ISSN (Online): 2583-648X

IJIRID

International Journal of Ingenious Research, Invention and Development

An International, High Impact Factor, Double-Blind Peer-Reviewed, Open-Access, Multidisciplinary Online Journal

www.ijirid.in

Volume 5 | Issue 2 | April 2026

EmotionLearn - Emotion-Aware Learning System

Ayan Israil Pathan[1], Dhiraj Nilkanth There[2], Shrikant Bharat Kadam[3], Nikita Pradip Sawai[4], Kartik Santosh Gadhave[5], Prof. S. N. Sawalkar[5]

[1,2,3,4,5]Student, CSE, Sipna College of Engineering and Technology, Amravati

[6]Assistant Professor, Sipna College of Engineering and Technology, Amravati

Abstract: *The rapid expansion of online education, especially following the COVID-19 pandemic, has transformed e-learning platforms into a dominant mode of academic delivery. Popular platforms like Coursera, edX, Udemy, and NPTEL serve millions of learners globally. However, these systems lack the ability to understand and respond to students' emotional states, resulting in a passive learning experience and contributing to high dropout rates. Unlike traditional classrooms, where instructors can interpret student expressions and adapt teaching methods accordingly, online platforms fail to provide such real-time feedback mechanisms. This project introduces EmotionLearn, an Affective Learning System inspired by the principles of Affective Computing proposed by Rosalind Picard. The system integrates real-time facial emotion recognition into a web-based learning environment to enhance student engagement and learning effectiveness. By leveraging advancements in deep learning and computer vision, particularly Convolutional Neural Networks (CNNs), the system detects key emotional states such as Happy, Neutral, Confused, Sad, and Angry during video-based learning sessions.*

Keyword: *Learning, Affective Learning System (ALS), Affective Computing, facial emotion recognition, Convolutional Neural Network (CNN), student engagement, focus score, real-time monitoring, deep learning, OpenCV, DeepFace, web-based learning system, emotion analytics, human-computer interaction (HCI).*

I. INTRODUCTION

The rapid advancement of digital technologies has significantly transformed the education sector, leading to the widespread adoption of e-learning platforms. This transition was further accelerated by the COVID-19 pandemic, which necessitated remote learning solutions across the globe. Platforms such as Coursera, edX, Udemy, and NPTEL have made education accessible to millions of learners. Despite their scalability and convenience, these platforms lack the ability to perceive and respond to students' emotional and cognitive states, resulting in a passive and less interactive learning experience [1].

In traditional classroom environments, teachers can observe students' facial expressions, gestures, and engagement levels to assess their understanding and adjust teaching methods accordingly. However, such real-time feedback mechanisms are absent in asynchronous online learning, often leaving students disconnected and unsupported. This limitation contributes to reduced engagement and high dropout rates in online courses [2].

To address this challenge, the concept of Affective Computing, introduced by Rosalind Picard, plays a crucial role. Affective computing enables systems to recognize, interpret, and respond to human

 DOI 10.5281/zenodo.19634752

ISSN (Online): 2583-648X
IJIRID
International Journal of Ingenious Research, Invention and Development
An International, High Impact Factor, Double-Blind Peer-Reviewed, Open-Access, Multidisciplinary Online Journal
Volume 5 | Issue 2 | April 2026
www.ijirid.in

emotions, thereby enhancing human-computer interaction. When applied to education, it gives rise to Affective Learning Systems (ALS), which aim to create emotionally aware learning environments[3]. This project presents EmotionLearn, a web-based intelligent learning system designed to integrate real-time facial emotion recognition into video-based educational content. By utilizing deep learning techniques, particularly Convolutional Neural Networks (CNNs), along with tools such as OpenCV and DeepFace, the system detects and classifies students' emotional states during learning sessions. It further computes a dynamic focus score based on facial presence and stability, providing a measurable indicator of student engagement [4].

