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# Emotion-Based Dashboard for Improving Virtual Learning

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**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. A key challenge in emotion recognition is dealing with occluded facial data caused by factors such as poor lighting, low resolution video, or face coverings. To address this, we employ a regenerative Generative Adversarial Network (GAN) capable of reconstructing occluded regions of the face while preserving critical emotional cues. The reconstructed data is processed using a deep learning model that predicts and classifies emotions into categories such as happiness, sadness, anger, surprise, fear, and neutrality. These emotional insights are then integrated into an intuitive dashboard that combines contextual data, 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 was validated using the CK+ dataset, achieving notable accuracy in classifying various emotions, even under conditions of partial facial occlusion. 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:** Analytical Dashboard, Regenerative Generative Adversarial Network (GAN), Occluded facial data, Real time emotion.

## I. INTRODUCTION

A dashboard is a visual interface that showcases essential performance indicators (KPIs) and other significant information in a clear and concise manner. Typically, dashboard visualizations include charts, graphs, tables, and other visual components that present data in an easily understandable format. They can be implemented in various forms, such as web applications, mobile applications, and desktop software. Overall, a dashboard serves as an effective tool for visualizing intricate data sets and facilitating improved decision-making. Users have the ability to personalize dashboards to showcase different types of visual data, including heat maps, scatter plots, or time-series data, based on their requirements.

Dashboards can depict various types of image data, including medical images, satellite images, and photographs, facilitating the detection of patterns and trends that might be challenging to discern in unprocessed data. Enhancing the accuracy of deep learning models for facial reconstruction can be accomplished by simulating occlusion data. This is done by combining the simulated occluded images with the original student images to form a training dataset.

## II. BACKGROUND AND CONTEXT

Our strategy involves utilizing deep learning methods, such as convolutional neural networks (CNNs) and generative adversarial networks (GANs), to establish the relationship between occluded images and the corresponding complete faces. These models can be trained on extensive datasets of faces to analyse the fundamental patterns and features of facial images. After reconstructing the complete face, facial landmarks and features can be extracted to recognize the shown facial emotions. For example, facial landmarks like the corners of the mouth, eyebrows, and eyes can indicate whether someone is smiling or frowning. Ultimately, the emotion is identified from the reconstructed image.

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### *A. Deep Learning- An Overview*

Deep learning is a subset of machine learning that enables computers to learn from large amounts of data by using artificial neural networks (ANNs) with multiple layers. It is inspired by the structure and function of the human brain, where neurons process and transmit information through interconnected layers. Unlike traditional machine learning, which requires manual feature extraction, deep learning models can automatically learn hierarchical patterns and representations from raw data, making them highly effective for complex tasks such as image recognition, speech processing, and natural language understanding. Deep learning has gained significant attention due to advancements in computational power (GPUs and TPUs), the availability of large datasets, and improved neural network architectures.

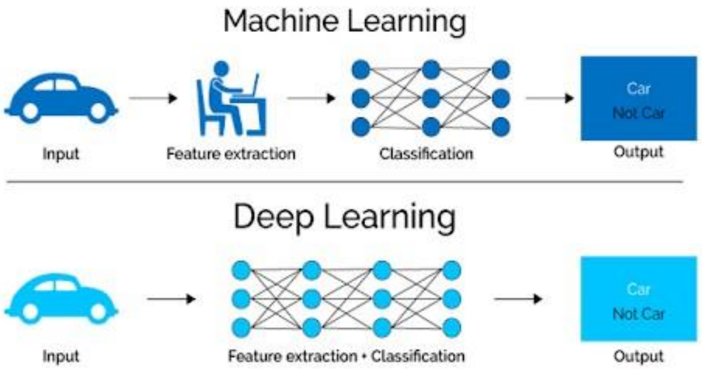


Fig 1: Comparison of machine learning and deep learning [31]

The success of deep learning in domains like computer vision, robotics, finance, and healthcare has made it one of the most widely adopted AI techniques. These models are trained using optimization algorithms such as gradient descent and backpropagation, allowing them to improve their accuracy over time. However, deep learning requires large datasets, extensive computational resources, and careful hyperparameter tuning to achieve high performance.

