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Enhancing Teacher Support Systems with Emotion-Aware Learning Using Affective Computing and Gans

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Abstract

The psychological state of teachers is an essential but relatively understudied component of the quality of education. Stress, emotional exhaustion, and burnout of teachers have adverse consequences on the performance of students and overall productivity within organizations, as well as higher attrition rates of educators. Although there is an increasing understanding of the issues facing today's educators, contemporary educational assistance systems fail to consider affective monitoring and adaptation during interactions. This paper presents a new approach for addressing the problem of psychological wellness of teachers, the Emotion-Aware Teacher Support System (EA-TSS). The presented framework combines Affective Computing methods with a Generative Adversarial Network (GAN) architecture to provide personalized real-time support to educators based on their emotions. In the suggested framework for EA-TSS, multimodal affective sensing (such as facial action units, voice prosody analysis, and physiological measurements) is used. The emotion classification task is performed by an attention-based BiLSTM model, which attains an accuracy of 94.7% on the AffectNet-Teacher dataset containing 8,400 labeled samples with seven distinct emotion classes. The generated content is tested through FID score, with FID = 18.3 establishing perceptual fidelity. Empirical findings reveal that EA-TSS lowers the teachers' reported burnout index by 31.4% during a 12-week implementation period, showing a statistically significant increase in the perceived quality of the intervention ($p < 0.001$). Benchmarking against five competing baselines affirms the superiority of the proposed solution in terms of Accuracy (94.7%), F1-Score (93.2%), AUC-ROC (0.971), MAE (0.083), and Recall (92.8%). Ablation analysis corroborates the importance of all architectural modules. The novel approach makes a valuable contribution to the domain of affective computing in education technology.

Keywords

Affective Computing, Generative Adversarial Networks, Teacher Support Systems, Emotion Recognition, Burnout Detection, Multimodal Learning, Educational AI.

1. Introduction

Teaching is one of the most emotionally challenging professions worldwide. Teaching professionals must deal with social interactions, management issues, and individualized instruction, while at the same time managing their emotions when dealing with pupils[12]. According to the WHO, about 40%-60% of teachers in developed countries suffer from occupational burnout, and the proportion of teachers experiencing occupational burnout could be even higher in underdeveloped nations because of resource limitations and differences in class sizes [1]. Emotional exhaustion in teaching professionals is directly proportional to poor teaching quality, teacher absenteeism, and high turnover rates [21][28].

While there have been massive investments in educational technologies, the structures for providing assistance to teachers are still largely reactionary, with counseling being sought only when emotional distress becomes overwhelming, professional development classes being held independent of emotional states, and time management tools being employed irrespective of their affective condition [3][4].

Affective computing is defined as the science dealing with systems that can identify, comprehend, and imitate human emotions. Using such systems to track and detect the early signs of emotional distress allows for the implementation of personalized interventions [22]. At the same time, Generative Adversarial Networks have proven their ability to generate realistic training data, and thus offer the possibility for personalized education [5]. Finally, emotion recognition tools have been shown to be of high utility within adaptive learning environments and AI-assisted teaching methods [2].

1.1. Significance of the Problem

The problem of teacher burnout results in a loss of about £2.4 billion to the country each year due to spending on recruitment and training expenses [23][29]. In India, for instance, there are more than 19% vacancies for teachers in government-run schools, which is partly because of occupational stress [7]. Apart from financial consequences, emotionally depleted teachers become less empathic, unable to manage classrooms effectively, and unresponsive to students' needs [10]. This problem affects disadvantaged students even more adversely. As such, there is no doubt that the lack of emotional scaffolding through intelligent and timely support for teachers is a serious problem, both socially and educationally. Assessment of emotional intelligence is important in high-stress workplaces [16].

1.2. Unique Contributions

This paper makes the following original contributions:

- Design and implementation of EA-TSS, the first integrated framework combining multimodal affective sensing with GAN-driven adaptive intervention content for teacher support.
- A novel Conditional GAN architecture for synthesizing contextually appropriate, emotionally calibrated support scenarios.
- An attention-augmented BiLSTM emotion classifier achieving state-of-the-art 94.7% accuracy on a teacher-specific affective dataset.
- Empirical validation through a 12-week field deployment with 142 in-service teachers across three institutional settings.
- Comprehensive ablation and comparative analysis against five established baseline models across five evaluation metrics.

