AffeX: a real-time emotion monitoring and visualization tool

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Abstract

Non-invasive, real-time emotion detection enables continuous and discreet monitoring of affective states, supporting system adaptability while safeguarding user privacy, an essential feature in clinical, educational, and research contexts. This paper presents AffeX, an intuitive tool for the real-time visualization and analysis of facial emotions, designed with a focus on privacy and data transparency. It offers customizable visual feedback, allowing the exploration of emotional responses without compromising identity. Unlike commercial solutions, AffeX ensures full control over data handling, enabling further analysis and multimodal integration, making it especially suitable for privacy-aware and adaptable research scenarios.

Keywords

human-computer interaction, real-time visualization, emotion monitoring, face anonymization

1. Introduction

Emotions play a key role in cognition, behavior, and interaction, influencing processes such as attention, memory, and decision making. Their automatic detection—whether through discrete categories or continuous models like valence and arousal—has become increasingly relevant for applications in healthcare, education, and human-computer interaction [1, 2].

Recent works have explored real-time emotional dashboards, combining facial data with other signals [3], or applying them to specific domains such as virtual classrooms [4] and educational video analysis [5]. In parallel, commercial solutions like FaceReader[1] or Kopernica[2] have emerged, though they often involve closed licenses, proprietary models, or the need for specific hardware.

This paper presents *AffeX*, an intuitive research tool for real-time analysis and visualization of emotions, with a primary focus on protecting user privacy through anonymization and facilitating further analyses in research contexts. This tool does not aim at competing with, nor substitute, existing commercial tools for emotion recognition, which indeed could provide highly specialized and well fine-tuned solutions in some niches, but complement them to enable real-time and research-oriented tasks in academic contexts. In this sense, the tool may be expanded in the future to be fed with multimodal signals coming from commercial emotion recognition engines instead of using the freely available models by DeepFace [6].

The remainder of this demo paper is organized as follows: Section 2 describes the architecture and modules. Section 3 addresses privacy, ethics, and limitations. Section 4 summarizes the main contributions and outlines future work.

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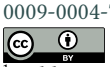

[1]Noldus Information Technology, *FaceReader*, 2025. https://www.noldus.com/facereader

[2]Kopernica AI, *Kopernica Platform*, 2025. https://www.kopernica.ai/?lang=es

2. System design and architecture

2.1. Modules of the system

The AffeX system, depicted in Figure 1-a, is composed of a set of modules that form a structured processing workflow, from the initial configuration to the visualization and storage of the user's emotional data, through the integration of computer vision technologies, deep learning, and web-based visualization tools. The modules are:

- **Device configuration:** The workflow begins with the administrator logging in and accessing an interface to configure the devices required for the experimental session. This includes selecting cameras, microphones, and external sensors. This configuration defines the consent form that will later be presented to the user participant, adapting it to the enabled devices.
- **User selection:** Once the environment is configured, the participant user accesses the system, accepts the customized terms of the informed consent, and activates the monitoring process. The system employs MediaPipe for fast and accurate real-time facial detection through its BlazeFace model [7]. If a single face remains visible for three seconds, it is automatically selected; otherwise, the administrator can manually select the face to be monitored.
- **Facial anonymization:** Once the participant user's face is selected, the system uses the face_recognition[3] library, based on deep neural networks (dlib), which converts faces into 128-dimensional feature vectors. This allows the user to be represented anonymously, without storing images, ensuring privacy throughout the entire process.
- **Emotion detection:** The system uses DeepFace to detect, in real time, the seven basic emotions (happiness, sadness, anger, fear, surprise, disgust, and neutrality), generating emotional weights that feed into interactive visualizations. These data are stored as lists in the repository, along with their corresponding valence, arousal, and dominance (VAD) values, derived from the emotional weights and updated at a frequency of 1 Hz.
- **Event marker:** During the session, the administrator can insert events that provide context to the collected data, improving data quality and enriching subsequent analysis.
- **Sensor data aggregation:** This module collects and synchronizes data from external sensors integrated into AffeX. When additional sensors (such as GSR) are activated, their records—stored in the proprietary repository—are retrieved and integrated with facial emotion data, enabling a multimodal emotional representation.

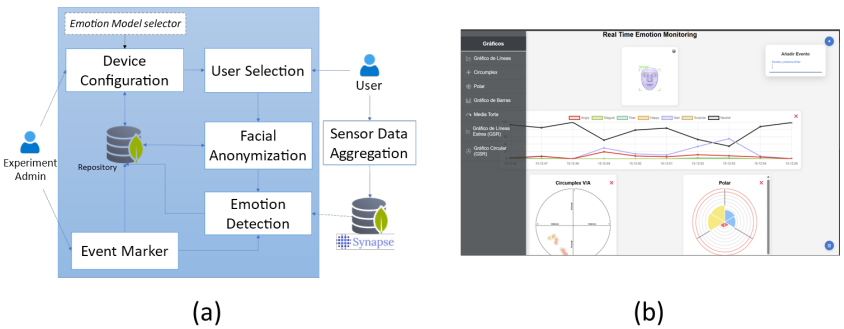

Figure 1: (a) General system architecture of AffeX. (b) UI of the application showing the graphs.

All emotional and physiological data collected by AffeX are securely stored in a proprietary repository under development, called SynapXAI, which enables data retrieval and reuse for future research. Stored data is anonymized through facial feature vectors, ensuring both user privacy and data traceability.