#### a. Types of Deep Learning Models

Deep learning models vary based on their architecture and application. The most widely used types include:

- **Convolutional Neural Networks (CNNs)**

CNNs are primarily used for image and video processing by recognizing spatial hierarchies in data. They consist of layers such as convolutional layers, pooling layers, activation functions, and fully connected layers, which help extract and classify features like edges, textures, and objects. CNNs are widely applied in facial recognition, medical imaging, self-driving cars, and object detection due to their ability to learn meaningful visual representations.

- **Recurrent Neural Networks (RNNs)**

RNNs are designed for sequential data processing and are widely used in time-series forecasting, speech recognition, and natural language processing (NLP). Unlike traditional neural networks, RNNs maintain a memory of previous inputs, making them suitable for tasks that require context retention. However, they suffer from the vanishing gradient problem, which limits their ability to learn long-term dependencies.

- **Long Short-Term Memory (LSTM) Networks**

LSTM networks are an advanced form of RNNs that solve the vanishing gradient problem by introducing gates (input, forget, and output gates) to regulate information flow. LSTMs are used in language translation, sentiment analysis, and handwriting recognition, where long-term dependencies are crucial. They have significantly improved applications like chatbots, voice assistants, and text prediction.

- **Transformer Networks**

Transformer networks, such as BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer), have revolutionized natural language processing by introducing self-attention mechanisms. Unlike RNNs, transformers process entire sequences in parallel, making them faster and more efficient. They are widely used in machine translation, text summarization, and conversational AI, enabling models like ChatGPT and Google's AI-driven search algorithms.

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- **Generative Adversarial Networks (GANs)**

GANs consist of two competing networks: a generator and a discriminator. The generator creates synthetic data, while the discriminator evaluates its authenticity. This adversarial process enables GANs to generate realistic images, videos, and text, making them useful in applications like deepfake creation, image super-resolution, and data augmentation. GANs have been widely used in art, gaming, and content generation, though they also pose ethical concerns regarding fake media and misinformation.
Each of these deep learning models plays a crucial role in advancing AI applications across various industries. While CNNs dominate computer vision, RNNs and transformers excel in language processing, and GANs enable generative AI innovations. Understanding these models helps in selecting the best approach for specific AI-driven tasks.

***B. Emotion Detection Using Deep Learning***

The deep learning models can then learn to reconstruct a complete face from an occluded image by recognizing the fundamental patterns and features of the facial data. When dealing with image data, visualization dashboards are especially valuable for observing trends and patterns within image datasets and pinpointing areas for improvement or potential problems. They enable the tracking of changes over time, such as variations in students' emotions during class. Facial recognition algorithms can evaluate a student's emotional expressions and anticipate their interests and preferences based on those expressions. Machine learning models can be trained using historical data to enhance accuracy over time. Various emotions, like happiness, surprise, or disgust, may correlate with different course preferences. By recognizing the key emotions linked to various courses, recommendations can be customized to align with a student's interests. Additionally, it can be tailored to present suggestions based on a student's interests and preferences. These suggestions can foster increased engagement and motivation by providing options relevant to their interests. Facial reconstruction involving occluded images poses a complex challenge in the realms of computer vision and image processing. Its objective is to rebuild the individual face even when portions are obscured or absent in the input image.

Presenting facial emotions in a dashboard can serve as an effective tool for recommending courses to students aligned with their interests and preferences. With the insights obtained from the dashboard, instructors can pinpoint areas needing improvement in operations, performance, or decision-making. It can also assist instructors in establishing realistic goals and targets based on the insights offered by data visualization. Such visualizations can empower instructors to foster continuous improvement and enhance operations to benefit student learning. Once course recommendations are made, instructors can utilize dashboards to track student engagement and performance. These visualizations can enable them to detect issues early and implement corrective measures as necessary.