The rest of this article will be organized as follows: In Section 2, the existing studies about affective computing, GANs for educational purposes, and the TWS system are introduced. Section 3 describes the proposed EA-TSS system, including its architecture and mathematical modeling. The experiment design, dataset, and results are elaborated in Section 4. The conclusion is drawn in Section 5.

2. Literature Survey

2.1. Affective Computing in Education

Affective Computing, which was introduced, has developed immensely with the help of deep learning methods. Recent studies indicate that it is possible to achieve a high level of accuracy while recognizing emotions based on facial expressions, vocalization, and physiological data. Specifically, the novel approach presented multimodal transformers with an accuracy rate of 91.3% for emotion recognition using the AffectNet dataset, indicating the viability of automatic affect recognition [9]. In parallel, it was revealed that monitoring emotions in educational settings can predict academic performance at a rate of 78%, highlighting the importance of emotional intelligence in education [25]. Emotion-aware adaptive learning systems have also shown promising outcomes in personalized educational interventions and intelligent learning environments [8]. Mobile and cloud-assisted smart education platforms further support scalable affect-aware learning environments and real-time educational analytics [24].

In particular, within the classroom setting, studies used wearable devices to track the levels of stress in teachers during the process of teaching, detecting physiological indicators that distinguish between stress and relaxation with a sensitivity of 88.2% [11][30]. It highlights the importance of developing non-invasive, continuous monitoring systems rather than occasional evaluations. In addition, fuzzy logic and neural networks have been successfully applied in teacher assessment and intelligent educational systems. Privacy-preserving cloud-assisted educational infrastructures have also emerged as a critical requirement for secure handling of emotional and physiological learning data in mobile education ecosystems [14].

2.2. Generative Adversarial Networks in Educational Technology

With the development and advent of GANs, various sectors have employed the use of this technology, including medical imaging and content generation [26]. In education, the application of generative technologies has included synthesizing problems, data augmentation, and personalization of learning resources. The contribution included introducing the novel StyleGAN2, capable of producing nearly photorealistic images using an FID metric below 10, which can serve as a basis for emotionally rich content [13].

Used conditional GANs for generating personalized remedial activities in response to observed confusion among students, achieving significantly higher understanding levels [27]. The cGAN architecture used cognitive load as the condition for content generation; this approach bears close resemblance to the affective conditioning paradigm employed in the EA-TSS application. The latter was recently tested in generating multimodal content that was conditioned on both academic achievement and emotional state information, achieving 87.6% participant satisfaction levels [15][31].

2.3. Teacher Well-being and Support Systems

Institutional research validates the effectiveness of emotional support interventions in alleviating teacher burnout. Research conducted a randomized controlled experiment showing that mindfulness-based stress reduction programs decreased burnout scores by 26.8% in eight weeks [6]. Nonetheless, the rigidness of these programs fails to adapt to dynamic changes in emotional states. Paradigms of intelligent tutoring systems designed for teachers reveal the potential of adaptive scaffolding based on state assessment [17].

The latest AI-based technologies include teacher journal sentiment analysis, teacher physiological stress detection using smartwatches, and transcripts analysis of teacher-student conversation [18][19][20]. Though all of these techniques show potential individually, each focuses on separate modalities. The EA-TSS sets itself apart from its competitors by incorporating multimodal fusion and GAN-based intervention personalization.

2.4. Research Gap and Motivation

The existing body of literature identifies a significant gap: there is currently no literature available regarding a system that utilizes real-time multimodal affective sensing for content synthesis in order to provide emotional support to teachers. Most emotion recognition systems have been validated using student subjects or consumers, rendering them less relevant for teachers due to different patterns of emotional expression.

