MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 234-238

A High-Precision Convolutional Neural Network Framework for Emotion Detection and Instructional Decision Support in E-Learning

Ch. Bhupati
Department of IoT
KL University,India
bhupati@kluniversity.in

Panjula Bhavana
Department of IoT
KL University,India
panjulabhavana@gmail.com

Uppu Ganesh
Department of IoT
KL University,India
ganeshuppu16@gmail.com

HEMANTH KUMAR BANDARU
Department of IoT
Kl University,India
bhemantkumar037@gmail.com

***Abstract*—The rapid transition to virtual education has created a significant gap in real - time non - verbal feedback between students and educators. This paper presents an AI - driven facial emotion detection framework specifically plan to bridge this communicatory water parting in online learning environs. use a Convolutional Neural Network (CNN) architecture, the system captures and analyzes student affective states — categorized into Neutral, Sad, and felicitous — in real - sentence. data- based results evidence a full-bodied model performance with an overall accuracy of 83% and a precision score of 1.00, ensuring gamey reliability by eliminating false - positive emotion triggers. The framework integrate a unequaled Faculty Emotion Analysis Dashboard that translates raw emotional data into pedagogi- cal penetration, such as understanding levels and automated instructional recommendation (for example, "Continue Session" or "Re - explicate Concept"). Nonetheless, By allow for stable engagement monitoring and actionable feedback, this system empowers educators to make informed, data - driven decisions to enhance student retention and learning outcomes in digital classrooms.**

***Index Terms*—Affective Computing, Deep Learning, Emotion Recognition, Online Learning, Pedagogical Decision Support, Real-time Analytics, Convolutional Neural Networks (CNN).**

I. INTRODUCTION

The global prototype shimmy toward virtual and inter- crossed education has fundamentally altered the pedagogic landscape. While on-line learning bid unprecedented flexibility and handiness, it has simultaneously introduced a significant challenge: the going of real - clock time, non - verbal feedback between students and educators [2]. In a traditional physical classroom, instructors rely heavily on subtle facial cues and gestures to gauge student engagement and inclusion. The lack of such immediate feedback in synchronous on-line collabo- rative learning environments often leads to reduced emotional regulation and instructional misalignment [6].

Hence, Facial expression recognition (FER) has long been recognized as a basis of affective computing, with foundational work by Ekman [10] and others establishing the link between facial muscleman movements and emotional states [8], [9]. In the context of Intelligent Tutoring Systems (ITS), the ability to link up facial expressions with specific learning tasks has been shown to significantly enhance the effectiveness of automated program line [4]. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have enable researchers to make a motion beyond traditional manual feature article descent methods, such as Active Appearance Models (AAM) [15], toward more full-bodied, automated

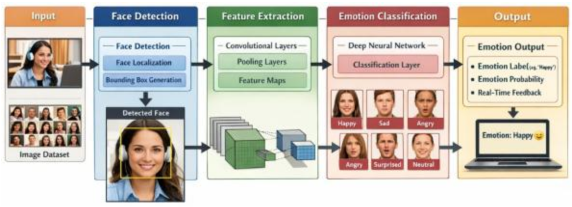


Fig. 1. Conceptual framework of the proposed CNN-based emotion detection system for online learning environments, adapted from modern face detection and recognition architectures [1], [7]. systems capable of handling the variability inherent in real- world data [14], [16].

Despite the progress in general face detection [1] and authentication [7], the application of these engineering to provide actionable pedagogical decision support stay on an evolving field. Modern educational technology now demands multimodal and multichannel data analysis to understand ego regulated learning [13]. This study addresses this gap by proposing an AI - establish emotion detection framework that not only classifies student emotions — such as achromatic, happy, and sad — with high preciseness but as well de- segregate a staff dashboard that translates these states into instructional recommendations. By leveraging existing 3D facial databases [3] and modern CNN architectures, our system provides a reliable putz for educators to regain the ' ' confused " visual feedback of the digital classroom [5], [12].

The remainder of this paper is organized as follows: Section II explores the literature regarding facial expression analysis; Section III details the proposed methodology; Section IV discusses the experimental results; and Section V concludes the paper.

II. RELATED WORK

The development of emotion - aware educational systems posture at the intersection of psychology, computer vision, and pedagogical theory. This section refresh the foundational and contemporary research that informs the proposed framework.