## III. RELATED WORKS

[2] This research studies the learning outcomes of facial expression recognition in virtual environment settings. A CNN model is employed to identify the emotions of learners in virtual classes, enabling teachers to modify their methods during a session. With FER-2013 as a training dataset, this model is capable of 55% accurate predictions although improvement is needed. The research points out the relevance of detecting emotions accurately to boost people's willingness to attend and participate in online sessions while admitting their low accuracy and high computational costs.

[3] We propose FROM (Face Recognition with Occlusion Masks), an end-to-end architecture for automatic face recognition that handles occlusions, such as masks or sunglasses. The model learns feature masks on-the-fly to remove damaged areas and increases recognition accuracy. As a result, it achieves 99.38% accuracy on the LFW dataset, outperforming other existing models. This technique is beneficial for face verification of masked individuals in security and surveillance tasks.

[4] This paper looks at the potential of super resolution techniques supported by deep learning to improve face morph images. The contribution of this paper is found in a detail enhancement module that combines multiple images of a target subject to recreate fine details. Certainly, the approach leads to improved perceptual quality and affords better performance than advanced techniques in objective and subjective evaluation criteria. Nevertheless, it is not without shortcomings as it lacks accuracy in generating high-frequency details and requires further fine tuning and alterations.

[5] Although the task of facial expression recognition (FER) suffers from occlusion artifacts, therefore the authors propose an auto-encoder model with skip connections aimed at reconstructing the missing facial regions in the optical flow sense. The model will be tested on CK+ and other occluded datasets, with results showing a significant reduction of the accuracy gap between occluded and non-occluded faces. This may help significantly augment the robustness of FER systems in real applications.

[6] In order to improve emotion categorization, this work analyses multimodal emotion detection by combining facial expressions, electroencephalograms, and galvanic skin response (GSR). The hybrid model outperforms single-modality techniques with an accuracy of 81.2% on the LUMED-2 dataset and 91.5% on the DEAP dataset. The results demonstrate how integrating
visual and physiological inputs improve emotion recognition, which makes it beneficial to affective computing and mental health monitoring.

[7] The current study provides an Internet of Things (IoT)-based sentiment analysis framework for e-learning that uses an Information Block Bidirectional LSTM (IB-BiLSTM) model to classify emotions from spoken expressions and textual input. The model is quite successful in identifying student emotions in animated virtual learning environments, with an accuracy of 93.92%. The study emphasizes how crucial sentiment analysis is to enhancing adaptive e-learning systems.

[8] In that study, we propose a privacy-preserving picture captioning system that preserves scene understanding while distorting sensitive image portions using a refractive lens. On the COCO dataset, the deep learning-based model achieves accuracy comparable to that of conventional captioning systems, guaranteeing that private attributes like faces are unidentified while maintaining captioning quality. For AI applications in settings where privacy is a concern, this strategy is beneficial.

[9] A CNN-based disguised face recognition system that concentrates on exposed skin areas for better identification verification is shown in this work. Enhanced with a marker-controlled watershed algorithm, the model shows strong performance against face changes including masks, sunglasses, and makeup, achieving 94.92% accuracy on 64×64 photos. For applications involving security and monitoring, this method is extremely vital.

[10] In order to deal with the increased post-pandemic need for masked face recognition, this study develops ResNet-50 with transfer learning. With 89% accuracy, the model—which was trained on a Real-World Masked Face detection Dataset—enables dependable detection even in the presence of face occlusions. The model's generalization to various illumination scenarios and severe occlusions still presents obstacles though.

[11] This study suggests a multi-modal engagement detection system that combines head movement analysis, eye tracking, and emotion identification. The technology offers real-time insights into students' attention levels by using CNN for expression categorization and Viola-Jones for face and eye identification. The results demonstrate that multi-modal data fusion improves engagement tracking in online education, despite the study's lack of accuracy specifications.

[12] This study uses machine learning classifiers (SVM, KNN, Naïve Bayes, and MLP) in conjunction with MediaPipe facial mesh and PCA feature decomposition to recognize emotions. With an accuracy of 97%, the MLP classifier surpasses conventional techniques. The suggested method can be used in robotic vision, affective computing, and human-computer interaction. It is also very scalable.