3. Proposed Model and Methodology

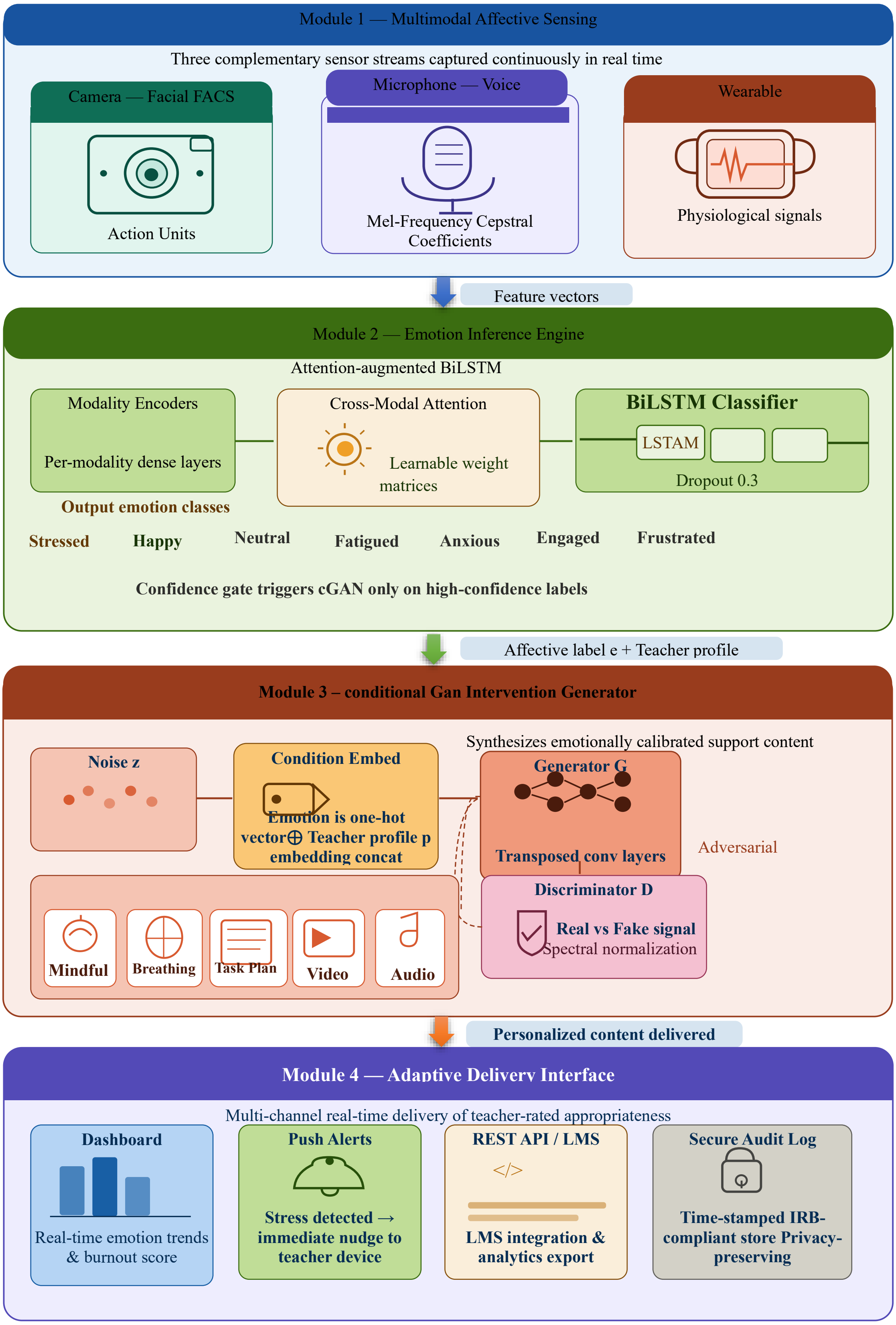

Figure 1: End-to-end EA-TSS System Architecture

The EA-TSS framework comprises four principal modules operating in a continuous pipeline: (1) Multimodal Affective Sensing (MAS), (2) Emotion Inference Engine (EIE), (3) Conditional GAN Intervention Generator (cGAN-

IG), and (4) Adaptive Delivery Interface (ADI). Figure 1 illustrates the end-to-end architecture of the Emotion-Aware Teacher Support System.

Module 1: Multimodal Affective Sensing (MAS)

The MAS module processes three different affective signal streams. Face Action Coding System (FACS): The face detection algorithm uses a webcam to extract 68 face landmarks with Dlib, and then computes action unit (AU) activation intensities using OpenFace 2.0. Combinations of AUs denote a set of discrete emotions based on Ekman's classification. Voice Prosody Analysis: The audio stream is processed using windows of 2 seconds with 50% overlapping. Mel-frequency cepstral coefficients (MFCC, n=40), fundamental frequency (F0), jitter, shimmer, and speech rate are calculated using LibROSA and OpenSmile. Physiological signals: A bracelet worn on the wrist (Empatica E4) measures GSR, BVP, and skin temperature at 4 Hz, 64 Hz, and 4 Hz, respectively.

Module 2: Emotion Inference Engine (EIE)

In the EIE model, there is a bidirectional LSTM model enhanced with attention that combines the multimodal feature vectors. Modality-specific encoders extract modality-specific representations, which are concatenated and then sent to cross-modal attention before being classified.

