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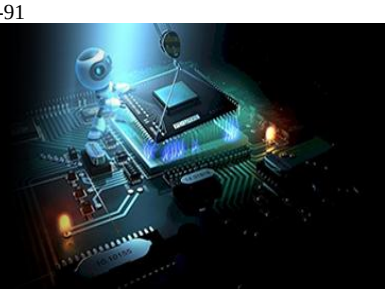

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# Emotion recognition in online learning using CNNs and RNNs

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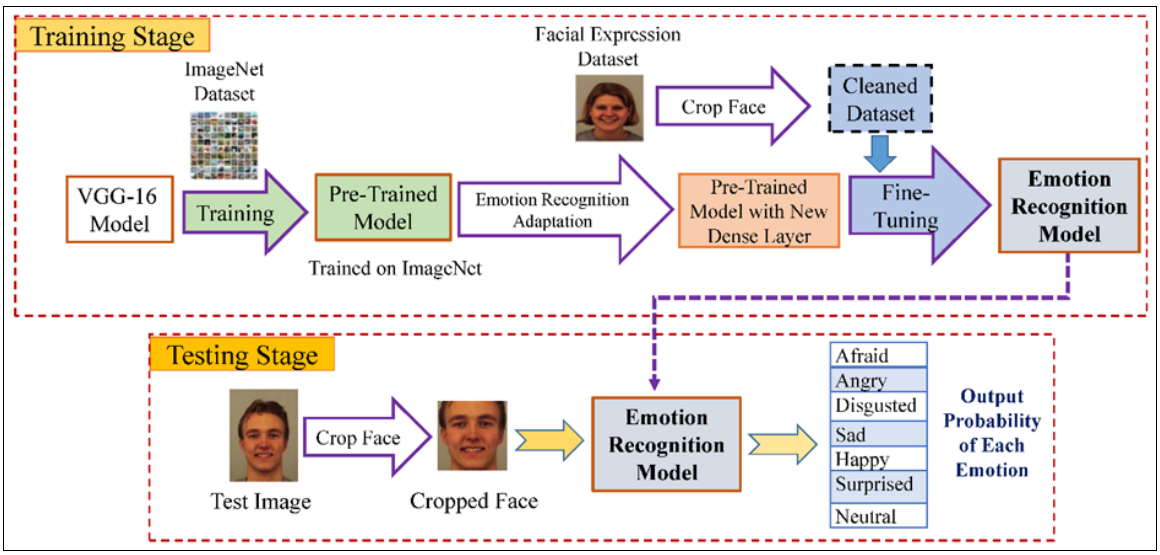
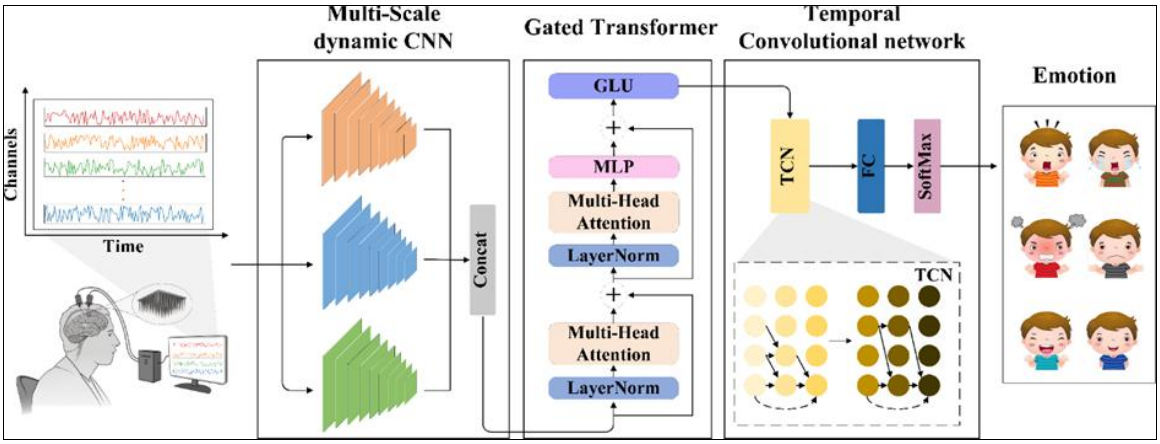
**Abstract**
Emotion recognition plays a crucial role in enhancing personalized learning experiences and engagement in online education. This research explores the application of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for detecting and analysing students' emotions in virtual learning environments. Drawing on recent studies, the paper highlights how CNNs effectively capture spatial features from learners' facial expressions, while RNNs, including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), capture temporal patterns over time. Hybrid CNN-RNN architectures, combined with attention mechanisms and multimodal inputs such as facial expressions, audio, and gaze tracking, have demonstrated superior performance compared to standalone models. The results of the literature review reveal the advantages of deep learning in affective computing, while also addressing challenges related to dataset variability, privacy, and deployment in real-time settings. By leveraging CNN-RNN-based models, online learning platforms can provide adaptive and emotionally responsive feedback, thereby improving engagement and academic performance. The study concludes with future directions emphasizing lightweight architectures, ethical considerations, and explainable AI.

**Keywords:** Emotion recognition, online learning, convolutional neural networks (CNNs), recurrent neural networks (RNNs), temporal emotion analysis, affective computing, deep learning, multimodal emotion recognition, adaptive e-learning systems