[13] The current research investigates the use of SVM and KNN classifiers in conjunction with a CNN-RNN hybrid model for video-based emotion classification. The RNN model shows its efficacy in capturing temporal emotion dynamics with the greatest accuracy of 95%. The study demonstrates how deep learning may be used to detect emotions in video information in real time, which has applications in media analysis, instructing, and surveillance.

[14] A deep learning-based method for tracking student involvement on online learning platforms is presented in this paper. Both fundamental emotions (such as joy, sadness, rage, etc.) and complex emotions (such as confusion, satisfaction, disappointment, and frustration) are categorized by the suggested CNN model. This model interprets continuous video frames with 95% accuracy, in contrast to earlier methods that analyse static images. The results show how real-time emotion identification might assist teachers in refining their methods and raising student interest.

[15] A CNN-based facial expression detection system tailored for human-robot interaction (HRI) is presented in this work. The model achieves 97.8% accuracy (Faster R-CNN) and 90.14% accuracy (ResNet for FER) by integrating Faster R-CNN, SSD CNN, ResNet, VGG, and Inception V3. The system is perfect for real-time human-robot communication because of the Rectified Adam (RAdam) optimizer, which further enhances generalization and resilience.

[16] A Pareto-optimized FaceNet model combined with data preparation methods is assessed in this work to improve face identification in situations where masks are worn. Utilizing synthetic datasets with Cut Mix and Mix-up augmentation, the model enhances feature extraction from nonoccluded areas of masked faces.

The model outperforms the conventional FaceNet and Arc Face models with an accuracy of about 94%, according to experimental data. It is also more compact and effective for practical implementation.

[17] In this study, the MOEMO system—a real-time learning analytics dashboard—is presented. It uses the Mini-Xception algorithm to detect emotions in online learners with an accuracy of 95.60%. The technology determines the degree of participation and concentration by analysing eye movements and facial expressions in lecture films that were recorded using webcams. Online class video data is included in the collection, and the system offers real-time insights regarding students' emotional states, level of interest, and ability to focus. Teachers benefit from the dashboard.

[18] The new anti-facial recognition (AFR) system CamPro, which creates protected images at the camera module level, is presented in this study. By altering the colour correction matrix (CCM) and gamma correction parameters of the camera's image signal processor (ISP), CamPro eliminates personally identifiable information (PII) without compromising non-sensitive vision applications like person detection. This is an alternative to post-processing obfuscation. According to test results, CamPro is very successful at protecting privacy in real-world camera applications, lowering face identification accuracy to just 0.3%.

[19] In this paper, a deep learning-based method for masked face recognition (MFR) called MEER (Multi-task generative mask decoupling face Recognition) is presented. By separating mask related and identity-related features using a mask decoupling module (MDM), the model enables unmasked face synthesis using a combined training approach. Tests on both simulated and real-world occlusion benchmarks show that MEER performs better than the most advanced MFR techniques, greatly increasing the recognition accuracy of obstructed facial images.

[20] For the purpose of to identify facial micro-expressions (FMEs), which are imperceptible and uncontrollable emotional reactions, this study suggests a 2D landmark feature map (LFM) method. By converting coordinate-based facial landmark data into image representations, the LFM approach increases the precision of micro-expression detection in naturalistic settings. When compared to conventional techniques, the CNN-LSTM-based model shows greater dependability in identifying subtle facial expressions, achieving 71% accuracy on the SMIC dataset and 74% accuracy on the CASME II dataset.

[21] This study investigates how eye-tracking characteristics including saccades, gaze fixation, and pupil diameter relate to emotion recognition. The study examines physiological eye reactions to emotional stimuli using the International Affective Picture System (IAPS) dataset. Although the method is more accurate at identifying fear and sadness, it has trouble identifying more complex emotions like joy, disgust, and indifference. The results imply that eye-tracking can improve affective computing and mental health monitoring when paired with AI-based statistical models.

