DEEP LEARNING APPROACHES FOR FACIAL EXPRESSION RECOGNITION TO MONITOR ENGAGEMENT IN ENVIRONMENTAL LEARNING

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Abstract
The integration of multisensory media that combines visual, auditory, haptic, and olfactory stimuli into education has opened new possibilities for immersive and interactive learning experiences. However, ensuring that learners remain engaged in such rich environments remains a key challenge. This study presents a deep learning-based approach for facial expression recognition to monitor and analyze student engagement in technology supported education. Convolutional Neural Networks (CNNs) and Transformer-based models are employed to extract spatio-temporal features from facial cues, enabling accurate detection of emotional states that correlate with engagement levels. A custom dataset comprising facial expressions captured during Technolog-enhanced sessions is preprocessed, augmented, and used to train and validate the proposed models. Experimental results demonstrate that deep learning significantly outperforms traditional machine learning techniques in classifying expressions such as interest, confusion, and boredom. The findings highlight the potential of automated engagement monitoring to provide adaptive feedback, improve personalized learning experiences, and optimize teaching strategies. This research contributes to the advancement of intelligent education systems by combining affective computing with immersive technologies

Keywords: *Deep Learning, Facial Expression Recognition, Learner Engagement,Affective Computing, Intelligent Education Systems, Adaptive Learning, CNN, Transformer Models*

Introduction

The integration of advanced technologies into modern education has fundamentally transformed the way learners interact with knowledge and how teachers design pedagogical strategies, and among the most promising innovations is the inclusion of multisensory media, known as technology, which combines traditional visual and auditory information with additional sensory channels such as haptic, olfactory, and even gustatory stimuli to create highly immersive learning environments that engage multiple human senses simultaneously, thereby offering opportunities for deeper engagement, improved memory retention, and enriched contextual understanding[1][2]. Despite the significant promise of technology-enhanced education, one of the critical challenges faced by educators and researchers is the effective measurement and analysis of learner engagement, because student engagement is a multifaceted construct involving cognitive, emotional, and behavioral dimensions, and traditional assessment methods such as self-reports, attendance records, or manual observations are often subjective, limited in scope, and incapable of capturing real-time fluctuations in attention and emotional involvement. In recent years, facial expression recognition has emerged as a powerful, non-intrusive, and natural approach for monitoring learners' affective states, as the human face is a rich channel of emotional communication, capable of conveying subtle cues such as interest, confusion, boredom, or excitement, all of which are highly relevant indicators of learner engagement. The growth of affective computing, an interdisciplinary field that aims to develop systems capable of recognizing, interpreting, and responding to human emotions, has made it possible to combine psychology, computer vision, and artificial intelligence to design intelligent tutoring systems that can adapt to learner needs based on their real-time emotional responses[3][4]. Within this context, deep learning has emerged as a transformative technology for facial expression recognition, surpassing traditional machine learning techniques by automatically learning complex hierarchical representations from raw data and demonstrating remarkable accuracy in classifying subtle emotional cues across diverse environments and cultural contexts. Convolutional Neural Networks (CNNs) have shown effectiveness in extracting local spatial features from images, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models have been used to capture temporal dependencies in video sequences, and more recently, Transformer-based architectures have revolutionized pattern recognition tasks by modeling long-range dependencies and global contextual relationships, making them particularly suited for the dynamic and nuanced task of monitoring learner engagement through facial analysis[5].