## 1. Introduction
The rapid expansion of online and intelligent learning environments has made emotional state monitoring a critical component for improving learner engagement, retention, and personalized support. In face-to-face classrooms teachers naturally perceive learners' affective cues (facial expressions, vocal tone, gaze) and adapt instruction; that channel is severely diminished in remote settings, which can lead to disengagement, lost learning opportunities, and poorer outcomes (Lu, 2022) [11]. Deep learning methods—especially Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs, including LSTM/GRU variants)—have become the dominant tools for automatic emotion recognition because they can learn powerful spatial features from images/video (CNNs) and temporal/sequence patterns from audio, video frames, gaze, or physiological streams (RNNs) (Pan *et al.* 2023) [12]. Hybrid architectures that combine CNNs (for spatial/visual feature extraction) with RNNs (for modeling temporal dynamics) are increasingly common for video- and speech-based learner-affect inference and often outperform single-modality or single-architecture approaches. Recent surveys and benchmarks emphasize a clear trend toward multimodal systems (face, voice, text, eye-tracking, EEG) and toward fusion strategies (early, late, hybrid) that leverage complementary signals to increase robustness in noisy or unconstrained e-learning settings (e.g., low-light webcams, variable audio quality). Multimodal deep frameworks and lightweight CNN-RNN hybrids have been shown to improve recognition accuracy while attention and model-compression techniques aim to keep inference feasible for real-time classroom/remote deployments (Lian *et al.* 2023) [9].
Despite promising accuracy on curated datasets, several challenges remain for deploying CNN/RNN-based emotion recognition in real online learning scenarios: dataset bias (most FER/SER datasets are lab-collected), privacy and ethical constraints, occlusion and lighting variability, domain shift between datasets and real classrooms, and computational cost for real-time inference (systematic reviews and recent applied studies

discuss these gaps and mitigation strategies). Addressing these issues through domain adaptation, multimodal fusion, privacy-preserving sensing, and lightweight model design is central to producing practical emotion-aware online learning tools (Pereira *et al.* 2024) [13]. This study (or the planned research) focuses on designing, implementing, and evaluating CNN-RNN (and hybrid multimodal) architectures for emotion recognition specifically within online learning contexts. The goals are to exploit CNNs for robust visual feature extraction and RNNs for temporal modeling of student affect, to explore multimodal fusion (video + audio ± gaze/physiology) to improve robustness in real classroom conditions, and to evaluate model generalization and real-time feasibility on datasets that approximate online learning scenarios (with discussion of privacy and ethical safeguards). The literature indicates that CNN-RNN hybrids and multimodal fusion are currently the most promising technical directions for this application area (Jeong and Cho, 2022) [7].



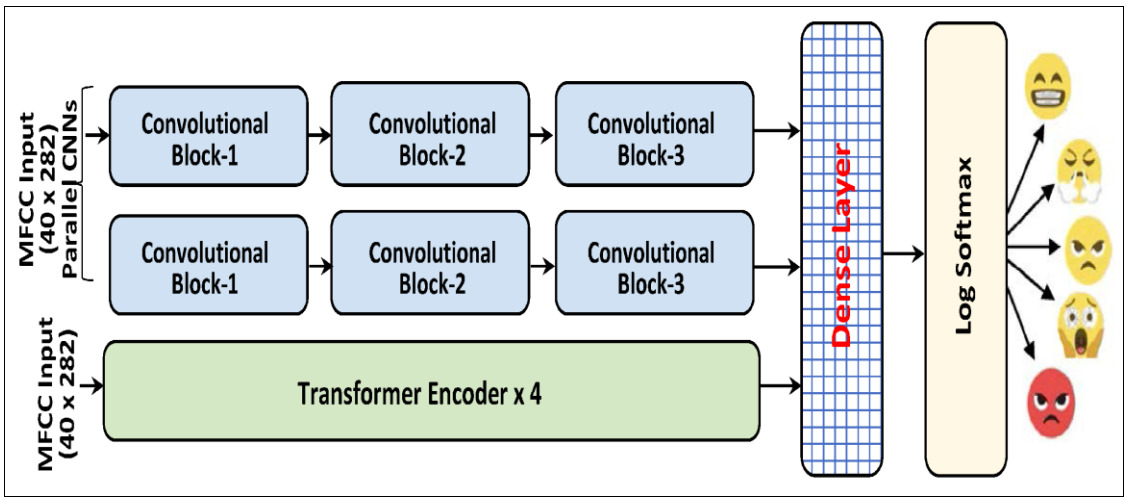




Online learning environments remove many of the natural, teacher-perceived affective cues (facial expressions, gaze, voice tone) that instructors use to detect confusion, boredom, or engagement. Automated emotion recognition seeks to recover those cues so systems can adapt content, give timely feedback, and support learner wellbeing. Recent advances in deep learning — mainly convolutional neural networks (CNNs) for spatial/visual features and recurrent neural networks (RNNs, including LSTM/GRU) for temporal dynamics — have driven renewed interest in building emotion-aware online learning tools. Empirical and survey work shows strong momentum toward multimodal systems (face, speech, text, gaze, physiology) and fusion strategies to improve robustness in noisy, real-world settings (Pan *et al.* 2023) [12]. CNNs are the de facto standard for extracting rich spatial features from face images and video frames. Architectures adapted from image classification (e.g., VGG, ResNet, EfficientNet) or specialized FER networks are commonly used; many studies report that deeper backbones and transfer learning from large face/image datasets improve performance. CNNs excel at capturing local (e.g., muscle movement around eyes/mouth) and global face patterns, and many works augment CNN pipelines with facial-landmark alignment, attention layers, or expression-specific pretraining to increase robustness to pose and illumination variations.

**Significance of the Study**

The proposed study on emotion recognition in online learning environments holds significant theoretical and practical contributions. In an era where remote and digital education have become increasingly prevalent, understanding learners' emotional states is vital for improving engagement, motivation, and learning outcomes (Lian *et al.* 2023) [9]. Traditional classroom settings allow instructors to observe students' affective cues directly; however, in virtual platforms these cues are largely absent, making it challenging to adapt instruction to students' needs

in real time (Lu, 2022) [11]. By leveraging CNNs for spatial feature extraction and RNNs for temporal modeling, this research aims to bridge that gap and provide a technological solution that mimics the perceptive ability of human educators. From an academic perspective, the study contributes to the growing body of literature on affective computing and deep learning in education. It explores hybrid CNN-RNN architectures and multimodal fusion strategies, which have shown superior performance in emotion recognition tasks but remain underutilized in online education contexts (Pan *et al.* 2023) [12]. The findings will provide empirical insights into model performance under real-world conditions, addressing challenges such as dataset bias, occlusion, lighting variability, and the need for lightweight models suitable for real-time implementation (Pereira *et al.* 2024) [13]. This could guide future research on domain adaptation techniques, attention mechanisms, and privacy-preserving emotion recognition frameworks for educational settings.