[22] This study addresses the time-consuming process data workers encounter when choosing appropriate data column combinations and producing many representations by introducing a deep learning-based approach for automating the building of analytical dashboards. The suggested method makes recommendations for data columns and various charts using deep learning, in contrast to conventional methods that rely on manually created design principles. The system functions as a mixed-initiative architecture, utilizing provenance data (such as authoring logs) to learn offline while permitting user input for column selection. A comparison with current graphical suggestion techniques and user research assessing the model's usefulness are used to illustrate its efficacy. By using this method, dashboard development becomes more relevant and efficient, resulting in a recommendation system that is more intelligent and dynamic.

[23] Academic emotion recognition by deep learning-based text analysis is the main topic of this research. The suggested BiGRU-Attention model achieves above 95% precision, recall, and F1score in classifying emotions from student talks in an academic online forum. Key emotional triggers are identified by the study, including peer relationships, career concerns, and academic stress. The findings demonstrate the efficacy of sentiment analysis based on deep learning in identifying academic emotions and promoting the wellbeing of students.

[24] The deep learning-based approach for emotion analysis of teaching evaluation texts presented in this study achieves a precision of 0.8214 and an accuracy of 0.9123. To boost long-term memory and concentrate on significant textual elements, the technique uses a Bidirectional Long Short-term Memory (BiLSTM) network that has been augmented with an attention mechanism. 126,208 teaching assessment texts from a university's educational administration system make up the dataset. Though it depends on set parameters and a lot of preprocessing, the model manages complicated text data well and accurately recognizes emotions to assist enhance the quality of instruction.

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[25] Having a 72.4% success rate in facial expression identification, this article examines emotions in online instruction using classroom video footage. The technique incorporates a tag attention mechanism to concentrate on important face areas and employs multi-task learning to concurrently conduct facial expression recognition and facial feature point placement. 1,250 classroom video pictures that have been labelled with emotions including joy, worry, and annoyance are included in the dataset. Although the model offers real-time emotion analysis for assessing the quality of instruction, it has a poor accuracy rate and may have trouble with facial images that are obscured or indistinct.

[26] This study proposes an enhanced Support Vector Machine (SVM) model that outperforms logistic regression, random forest, and decision tree models in analysing emotions in online instruction. By reducing feature size from 100 to 60, the technique maximizes training time and space while preserving consistent performance. 12,600 comments from online teaching evaluations, both favourable and negative, are included in the dataset. The enhanced SVM model may not have the sophisticated comprehension of more sophisticated deep learning models, but it is efficient and effective for categorizing emotional reactions.

[27] The Student Emotion Recognition System (SERS), which tracks learners' focus and involvement in an online learning environment, is presented in this paper. Without the need of physical contact devices, the system uses Viola-Jones and Local Binary Pattern (LBP) algorithms to detect head rotation and eye movement. The technique tracks attention patterns and plots them to provide teachers with feedback on the high, medium, and low levels of learner engagement. The findings show that real-time emotion monitoring is an effective way to improve e-learning content, with an accuracy of 89% in identifying students' degrees of attentiveness.

[28] The paper investigates the way deep learning in online education is affected by audio peer feedback. Utilizing a mixed-method approach that includes surveys and interviews, the study examines the responses of students enrolled in Small Private Online Courses (SPOCs) and Massive Open Online Courses (MOOCs). According to research, aural feedback increases self-regulated learning, personal commitment, and supports deeper engagement. The findings demonstrate that students who gave audio peer comments demonstrated more critical thinking skills and deeper learning than those who only received input, underscoring the potential of audio-based evaluations to enhance online education.

[29] A deep learning-based system for real-time emotion recognition in online learning settings is presented in this study. The system uses Convolutional Neural Networks (CNNs) and a multitask learning strategy to evaluate students' cognitive states by analysing their head posture, facial landmarks, and expressions. The CK+ dataset was used to train the model, which achieved 94% accuracy in identifying the emotions and levels of focus of learners. Personalized learning experiences can be greatly improved by real-time monitoring of cognitive and emotional states, according to the research.

[30] The paper includes a thorough analysis of eye-tracking technology-based emotion identification, emphasizing important methods such saccades, gaze fixation, and pupil dilation. The combination of deep learning models, EEG, and GSR to increase accuracy in human-computer interface (HCI) applications is covered in the paper. Even while eye tracking by itself might not be very accurate, it is a promising modality when paired with facial and physiological identification techniques. While the paper provides a taxonomy and critical assessment of current methodologies, it does not specify accuracy.