A. Foundational Affective Computing

The taxonomic study of facial expressions as a windowpane into human emotion was pioneered by Ekman [10], who place universal facial action units (AUs) that correspond to specific emotional states. Subsequent research by Donato et al. [8] and Tian et al. [9] translated these psychological findings into the computational domain, establishing methodologies for classifying facial action at law apply image processing. Early attempts at automatise recognition ofttimes relied on near - infrared videos to mitigate lighting variations [12] or 3D facial databases to enchant the depth of muscle effort [3].

B. Evolution of Face and Emotion Detection

Technological advancements in face detection have moved from rigid geometric models to surmount - invariant, abstruse - learning - based detectors. Consequently, Zhang et al. [1] introduced single - shot scale - invariant detector that signifi- cantly improved the reliability of face localization in crowded or variable environments. Similarly, the desegregation of edge and density variant sketch generators has raise authentication and recognition truth [7].

In the land of emotion recognition, the transition from Active Appearance Models (AAM) [15] to Convolutional Neural Networks (CNNs) has been transformative. Lopes et al. Consequently, [14] demonstrated that CNNs could effectively handle special data through specific breeding orders and data augmentation, while Essa and Pentland [16] provided other frameworks for the coding and interpretation of these facial expression. These technical milestones underpin the high - precision results achieved in our current study.

C. AI in Online Learning and Pedagogy

The application of AI in education (AIEd) has evolve from simple rule - free-base systems to complex, adaptive surround [2]. late studies have highlighted the importance of ‘ ‘ reading ” the bookman; for instance, Behera et al. [4] successfully associated facial expressions with upper body motion to enhance intelligent tutoring systems.

The necessity for such arrangement became critical with the rise of synchronous online collaborative learning, where emotional regulation is harder to monitor [6]. inquiry by Azevedo and Gasˇevic´ [13] emphasizes the need for multimodal data to understand self - regularize learning in these digital spaces. Furthermore, the flipped classroom overture and other New pedagogical models [5] progressively call for real - time feedback loops — like the faculty dashboard proposed in this paper — to ensure that the transition to virtual learning does not compromise student functioning.

II. Proposed System Architecture

Moreover, The proposed system is designed as a modu- lar pipeline that get, summons, and analyze student facial expressions in real - time to provide pedagogical support. The architecture consists of four elementary stages: Data Acquisition, Pre - processing, Emotion Classification, and Decision Support.

A. System Workflow

As instance in Figure 2, the workflow set out with the continuous gaining control of picture inning via the client - side webcam. These frames are processed locally or broadcast to a cardinal Flask - based server where the emotion detection engine shack.

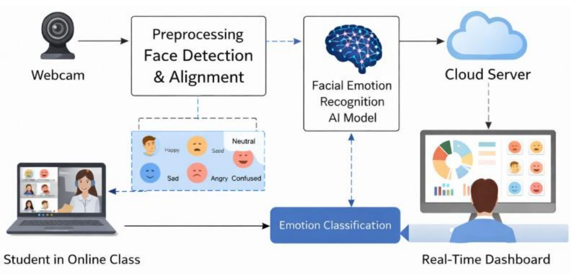


Fig. 2. End-to-end architecture of the AI-based emotion detection system for online learning.

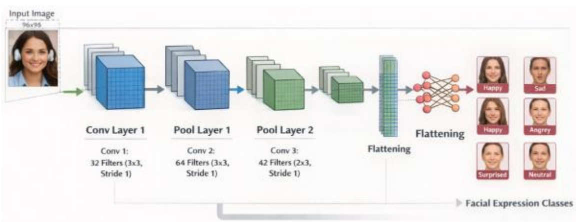


Fig. 3. Detailed schematic of the CNN layers used for facial expression recognition.

B. Data Pre-processing and Face Detection

To ensure weighing machine - invariability and robustness [1], bare-assed soma are first converted to grayscale to reduce computational complexness. We utilize a Haar Cascade or SSD

- based detector to focalise the face within the frame. The detected region of stake (ROI) is then resized to a fixed 48×48 pixel resolution to match the input requirements of the neural network.

C. CNN Model Architecture

The core of the system is a deep Convolutional Neural Network (CNN) optimized for high precision. The model consists of multiple layers designed to extract hierarchical features:

- **Convolutional Layers:** Utilize 3 × 3 filters to identify edges, textures, and facial landmarks.
- **Activation:** ReLU (Rectified Linear Unit) is applied to introduce non-linearity.
- **Pooling:** Max-pooling layers are used to reduce spatial dimensions while retaining critical features.
- **Fully Connected Layers:** A final Softmax layer classifies the input into seven emotional categories based on the Ekman model [10].