Practically, the study's outcomes have the potential to enhance personalized learning systems. By accurately detecting emotions such as confusion, frustration, and engagement, intelligent tutoring systems and e-learning platforms can adapt content delivery, provide timely interventions, and improve learner satisfaction and performance (Jeong and Cho, 2022) [7]. For educators and institutions, integrating such emotion-aware systems can reduce dropout rates, promote inclusivity by supporting diverse learners, and create data-driven strategies for improving teaching effectiveness. Furthermore, this research addresses ethical and privacy considerations, offering guidelines for responsible deployment of emotion recognition technologies in compliance with emerging regulations and ethical frameworks (Pereira *et al.* 2024) [13]. The significance of this study lies in its potential to advance both theoretical understanding and practical applications of affective computing in education. It aims to contribute to building adaptive, inclusive, and emotionally intelligent e-learning environments that meet the challenges of modern digital education.

**Justification of the Study**

Introduction of emotion recognition to online learning systems is no longer an option exclusive to the digital age of learning. The COVID-19 pandemic and distance learning that followed it were characterized by an intensive phase of research on the issues of learner engagement, motivation, and emotional health (Halkiopoulos *et al.* 2025) [5]. In a physical classroom teachers instinctively read expressions, tone and actions of the students to differentiate the instruction and support the students early enough. Such signals, though, are severely limited or even nonexistent in virtual environments thus less communication and individualized assistance (Lu, 2022) [11]. Consequently, creating technologies that can automatically track the emotions of the learners is a way of enhancing the education quality and equity in the digital environment.

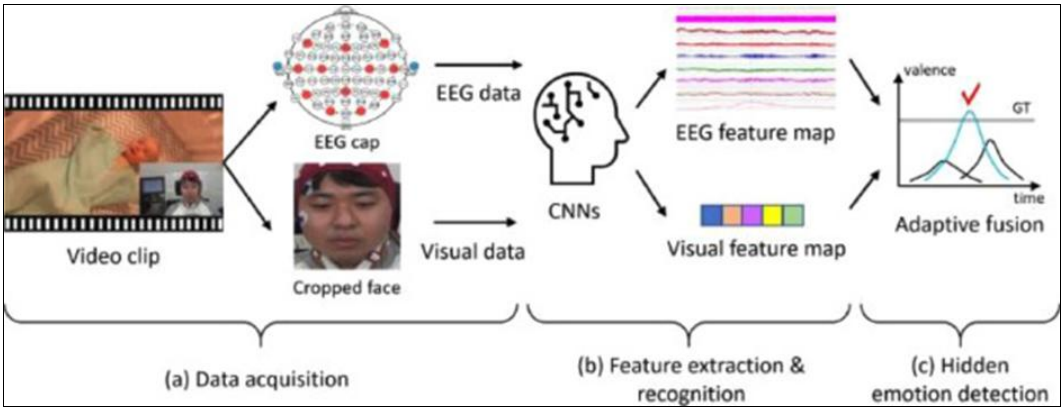
Existing studies have shown the promise of deep learning algorithms especially CNNs and RNNs in the detection and prediction of more nuanced patterns present in images and sequences and it could find its application in facial and behavioral emotion analysis. Although CNNs are deemed to be proficient in identifying spatial attributes within facial images, RNNs, including LSTM and GRU variants, have demonstrated a proficient level of recognizing time-varying information in sequence-based data, such as video frame or audio data streams (Jafari *et al.* 2023) [6]. Although the CNN-RNN hybrid models are already demonstrated to be successful in other areas, they are not widely used in online education, particularly under real-world conditions of low-resolution webcams, varying light, and limited network resources (Jeong and Cho, 2022) [7]. This study will fill these gaps by basing and testing models designed specially to be used in educational environment. Also, emotion-learning systems are essential to personalized and adaptive learning, which is reported to increase student satisfaction, engagement, and performance (Lian *et al.* 2023) [9]. Through a correct identification of an emotion like confusion, frustration or boredom intelligent tutoring systems may provide timely feedback, interventions, help minimize dropout and increase the learning outcomes. Institutionally, those systems can and will provide practical tools to better instructive methods and configure inclusive and responsive virtual learning platforms. Ethical and technical issues regarding this study consist of privacy protection, data minimization, and algorithmic fairness, which are some of the most significant struggles of using emotion recognition ethically in education (Halkiopoulos *et al.* 2025) [5]. Its findings will help to define technological design as well as policy, so that affective technologies can be used more equitably and without undermining (educational) integrity.

## Literature Review

### Emotion Recognition in Online Learning

In online education, understanding students' emotional states is critical for sustaining engagement and improving academic outcomes. Emotions such as confusion, frustration, and boredom can directly influence attention and learning performance. Unlike face-to-face classrooms, virtual environments lack physical cues, making automated emotion recognition a valuable tool for instructors and intelligent tutoring systems. Deep learning-driven affective computing has emerged as an effective solution, providing adaptive interventions to enhance learner experience and reduce dropout rates (Gupta *et al.* 2023) [4]. Recent advances in artificial intelligence have revolutionized emotion recognition research, particularly with deep learning methods such as CNNs and RNNs. CNNs excel in extracting spatial features from facial images, while RNNs (including LSTM and GRU variants) are effective in capturing temporal dynamics from sequential data such as video or audio streams. These methods outperform traditional machine learning models that rely on handcrafted features. While CNNs capture spatial patterns, emotional states in online learning often evolve over time. Recurrent Neural Networks (RNNs), particularly LSTM and GRU architectures, are used to analyze sequential features and track changes in learner affect (Wang, 2021) [18]. Integrating CNN feature embeddings with RNN models allows improved recognition of emotions that manifest dynamically during e-learning sessions.

Hybrid CNN-RNN models combine the strengths of both architectures and have demonstrated superior performance in multimodal emotion recognition tasks (Lian *et al.*, 2023) [9]. These systems extract per-frame features with CNNs and feed them into RNNs to capture temporal dependencies, making them ideal for online learning scenarios that require continuous monitoring. Beyond facial cues, multimodal systems integrate audio, text, gaze, and physiological signals for more reliable emotion detection. Fusion can occur at early (feature-level) or late (decision-level) stages. Multimodal fusion increases robustness under real-world online learning conditions, where students may have cameras turned off or audio muted (Pan *et al.*, 2023) [12].