## IV. SYSTEMATIC ANALYSIS

| Ref. Nos. | Method Used | Dataset | Merits | Demerits | Inference |
|---|---|---|---|---|---|
| Ganesan P. Et.al. [1] | GAN-based facial emotion analysis With interactive dashboard | CK+ | Real-time student emotion tracking, Enhances online learning | Requires facial reconstruction for occlusions, may face privacy concerns | Useful for adaptive teaching by analysing student emotions |
| Das I. Et.al. [2] | CNN for facial expression recognition in virtual learning | FER-2013 | Provides Realtime feedback for teachers | Low accuracy compared to other deep learning models | Helps improve engagement in online education |

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|---|---|---|---|---|---|
| Haibo Qiu. Et.al. [3] | FROM model (Feature Masking) | LFW, Mega face, RMF2, AR | Works well with occlusions, no need for external detectors | Requires largescale training data | Robust occluded face recognition for real-world applications |
| Zhang, Z Et.al. [4] | CNN | FEI and Multi PIE | Improves image clarity, transfers high-frequency details | Still has shortcomings requiring further research | Enhances face images for biometric recognition and surveillance |
| Delphine Poux Et.al. [5] | Auto-encoder with skip connections in optical flow domain | CK+ (with generated occlusions) | Directly reconstructs facial movement, robust against occlusions | Requires optical flow computation | Improves video-based emotion recognition under occlusions |
| Çimtay Y. Et.al. [6] | Hybrid fusion of CNN + physiological signals (EEG, GSR) | LUMED-2, DEAP | Robust to deceptive facial expressions, high accuracy | Requires multimodal data collection | Enhances emotion recognition in affective computing |
| Mao J. Et.al. [7] | IB-BiLSTM with IoT data | TensorFlow Framework + Multimodal data | Captures Realtime student sentiment | Requires extensive preprocessing and multimodal data collection | Improves personalization in online education |
| Arguello P. Et.al. [8] | Refractive Lens + Image Captioning Network | COCO | Protects user privacy while enabling scene understanding | May distort non-private regions as well | Useful for privacy sensitive AI applications |
| G. P. Kotegar Et.al. [9] | CNN with Marker Controlled Watershed Algorithm | Sejong dataset | Works well under disguises (masks, sunglasses) | Limited performance on extreme disguises | Enhances security and surveillance applications |

| **Ref. Nos.** | **Method Used** | **Dataset** | **Merits** | **Demerits** | **Inference** |
|---|---|---|---|---|---|
| Mandal, B Et.al. [10] | ResNet-50 with Transfer Learning | Real-World Masked Face Recognition Dataset | Works well with masked faces, fine-tuned model | May not generalize to all real-world conditions | Helps adapt existing recognition systems to pandemic scenarios |
| Sharma, P Et.al. [11] | CNN + Viola-Jones Algorithm | FER2013 | Multi-modal engagement tracking | Requires webcam-based monitoring | Provides real-time student engagement assessment in eLearning |

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|---|---|---|---|---|---|
| Siam, A Et.al. [12] | MediaPipe + PCA + SVM/KNN/MLP | CK+, JAFFE, RAF-DB | High accuracy for emotion recognition | Requires feature decomposition | Enhances robotic vision and human computer interaction |
| Prathwini Et.al. [13] | CNN + RNN + SVM + KNN | FER-net | High accuracy for video emotion analysis | Computationally intensive | Useful for video-based emotion detection applications |
| Nair R. R Et.al. [14] | CNN-based facial expression analysis with dynamic frame processing | FER dataset | Identifies complex emotions like confusion, satisfaction, disappointment, and frustration | Requires continuous video processing, may be affected by low video quality | Helps teachers monitor engagement levels in online learning and adapt teaching strategies |
| Melinte D.O. Et.al. [15] | Faster R-CNN + SSD CNN + ResNet/VGG/Inc e ption V3 | PASCAL VOCs | High-speed, high-accuracy emotion recognition | Requires optimization tuning | Enhances human-robot interaction systems |
| Akingbesote D Et.al. [16] | Pareto-optimized FaceNet | The CASIA-WebFace+ And VGG-Face dataset | Better model size and is a much smaller and more efficient version than the original FaceNet | The study was limited to the use of the CASIA and VGG-Face datasets And factors such as lighting and camera angle was not considered in the study. | Helps to reduce the inference time and making it more practical for use in real-life applications |
| Hasnine M. N. Et.al. [17] | Multi-task Cascade Convolutional Neural Network, Mini–Xception model | FDDB, WIDER FACE, FER-2013 | Real-time affective state monitoring | Dependent on facial visibility | Enhances adaptive learning experiences |