EmotionLearn not only enhances interactivity but also provides valuable insights through performance analytics, enabling students to reflect on their learning behavior. With features such as role-based access, course management, and feedback mechanisms, the system aims to bridge the gap between traditional and digital education by introducing emotional intelligence into e-learning environments [5].

II. LITERATURE ANALYSIS

The literature on emotion-aware systems highlights the evolution of techniques used for recognizing and analyzing human emotions in computational environments. Early work by Rosalind Picard (1997) introduced the concept of Affective Computing, laying the foundation for emotion-sensitive applications. Prior to this, Paul Ekman and Wallace V. Friesen (1978) developed the Facial Action Coding System (FACS), which enabled systematic analysis of facial expressions. With advancements in deep learning, researchers like Ian Goodfellow et al. (2013) demonstrated the effectiveness of Convolutional Neural Network (CNN) models in image-based emotion recognition tasks. More recent studies, such as Li and Deng (2020), have focused on improving CNN-based facial expression recognition under real-world conditions, while Koelstra et al. (2012) introduced multimodal approaches by combining physiological and visual data through the DEAP dataset. Collectively, these works indicate a shift toward more accurate, robust, and real-time emotion detection systems, with future scope in multimodal integration and adaptive intelligent applications.

TABLE I: LITERATURE WORK

Author & Year	Methods	Future Scope
Rosalind Picard (1997)	Introduced Affective Computing, enabling systems to recognize and respond to human emotions using facial expressions and physiological signals.	Integration of emotion-aware systems in real-time applications like education, healthcare, and smart interfaces.
Paul Ekman & Wallace V. Friesen (1978)	Developed Facial Action Coding System (FACS) to map facial muscle movements to specific emotions.	Automation of facial expression recognition using AI and real-time monitoring systems.
Ian Goodfellow et al. (2013)	Applied deep learning techniques, especially Convolutional Neural Network (CNN), for image-based emotion recognition.	Enhancing model performance and deploying lightweight models for real-time applications.

 DOI 10.5281/zenodo.19634752

Li & Deng (2020)	Surveyed deep facial expression recognition methods using CNNs and benchmark datasets like FER2013.	Improving robustness against lighting variations, occlusions, and real-world challenges.
Koelstra et al. (2012)	Proposed DEAP dataset combining physiological signals and facial data for emotion analysis.	Development of multimodal emotion recognition systems combining facial, voice, and sensor data.

III. CNN ALGORITHM

The use of Convolutional Neural Network (CNN) in the EmotionLearn system follows a structured pipeline for real-time emotion detection:

Frame Capture: The system captures an image frame from the user's webcam at regular intervals (every 3 seconds) using the browser.

Image Preprocessing: The captured frame is converted into a suitable format (grayscale or resized image) to reduce complexity and improve processing efficiency.

Face Detection: The system uses OpenCV to detect the presence and location of a face within the frame using Haar Cascade classifiers.

Face Extraction: The detected face region is cropped from the original image so that only relevant facial features are analyzed.

Input to CNN Model: The cropped face image is passed to the CNN-based model via DeepFace for emotion analysis.

Feature Extraction (CNN Layers): The CNN automatically extracts important features such as edges, textures, and facial patterns through convolution and pooling layers.

Emotion Classification: The fully connected layers of the CNN classify the extracted features into emotions like Happy, Neutral, Confused, Sad, and Angry.

Confidence Score Generation: The model provides a confidence score indicating how certain the prediction is.

Focus Score Calculation: Based on emotion and face presence, the system computes a focus score representing student engagement.

Result Display and Storage: The detected emotion, confidence, and focus score are displayed to the user and stored in the database for analytics.