[3] face_recognition, *Documentation*, 2025. Available at: https://face-recognition.readthedocs.io/en/latest/

2.2. Visualization and user options

The user interface (see Figure 1-b) allows for intuitive real-time monitoring of emotions, offering visualization and configuration options tailored to the needs of either the participant or the administrator. AffeX generates dynamic visualizations using Chart.js, integrated into a customizable interface built with GridStack. Detected emotions are displayed in real time through several graphs:

- **Line chart:** Depicts temporal evolution of the seven detected emotions. *(Categorical, Temporal).*
- **Circumplex VA:** A two-dimensional heatmap that positions emotions according to valence (positive/negative) and arousal (high/low), based on Russell's model. *(Dimensional, Non-temporal).*
- **Polar VAD chart**: A radial diagram that shows average emotions in the VAD three-dimensional space, updated every 10 seconds. *(Dimensional, Temporal).*
- **Bar chart:** Summarizes emotional averages every minute. *(Categorical, Temporal).*
- **GSR graphs (if enabled):** Display stress levels from 1 to 5 in linear and circular formats, complementing the emotional analysis from electrodermal activity (EDA) sensors. *(Categorical, Temporal/Non-temporal).*

Visualizations can be reorganized, resized, or removed according to the user's preferences. It can be chosen to view either the original video or the facial mesh overlay as generated by MediaPipe.

Table 1
Performance of Models Used in AffeX (see model indicators at [8, 9])

System Module	Model	Role	Metric
Facial Detection	MediaPipe (BlazeFace)	Real-time face detection	Accuracy: 99.9% Recall: 98.4%
Facial Encoding	face_recognition (dlib)	Face anonymization and encoding	Accuracy: 99.38%
Emotion Analysis	DeepFace	Emotional analysis	Accuracy: 87.25% Recall: 80.2%

3. Privacy, ethics and limitations

The tool was designed based on principles of ethics and privacy by design, avoiding invasive practices and ensuring that the user retains control over their visualization at all times. No images or raw visual data are stored; instead, faces are converted into numerical representations that capture their features without retaining directly identifiable information or raw data. Informed consent is requested at the beginning of the usage flow and is adapted to the configuration previously established by the experiment administrator, who defines the active devices and monitoring parameters. The interface, designed for educational, clinical, or experimental settings, offers a configurable and intuitive experience that allows users to decide what information to visualize and how to interact with the charts in real time, without compromising privacy. The entire design is aligned with the principles of the General Data Protection Regulation (GDPR) and AI act, including data minimization, and transparency in processing.

This demonstrator presents some limitations derived from its technical design. First, face detection: the BlazeFace model from MediaPipe is optimized for detecting faces at short distances and loses accuracy when users are far from the camera, limiting its use in environments with variable changing positions. By design, AffeX focuses on monitoring a single user at a time, aligning with typical experimental settings in which the emotional state of one subject is the primary target of analysis. This intentional constraint reinforces data minimization principles and helps ensure privacy and clarity in data interpretation. However, we acknowledge that some research scenarios may require multi-user analysis. In such cases, future versions of AffeX could be extended to support this functionality.

Although AffeX currently integrates a single emotion recognition model, this choice was guided by its performance, as shown in Table 1. Accuracy and recall served as key selection criteria to ensure reliable real-time results. The system's modular architecture is designed to support additional models in future versions.

4. Conclusion

This work presented an interactive tool for real-time facial emotion detection and visualization, integrating technologies such as MediaPipe, face_recognition, and DeepFace, with a user-centered focus on privacy and usability. The proposed modular architecture enabled the efficient integration of computer vision, deep learning, and web visualization components. To facilitate compliance with ethical and legal principles the tool works without storing images. Additionally, the interface offers flexibility and user control, which is especially valuable in educational, clinical, and experimental contexts. Overall, we expect AffeX to facilitate experimenters to run lab experiments.Future work will focus on expanding the range of detectable emotions, integrating additional physiological sensors, and enabling the detection of multiple users simultaneously, which would be useful for typical research settings involving dyads.

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Declaration on Generative AI

During the preparation of this work, the author(s) used Grammarly for Grammar and spelling checks.

References

[1] P. Ekman, An argument for basic emotions, Cogn. Emot. 6 (1992) 169–200. doi:10.1080/02699939208411068.

[2] L. Shu, J. Xie, M. Yang, Z. Li, Z. Li, D. Liao, X. Xu, X. Yang, A review of emotion recognition using physiological signals, Sensors 18 (2018). doi:10.3390/s18072074.

[3] H. Jo, J. Lee, H. W. Park, M. Kim, Y. Kim, W. H. Lee, Developing an integrated dashboard to analyze multimodal data for user experience evaluation, in: 2023 IEEE International Conference on Consumer Electronics-Asia (ICCE-Asia), 2023, pp. 1–4.

[4] A. Sassi, W. Jaafar, S. Cherif, J. B. Abderrazak, H. Yanikomeroglu, Video traffic analysis for real-time emotion recognition and visualization in online learning, IEEE Access 11 (2023) 99376–99386.

[5] Emodash: A dashboard supporting retrospective awareness of emotions in online learning, International Journal of Human-Computer Studies 139 (2020) 102411.

[6] S. Serengil, A. Ozpinar, A benchmark of facial recognition pipelines and co-usability performances of modules, Journal of Information Technologies 17 (2024) 95–107. doi:10.17671/gazibtd.1399077.

[7] V. Bazarevsky, Y. Kartynnik, A. Vakunov, K. Raveendran, M. Grundmann, Blazeface: Sub-millisecond neural face detection on mobile gpus, arXiv (2020). URL: https://arxiv.org/pdf/1907.05047.

[8] B. et al., Mediapipe blazeface model card, 2021. URL: https://storage.googleapis.com/mediapipe-assets/MediaPipe%20BlazeFace%20Model%20Card%20(Short%20Range).pdf.

[9] V. et al., Human emotion detection using deepface ai, Eng. Proc. 59 (2023). doi:10.3390/engproc2023059037, see Table 3 for accuracy metrics of the proposed emotion detection method.