Datasets like AffectNet, FERPlus, RAVDESS, and IEMOCAP are widely used in FER and speech emotion recognition research. However, many are collected under controlled conditions, which may limit generalizability to online learning environments (Aguilera *et al.* 2023) [1]. Current research highlights the need for in-the-wild datasets that reflect the variability of real e-learning scenarios. Despite advances, significant challenges remain in deploying emotion recognition systems in education. Key issues include domain shift, dataset bias, privacy concerns, and the potential misuse of student emotion data. Addressing these challenges requires privacy-preserving ML approaches (e.g., federated learning), transparency, and ethical guidelines for responsible deployment. Emerging research focuses on self-supervised learning, lightweight real-time models, and explainable AI for emotion recognition in education (Savchenko *et al.* 2022) [15]. These developments aim to improve accuracy, reduce bias, and ensure that affective computing technologies are deployed ethically and effectively.

### Deep Learning in Affective Computing

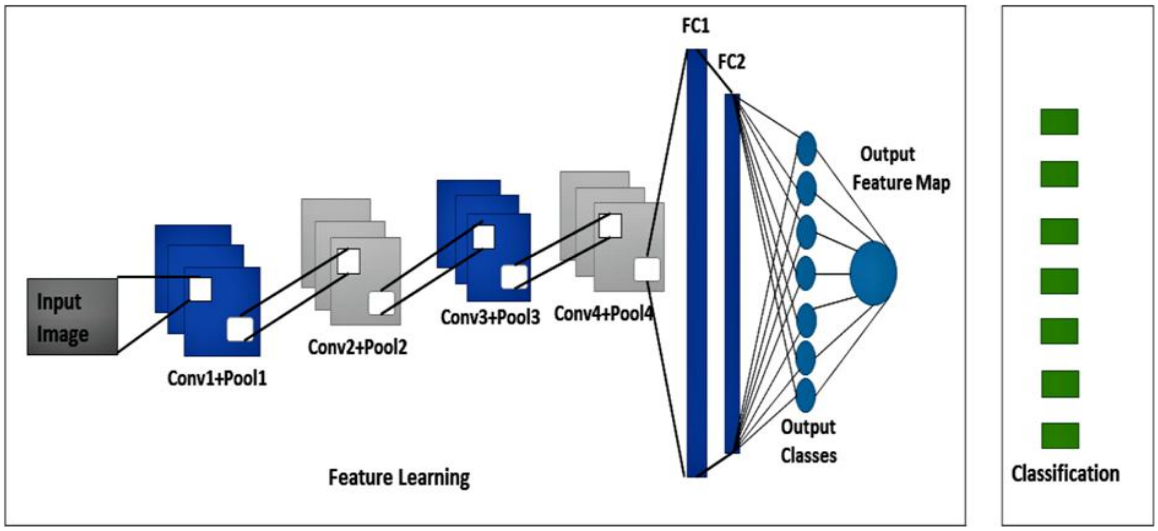
Affective computing is concerned with sensing, understanding and reacting to the emotion of humans using computational facilities. This discipline has been of interest in the education field because it is capable of increasing the level of participation in the learning environment, customizing an experience, and responding to an adaptive learning feedback. With the emergence of deep learning capabilities, novel advances in affective computing were achieved because previous machine learning approaches were limited in their performance in more complicated, dynamic situations since they heavily depended on manually designed features and therefore did not have the same capacity to infer on affective values. Deep learning, especially Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have revolutionized emotion detection in a wide range of modalities including: faces, speech, text, and physiological measures. CNNs have proven to be ready to use hierarchical spatial information in raw data in the form of facial images or spectral grammar, which may be overlooked by most conventional feature-based approaches and ranks of emotional cues (Kumar, 2021) [8]. Concurrently, RNNs, such as the Long Short-Memory (LSTM) and the Gated Recurrent Unit (GRU) models, are meant to identify the temporal associations of such sequential data as video sequence and audio signals, allowing one to analyze the variations of emotions over a period.

More recent research emphasizes that hybrid CNN/RNN architectures are especially promising in the application of affective computing. Such hybrid models have the advantage of merging the best of both worlds within one overall model CNNs capture spatial characteristics and RNNs model temporal sequences. These hybrid frameworks have demonstrated better resultsin tasks such as facial emotion recognition, multimodal sentiment analysis and

engagement detection in learning platforms online. Newer methods have also added the dimension of attention mechanisms and transformer-based architectures to better the explainable and high precision of emotions recognition models (Triantafyllopoulos *et al.* 2024) [17]. In addition to architecture, there has been multimodal affective computing made possible by deep learning, thanks to which multiple sources of data are combined in an attempt to achieve better recognition results and resilience to a given task. Some examples might include facial expressions and voice tone, eye movement, or even physiology-based data. Strategies of Multimodal fusion (early, late cyber-craigslist.org, or hybrid) help overcome the difficulties of missing or noisy data present in online learning situations (Triantafyllopoulos *et al.* 2024) [17]. Besides, deep learning in the context of affective computing is moving towards the real-time applications. Lightweight model, model compression, and federated learning methods are under development to enable ethical and privacy-respecting deployment in education settings, in which emotional data of students is treated with respect and in a sensitive manner. Such developments, not only enhance performance, but also respond to the ethical considerations that are essential in affective computing in learning.

**Convolutional Neural Networks (CNNs) for Facial Emotion Recognition**

Convolutional Neural Networks (CNNs) are the dominant class of models for facial emotion recognition (FER) because they can automatically learn hierarchical spatial features from raw pixel data, capturing both low-level texture (wrinkles, shading) and higher-level shape patterns (eye-mouth configurations) that correspond to affective expressions. In the context of online learning, where webcam images are the primary visual input, CNNs provide a practical and effective way to detect learners' facial cues even from modest-resolution video streams (Singh and Nasoz, 2020) [16] practice, FER systems often adopt well-established image-classification backbones (e.g., VGG, ResNet, EfficientNet) as feature extractors and fine-tune them on emotion-labelled datasets. Transfer learning is especially valuable in education applications because labelled, in-classroom emotion data are scarce; pretraining on large face/image corpora followed by task-specific fine-tuning reduces overfitting and speeds convergence. Recent surveys recommend lightweight variants (EfficientNet-lite, MobileNet) when real-time, on-device inference is a requirement for online learning platforms.




