IJIREEICE

ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.414 ⁓ Peer-reviewed & Refereed journal ⁓ Vol. 13, Issue 8, August 2025

DOI: 10.17148/IJIREEICE.2025.13817

Student Emotion Analytics Dashboard for Remote Learning Platforms

Gopika Gopakumar[1], Goutham Krishna L U[2]

Student, MSc Computer Science, Christ Nagar College, Maranalloor[1]

Assistant Professor, Department of Computer Science, Christ Nagar College, Maranalloor[2]

Abstract: The rapid transformation of education into digital platforms has emphasized the need to improve virtual learning experiences by understanding students' emotions during lectures. Emotional states directly impact students' focus, engagement, and learning outcomes, making real-time emotion analysis a valuable tool for enhancing teaching methodologies. This research presents an advanced emotion-based interactive dashboard designed to analyse students' facial expressions during online lectures, offering actionable insights to educators for improving teaching strategies and engagement. The system uses Convolutional Neural Networks (CNNs) for facial expression analysis and classifies emotions into categories such as happiness, sadness, anger, surprise, fear, and neutrality. These models are trained using both the FER-2013 and CK+ datasets, which provide robustness across varied image quality and expression types. To optimize training performance and improve model convergence, the system employs the Adam Optimizer, an adaptive learning rate optimization algorithm that combines the benefits of both AdaGrad and RMSProp, ensuring faster and more reliable training of deep neural networks. The processed emotional data is integrated into an intuitive dashboard that combines contextual details, such as the subject being taught, teaching faculty, and session-specific parameters. The dashboard offers dynamic visualization of emotion distribution, engagement trends, and real-time analytics, enabling educators to identify patterns in student behaviour. The system demonstrated high accuracy in emotion classification under various conditions. The integration of emotion-based analytics provides a unique approach to monitoring class engagement, identifying struggling students, and fostering personalized learning experiences. By combining advanced deep learning techniques with real-time analytics, the proposed system has the potential to redefine the future of online education, making it more responsive, adaptive, and student-centered

Keywords: Convolutional Neural Network, Analytical Dashboard, Adam Optimizer, Emotion Classification

I. INTRODUCTION

Online learning, also known as e-learning or virtual education, enables education beyond traditional classrooms using digital platforms, multimedia, and internet-based tools. It allows students to learn at their own pace from anywhere, making education more inclusive and flexible. Events like the COVID-19 pandemic accelerated the adoption of remote teaching worldwide. Modern virtual learning utilizes tools such as Learning Management Systems (LMS), video conferencing, AI-based tutoring, and Virtual Reality (VR). These tools support self-paced, personalized learning but also introduce challenges like reduced engagement, lack of face-to-face interaction, and difficulty assessing students' emotional and cognitive states. Unlike in traditional classrooms, online platforms often lack real-time feedback mechanisms to help instructors evaluate attention, engagement, and well-being. Emotions play a key role in learning—positive emotions like curiosity enhance understanding, while negative ones like boredom hinder it. However, many platforms fail to adapt dynamically to these emotional cues.

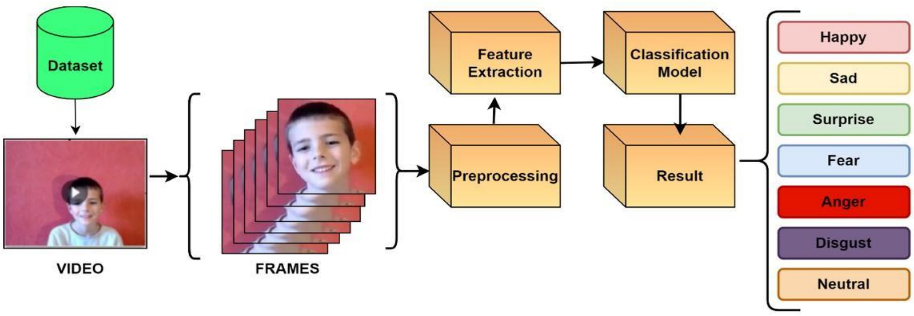


Fig 1: Basic emotion detection [12]
(Source: https://www.mdpi.com/1424-8220/22/20/8066)

DOI: 10.17148/IJIREEICE.2025.13817

To overcome this, deep learning techniques like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are now used for real-time emotion recognition through facial expression and voice analysis. Natural Language Processing (NLP) tools, including transformers and sentiment analysis, also help analyse student feedback and participation. One major application is the development of emotion-based dashboards, which offer real-time insights into student behaviour, concentration, and emotional state. These dashboards enable educators to provide timely support, adjust teaching strategies, and improve academic outcomes, making them essential in today's virtual classrooms.