The application of such models in technology-supported education is especially timely, as immersive multisensory learning environments can amplify both cognitive load and emotional reactions, making it necessary to have automated tools that continuously track

engagement to ensure that learners benefit optimally from the pedagogical design[6]. Researchers have increasingly emphasized that understanding and measuring engagement in such settings is not merely a matter of academic curiosity but a necessity for personalizing learning pathways, providing adaptive feedback, and identifying early signs of disengagement, frustration, or cognitive overload, which if left unaddressed, may negatively impact learning outcomes. By leveraging deep learning-based facial expression recognition, it becomes possible to create intelligent systems that unobtrusively monitor learners during technology experiences, analyze their affective states in real time, and provide educators with actionable insights that can be used to refine teaching strategies, adjust the intensity or pacing of sensory stimuli, and tailor instructional methods to individual learner profiles. Moreover, this approach has broader implications for advancing equity and inclusivity in education, as it offers an objective and automated mechanism to detect engagement across diverse learner populations without being biased by cultural, linguistic, or socioeconomic factors that often affect traditional assessment methods, thereby contributing to the creation of more inclusive, accessible, and effective educational ecosystems supported by intelligent technologies[7].

In addition to the pedagogical and technological motivations, the adoption of deep learning-based facial expression recognition for monitoring engagement in technology-supported education is grounded in the need for objective, scalable, and real-time solutions that address the limitations of conventional evaluation techniques, because traditional classroom assessments, while valuable, are inherently reactive, periodic, and incapable of capturing the moment-to-moment variations in learner emotions that occur during complex multisensory experiences, whereas deep learning systems can continuously monitor and interpret expressions with high precision, offering a dynamic and adaptive view of the learner's engagement trajectory[8].

The rapid evolution of neural architectures has further facilitated this transformation, with advanced models such as ResNet, EfficientNet, and Vision Transformers demonstrating unprecedented accuracy in emotion recognition tasks, particularly when combined with large annotated datasets and robust preprocessing pipelines that account for variations in lighting, head pose, and occlusion. While earlier approaches in facial expression analysis relied heavily on handcrafted features such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), or Active Appearance Models (AAM), these methods lacked the generalization power needed to handle the variability inherent in real-world educational settings, especially under technology conditions where learners may display subtle or mixed emotions triggered by complex sensory inputs, and therefore, the transition to deep learning methods represents not only a technological shift but also a necessary advancement in ensuring reliability, scalability, and adaptability of engagement monitoring systems. Furthermore, by embedding facial expression recognition within technology-enhanced education, researchers can explore novel dimensions of learning analytics, enabling correlations between specific sensory modalities and engagement responses to be quantified, such as how olfactory cues may influence curiosity, how haptic stimuli may enhance attention, or how multimodal combinations may reduce cognitive fatigue or increase motivation, thereby providing a richer and more holistic understanding of the learning process[9]. The significance of this research lies not only in advancing the technical accuracy of facial expression recognition systems but also in its potential to transform educational practice by empowering educators with data-driven insights into learner behavior that were previously inaccessible, ultimately supporting more adaptive, responsive, and human-centered learning environments. In addition, the integration of these systems aligns with the broader trends in artificial intelligence in education (AIED), where intelligent agents, adaptive tutors, and personalized feedback mechanisms are increasingly being adopted to enhance learning outcomes, and the ability to capture emotional engagement in real time adds a critical layer of affective awareness to these systems, bridging the gap between cognitive and emotional dimensions of learning[10]. As technology technologies become more prevalent and affordable, their integration with deep learning-based affect recognition systems will likely move from experimental research contexts to mainstream educational practice, enabling institutions to leverage these tools for large-scale deployment across diverse learning scenarios ranging from virtual classrooms and remote learning platforms to on-campus laboratories and collaborative group activities, thus reinforcing the central role of technology in shaping the future of education