| **Ref. Nos.** | **Method Used** | **Dataset** | **Merits** | **Demerits** | **Inference** |
|---|---|---|---|---|---|
| Zhu W Et.al. [18] | ArcFaceIResNet50, SoftMax | CELEB A, LFW, COCO | Preserve a certain degree of privacy, even if the adversary has complete knowledge of CamPro No additional Hardware required | Not suitable where user's face fidelity is required | serves as the first attempt at privacy preservation by birth leveraging built-in ISP functions in the camera module |

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|---|---|---|---|---|---|
| Wang Z Et.al. [19] | A multi-task generative mask decoupling face Recognition (MEER) network | MS1M v2-Aug, RMFD, MFR2, (MLFW, LFW-masked | An attention-based mask decoupling module to separate the mask-related and identity-related feature from a hybrid high-level feature. | It is risky to use noisy segmentation labels to purify facial feature, which will result in recognition performance degradation. | It employs mask in formation suppression with both adversarial and reconstruction loss in the process of image econstruction. Therefore, the mask removal results contain less artifacts. |
| Choi D. Y Et.al. [20] | 2D Landmark Feature Map (LFM) + CNN + LSTM | SMIC, CASME II, SAMM, CK, MAHNOB-HCI, MEVIEW | Works well for subtle micro expressions, independent of intensity | More computationally intensive due to CNN-LSTM integration | Improves micro expression recognition in AI-human interaction and emotion monitoring |
| Collins M. L Et.al. [21] | Statistical analysis of eye-tracking features (pupil diameter, saccades) for emotion detection | International Affective Picture System (IAPS) | Non-contact method for emotion recognition, potential for assistive communication devices | Lower accuracy for complex emotions like joy, indifference, and disgust | Eye-tracking features can be used for monitoring mental well-being and emotion recognition |
| Kanagaraju P Et.al. [22] | CNN-based VGG16 architecture. Image preprocessing (resizing, colour mode change). Real-time testing using Haar Cascade and webcam. | FER-2013 | Real-time emotion detection. - Automatically provides video-based solutions for negative emotions (sad, angry, fearful). - Uses a pretrained CNN model for quick predictions. | Moderate accuracy (64.52%). Requires computational resources for training. Limited to six basic emotions. | The system can detect six basic emotions (Happy, sad, angry, fearful, surprised, neutral) in real-time. Itprovides automated solutions (videos) for negative emotions like sadness, anger, and fear. The model achieves moderate accuracy and can be improved with further optimization. |

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| Ref. Nos. | Method Used | Dataset | Merits | Demerits | Inference |
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| Kanagaraju P Et.al. [22] | CNN-based VGG16 architecture. - Image preprocessing (resizing, colour mode change). - Real-time testing using Haar Cascade and webcam. | FER-2013 | Real-time emotion detection. - Automatically provides video-based solutions for negative emotions (sad, angry, fearful). - Uses a pretrained CNN model for quick predictions. | Moderate accuracy (64.52%). Requires computational resources for training. Limited to six basic emotions. | The system can detect six basic emotions (Happy, sad, angry, fearful, surprised, neutral) in real-time. It provides automated solutions (videos) for negative emotions like sadness, anger, and fear. Themodel achieves moderate accuracy and can be improved with further optimization. |
| Xu Q. Et.al. [23] | BiGRU-Attention model for text-based academic emotion detection. | Online Academic Forum Data | Effective in detecting hidden academic emotions, useful for student mental health monitoring | Requires large labelled datasets, limited to text-based analysis | BiGRU-Attention model accurately classifies academic emotions and identifies key stress factors among graduate students |
| Li L. Et.al. [24] | Bidirectional Long Short-Term Memory (BiLSTM) | Teaching evaluation texts from a university's educational administrati on system | High accuracy and precision in emotion recognition. The attention mechanism helps focus on important information in the text. The model can handle complex and unstructured text data effectively. | The model parameters are fixed and cannot automatically adjust based on data characteristics. Relies heavily on the quality of the dataset and preprocessing steps. | Effective for analysing emotions in teaching evaluation texts, which can help improve teaching quality by identifying areas of dissatisfaction or satisfaction among students. |