 DOI 10.5281/zenodo.19634752

ISSN (Online): 2583-648X
IJIRID
International Journal of Ingenious Research, Invention and Development
An International, High Impact Factor, Double-Blind Peer-Reviewed, Open-Access, Multidisciplinary Online Journal
Volume 5 | Issue 2 | April 2026
www.ijirid.in

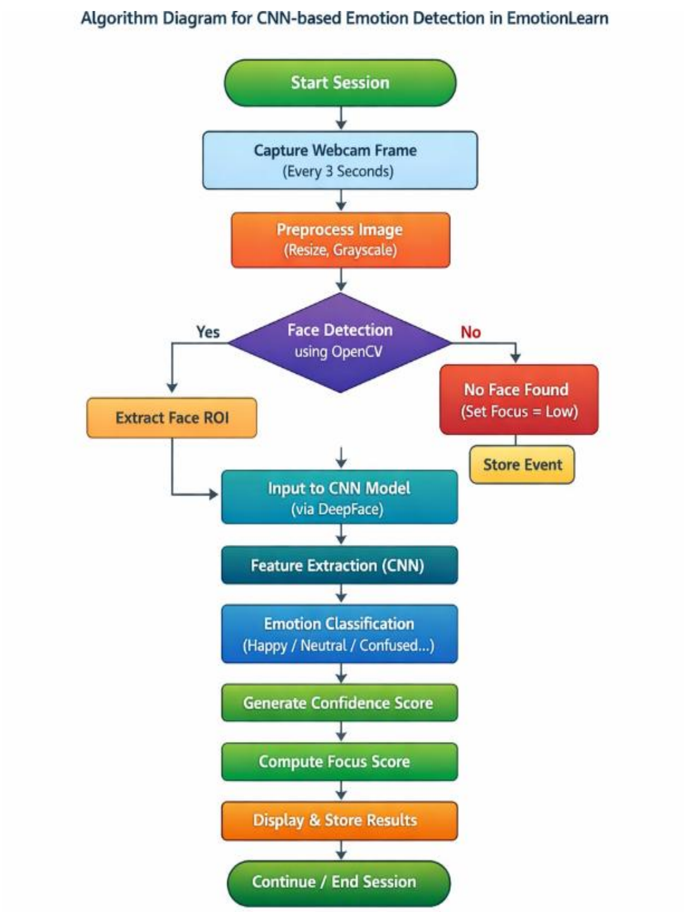


Figure 1: Algorithm Diagram for CNN-Based Emotion Detection in EmotionLearn

IV. WORKING METHODOLOGY

The proposed system, EmotionLearn, follows a structured and systematic methodology to integrate real-time emotion detection with online learning. The working methodology is designed to ensure efficient interaction between the frontend, backend, and emotion recognition components, resulting in an intelligent and responsive e-learning environment.

The system begins with user authentication, where students and teachers log into the platform using secure credentials. Role-based access control ensures that each user interacts with functionalities specific to their role. Teachers can upload and manage course content, while students can browse and access video lectures.

When a student starts a learning session, the system activates the webcam using the browser's MediaDevices API. At regular intervals (every 3 seconds), image frames are captured and sent to the backend server for processing. These frames are preprocessed to enhance quality and reduce computational complexity. The system then utilizes OpenCV to detect the presence of a human face within the captured frame.

If a face is detected, the relevant facial region is extracted and passed to the emotion detection module powered by DeepFace, which internally uses a Convolutional Neural Network (CNN). The CNN

 DOI 10.5281/zenodo.19634752

ISSN (Online): 2583-648X
IJIRID
International Journal of Ingenious Research, Invention and Development
An International, High Impact Factor, Double-Blind Peer-Reviewed, Open-Access, Multidisciplinary Online Journal
Volume 5 | Issue 2 | April 2026
www.ijirid.in

analyzes facial features and classifies the emotion into predefined categories such as Happy, Neutral, Confused, Sad, and Angry. Along with the predicted emotion, a confidence score is generated to indicate the accuracy of the prediction.

Based on the detected emotion and face presence, the system computes a focus score that reflects the student's level of engagement during the session. If no face is detected, the system assigns a lower focus score, indicating reduced attention. All detected emotions, confidence scores, and focus values are stored as session events in the database.

These stored data are later aggregated to generate meaningful insights in the analytics dashboard. The system calculates emotion distribution, session-wise focus trends, and overall engagement patterns. This helps students analyze their learning behavior and improve their study habits.