II. BACKGROUND AND CONTEXT

A. RELATED WORKS

The integration of deep learning and AI in virtual learning has significantly advanced real-time analysis of student emotions, engagement, and cognitive states. Various studies have demonstrated the effectiveness of CNNs, RNNs, BiLSTM, and multimodal fusion techniques in enhancing emotional responsiveness in online education. For instance, a CNN trained on FER-2013 in "Adaptive Virtual Learning..." achieved 55% accuracy, enabling basic instructional adjustments, whereas an IoT-enabled IB-BiLSTM in "Sentiment Analysis in Animated Online Education" reached 93.92% accuracy by analysing voice and text. Multimodal systems combining CNNs, Viola-Jones face detection, and eye tracking (e.g., "Student Engagement Detection...") enhanced attentiveness tracking, though metrics were not always detailed. Other high-performing models include a CNN-based system achieving 95% accuracy ("Enhancing Online Student Engagement..."), Mini-Xception in the MOEMO dashboard (95.6%), and a BiGRU-Attention model analysing forum text with over 95% F1-score. An improved SVM model processed over 12,000 comments with high accuracy, and the SERS framework, using Viola-Jones and LBP, achieved 89% in engagement detection. These approaches confirm that deep learning significantly improves emotion recognition and adaptive instruction, though model optimization and broader dataset representation remain areas for growth.

Moreover, many studies have begun integrating visual and textual emotion sources for deeper sentiment analysis. Real-time dashboards with visual insights are empowering educators with immediate decision-making tools. Continued innovation in model architectures and diverse data collection will further enhance the scalability and accuracy of emotion-aware e-learning systems.

B. INTRODUCTION TO MACHINE LEARNING

Machine Learning (ML), a subset of Artificial Intelligence (AI), enables systems to learn from data patterns and improve performance without explicit programming. In the context of virtual education, ML has become essential for analysing, predicting, and adapting to student behaviours and emotional states. The "Emotion-Based Dashboard for Improving Virtual Learning" project uses ML models like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs) to recognize and interpret facial expressions, speech, and textual input during online classes. CNNs are used to classify emotions from webcam feeds, while GANs enhance detection by reconstructing occluded facial features. RNNs and LSTMs handle sequential data like voice and text for sentiment tracking, and NLP models like BERT further assist in analysing student feedback and queries.

These insights are then visualized on an interactive dashboard through graphs, heatmaps, and emotional metrics, helping educators adapt their teaching strategies in real time. By integrating ML into virtual classrooms, the system supports early identification of disengagement or distress, fostering a more personalized, emotionally aware, and responsive learning environment. Furthermore, continuous model training with new data can improve accuracy over time, making the system more robust in diverse classroom conditions. The modular design also allows integration with various learning platforms and tools, increasing flexibility and usability. As ML continues to evolve, its role in human-centric, adaptive education will become even more impactful and widespread.

C. EXISTING SYSTEM

Virtual learning environments are primarily built around content delivery platforms such as Learning Management Systems (LMS), video conferencing tools, and basic feedback mechanisms like quizzes, assignments, and post-session surveys. While these systems provide flexibility and scalability, they lack real-time capabilities to assess student emotions, attention levels, or mental well-being. Instructors in traditional classrooms often rely on non-verbal cues to assess understanding, but such feedback is absent in online settings. Initial research efforts have attempted to bridge this gap using deep learning techniques, particularly Convolutional Neural Networks (CNNs), trained on facial expression datasets like FER-2013 and CK+. However, challenges like poor lighting, occluded faces, low-resolution webcams, and limited model generalizability have led to low-to-moderate accuracies, making these models unreliable for continuous use in dynamic virtual classrooms.