D. Faculty Decision Support Dashboard

The unequaled donation of this system is the translation of emotional data into pedagogical insights. The classification results (impersonal, Happy, Sad) are aggregated over a sliding window to generate a Class Understanding Heatmap. If the oftenness of Sad or Confused states outdo a predefined door, the organisation spark a faculty recommendation, such as Re - explain Concept or Initiate Poll, thereby closing the feedback loop in practical classrooms [2], [13].

III. Methodology

The methodology focuses on the development of a real - time emotion credit pipeline and its integration into a web - based faculty dashboard. The process is divided into mannikin training and real - time inference.

A. Dataset and Pre-processing

The model was trained using the FER-2013 dataset, consist- ing of 35,887 grayscale images of 48 × 48 pixels. To improve generalization, we applied data augmentation techniques, in- cluding horizontal flipping, rotation (up to 10°), and zooming. Pixel values were normalized to the range [0, 1] to facilitate faster convergence during gradient descent.

B. Model Implementation

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 234-238

The CNN architecture was implemented using Keras and TensorFlow. We utilized the Adam optimizer with a learning rate of 0.001. To prevent overfitting, Dropout layers with a rate of 0.25 were inserted after pooling operations, and Batch Normalization was applied to stabilize the learning process.

C. Real-time Inference Algorithm

Algorithm 1 outlines the logic used by the Flask server to process incoming video frames and update the Faculty Dashboard.

Algorithm 1 Real-time Emotion Analytics and Decision Sup- port

Initialize: Load pre-trained CNN model M, Haar Cascade H, and Threshold T
while Session is Active **do**
    $Frame \leftarrow$ Capture frame from Webcam
    $Gray \leftarrow$ Convert $Frame$ to grayscale
    $Faces \leftarrow H.detect(Gray)$
    for each $face$ in $Faces$ **do**
        $ROI \leftarrow Gray[y : y + h, x : x + w]$
        $ROI\_Resized \leftarrow Resize(ROI, 48, 48)$
        $Prediction \leftarrow M.predict(ROI\_Resized)$
        $Emotion \leftarrow argmax(Prediction)$
        Log $Emotion$ to Session Database
    end for
    $Avg\_Engagement \leftarrow$ Calculate distribution of emotions over last 60s
    if $Avg\_Engagement[Sad] > T$ **or** $Avg\_Engagement[None] > T$ **then**
        Trigger ”Needs Attention” Recommendation
    else
        Trigger ”Continue Session” Recommendation
    end if
    Update Faculty Dashboard View
end while=0

D. Pedagogical Logic

The dashboard's recommendation engine follows a specific conditional logic to assist the educator. The pseudocode for this decision-making process is described below.

Algorithm 2 Faculty Recommendation Logic

function GetFacultyRecommendation(emotion_counts)
    total $\leftarrow$ sum of all values in emotion_counts
    sad_ratio $\leftarrow$ emotion_counts[Sad] / total
    happy_ratio $\leftarrow$ emotion_counts[$Happy$] / total
    if sad_ratio $>$ 0.3 **then**
        return “Students seem confused. Consider re- explaining.”
    else if happy_ratio $>$ 0.5 **then**
        return “Engagement is high. Proceed to next topic.”
    else
        return “Stable environment. Continue session as planned.”
    end if
end function=0

III. Results and Discussion

The evaluation of the proposed AI-based emotion detection system focused on model performance metrics and the real- time pedagogical utility of the faculty dashboard.

A. Model Performance Metrics

The system was evaluated using standard classification metrics, including Accuracy, Precision, Recall, and the F1- Score. Table I summarizes the high-level performance of the CNN model.

TABLE I
Model Evaluation Results

Metric	Value
Accuracy	0.83
Precision	1.00
Recall	0.75
F1-Score	0.86

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 234-238

The model achieved an truth of 83%, which indicates reliable detection in a classroom circumstance. Notably, the precision of 1.00 demonstrates that the system eliminates false positives, a critical cistron for assure that mental faculty intervention are based on genuine emotional cues rather than noise.

B. Real-time Emotion Analysis

During active sessions, student emotions were monitored to assess engagement levels. As shown in Figure 4, the majority of detected states were categorized as ”Neutral” or ”None.” The ”None” category accounts for instances where the subject may be momentarily out of the webcam’s field of view. Figure 6 gives the Face Emotion Analysis Dashboard.