The architecture of the system follows a three-tier model, consisting of a frontend interface (React), a backend processing unit (Python-based API), and a database layer for data storage. Communication between these layers is handled through RESTful APIs, ensuring modularity and scalability.

Overall, the working methodology enables continuous monitoring, analysis, and feedback of student engagement, thereby transforming traditional passive e-learning into an interactive and emotionally aware learning experience.

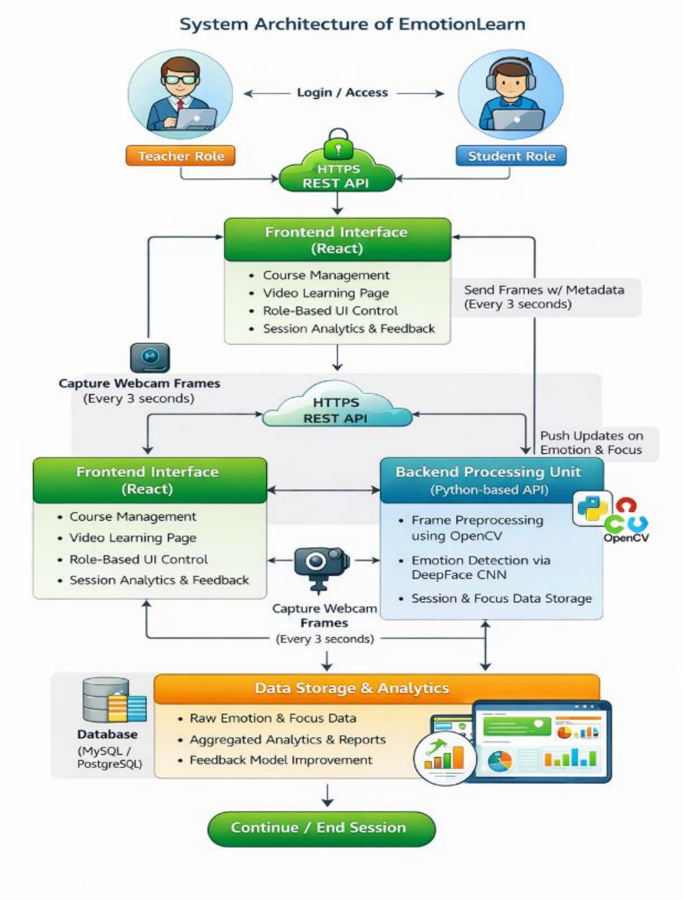


Figure 2: System Diagram

 DOI 10.5281/zenodo.19634752

ISSN (Online): 2583-648X

IJIRID

International Journal of Ingenious Research, Invention and Development

An International, High Impact Factor, Double-Blind Peer-Reviewed, Open-Access, Multidisciplinary Online Journal

www.ijirid.in

Volume 5 | Issue 2 | April 2026

V. RESULTS AND DISCUSSION

The implementation of the EmotionLearn system demonstrates the effectiveness of integrating real-time emotion recognition into an e-learning environment. The system was successfully developed using a three-tier architecture consisting of a React-based frontend, a Python-based backend, and a relational database. The emotion detection module, powered by DeepFace and supported by OpenCV, performed efficiently on standard hardware without requiring GPU acceleration.

During testing, the Convolutional Neural Network (CNN) model was able to classify facial emotions into five categories—Happy, Neutral, Confused, Sad, and Angry—with satisfactory accuracy under normal lighting conditions. The system responded in near real-time, processing frames at 3-second intervals and returning emotion predictions along with confidence scores. The average response time remained within acceptable limits, ensuring a smooth user experience without noticeable lag.

The focus score mechanism proved to be an effective metric for measuring student engagement. Sessions where the student maintained consistent face presence and stable posture resulted in higher focus scores, while frequent absence or erratic movement led to lower scores. This provided a meaningful quantitative representation of attention levels during video lectures.