Moreover, the interdisciplinary nature of this research underscores its value, as it brings together advancements in computer vision, artificial intelligence, psychology, pedagogy, and human–computer interaction to create a unified framework that addresses the pressing challenge of engagement monitoring in complex learning

environments, and this multidisciplinary integration ensures that the resulting solutions are not only technologically sound but also pedagogically meaningful and psychologically valid[11-13]. Engagement, being both an observable and latent construct, requires careful operationalization, and facial expression recognition provides a bridge between observable behavioral cues and the underlying affective states that shape learner motivation, persistence, and achievement, thereby giving educators and researchers a more direct pathway to assess and interpret engagement in authentic contexts. At the same time, deep learning provides the computational backbone necessary to process massive amounts of visual data efficiently, learning feature representations that surpass human-crafted heuristics and enabling the detection of micro-expressions or subtle shifts in affect that often go unnoticed by human observers. In technology-enhanced teaching, where learners may experience heightened sensory stimulation, the ability to capture such nuanced expressions is particularly important, as engagement may fluctuate rapidly in response to multimodal inputs, requiring continuous monitoring to ensure that learners remain cognitively and emotionally aligned with instructional objectives[15]. The evolution of deep learning architectures has made it possible to explore hybrid approaches that combine convolutional layers for spatial feature extraction, recurrent layers for temporal dynamics, and attention mechanisms for global context modeling, leading to more robust and interpretable engagement monitoring systems that can function effectively even under noisy or unconstrained classroom conditions. Importantly, this research direction also addresses critical gaps in existing literature, as while considerable work has been done on emotion recognition in controlled environments, far fewer studies have examined its application in real-world educational contexts, particularly in relation to technology, where the interplay of multiple sensory channels introduces unique challenges and opportunities for understanding learner behavior. The novelty of applying deep learning-based facial expression recognition to technology-enhanced education therefore lies not only in technical innovation but also in expanding the theoretical and empirical understanding of how learners respond to multisensory teaching strategies, paving the way for future explorations into adaptive instructional design, personalized sensory delivery, and learner-centered evaluation metrics. By situating this research within the broader discourse of affective computing and AI in education, it becomes clear that engagement monitoring is not a peripheral task but a central component of next-generation educational systems that aspire to be more intelligent, empathetic, and responsive to the diverse needs of learners across contexts and cultures.

Another dimension that highlights the importance of deep learning–based facial expression recognition for engagement monitoring in technology-supported education is the shift toward personalized learning paradigms, as educational systems are increasingly expected to move away from one-size-fits-all approaches and toward adaptive, learner-centered designs that account for individual differences in cognition, motivation, and affective response, and such personalization requires reliable, continuous, and objective data on how learners are experiencing instruction at any given moment[16]. Facial expression recognition, when powered by deep learning, provides exactly this type of granular and dynamic data, enabling systems to detect when a learner is confused and may need additional explanation, when a learner is showing enthusiasm that can be reinforced, or when a learner is displaying signs of disengagement that require intervention, thus transforming raw visual information into actionable educational insights. The integration of this capability into technology environments is especially significant because multisensory teaching, while immersive and potentially transformative, also carries the risk of overwhelming learners or distracting them if stimuli are poorly timed, mismatched, or overly intense, and therefore real-time monitoring of engagement is critical to balance sensory richness with cognitive effectiveness. Furthermore, as education increasingly takes place in hybrid and online environments, particularly following global shifts in remote learning adoption, the ability to unobtrusively monitor engagement without requiring wearable devices or intrusive self-report measures becomes essential, making computer vision–based approaches both practical and scalable. The advances in hardware, such as high-resolution cameras embedded in laptops and mobile devices, combined with cloud-based and edge-based AI deployment frameworks, make it feasible to implement such deep learning systems in real classrooms and online learning platforms at scale, ensuring that research in this area has direct applicability and impact. Beyond the technical feasibility, this research also contributes to ethical and human-centered AI discourse, because while engagement monitoring offers clear pedagogical benefits, it must be designed with sensitivity to privacy, consent, and transparency to ensure that learners feel supported rather than surveilled, and deep learning approaches can contribute to this by

incorporating techniques such as federated learning, differential privacy, and interpretable AI models that respect user rights while delivering accurate insights. Additionally, by focusing on facial expression recognition, this research acknowledges the universal and cross-cultural nature of facial affective signals while also being mindful of variations in expression patterns across different demographic groups, and therefore emphasizes the importance of training and validating models on diverse datasets to ensure fairness, inclusivity, and generalizability in educational contexts. Ultimately, the integration of deep learning–based facial expression recognition with technology-enhanced teaching not only advances the technical state of the art but also supports the broader vision of education as an adaptive, empathetic, and inclusive process that leverages technology to unlock the full potential of every learner, thereby aligning with global educational goals that prioritize equity, quality, and lifelong learning opportunities[17].