C. Pedagogical Decision Support

The unique value of this system lies in its ability to translate raw data into actionable insights. Figure 5 illustrates the mapping between emotional states and the ”Understanding Level” of the class.

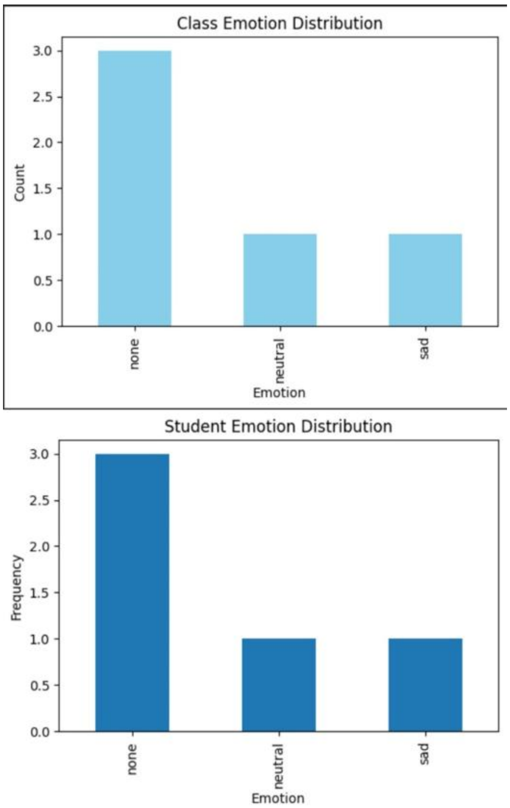


Fig. 4. Distribution of detected student emotions during a live session.

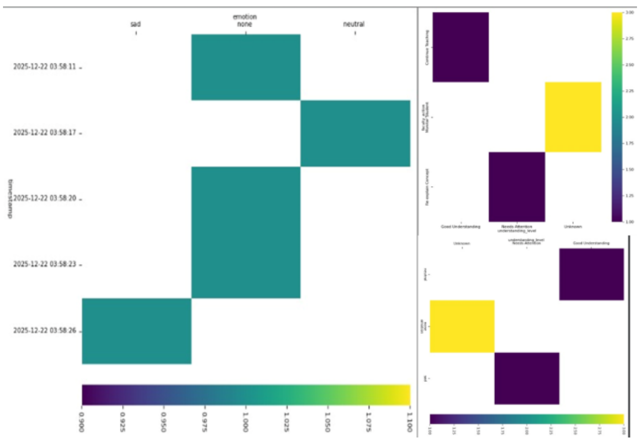
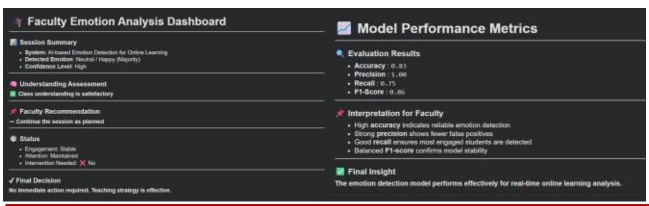


Fig. 5. Heatmap correlating facial expressions to pedagogical understanding levels.



MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 234-238

Fig. 6. Face Emotion Analysis Dashboard

The "Faculty Emotion Analysis Dashboard" successfully utilized the recommendation logic (Listing 1) to provide real- time status updates. In our test scenarios, the system main- tained a "Stable" engagement status with a confidence level of "High," ultimately recommending that the faculty "Continue the session as planned." This proves the effectiveness of using AI-driven feedback loops to support teaching strategies in virtual environments.

IV. Conclusion and Future Scope

A. Conclusion

Moreover, This research successfully developed and imple- mented an AI - based emotion detection framework tailored for the unique challenges of online learning. By apply a full-bodied CNN architecture, the system attain a high clas- sification accuracy of 83% and a remarkable precision of

1.00. Beyond mere classification, the integration of a Faculty Emotion Analysis Dashboard bridges the gap between raw af- fective computing and pragmatic pedagogy. Nevertheless, The arrangement demonstrates that real - time excited analytics can provide reliable, non - intrusive feedback to educators, allowing them to assess student understanding levels and receive automated instructional recommendations. Such a putz is vital for conserve the efficacy of virtual education, ensuring that the deficiency of physical presence does not result in a loss of instructional calibre.