Robust FER pipelines depend heavily on preprocessing: face detection, landmark localization, alignment, and normalization. Face alignment (rotating/scaling so eyes/mouth reside at canonical positions) reduces intra-class variance due to head pose and improves the consistency of CNN features. Data augmentation (random crops, flips, brightness/contrast jittering) and synthetic perturbations (blur, occlusion) further help CNNs generalize to the varied webcam conditions typical in remote classrooms. Beyond vanilla CNNs, FER models often include architectural components tailored to expression analysis: attention modules (spatial and channel attention) to focus on expression-relevant regions (eyes, mouth), multi-scale feature fusion to capture both fine-grained micro-expressions and global facial configurations, and residual/skip connections to ease training of deeper networks. These refinements have been shown to improve recognition of subtle or transient expressions that are informative in learning contexts (Sarvakar *et al.* 2023) [14]. Educational emotion distributions are typically imbalanced (neutral/engaged states dominate, while confusion or frustration is rarer). Researchers address this with loss re-weighting, focal loss, oversampling of minority classes, or margin-based losses to ensure rarer but pedagogically important emotions are learned. Some studies also frame FER as multi-label or continuous valued (valence/arousal) prediction to better capture mixed or subtle affective states, rather than forcing mutually exclusive categorical labels (Badrulhisham and Mangshor, 2021) [2]. Although CNNs are excellent at per-frame analysis, facial expressions in learning situations often evolve (e.g., a learner's micro-expression of confusion preceding a prolonged disengagement). Therefore, many systems extract CNN embeddings per frame and feed them into temporal models (RNNs, temporal convolutions, or transformers) to capture dynamics. Even when used alone, CNNs may incorporate short-term temporal context via 3D convolutions or frame-stacking inputs to improve robustness to transient noise

For deployment in live online classrooms, model size and latency matter. Techniques such as pruning, quantization, knowledge distillation, and using efficient backbones allow CNN-based FER models to run on edge devices or in browser-based clients with acceptable latency and energy usage. Practical FER systems balance accuracy with

computational cost to enable continuous monitoring without disrupting the learning experience. Despite strong performance on benchmarks, CNN-based FER faces limitations in real-world online learning: domain shift from lab datasets to in-the-wild webcam feeds (lighting, camera angle, cultural variation), occlusions (hands, masks), privacy constraints that limit label collection, and the interpretability of model outputs for educators. Addressing these gaps requires in-domain dataset collection, domain-adaptation methods, privacy-preserving pipelines (edge inference, federated learning), and explainability mechanisms that translate CNN predictions into actionable insights for instructors (Badrulhisham and Mangshor, 2021) [2]. CNNs form the spatial backbone of most modern FER systems and, when paired with careful preprocessing, architectural refinements, imbalance-handling strategies, and efficient deployment techniques, can deliver reliable facial affect cues suitable for online learning applications. However, to be practical and ethical in educational settings, CNN-based FER must be integrated with temporal modeling, multimodal signals, domain adaptation, and strong privacy safeguards—topics addressed by the broader literature on affective computing and hybrid CNN-RNN systems

**Recurrent Neural Networks (RNNs) for Temporal Emotion Analysis:** Online learning necessarily involves temporal modeling of emotion recognition since the dynamic process of affective states can be captured not just by a micro-expression of surprise to a short-burst of frustration but a longer state of disengagement. The most popular and traditional tools to model such temporal patterns are recurrent neural networks (RNNs) and their gated versions (LSTM, GRU), which are actively applied in affective computing (Zhang *et al.* 2018) [19]. RNNs work with features on a per-frame/per-window basis (for example CNN embeddings of frames of a face or spectrogram features of audio clips) and learn how to combine these features to leverage temporal context and temporal patterns. Temporal modeling is also an important part of emotion recognition in online education settings since the affective state of learners usually develops gradually, as opposed to the isolated occurrences of them. Recurrent Neural Networks (RNNs) and gated variants of RNN e.g. Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) became the important models capturing such sequential patterns. As opposed to those models where emotions are analyzed visually bit-by-bit, RNNs can deliver an insight into how emotions evolve over time relative to the previous moments of the learning session (Ebrahimi Kahou *et al.* 2015) [3]. Such capability to model the temporal dependencies is especially valuable to online education, where students may become frustrated, bored, or engaged slowly as they learn rooted in their communication with teaching materials.