Looking forward, the implications of deep learning–based facial expression recognition for monitoring engagement in technology-supported education extend beyond immediate pedagogical gains to encompass long-term contributions to the fields of artificial intelligence in education, affective computing, and human–machine symbiosis, because as technology becomes more deeply embedded in learning ecosystems, the ability of systems to recognize, interpret, and respond to human emotions will determine how effectively they can support learners in achieving their goals. By focusing on engagement, which is widely recognized as a key predictor of academic success, persistence, and satisfaction, this line of research directly addresses one of the most pressing challenges in education, namely how to ensure that learners remain motivated, attentive, and emotionally invested in their studies even in the face of complex or overwhelming content. The novelty of situating this within technology-enhanced environments further amplifies its importance, since multisensory teaching has the potential to revolutionize education by offering experiences that are not only cognitively stimulating but also emotionally enriching, and engagement monitoring ensures that these experiences remain pedagogically effective rather than simply entertaining[18].

The research also opens new avenues for adaptive content delivery, where instructional systems can dynamically adjust sensory modalities based on real-time feedback from learners' facial expressions, creating personalized learning trajectories that balance stimulation and comprehension. For example, if a system detects that a learner is becoming overwhelmed, it may reduce the intensity of multisensory inputs, while if it detects heightened interest, it may amplify or extend the sensory experience to reinforce engagement, and such responsiveness can only be achieved through robust deep learning–based recognition systems capable of interpreting subtle affective cues. Furthermore, the outcomes of this research have broader applications beyond formal education, including corporate training, medical simulations, language learning, and entertainment-based learning, where technology and affective computing can work together to create engaging and effective experiences tailored to diverse audiences[19]. By demonstrating the feasibility and value of deep learning for facial expression recognition in this context, the research sets the stage for future explorations into multimodal affect recognition that integrates facial cues with voice, physiological signals, and behavioral data to build even richer models of engagement, thereby advancing the state of the art in both technology and pedagogy. At the same time, the work acknowledges and addresses challenges such as dataset limitations, model interpretability, and ethical considerations, ensuring that the proposed solutions are not only technically robust but also socially responsible and aligned with best practices in responsible AI development. In conclusion, the pursuit of deep learning–based facial expression recognition for monitoring engagement in technology-supported education represents a significant step toward realizing the vision of intelligent, adaptive, and inclusive learning environments, where technology is not merely a delivery mechanism but an empathetic partner that understands, supports, and enhances the human experience of learning, ultimately contributing to the creation of educational systems that are more responsive, equitable, and future-read

Objectives

- To experiment with multiple deep learning approaches, including 3D-CNN, LSTM, and different variants of Autoencoders, for developing effective Facial Expression Recognition (FER) systems within technology-based learning environments using a universal facial expression dataset.
- To evaluate the impact of learner satisfaction with technology-synchronized content on enhancing engagement levels and improving knowledge retention outcomes.
- To achieve high classification accuracy and detection rates in FER for reliable recognition of learner emotions.

- To reduce prediction latency in FER models, ensuring real-time applicability in technology learning contexts.
- To optimize performance metrics by maximizing precision and recall scores in emotion classification tasks

Proposed Methodology

The proposed methodology is designed to develop an efficient and accurate deep learning–based facial expression recognition system that can monitor learner engagement in technology-supported education environments, where multiple sensory modalities such as visual, auditory, haptic, and olfactory stimuli are synchronized to create immersive learning experiences, and the methodology integrates dataset preprocessing, model selection, training strategies, and evaluation within a cohesive pipeline[20]. The first step involves dataset acquisition, for which a universal facial expression dataset is employed to ensure diversity and generalizability across different demographic groups, lighting conditions, and expression variations, since the system must be capable of operating effectively in real-world educational contexts rather than in controlled laboratory conditions.