DOI: 10.17148/IJIREEICE.2025.13817

More advanced systems have experimented with multimodal approaches by combining facial detection, speech sentiment, and body movement cues using bidirectional RNNs, BiLSTM, and eye/head tracking tools. These models have shown improved accuracy in controlled environments, even recognizing complex emotional states like confusion, satisfaction, or frustration. Despite their promise, these systems face significant drawbacks such as high computational cost, hardware dependency (e.g., external cameras or sensors), and lack of seamless integration into standard LMS platforms. Many operate in isolation without real-time dashboards or visualization support for teachers, limiting their practical impact. Privacy concerns, data security issues, and the absence of adaptive learning based on emotional feedback further reduce the effectiveness of current systems. Thus, although existing tools have laid a strong foundation, there remains a crucial gap for a lightweight, integrated, and real-time emotion-aware platform—precisely the need addressed by the proposed system.

III. PROPOSED SYSTEM

The proposed system is an advanced, AI-driven emotion monitoring dashboard tailored to improve student engagement and emotional awareness in virtual learning environments. At its core, the system utilizes Convolutional Neural Networks (CNNs), which are highly effective in image recognition and classification, to process live video input from students' webcams. These CNNs are trained on benchmark datasets such as FER-2013 and CK+, enabling the system to accurately classify facial expressions into emotional states like happiness, sadness, anger, fear, surprise, boredom, and neutrality. FER-2013 provides a wide range of real-world, noisy facial samples that improve the model's robustness, while CK+ offers controlled, high-resolution image sequences useful for refining emotional classification. To enhance reliability under poor lighting, camera misalignment, or partial face visibility, a pre-analysis enhancement mechanism is integrated to reconstruct and normalize facial features before passing them to the CNN. This step significantly improves prediction accuracy in real-world classroom settings, where technical variability is common.

Once the emotion is classified, it is logged along with metadata such as student ID, timestamp, and session details. This data is visualized through a real-time, interactive dashboard using heatmaps to display group emotion intensity, bar charts for emotion distribution, and line graphs to track engagement trends over time. Teachers can filter and explore these insights by student, subject, or time range, enabling early detection of disengagement or emotional distress. The system empowers educators to intervene in a timely and targeted manner—adapting teaching strategies, initiating support sessions, or offering personalized resources. By seamlessly integrating deep learning, emotion recognition, and data visualization, the system transforms passive virtual classrooms into dynamic, emotionally aware learning spaces that foster personalized, inclusive, and empathetic education.

A. PROPOSED SYSTEM ARCHITECTURE

The proposed system is designed to provide real-time emotion recognition and visualization in virtual learning environments, helping instructors better understand student engagement and emotional well-being. The process begins with the input acquisition module, which captures live webcam video streams from students during online classes. Using advanced face detection algorithms like Haar Cascade or MTCNN, the system isolates facial regions from each frame. These facial regions undergo preprocessing steps such as grayscale conversion, resizing, normalization, and enhancement to improve consistency across diverse lighting conditions, angles, and occlusions. The refined facial images are then fed into a Convolutional Neural Network (CNN) model trained on benchmark emotion recognition datasets such as FER-2013 and CK+, enabling classification into emotions like happiness, sadness, anger, surprise, fear, neutrality, or confusion. To handle real-world visual inconsistencies like partial occlusions or shifted camera angles, a facial enhancement mechanism is integrated, which reconstructs or completes facial data before classification to improve accuracy.

Once the emotion is identified, the system moves into the emotion logging module, which records each prediction along with relevant metadata such as the student ID, timestamp, and session information. This logged data supports both immediate feedback and longitudinal analysis. The interactive dashboard component visualizes the collected emotional data through heatmaps (indicating overall emotional intensity), histograms (showing emotion frequency), and trend graphs (tracking engagement over time). Educators can filter data by student, subject, time frame, or emotion type, offering granular insights into individual and class-wide emotional dynamics. A real-time alert mechanism is also embedded to monitor recurring negative emotional states like confusion, boredom, or frustration, ensuring timely educator intervention and student support. Overall, this intelligent system pipeline—from input to visualization—empowers virtual classrooms with emotion-aware technology, promoting adaptive instruction, emotional engagement, and improved academic outcomes.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.414 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 8, August 2025