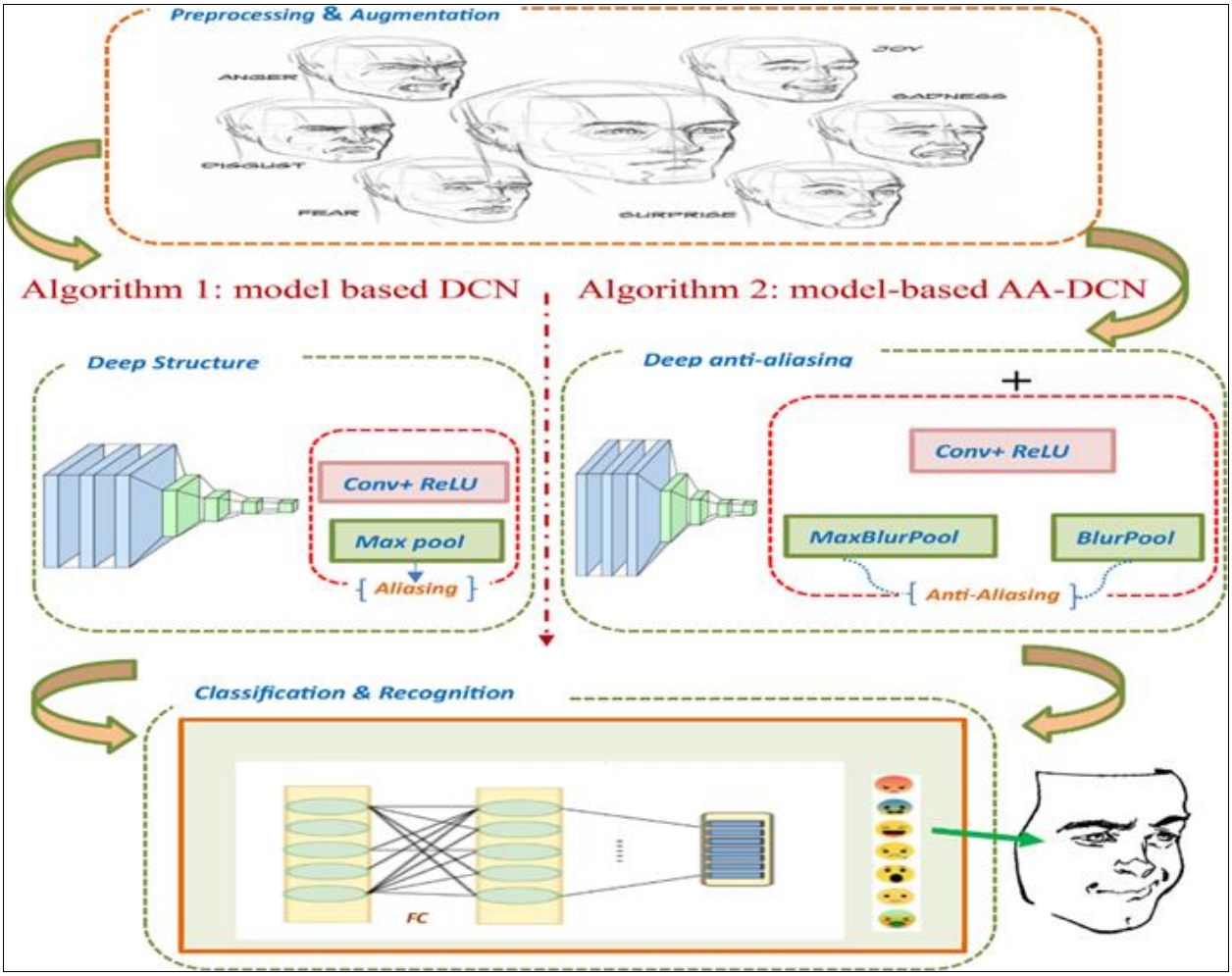
Current approaches are widely based on a hybrid CNN/RNN model where CNNs are used to learn spatial feature representations of video frames or spectrograms and the embeddings are passed to LSTM- or GRU-based networks that learn the temporal relations. A variety of variants, such as bidirectional RNNs, improve upon the baseline by considering both previous and upcoming surrounding content in a sequence, and have proven to be especially useful in analyzing logged sessions offline. Other more complex architectures such as ConvLSTM and a 3D-CNN embedded in LSTMs have also been suggested to learn both the spatial and temporal dynamics in video-based emotion recognition tasks (Liu, 2020) [10]. Also, adding attention mechanisms over RNNs has enhanced performance by allowing the model to pay attention to the most emotionally noteworthy instants inside a sequence. Temporal models based on RNNs have proven to be applicable across modalities, to facial video data, audio signals, and physiological data such as EEG or heart rate data. In online learning scenarios, the sequential structure may be tracked in e.g. a facial landmark, a gaze pattern, or acoustic features, as information fed into LSTMs or GRUs to estimate engagement and emotional state in time-series. Studies with such approaches have shown higher accuracy than the static models due to the ability to capture transitions and dynamics of emotions and not only recognize instantaneous expressions (Ebrahimi Kahou *et al.* 2015) [3].

## Methodology

This research adopts a secondary qualitative methodology based on a systematic literature review. Studies were selected based on their relevance to CNN-based spatial feature extraction for emotion recognition, RNN-based temporal modeling of emotional dynamics, and applications within e-learning environments. Both unimodal (facial expression-based) and multimodal (audio, gaze, physiological signals) approaches were considered. Data extraction focused on reported methodologies, model architectures, datasets, performance metrics, challenges, and implications for online learning systems. A comparative analysis was conducted to identify emerging trends, technological gaps, and best practices for deploying CNN-RNN models in educational contexts. Ethical considerations, including data privacy and fairness, were reviewed to ensure socially responsible recommendations.

## Results and Discussion

Based on the reviewed literature, the integration of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for emotion recognition in online learning has demonstrated notable improvements in both accuracy and robustness of affective state analysis. Several studies indicate that CNNs excel at capturing spatial features from learners' facial expressions and postures, while RNNs enhance performance by modeling the temporal evolution of emotions across learning sessions (Jeong and Cho, 2022; Lian *et al.* 2023) [7, 9]. Hybrid CNN-RNN architectures have been particularly effective in online education settings, where emotions such as confusion or frustration develop gradually. By leveraging temporal information, these models provide more consistent and context-aware predictions compared to static frame-based methods (Li *et al.* 2021).