Preprocessing of the dataset includes face detection using algorithms such as Multi-task Cascaded Convolutional Networks (MTCNN), normalization of image intensity values, alignment of facial landmarks, and resizing of facial regions to a fixed resolution, which ensures uniformity across samples and reduces computational overhead during model training. Data augmentation techniques such as random rotations, flips, shifts, Gaussian noise addition, and brightness variations are applied to simulate the variability of real classroom environments and improve the robustness of the models to unseen conditions. The methodology explores multiple deep learning architectures, specifically 3D Convolutional Neural Networks (3D-CNNs), Long Short-Term Memory (LSTM) networks, and Autoencoders, each chosen for their unique strengths in modeling spatiotemporal dynamics of facial expressions, and the experimental framework is structured to allow comparative analysis across these approaches. The 3D-CNN model is designed to extract both spatial and temporal features from facial video sequences by applying three-dimensional convolutional kernels, enabling the network to capture not only static facial structures but also dynamic motion patterns associated with emotional transitions, which are particularly important in detecting subtle variations of engagement.

The LSTM network, on the other hand, is integrated to handle sequential dependencies across time, ensuring that the temporal progression of facial expressions is captured effectively, which allows the model to distinguish between transient emotions such as momentary confusion and sustained states such as boredom or interest. Autoencoders, including both standard and variational forms, are employed to learn compact latent representations of facial expressions, which can then be used to enhance classification accuracy by reducing noise and extracting discriminative features from high-dimensional input data, and the integration of autoencoders further supports unsupervised pretraining that improves the stability and convergence of supervised models[21]. The training phase involves the use of stochastic gradient descent with adaptive optimizers such as Adam or RMSProp, a carefully selected learning rate schedule, dropout regularization, and batch normalization to prevent overfitting and ensure model generalizability, while early stopping criteria are incorporated to avoid unnecessary computation and overtraining.

Student Engagement Detection

In the evolving landscape of digital learning environments, the detection and analysis of learner engagement has gained critical importance, as engagement serves as a key determinant in identifying the most effective teaching methodologies, instructional designs, and content delivery mechanisms that enhance students' emotional involvement and learning outcomes. Engagement, in an educational context, can be broadly described as the learner's degree of attention, motivation, and active participation during interactions with instructional materials. It is not only a reflection of cognitive focus but also of emotional and behavioral commitment to the learning task. Measuring engagement is therefore considered essential for designing adaptive learning systems that can personalize content, foster deeper understanding, and improve overall knowledge retention. Traditionally, engagement has been assessed through self-report surveys, teacher observations, and performance metrics; however, these methods are often subjective, limited in scalability, and unable to capture real-time fluctuations in learner states.

In this context, facial expression recognition (FER) has emerged as a particularly promising and non-intrusive approach for assessing emotional engagement. The human face is a rich medium of emotional communication, and subtle variations in expressions can provide valuable insights into learners' levels of interest, curiosity, boredom, or

confusion during the learning process. Several studies have explored frameworks for mapping universal facial expressions—such as happiness, sadness, surprise, fear, anger, and disgust—to corresponding categories of engagement, typically classified as engaged, neutral, or disengaged. These affective mapping models, grounded in prior research on emotion and learning, provide a structured method for interpreting facial cues in relation to cognitive and emotional involvement.