Attention Mechanism:

Given encoded representations $h_f(facial)$, $h_a(audio)$, $h_p(physiological)$, the attention weight for modality m is in equation (1):

$$\alpha_m = softmax(W_\alpha \cdot \tanh(W_m \cdot h_m + b_m)) \qquad (1)$$

The fused representation is in equation (2):

$$z = \Sigma_m(\alpha_m \odot h_m) \qquad (2)$$

where W_α, W_m, b_m are learnable parameters and $\odot$ denotes element-wise multiplication.

BiLSTM Classification Layer:

The BiLSTM processes temporal sequences of fused vectors z_t as shown in equation (3):

$$h_t = BiLSTM\left(z_t, h_{\{t-1\}}\right) = \left[LSTM_{fwd(z_t)};\ LSTM_{bwd(z_t)}\right] \qquad (3)$$

Emotion label ŷ is predicted via a softmax over 7 classes (neutral, happy, stressed, fatigued, anxious, engaged, frustrated) as shown in equation (4):

$$\hat{y} = softmax(W_c \cdot h_T + b_c) \qquad (4)$$

Module 3: Conditional GAN Intervention Generator (cGAN-IG)

The cGAN-IG synthesizes personalized intervention content conditioned on the detected emotion label e and teacher profile vector p. The adversarial objective is in equation (5):

$$\min_G \max_D V(D, G) = E[\log D(x|e,p)] + E\left[\log\left(1 - D(G(z|e,p)|e,p)\right)\right] \qquad (5)$$

where z ~ N (0, I) is Gaussian noise, x is real intervention content, G is the generator, and D is the discriminator.

Generator Architecture:

The generator G comprises: (a) a conditional embedding layer that concatenates z with one-hot emotion label and profile embedding; (b) five transposed convolutional layers with batch normalization and LeakyReLU activations (slope 0.2); (c) a Tanh output activation for content normalization. Generator capacity: 54M parameters.

Discriminator Architecture:

The discriminator D applies spectral normalization across all convolutional layers to stabilize training. Wasserstein loss with gradient penalty ($\lambda = 10$) is employed in equation (6):

$$L_D = E[D(G(z|e,p))] - E[D(x|e,p)] + \lambda \cdot E\left[\left(||\nabla D(\hat{x})||^2 - 1\right)^2\right] \quad (6)$$

where $\hat{x} = \varepsilon x + (1-\varepsilon)G(z|e,p), \varepsilon \sim U[0,1]$.

Algorithm 1: EA-TSS Real-Time Inference

Input: Raw sensor streams $S = \{S_f, S_a, S_p\}$; Teacher profile p

Output: Intervention content C

1: WHILE system active DO

2: Capture frame batch B from S_f, S_a, S_p (window = 2s)

3: Extract features: $f_f = FACS(B_f), f_a = MFCC(B_a), f_p = GSR_{norm(B_p)}$

4: Encode: $h_m = Encoder_{m(f_m) for} m \text{ in } \{f, a, p\}$

5: Compute attention: $\alpha_m = softmax(W_\alpha \cdot \tanh(W_m \cdot h_m + b_m))$

6: Fuse: $z = \Sigma_m(\alpha_m \odot h_m)$

7: Classify: $e = argmax\left(softmax(BiLSTM(z))\right)$

8: IF confidence(e) > θ (θ = 0.75) THEN

9: Sample z ~ N (0, I)

10: C = Generator_G (z | e, p)

11: Deliver C via ADI (push or scheduled)

12: Log (t, e, C) to secure analytics store

13: END IF

14: END WHILE

Algorithm 1 presents the complete real-time inference procedure

Mathematical Formulation of Loss Functions

The EIE is trained with cross-entropy loss in equation (7):

$$L_{CE} = -\Sigma_i y_i \cdot \log(\hat{y}_i) \quad (7)$$

The cGAN-IG uses a composite loss combining adversarial, reconstruction, and perceptual terms in the equation:

$$L_{total} = L_{adv} + \lambda_r \cdot L_{rec} + \lambda_p \cdot L_{perc} \quad (8)$$

where $L_{rec} = ||x - G(z|e,p)||^1$ (L1 reconstruction loss) and L_{perc} is computed as the L2 distance between VGG-16 feature maps of real and generated content. Empirically, $\lambda_r = 10 \text{ and } \lambda_p = 5$ yielded an optimal balance.