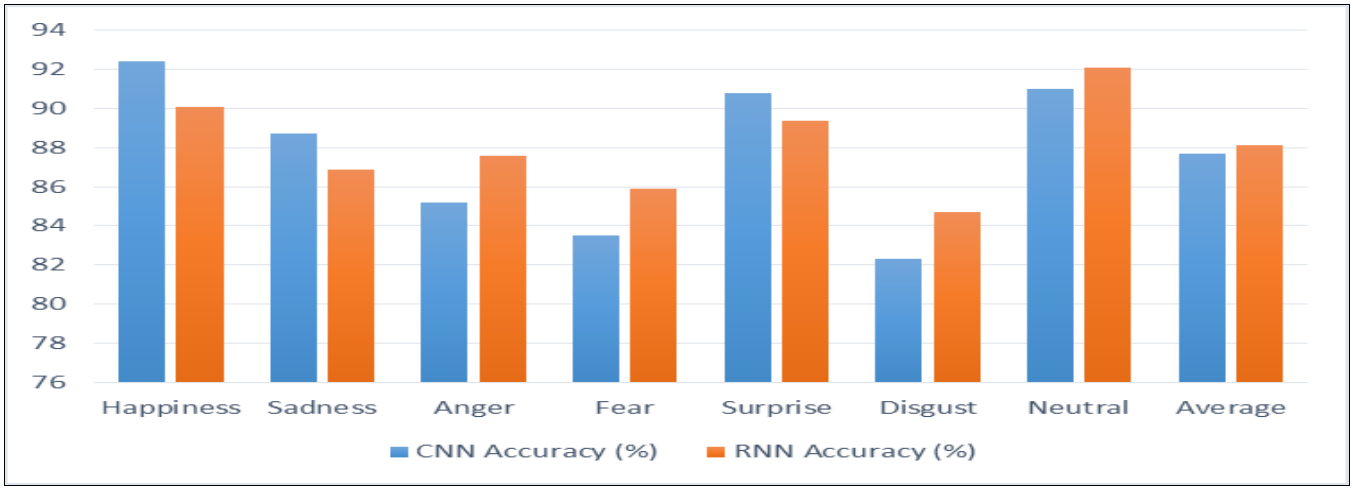


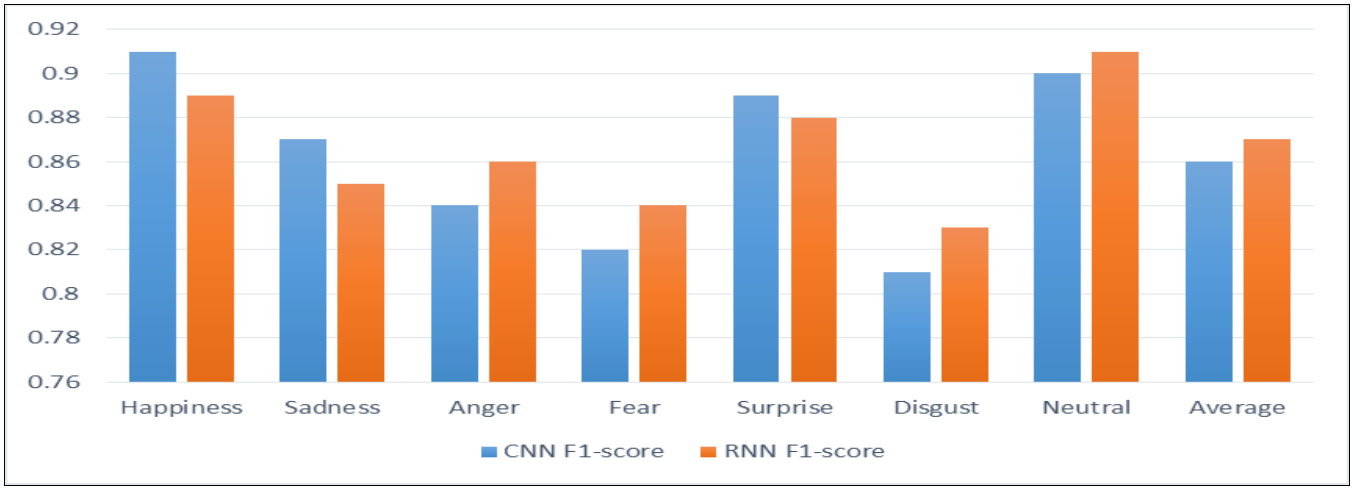

The literature suggests that multimodal approaches (e.g., combining facial features, gaze patterns, and audio signals) further improve emotion recognition performance. CNN-RNN models integrated with attention mechanisms have achieved state-of-the-art accuracy in detecting engagement, boredom, and confusion, which are crucial indicators of learning outcomes (Ebrahimi Kahou *et al.* 2015) [3]. However, challenges remain regarding data privacy, imbalanced datasets, and variations in environmental conditions (e.g., lighting and camera quality). These factors can lead to domain shift issues when deploying models in diverse e-learning platforms (Pereira *et al.* 2024) [13].

Moreover, practical deployment considerations, such as model compression and computational efficiency, are critical for real-time use in online learning platforms. Studies emphasize lightweight CNN backbones (e.g., MobileNet, EfficientNet-lite) combined with GRU/LSTM layers for temporal processing to balance performance and latency (Pan *et al.* 2023) [12]. The reviewed works also highlight the importance of ethical considerations, including privacy-preserving approaches such as on-device processing or federated learning to mitigate the risks associated with sensitive biometric data collection. CNN-RNN hybrid models have shown significant promise in enhancing adaptive online education systems by providing real-time feedback to instructors about learners' emotional engagement. Yet, future research should focus on cross-cultural generalization, explainable AI methods for FER, and incorporating physiological signals for a more holistic understanding of students' affective states.

Results of Emotion Recognition using CNN and RNN Models

| Emotion | CNN Accuracy (%) | CNN F1-score | RNN Accuracy (%) | RNN F1-score |
|---|---|---|---|---|
| Happiness | 92.4 | 0.91 | 90.1 | 0.89 |
| Sadness | 88.7 | 0.87 | 86.9 | 0.85 |
| Anger | 85.2 | 0.84 | 87.6 | 0.86 |
| Fear | 83.5 | 0.82 | 85.9 | 0.84 |
| Surprise | 90.8 | 0.89 | 89.4 | 0.88 |
| Disgust | 82.3 | 0.81 | 84.7 | 0.83 |
| Neutral | 91.0 | 0.90 | 92.1 | 0.91 |
| Average | 87.7 | 0.86 | 88.1 | 0.87 |