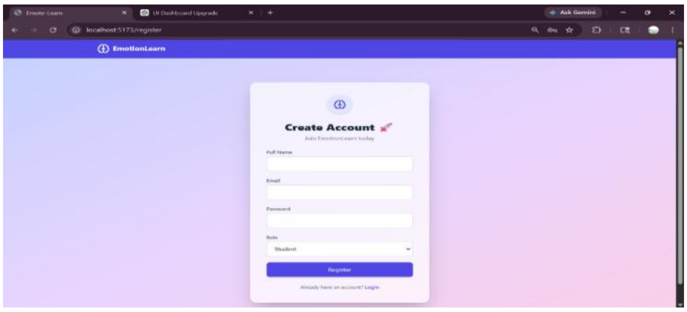
The analytics dashboard successfully visualized user performance through emotion distribution charts and session-wise focus trends. Students were able to identify patterns such as frequent confusion during specific lectures or reduced attention spans over time. This self-awareness can help learners improve their study habits and engagement levels.

However, certain limitations were observed during experimentation. The accuracy of emotion detection was affected by poor lighting conditions, occlusions (such as glasses or masks), and extreme head rotations. Additionally, the system assumes that facial expressions directly correspond to emotional states, which may not always hold true in real-world scenarios.

Despite these limitations, the system achieved its primary objective of making e-learning more interactive and emotionally aware. Compared to traditional platforms, EmotionLearn introduces a feedback loop that bridges the gap between instructor observation and student experience.

In conclusion, the results validate that integrating emotion recognition using deep learning techniques can significantly enhance the quality of digital learning. Future improvements can include higher accuracy models, adaptive content delivery based on emotions, and real-time teacher notifications for better intervention strategies.

Signup Page



 DOI 10.5281/zenodo.19634752

ISSN (Online): 2583-648X

IJIRID

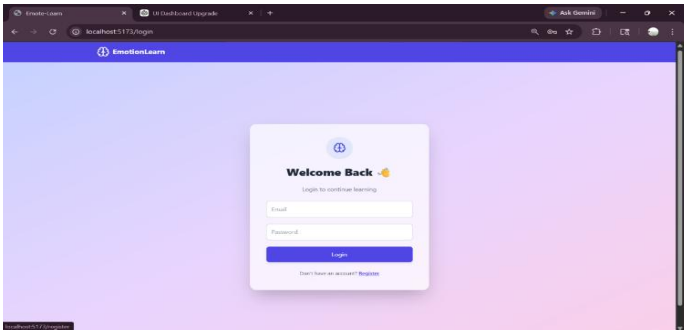
International Journal of Ingenious Research, Invention and Development

An International, High Impact Factor, Double-Blind Peer-Reviewed, Open-Access, Multidisciplinary Online Journal