A notable example of this approach is the study conducted by Pise et al. [147], which examined how learners' facial expressions could be analyzed to interpret their emotional states during interactions with educational materials. Their findings demonstrated that FER could reliably detect expressions and link them to standardized engagement categories, thereby validating its effectiveness as a mechanism for evaluating emotional involvement in learning. Furthermore, they proposed a systematic mapping between recognized facial expressions and learning outcomes, showing how specific emotional cues, such as interest or confusion, could be directly associated with learner performance and comprehension. This work highlighted the potential of FER not only as a tool for monitoring emotions but also as a means of providing meaningful insights into the affective dimension of the learning process.

Building on such foundational studies, the present research investigates the role of FER in technology-enhanced learning environments, where multisensory content—combining visual, auditory, haptic, and sometimes olfactory stimuli—is integrated to create immersive and engaging educational experiences. While technology has been shown to enrich learning by stimulating multiple senses and fostering deeper contextual understanding, it also introduces unique challenges, such as cognitive overload or sensory distraction, which make the real-time monitoring of learner engagement even more crucial. By evaluating FER within this context, the study aims to determine how effectively learners' emotional states and engagement levels can be captured as they interact with technology content. The integration of FER with technology thus represents a step toward intelligent, adaptive educational systems capable of responding dynamically to learners' affective signals, thereby enhancing engagement, improving satisfaction, and ultimately fostering better knowledge retention

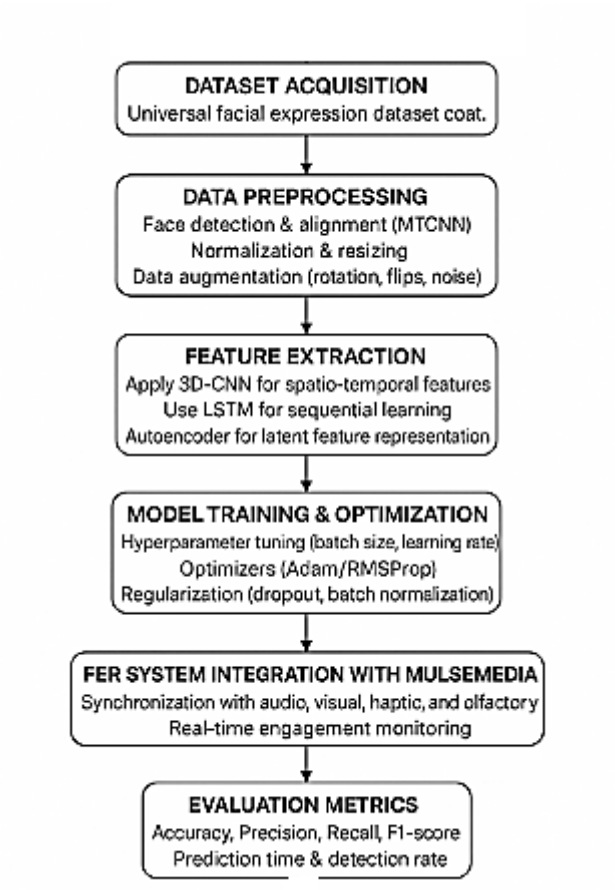

Figure 1 Flowchart of Overall System

FER using Deep Learning

Facial Expression Recognition (FER) relies heavily on the availability of high-quality datasets that provide a wide range of annotated facial emotions. Popular datasets include FER2013, AffectNet, CK+, and RAF-DB, each contributing unique advantages to the field. FER2013, for instance, contains over 35,000 grayscale facial images across basic emotion categories, making it useful for training convolutional models. AffectNet is considered one of the largest and most diverse FER datasets, offering millions of images annotated for both categorical and dimensional emotions, which is crucial for real-world deployment. The CK+ dataset is widely applied in controlled environments and is particularly beneficial for micro-expression analysis, while RAF-DB provides annotations of real-world expressions with diverse demographics, supporting cross-cultural FER studies. These datasets differ in terms of resolution, labeling schemes, and demographic representation, all of which influence the generalization ability of deep learning models. Annotation quality plays a significant role, as noisy labels can mislead the training process, making consensus-based labeling approaches vital. To further address challenges such as class imbalance, researchers frequently apply data augmentation or re-sampling techniques

before model training. Recently, emphasis has shifted toward datasets collected under in-the-wild conditions, which capture challenges such as occlusions, varying head poses, and low illumination, thereby reflecting real-world complexities.