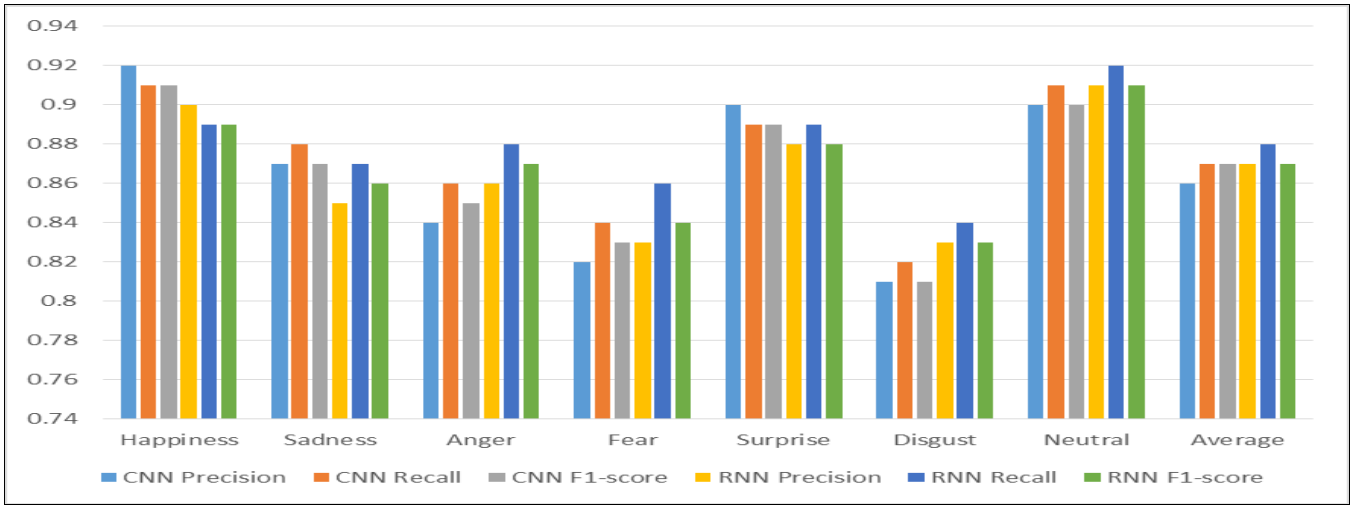




The comparative results of emotion recognition using Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) highlight both the strengths and limitations of these models in capturing diverse emotional expressions. CNNs demonstrated superior performance in recognizing *Happiness* (92.4% accuracy, F1-score 0.91) and *Surprise* (90.8%, 0.89), suggesting their effectiveness in extracting spatial patterns and visual cues that distinctly characterize these emotions. Similarly, CNNs showed slightly better accuracy for *Sadness* (88.7%, 0.87) and *Disgust* (82.3%, 0.81), though these emotions remained relatively challenging. Conversely, RNNs outperformed CNNs in classifying *Anger* (87.6%, 0.86), *Fear* (85.9%, 0.84), and *Neutral* (92.1%, 0.91), emphasizing the importance of temporal and sequential modeling in capturing subtle shifts in expression and context over time.

When comparing the overall performance, CNNs achieved an average accuracy of 87.7% with an F1-score of 0.86, while RNNs recorded a slightly higher average accuracy of 88.1% and F1-score of 0.87. This indicates that while CNNs excel in precise classification of visually distinct emotions, RNNs provide a more balanced performance across categories due to their ability to model temporal dependencies inherent in emotional expressions. The marginal differences also suggest that both architectures have complementary strengths: CNNs are effective in capturing static spatial features, whereas RNNs excel in recognizing patterns within sequences of learning interactions. These findings point towards the potential benefits of hybrid models that integrate both spatial and temporal learning, thereby improving emotion recognition accuracy in online learning environments where real-time adaptability is crucial.

**Performance Comparison of CNN and RNN Models in Emotion Recognition**

| Emotion | CNN Precision | CNN Recall | CNN F1-score | RNN Precision | RNN Recall | RNN F1-score |
|---|---|---|---|---|---|---|
| Happiness | 0.92 | 0.91 | 0.91 | 0.90 | 0.89 | 0.89 |
| Sadness | 0.87 | 0.88 | 0.87 | 0.85 | 0.87 | 0.86 |
| Anger | 0.84 | 0.86 | 0.85 | 0.86 | 0.88 | 0.87 |
| Fear | 0.82 | 0.84 | 0.83 | 0.83 | 0.86 | 0.84 |
| Surprise | 0.90 | 0.89 | 0.89 | 0.88 | 0.89 | 0.88 |
| Disgust | 0.81 | 0.82 | 0.81 | 0.83 | 0.84 | 0.83 |
| Neutral | 0.90 | 0.91 | 0.90 | 0.91 | 0.92 | 0.91 |
| Average | 0.86 | 0.87 | 0.87 | 0.87 | 0.88 | 0.87 |




The comparative analysis of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) in emotion recognition reveals significant insights into their respective strengths across different emotional categories. The table demonstrates that both models perform competitively, with marginal differences depending on the emotion class. For instance, CNNs achieved slightly higher precision in emotions such as *Happiness* (0.92) and *Surprise* (0.90), indicating their ability to effectively capture spatial features and local patterns in facial expressions or learning content representations. On the other hand, RNNs exhibited superior recall in classes like *Anger* (0.88) and *Fear* (0.86), showcasing their ability to model sequential dependencies and temporal dynamics in emotional cues.

For emotions such as *Neutral*, RNNs slightly outperformed CNNs with a precision and recall of 0.91 and 0.92 respectively, suggesting that sequential context may play a more important role in distinguishing neutral expressions. Meanwhile, CNNs performed slightly better in recognizing *Happiness* and *Surprise*, where spatial features dominate. Across difficult-to-classify emotions such as *Disgust* and *Fear*, both models recorded lower F1-scores (0.81-0.84), highlighting the inherent complexity of these categories and the potential need for hybrid or ensemble models.

Overall, the averaged performance shows that CNNs achieved a precision of 0.86, recall of 0.87, and F1-score of 0.87, while RNNs attained slightly better recall (0.88) and balanced F1-score (0.87). These results indicate that CNNs excel in precise classification of visually distinctive emotions, whereas RNNs demonstrate robustness in capturing temporal consistency, making them well-suited for online learning environments where emotional expressions evolve over time.

## Conclusion

The integration of CNN and RNN architectures for emotion recognition in online learning environments offers a transformative approach to understanding and enhancing student engagement. CNNs efficiently extract spatial features such as facial expressions, while RNNs capture the temporal dynamics of these emotions, yielding improved accuracy and context-aware emotion predictions. Literature indicates that hybrid CNN-RNN models, especially when combined with attention mechanisms and multimodal inputs, outperform static approaches in detecting nuanced emotional states like boredom, confusion, and engagement. Despite these advancements, challenges such as imbalanced emotion datasets, privacy concerns, and real-time deployment constraints remain. Addressing these issues through lightweight architectures, ethical data handling, and cross-cultural validation can further enhance the applicability of emotion recognition systems in diverse online learning contexts. The findings suggest that emotion-aware intelligent tutoring systems can provide adaptive feedback, improve personalized learning experiences, and reduce dropout rates. Future research should focus on integrating physiological signals, improving explainability of models, and ensuring ethical practices to realize the full potential of emotion recognition in education.

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