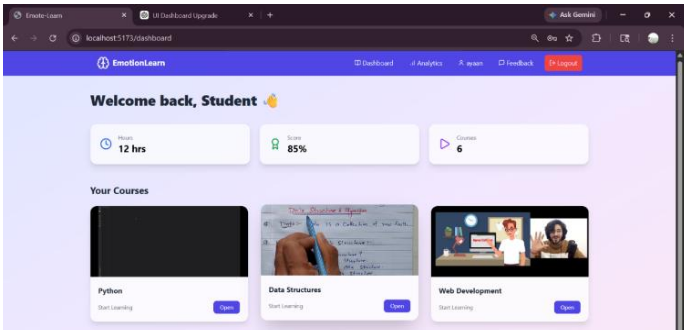
Volume 5 | Issue 2 | April 2026

www.ijirid.in

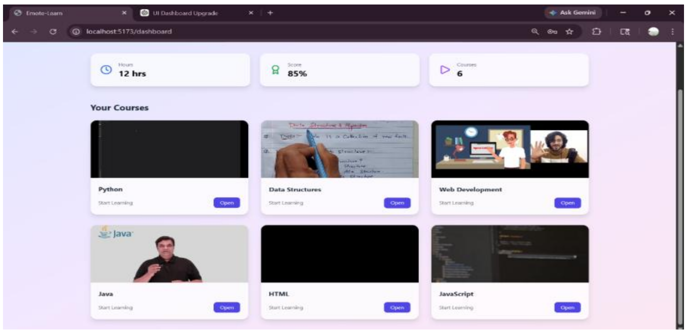
Login Page



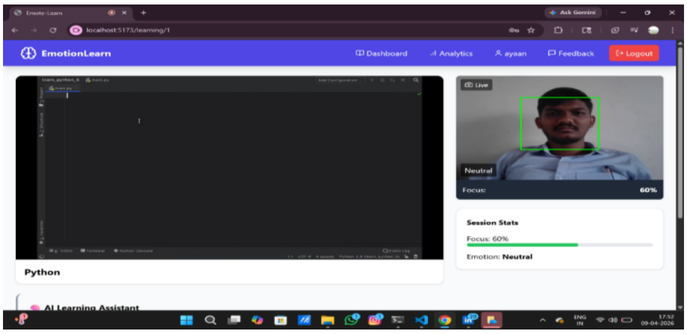
Student Dashboard



Learning Interface



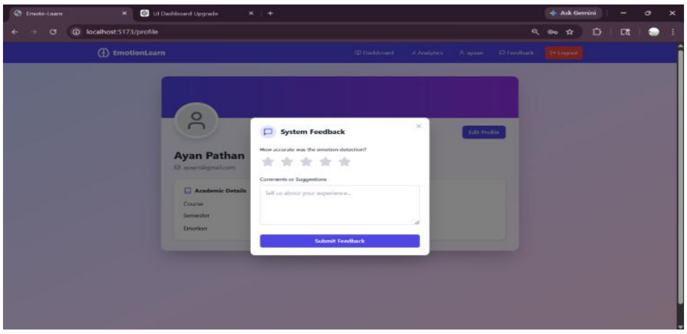
Emotion Detection Screen



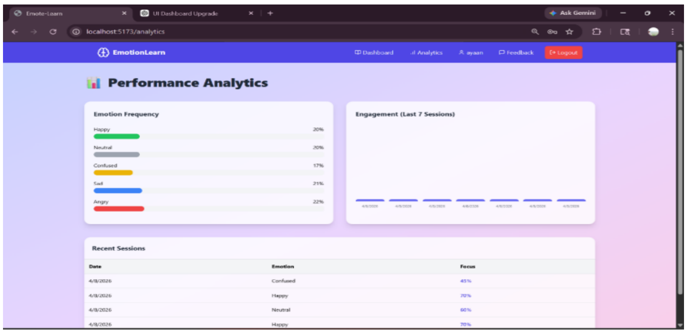
 DOI 10.5281/zenodo.19634752

ISSN (Online): 2583-648X
IJIRID
International Journal of Ingenious Research, Invention and Development
An International, High Impact Factor, Double-Blind Peer-Reviewed, Open-Access, Multidisciplinary Online Journal
Volume 5 | Issue 2 | April 2026
www.ijirid.in

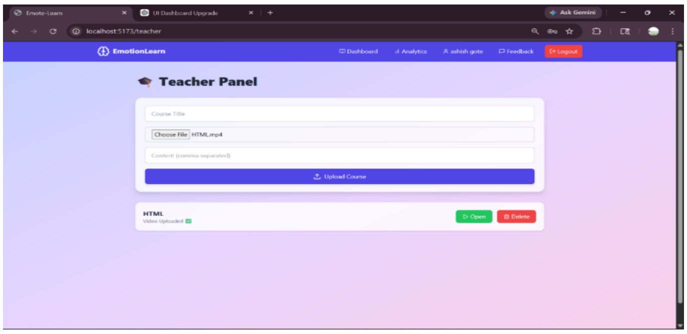
Feedback System



Performance Analysis



Teacher Pannel



VI. CONCLUSION

The EmotionLearn system successfully demonstrates how emotional intelligence can be integrated into modern e-learning platforms to enhance student engagement and learning outcomes. By leveraging concepts from Affective Computing and implementing real-time facial emotion recognition using a Convolutional Neural Network (CNN), the system transforms traditional passive online learning into a more interactive and responsive experience.