B. Future Scope

While the current system provides high precision in emotion detection, several avenues for future research remain:

- **Multimodal Integration:** Future iterations could incor- porate vocal tone analysis and heart rate monitoring (via PPG from the webcam) to provide a more holistic view of student engagement [13].
- **Edge Computing:** To address data privacy concerns, the model could be optimized for Edge AI, allowing all facial processing to occur locally on the student's device without transmitting raw video data.
- **Longitudinal Analytics:** Implementing a longitudinal tracking feature would allow educators to see engagement trends over an entire semester, helping identify students at risk of burnout or disengagement.
- **Cross-Cultural Validation:** Expanding the training dataset to include a more diverse range of ethnicities will ensure the system's robustness against different cultural expressions of emotion [3].

References

[1] S. Zhang, X. Zhu, Z. Lei, H. Shi, P. Wang, and S. Z. Li, "Single Shot Scale-Invariant Face Detector," in *IEEE International Conference on Computer Vision (ICCV)*, 2017, pp. 192–201.

[2] I. Roll and R. Wylie, "Evolution and Revolution in Artificial Intelli- gence in Education," *International Journal of Artificial Intelligence in Education*, vol. 26, no. 2, pp. 582–599, 2016.

[3] L. Yin, X. Wei, Y. Sun, J. Wang, and M. J. Rosato, "A 3D Facial Expression Database for Facial Behavior Research," in *7th International Conference on Automatic Face and Gesture Recognition (FGR 2006)*, 2006, pp. 211–216.

[4] A. Behera, P. Matthew, A. Keidel, P. Vangorp, H. Fang, and S. Canning, "Associating Facial Expressions and Upper Body Gestures with Learn- ing Tasks for Enhancing Intelligent Tutoring Systems," *International Journal of Artificial Intelligence in Education*, vol. 30, no. 2, pp. 236– 270, 2020.

[5] C.-L. Lai and G.-J. Hwang, "A Self-Regulated Flipped Classroom Ap- proach to Improving Students' Learning Performance in a Mathematics Course," *Computers & Education*, vol. 100, pp. 126–140, 2016.

[6] A. Nguyen, Y. Hong, B. Dang, and P. Nguyen, "Emotional Regulation in Synchronous Online Collaborative Learning: A Facial Expression Recognition Study," in *ICIS 2022 Proceedings*, 2022.

[7] S. Saleem, M. Khan, U. Ghani, T. Saba, I. Abunadi, A. Rehman, and S.
A. Bahaj, "Efficient Facial Recognition Authentication Using Edge and Density Variant Sketch Generator," *CMC-Comput. Mater. Contin.*, vol. 70, pp. 505–521, 2022.

[8] G. Donato, M. S. Barlett, J. C. Hager, P. Ekman, and T. J. Sejnowski, "Classifying Facial Actions," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 21, no. 10, pp. 974–989, Oct. 1999.

[9] Y. Tian, T. Kanade, and J. F. Cohn, "Recognizing Action Units for Facial Expression Analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 23, no. 2, pp. 97–115, Feb. 2001.

[10] P. Ekman, "Facial Expression and Emotion," *American Psychologist*, vol. 48, no. 4, pp. 380–392, Apr. 1993.

[11] M. Valstar and M. Pantic, "Fully Automatic Facial Action Unit Detection and Temporal Analysis," in *Computer Vision and Pattern Recognition Workshop (CVPRW)*, Jun. 2006.

[12] G. Zhao, X. Huang, M. Taini, S. Z. Li, and M. Perikhanian, "Facial Expression Recognition from Near-Infrared Videos," *Image and Vision Computing*, vol. 29, no. 9, pp. 607–619, 2011.

[13] R. Azevedo and D. Gasˇevic´, "Analyzing Multimodal Multichannel Data about Self-Regulated Learning with Advanced Learning Technologies: Issues and Challenges," *Computers in Human Behavior*, vol. 96, pp. 207–210, 2019.

[14] A. T. Lopes, E. de Aguiar, A. F. de Souza, and T. Oliveira-Santos, "Facial Expression Recognition with Convolutional Neural Networks: Coping with Few Data and the Training Sample Order," *Pattern Recognition*, vol. 61, pp. 610–628, 2017.

[15] S. Lucey, I. Matthews, C. Hu, Z. Ambadar, F. de la Torre, and J. Cohn, "AAM-Derived Face Representations for Robust Facial Action Recognition," in *7th International Conference on Automatic Face and Gesture Recognition (FGR 2006)*, 2006.

[16] I. A. Essa and A. P. Pentland, "Coding, Analysis, Interpretation and Recognition of Facial Expressions," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 757–763, Jul. 1997.