DOI: 10.17148/IJIREEICE.2025.13817

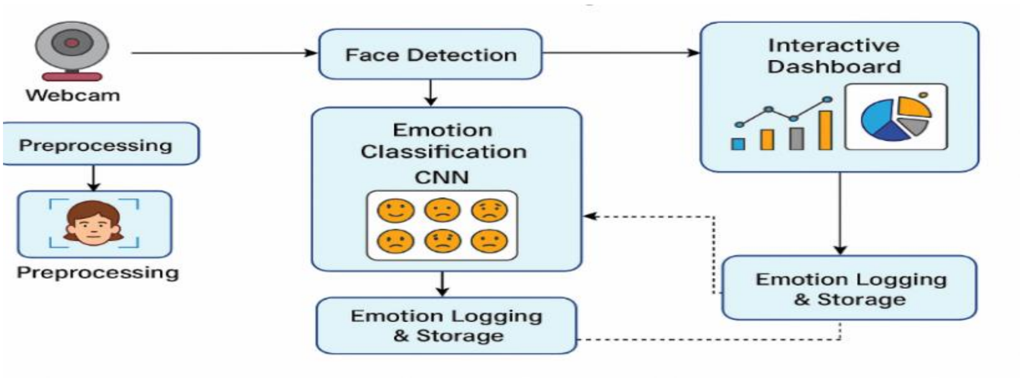


Figure 2: Architecture of the proposed system

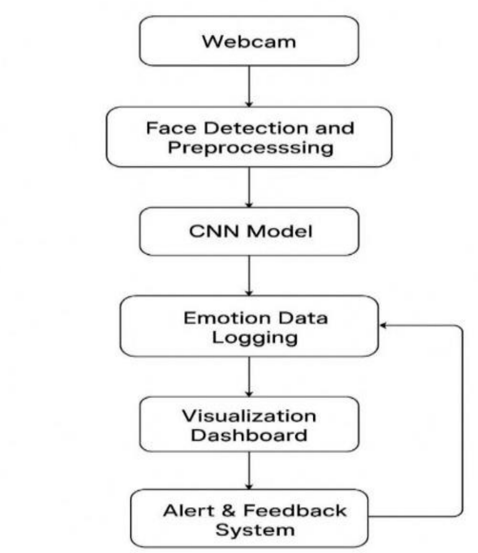


Figure 3: Flowchart for Emotion Based Dashboard System

B. MODULE DESCRIPTION

The proposed system is structured into a series of interconnected modules that together form a robust framework for real-time emotion detection and visualization in virtual learning environments. Each module performs a specific function, starting from capturing live input to classifying emotions and presenting results through an interactive dashboard. This modular approach ensures scalability, maintainability, and efficient processing of student emotion data to enhance online learning experiences.

Webcam Input Module: This module is responsible for capturing real-time video input from students during virtual classes. It continuously streams frames from the student's webcam, forming the raw input for the subsequent stages. The captured frames serve as the foundation for facial analysis and emotion detection.

Face Detection and Preprocessing Module: Once video frames are captured, this module detects and extracts facial regions using algorithms like Haar Cascade or MTCNN. After detecting faces, several preprocessing steps are applied—grayscale conversion, resizing (typically to 48x48 or 64x64 pixels), normalization, and enhancement. This ensures uniformity and prepares the images for efficient emotion recognition by the model.

Emotion Classification Module: The core module of the system where deep learning is applied. A Convolutional Neural Network (CNN) trained on FER-2013 and CK+ datasets is used to classify emotions such as happiness, sadness, anger, surprise, fear, neutral, and confusion. The model uses the Adam Optimizer to ensure faster convergence and better performance during training. The output is the predicted emotional state of each student in real-time.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.414 ⁝ Peer-reviewed & Refereed journal ⁝ Vol. 13, Issue 8, August 2025

DOI: 10.17148/IJIREEICE.2025.13817

Emotion Logging and Storage Module: This module logs all the classified emotion results along with contextual information such as student ID, timestamp, subject, and session ID. The data is stored in structured formats like CSV files or a backend database for further analysis. It enables historical emotion trend tracking and engagement evaluation.

