. Mejbri, N., Essalmi, F., Jemni, M., & Alyoubi, B. A. (2021). Trends in the use of affective computing in e-learning environments. Education and Information Technologies, 27, 3867–3889.
25. Mellouk, W., & Handouzi, W. (2020). Facial emotion recognition using deep learning: Review and insights. FNC/MobiSPC.
26. Mendes, W. B., Major, B., Mccoy, S. K., & Blascovich, J. (2008). How attributional ambiguity shapes physiological and emotional responses to social rejection and acceptance. Journal of personality and social psychology, 94 2, 278–291.
27. Meyer, M., Helmholz, P., Rupprecht, M., Seemann, J., Tönnishoff, T., & Robra-Bissantz, S. (2019). From the Inside Out: A Literature Review on Possibilities of Mobile Emotion Measurement and Recognition. Bled eConference.
28. Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., Desmaison, A., Köpf, A., Yang, E., DeVito, Z., Raison, M., Tejani, A., Chilamkurthy, S., Steiner, B., Fang, L., … Chintala, S. (2019). PyTorch: An Imperative Style, High-Performance Deep Learning Library. ArXiv, abs/1912.01703.
29. Pei, W., Lo, T. T. S., & Guo, X. (2020). A Biofeedback Process: Detecting Architectural Space with the Integration of Emotion Recognition and Eye-tracking Technology. CAADRIA proceedings.
30. Pekrun, R. (2021). Emotions in Reading and Learning from Texts: Progress and Open Problems. Discourse Processes, 59, 116–125.
31. Rimm-Kaufman, S. E., & Kagan, J. (1996). The psychological significance of changes in skin temperature. Motivation and Emotion, 20, 63–78.
32. Russell, J. A., & Mehrabian, A. (1977). Evidence for a three-factor theory of emotions. Journal of Research in Personality, 11, 273–294.
33. Sainz-de-Baranda Andujar, C., Gutiérrez-Martín, L., Miranda–Calero, J. Á., Blanco-Ruiz, M., & López-Ongil, C. (2022). Gender biases in the training methods of affective computing: Redesign and validation of the Self-Assessment Manikin in measuring emotions via audiovisual clips. Frontiers in Psychology, 13.
34. Semerci, Y. C., Akgün, G., Toprak, E., & Barkana, D. E. (2022). A Comparative Analysis of Deep Learning Methods for Emotion Recognition using

Physiological Signals for Robot-Based Intervention Studies. 2022 Medical Technologies Congress (TIPTEKNO), 1–4.
35. Stöckli, S., Schulte-Mecklenbeck, M., Borer, S., & Samson, A. C. (2018). Facial expression analysis with AFFDEX and FACET: A validation study. Behavior Research Methods, 50, 1446–1460.
36. Taurah, S. P., Bhoyedhur, J., & Sungkur, R. K. (2019). Emotion-Based Adaptive Learning Systems. International Conference on Machine Learning for Networking.
37. Tyng, C. M., Amin, H. U., Saad, M. N. M., & Malik, A. S. (2017). The Influences of Emotion on Learning and Memory. Frontiers in Psychology, 8.
38. Usán Supervía, P., & Quílez Robres, A. (2021). Emotional Regulation and Academic Performance in the Academic Context: The Mediating Role of Self-Efficacy in Secondary Education Students. International Journal of Environmental Research and Public Health, 18.
39. Xie, T., Cao, M., & Pan, Z. (2020). Applying Self-Assessment Manikin (SAM) to Evaluate the Affective Arousal Effects of VR Games. Proceedings of the 2020 3rd International Conference on Image and Graphics Processing.
40. Yang, W., Makita, K., Nakao, T., Kanayama, N., Machizawa, M. G., Sasaoka, T., Sugata, A., Kobayashi, R., Hiramoto, R., Yamawaki, S., Iwanaga, M., & Miyatani, M. (2018). Affective auditory stimulus database: An expanded version of the International Affective Digitized Sounds (IADS-E). Behavior Research Methods, 50, 1415–1429.
41. Zhao, K., Chen, T., Chen, L., Fu, X., Meng, H., Yap, M. H., Yuan, J., & Davison, A. K. (2022). Editorial: Facial Expression Recognition and Computing: An Interdisciplinary Perspective. Frontiers in Psychology, 13.