The developed system effectively captures and analyzes student emotions during video-based learning sessions using tools such as OpenCV and DeepFace. The introduction of a dynamic focus score provides a quantitative measure of student attention, while the analytics dashboard enables users to gain meaningful insights into their learning behavior. Additionally, the implementation of role-based

 DOI 10.5281/zenodo.19634752

ISSN (Online): 2583-648X

IJIRID

International Journal of Ingenious Research, Invention and Development

An International, High Impact Factor, Double-Blind Peer-Reviewed, Open-Access, Multidisciplinary Online Journal

Volume 5 | Issue 2 | April 2026

www.ijirid.in

access, course management features, and feedback mechanisms contributes to a comprehensive and user-friendly platform.

The results indicate that incorporating emotion detection into e-learning systems can significantly improve learner awareness and engagement. Although certain challenges such as environmental sensitivity and limitations in emotion interpretation persist, the system lays a strong foundation for future advancements in intelligent educational technologies.

In conclusion, EmotionLearn bridges the gap between traditional classroom interaction and digital learning environments by introducing real-time emotional feedback. Future enhancements may include improved model accuracy, adaptive content delivery, and integration of advanced analytics to further personalize the learning experience and maximize educational effectiveness.

REFERENCES

[1] Rosalind Picard, Affective Computing. Cambridge, MA, USA: MIT Press, 1997.

[2] Paul Ekman and Wallace V. Friesen, Facial Action Coding System: A Technique for the Measurement of Facial Movement. Palo Alto, CA, USA: Consulting Psychologists Press, 1978.

[3] Ian Goodfellow et al., “Challenges in representation learning: A report on three machine learning contests,” Neural Networks, vol. 64, pp. 59–63, 2013.

[4] S. Li and W. Deng, “Deep facial expression recognition: A survey,” IEEE Trans. Affective Comput., vol. 13, no. 3, pp. 1195–1215, 2020.

[5] S. Koelstra et al., “DEAP: A database for emotion analysis using physiological signals,” IEEE Trans. Affective Comput., vol. 3, no. 1, pp. 18–31, 2012.

[6] A. Mollahosseini, B. Hasani, and M. H. Mahoor, “AffectNet: A database for facial expression, valence, and arousal computing in the wild,” IEEE Trans. Affective Comput., vol. 10, no. 1, pp. 18–31, 2017.

[7] P. Viola and M. Jones, “Rapid object detection using a boosted cascade of simple features,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2001, pp. 511–518.

[8] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” in Proc. Int. Conf. Learn. Represent. (ICLR), 2015.

[9] K. Zhang, Z. Zhang, Z. Li, and Y. Qiao, “Joint face detection and alignment using multi-task cascaded convolutional networks,” IEEE Signal Process. Lett., vol. 23, no. 10, pp. 1499–1503, 2016.

[10] T. Baltrušaitis, P. Robinson, and L. P. Morency, “OpenFace: An open source facial behavior analysis toolkit,” in Proc. IEEE Winter Conf. Appl. Comput. Vis. (WACV), 2016, pp. 1–10.

[11] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2016.

[12] M. Abadi et al., “TensorFlow: Large-scale machine learning on heterogeneous systems,” 2016.

[13] OpenCV, “Open source computer vision library,” 2020.

[14] S. I. Serengil and A. Ozpinar, “LightFace: A hybrid deep face recognition framework,” 2020.

[15] G. B. Huang et al., “Labeled Faces in the Wild: A database for studying face recognition in unconstrained environments,” Univ. Massachusetts, Amherst, MA, USA, Tech. Rep., 2007.

 DOI 10.5281/zenodo.19634752