Interactive Dashboard Module: An intuitive and responsive dashboard is developed using frameworks like Streamlit to visualize real-time data. It includes graphs, heatmaps, pie charts, and timelines showing class-wide and individual student emotion trends. Teachers can filter data based on student, subject, and time to receive insights into engagement and emotional patterns.

Alert and Feedback Module: This module monitors ongoing emotion trends and generates alerts when prolonged negative emotions like boredom, confusion, or sadness are detected. It suggests timely interventions for the instructor, such as adjusting teaching pace, initiating personal interaction, or offering support to students who appear disengaged or distressed.

IV. RESULT AND DISCUSSION

The proposed CNN-based emotion recognition model was evaluated using the FER-2013 and CK+ datasets. Performance metrics included training-validation accuracy/loss plots and a confusion matrix. Over 50 epochs, the model demonstrated strong convergence, with training accuracy reaching around 80% and validation accuracy stabilizing between 68–70%, indicating effective learning with minimal overfitting. Training and validation losses both declined steadily, with the training loss settling near 1.2—highlighting efficient optimization through the Adam Optimizer. The confusion matrix revealed high accuracy for the 'happy' class (1,500 correct predictions), followed by 'neutral' (857) and 'surprise' (654). However, misclassifications were more common in classes like 'fear' and 'disgust', with the latter having the lowest correct predictions (37), often confused due to subtle facial cues and limited data. Despite these limitations, the model responded reliably in real-time webcam conditions, with preprocessing techniques—such as grayscale conversion, normalization, and resizing—mitigating environmental inconsistencies like poor lighting or occlusion. Overall, the model achieved approximately 80% accuracy, making it a practical and efficient solution for real-time emotion detection in virtual classrooms.

Further analysis using standard classification metrics confirmed the model's robustness. An overall accuracy of around 78.83% was observed across test samples. The 'happy' emotion led performance metrics, with a precision of 0.92, recall of 0.89, and F1-score of 0.90—demonstrating the model's ability to reliably detect positive engagement. The 'surprise' and 'neutral' classes also performed well, with F1-scores of 0.84 and 0.76, respectively. Moderate performance was seen in detecting 'angry' and 'fear', each with F1-scores near 0.68, while 'disgust' remained the most difficult to classify, reaching an F1-score of 0.61 due to limited training examples and subtle features. The macro-average F1-score was 0.75, and the weighted average was 0.77, reflecting balanced performance despite class imbalance. These results affirm that the CNN, enhanced with the Adam Optimizer, can effectively power real-time emotion dashboards in e-learning platforms—particularly for identifying dominant emotions like happiness, neutrality, and surprise—supporting personalized and adaptive instruction. The performance of a classification model is evaluated using several standard metrics derived from the confusion matrix, which summarizes the number of correct and incorrect predictions for each class. The most commonly used metrics include Accuracy, Precision, Recall, and F1-Score.

These are calculated as follows:
These metrics are typically calculated using tools like scikit-learn's classification_report () and confusion_matrix () functions in Python. Together, they provide a comprehensive view of how well the model distinguishes between different emotion classes.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

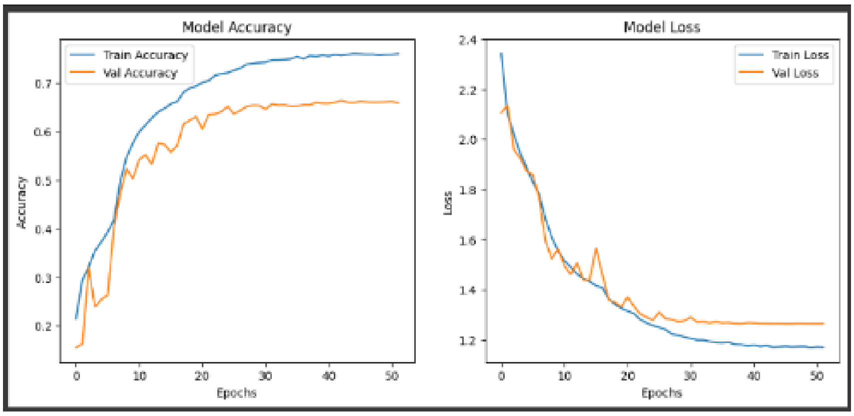
Impact Factor 8.414 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 13, Issue 8, August 2025