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| Wang S Et.al. [25] | Multi-task learning and Tag attention mechanism | Classroom video images with emotion tags | Real-time switching between tasks (expression recognition and feature point location). The attention mechanism improves the model's ability to focus on important facial regions. | The accuracy of facial expression recognition is relatively low (72.4%). The model may struggle with occluded or unclear facial images. | Useful for evaluating online teaching quality by analysing the emotional states of teachers and students, but it may need further improvement in accuracy. |

| Ref. Nos. | Method Used | Dataset | Merits | Demerits | Inference |
|---|---|---|---|---|---|
| Wu H Et.al. [26] | Support Vector Machine (SVM) model | 12,600 positive and 12,600 negative comments | The improved SVM model is efficient and reduces the dimensionality of feature vectors. It performs well in classifying both positive and negative comments. The model is less affected by changes in dimensions and maintains stable performance. | The model requires significant time for training, especially with large datasets. It may not capture complex emotional nuances as effectively as deep learning models. | Effective for analysing emotions in online teaching and can help optimize teaching strategies by understanding students' emotional responses. |
| LB N. K Et.al. [27] | Viola-Jones and LBP algorithms for face and eye detection | Real-time webcam data | Contactless monitoring, real-time feedback, enhances eLearning experience | Limited generalization, affected by lighting and camera quality | Effective for tracking student concentration levels in e-learning |
| Filius R. M. Et.al. [28] | Mixed-method approach, including questionnaires and interviews | MOOCs and SPOCs platforms | Enhances engagement, promotes self-regulated learning | Requires student adaptation, may not be effective for all learners | Audio feedback fosters deeper learning and critical thinking |
| Aruna S. Et.al. [29] | Multi-task CNN for facial expression and head posture analysis | CK+ dataset | Real-time emotion detection, enhances personalized learning | High computational cost, requires high-quality data | Real-time cognitive state monitoring can improve learning engagement |

 

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|---|---|---|---|---|---|
| Lim J. Z Et.al. [30] | Review of eye tracking-based emotion recognition techniques | Various research studies on eye-tracking | Covers various modalities (EEG, GSR, pupil tracking), useful for HCI applications | Eye-tracking alone may not be sufficient for precise emotion detection | Eye-tracking is a promising but developing modality for emotion recognition |

## V. CONCLUSION

The proposed deep learning-based interactive dashboard presents an innovative solution for improving student engagement in online education through real-time emotion analysis. By leveraging Convolutional Neural Networks (CNNs) for emotion classification and Generative Adversarial Networks (GANs) for occlusion reconstruction, the system ensures accurate emotion recognition despite challenges like facial occlusion and varying lighting conditions. Unlike conventional emotion detection tools, this approach integrates real-time data visualization, enabling educators to track student engagement effectively. The use of heatmaps, histograms, and emotion trend analysis provides actionable insights, allowing for dynamic adaptations in teaching methodologies. Compared to previous research, which focused on facial recognition and analytics, this study offers a more adaptive and intelligent approach tailored to virtual classrooms. Beyond online education, this research has potential applications in corporate training, healthcare, and human-computer interaction, providing a scalable and adaptive approach to real-time emotion analysis. As digital learning environments continue to evolve, integrating AI-driven emotion insights will be crucial for enhancing student engagement, motivation, and overall learning outcomes.

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