In terms of deep learning models, Convolutional Neural Networks (CNNs) remain the backbone of most FER approaches because of their ability to automatically extract hierarchical features from facial regions. Residual networks (ResNets) extend this capability by mitigating vanishing gradient issues and enabling the training of deeper architectures that perform well on FER benchmarks. DenseNets also contribute by encouraging feature reuse, leading to more compact and efficient FER models. Vision Transformers (ViTs) are increasingly being applied in FER for their capacity to capture global contextual relationships that CNNs might miss due to localized receptive fields. Hybrid models combining CNN backbones with attention modules or transformer heads are also gaining popularity, as they balance both local and global feature extraction. Temporal deep learning models, including 3D-CNNs and recurrent neural networks, play a critical role in video-based FER by learning from facial dynamics rather than static frames. Multi-task learning approaches, where the model jointly predicts facial action units, head pose, and expressions, have shown to improve robustness and generalization. Lightweight architectures optimized through pruning and quantization further extend FER applications to mobile and embedded devices, enabling real-time processing in constrained environments.

Preprocessing is another critical stage in FER pipelines, ensuring that models receive consistent and high-quality input. The first step typically involves **face detection**, where algorithms such as Haar cascades, Viola-Jones, or modern DNN-based detectors identify and crop facial regions. Once detected, **face alignment** techniques are applied using landmark detection to normalize orientation, ensuring that eyes, nose, and mouth are properly positioned for reliable analysis. Illumination variations are handled with normalization techniques such as histogram equalization or gamma correction, improving feature stability across diverse lighting conditions. Occlusions from glasses, masks, or hands often pose challenges, and preprocessing may include occlusion-aware filtering or augmentation strategies to improve robustness. Data augmentation techniques such as rotation, scaling, flipping, and photometric transformations help improve generalization to unseen conditions. Spatial transformer networks also introduce learnable alignment within end-to-end FER architectures, minimizing reliance on handcrafted preprocessing. Together, these preprocessing steps standardize inputs, reduce dataset bias, and ultimately enhance the accuracy and reliability of deep learning-based FER models in real-world applications

Conclusion

Deep learning approaches for Facial Expression Recognition (FER) offer a powerful and scalable means to monitor learner engagement in multimedial-supported education environments. By automatically detecting and interpreting subtle facial cues, these systems can provide real-time insights into students' levels of attention, interest, and emotional states, enabling educators to adapt content, teaching strategies, and interaction modalities accordingly. Convolutional Neural Networks (CNNs), Residual Networks (ResNets), DenseNets, and more recently Vision Transformers (ViTs) have demonstrated remarkable performance in capturing both local and global facial features, while temporal models such as 3D-CNNs and RNNs help track dynamic expressions in video-based learning sessions. Preprocessing techniques, including face detection, alignment, normalization, and data augmentation, ensure consistent and high-quality inputs, improving model robustness against challenges such as occlusion, varying illumination, and head pose variations. The use of large-scale, diverse datasets like FER2013, AffectNet, CK+, and RAF-DB has accelerated the development of reliable FER systems capable of operating in real-world educational settings. Moreover, hybrid and attention-based architectures enhance the interpretability and context-awareness of engagement monitoring. Despite these advances, challenges remain in addressing cultural variations in expression, class imbalance, and ensuring student privacy. Future work should emphasize multimodal integration, combining facial cues with voice, gestures, or physiological signals to obtain a richer, more holistic understanding of engagement. Overall, deep learning-based FER provides a promising avenue for optimizing multimedial-supported education by creating adaptive, responsive, and emotionally-aware learning environments that enhance student motivation and learning outcomes

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