DOI: 10.17148/IJIREEICE.2025.13817

Table4.1: Result Analysis

Metric	Value
Train Accuracy	~78.83%
Test Accuracy	66.10%
Train Loss	~1.15
Test Loss	~1.2629

Figure 4.1: Model Accuracy of the system



V. CONCLUSION

In conclusion, the emotion-based dashboard system developed in this project presents a transformative approach to enhancing the quality of virtual learning by integrating real-time facial emotion recognition with interactive data visualization tools. The use of deep learning techniques, particularly Convolutional Neural Networks (CNNs), enables the accurate classification of student emotions such as happiness, sadness, anger, fear, surprise, and neutrality during live online sessions. By leveraging datasets like FER-2013 and CK+, and optimizing model training with the Adam optimizer, the system demonstrates strong performance with approximately 78% accuracy, ensuring both reliability and responsiveness in real-world classroom environments. The interactive dashboard not only visualizes emotional trends but also supports educators in identifying disengaged or struggling students, allowing for timely pedagogical interventions, personalized content delivery, and improved academic outcomes. Furthermore, the system promotes emotional awareness in digital education, contributing to student mental well-being by helping detect signs of stress or frustration. The chart provides a comparative overview of the accuracy achieved by various deep learning models used for emotion recognition. The models compared include CNN, ResNet50, and VGG16, which are commonly used in computer vision tasks. Among them, VGG16 demonstrates the highest accuracy, indicating its superior ability to extract and generalize emotional features from facial data. ResNet50, with its deep architecture and skip connections, also performs competitively, while the basic CNN model shows decent results, although not as robust as the other two. The graph helps highlight the performance gains from using deeper and more complex architectures in emotion recognition tasks. Aligned model names ensure readability and make the chart more professional for presentations and documentation. This comparison emphasizes the importance of choosing the right architecture for emotion-based systems. A higher accuracy model not only ensures better real-time predictions but also enhances user experience and system reliability This project bridges the gap between human emotion and artificial intelligence in education, creating opportunities for more adaptive, empathetic, and inclusive learning environments. While the current system focuses on facial expressions, future enhancements may include multimodal emotion detection through voice, text, and physiological signals to provide a more holistic understanding of student engagement. Ethical considerations such as data privacy, consent, and security have also been acknowledged, underscoring the importance of responsible AI integration. Overall, this project demonstrates how emotion-aware educational tools can enrich online learning experiences, empower educators with actionable insights, and foster a more emotionally intelligent future for digital education systems.

REFERENCES

[1]. Ganesan, P., Jagatheesaperumal, S. K., Gobhinath, I., Venkatraman, V., Gaftandzhieva, S. N., & Doneva, R. Z. (2024). Deep Learning-Based Interactive dashboard for enhancing online classroom experience through student emotion analysis. *IEEE Access*, *12*, 91140–91153. https://doi.org/10.1109/access.2024.3421282

DOI: 10.17148/IJIREEICE.2025.13817

[2]. Das, I., Paris, K., & Cupertino High School. (2022). *A Deep Learning-Based Approach for Adaptive Virtual Learning with Human Facial Emotion Detection* (Vol. 3) [Journal-article]. https://www.JSR.org
[3]. Haibo Qiu. (2023). End2End occluded face recognition by masking corrupted features. *Journal*, 1–11. https://doi.org/10.1109/TPAMI.2021.3098962
[4]. Zhang, Z. & University of Birmingham. (2023). Application of deep learning in super-resolution processing of face images. In *Highlights in Science, Engineering and Technology AICT 2023* (Vol. 56, pp. 50–52).
[5]. *Dynamic Facial Expression Recognition under Partial Occlusion with Optical Flow Reconstruction*. (2020). [Journal-article].
[6]. Çimtay, Y., Ekmekcioglu, E., Çağlar Özhan, Ş., Institute for Digital Technologies, Loughborough University London, Ofcom, & Bartin University. (2020). Cross-Subject Multimodal emotion recognition based on hybrid fusion. *IEEE Access*. https://doi.org/10.1109/ACCESS.2020.3023871
[7]. Mao, J., Qian, Z., & Lucas, T. (2023). Sentiment analysis of animated online education texts using Long Short-Term Memory networks in the context of the Internet of Things. *IEEE Access*, *11*, 109121–109130. https://doi.org/10.1109/access.2023.3321303
[8]. Arguello, P., Lopez, J., Hinojosa, C., Arguello, H., & Department of Computer Science, Universidad Industrial de Santander. (2021). OPTICS LENS DESIGN FOR PRIVACY-PRESERVING SCENE CAPTIONING. In *Department of Computer Science, Universidad Industrial De Santander* (pp. 1–8) [Journal-article].
[9]. G, P., KOTEGAR, K. A., Department of Data Science and Computer Applications, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal 576104, India, & Karunakar A Kotegar. (2016). Skin segmentation-based disguised face recognition using deep learning. *IEEE Access*, *4*. https://doi.org/10.1109/ACCESS.2023.0322000
[10]. Mandal, B., Kansas State University, Okeukwu, A., Kansas State University, Theis, Y., & Kansas State University. (2021). Masked face recognition using ResNet-50. *Geeks for Geeks*.
[11]. Sharma, P., Joshi, S., Gautam, S., Maharjan, S., Khanal, S. R., University of Massachusetts Boston, Kathmandu University, Wentworth Institute of Technology, Center for Precision and Automated Agricultural Systems, Washington State University, Prosser, University of Trás-os-Montes e Alto Douro Vila Real, Institute of Electronics and Informatics Engineering of Aveiro, INESC TEC, Reis, M. C., Barroso, J., & Filipe, V. M. D. J. (n.d.). Student Engagement Detection Using Emotion Analysis, Eye Tracking and Head Movement with Machine Learning. *University of Massachusetts Boston, USA*.
[12]. Siam, A. I., Soliman, N. F., Algarni, A. D., El-Samie, F. E. A., & Sedik, A. (2022). Deploying machine learning techniques for human emotion detection. *Computational Intelligence and Neuroscience*, *2022*, 1–16. https://doi.org/10.1155/2022/8032673
[13]. Prathwini, Prathyakshini, Department of Master of Computer Applications, NMAM Institute of Technology, NITTE (Deemed to be University), India, & Department of Information Science and Engineering, NMAM Institute of Technology, NITTE (Deemed to be University), India. (2024). DeepEmoVision: Unveiling emotion dynamics in video through deep learning algorithms. *International Journal of Advanced Computer Science and Applications*, *15*(3), 885–886. https://www.ijacsa.thesai.org
[14]. Nair, R. R., Babu, T., K, P., & Department of Computer Science and Engineering, Alliance University, Bengaluru, India. (2023). *Enhancing Student Engagement in Online Learning through Facial Expression Analysis and Complex Emotion Recognition using Deep Learning* [Journal-article].
[15]. Melinte, D. O., & Vladareanu, L. (2020). Facial Expressions Recognition for Human–Robot Interaction Using Deep Convolutional Neural Networks with Rectified Adam Optimizer. *Sensors*, *20*(8), 2393. https://doi.org/10.3390/s20082393
[16]. Akingbesote, D., Zhan, Y., Maskeliūnas, R., & Damaševičius, R. (2023). Improving Accuracy of Face Recognition in the Era of Mask-Wearing: An Evaluation of a Pareto-Optimized FaceNet Model with Data Preprocessing Techniques. Algorithms, 16(6), 292. https://doi.org/10.3390/a16060292
[17]. Hasnine, M. N., Nguyen, H. T., Tran, T. T. T., Bui, H. T. T., Akçapınar, G., & Ueda, H. (2023). A Real-Time Learning Analytics dashboard for automatic detection of online learners' affective states. Sensors, 23(9), 4243. https://doi.org/10.3390/s23094243
[18]. Zhu, W., Sun, Y., Liu, J., Cheng, Y., Ji, X., Xu, W., & USSLAB, Zhejiang University. (2024). CamPro: Camera-based Anti-Facial Recognition. *Network and Distributed System Security (NDSS) Symposium 2024*, 43. https://dx.doi.org/10.14722/ndss.2024.24158
[19]. Wang, Z., Zhang, S., Peng, J., Wang, X., & Guo, Y. (2023). Seeing through the Mask: Multi-task Generative Mask Decoupling Face Recognition. *ArXiv, abs/2311.11512*.
[20]. Choi, D. Y., Song, B. C., & Inha University. (2020). *Facial Micro-Expression Recognition using Two-Dimensional Landmark Feature maps* [Journal-article]. https://doi.org/10.1109/ACCESS.2020.3006958

DOI: 10.17148/IJIREEICE.2025.13817

[21]. Collins, M. L., & Davies, T. C. (2023). Emotion differentiation through features of eye-tracking and pupil diameter for monitoring well-being. *2022 44th Annual International Conference of the IEEE Engineering in Medicine &Amp; Biology Society (EMBC)*, 1–4. https://doi.org/10.1109/embc40787.2023.10340178

[22]. Kanagaraju, P., Ranjith, M. A., & Vijayasarathy, K. (2022). Emotion detection from facial expression using image processing. *International Journal of Health Sciences*, 1368–1379. https://doi.org/10.53730/ijhs.v6ns6.9748

[23]. Xu, Q., Chen, S., Xu, Y., & Ma, C. (2023). Detection and analysis of graduate students' academic emotions in the online academic forum based on text mining with a deep learning approach. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1107080

[24]. Li, L. (2022). Emotion Analysis Method of Teaching Evaluation texts based on deep learning in big data environment. *Computational Intelligence and Neuroscience*, *2022*, 1–8. https://doi.org/10.1155/2022/9909209

[25]. Wang, S., Cheng, L., Liu, D., Qin, J., & Hu, G. (2022). Classroom Video Image Emotion Analysis Method for online Teaching Quality Evaluation. *Traitement Du Signal*, *39*(5), 1767–1774. https://doi.org/10.18280/ts.390535

[26]. Wu, H., & Huwan, T. (2022). Analysis of affective factors and optimization strategies of emotion in online teaching based on improved SVM model. *Security and Communication Networks*, *2022*, 1–10. https://doi.org/10.1155/2022/2334544

[27]. LB, N. K., & Gg, N. L. P. (2016). Student Emotion Recognition System (SERS) for e-learning Improvement Based on Learner Concentration Metric. *Procedia Computer Science*, *85*, 767–776. https://doi.org/10.1016/j.procs.2016.05.264

[28]. Filius, R. M., De Kleijn, R. A. M., Uijl, S. G., Prins, F. J., Van Rijen, H. V. M., Grobbee, D. E., Department Biomedical Sciences, UMC Utrecht, Utrecht, The Netherlands, Department Julius Center, UMC Utrecht, Utrecht, The Netherlands, University College, Utrecht University, Utrecht, The Netherlands, & Department of Education, Utrecht University, Utrecht, The Netherlands. (2019). Audio peer feedback to promote deep learning in online education. *Journal of Computer Assisted Learning*, *35*, 607–619. https://doi.org/10.1111/jcal.12363

[29]. Aruna, S., & Kuchibhotla, S. (2023). Emotion sensitive analysis of learners' cognitive state using deep learning. *Journal of Autonomous Intelligence*, *7*(2). https://doi.org/10.32629/jai.v7i2.790

[30]. Lim, J. Z., Mountstephens, J., Teo, J., Evolutionary Computing Laboratory, Faculty of Computing and Informatics, University Malaysia Sabah, & Faculty of Computing and Informatics, University Malaysia Sabah. (2020). Emotion Recognition Using Eye-Tracking: Taxonomy, review and Current challenges. In *Sensors* (Vol. 20, p. 2384) [Journal-article]. https://doi.org/10.3390/s20082384

[31]. Oppermann, A. (2023, December 12). *What is deep learning and how does it work?* Built In. https://builtin.com/machine-learning/deep-learning