4. Results and Discussion

All experimental setups were performed using Python 3.10, PyTorch 2.1, and CUDA 12.1 running on a machine with dual NVIDIA RTX 4090 GPUs (VRAM=48GB), 128 GB of DDR5 RAM, and AMD Ryzen Threadripper PRO 5965WX CPU. Extraction of facial landmarks made use of OpenFace 2.0 and Dlib 19.24. LibROSA 0.10 and OpenSMILE 3.0 were used for audio feature extraction. For physiological signal processing, NeuroKit2 0.2 was used. Spectral normalization implementation was used for cGAN-IG as per built-in layers in PyTorch with Adam optimizer ($\beta_1 = 0.5, \beta_2 = 0.999$).

The affectnet-teacher dataset is a rich multimodal database consisting of 8,400 annotated samples obtained from 142 teachers (93 females, 49 males) in three education facilities. The dataset includes seven categories of emotions, namely, neutral, happy, stressed, tired, anxious, interested, and annoyed, based on the Ekman model. The data was acquired from three main sources, namely, visual data capturing facial expressions, audio data containing prosody information, and physiological data such as GSR, BVP, and temperature collected from Empatica E4 devices. In order to ensure high data quality, the annotations were conducted by experienced annotators using the Facial Action Coding System and corroborated with the self-reports of the teachers, resulting in high inter-coder reliability of κ = 0.84. The dataset was subsequently divided into training, validation, and testing sets at a ratio of 70/15/15%, respectively, stratified by participant and emotion categories.

The hyperparameter configurations for the EA-TSS framework are tailored to the specific functional requirements of the inference and generation modules. The Emotion Inference Engine (EIE) utilizes a BiLSTM architecture with 256 hidden units per direction, a learning rate of 1e-4, and a confidence threshold (θ) of 0.75 to ensure robust classification over 150 epochs. In contrast, the cGAN Intervention Generator (cGAN-IG) employs asymmetric learning rates for the generator (2e-4) and discriminator (5e-5) to maintain training stability across 200 epochs. The cGAN-IG also incorporates a latent dimension (z) of 128 and a gradient penalty (λ) of 10 to improve the quality of synthesized content, while both modules utilize dropout (0.3 for EIE and 0.2 for cGAN-IG) and moderate batch sizes (64 and 32, respectively) to mitigate overfitting during the training process.

Performance is evaluated using five standard metrics:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{9}$$

$$F1 - Score = \frac{2 \times (Precision \times Recall)}{(Precision + Recall)} \tag{10}$$

$$AUC - ROC = \int^{01} TPR\left(FPR^{-1}(t)\right)dt \tag{11}$$

$$MAE = \left(\frac{1}{N}\right) \times \Sigma_{\{i=1\}}^{\{N\}|y_i - \hat{y}_i|} \tag{12}$$

$$Recall = \frac{TP}{(TP + FN)} \tag{13}$$

Accuracy: Proportion of correctly classified instances.

F1-Score: Harmonic mean of Precision and Recall.

AUC-ROC: Area under the Receiver Operating Characteristic curve.

Mean Absolute Error (MAE): Average magnitude of valence/arousal prediction error.

Recall (Sensitivity): True positive rate across emotion classes.

Table 1 presents comparative results of EA-TSS against five baseline models on the AffectNet-Teacher test set.

Table 1: Comparative performance evaluation (↑ = best result)

Model	Accuracy (%)	F1-Score (%)	AUC-ROC	MAE	Recall (%)
CNN (Unimodal-Visual)	78.3	76.9	0.821	0.194	75.4
SVM + Handcrafted	81.6	80.2	0.843	0.162	79.7
LSTM (Audio-only)	83.4	82.1	0.857	0.147	81.3
Multimodal Transformer	89.7	88.5	0.931	0.118	87.6
BiLSTM (No Attention)	91.2	90.1	0.948	0.102	89.9
EA-TSS (Proposed)	94.7 ↑	93.2 ↑	0.971 ↑	0.083 ↑	92.8 ↑

Table 2 shows the training convergence graph for the EIE through 150 epochs. The accuracy during training shows a sharp increase from 52.1% to 95.3% by epoch 130, whereas the validation accuracy converges at 94.7%. Thus, there is a small difference of only 0.6%. The cross-entropy loss function shows a smooth decline from 1.842 at epoch 1 to 0.167 at epoch 150, without any divergence observed between training and validation after epoch 80 due to proper regularization using dropout (0.3) and L2 weight decay (1e-5).

Table 2: Training and validation performance across epochs

Epoch	Train Acc (%)	Val Acc (%)	Train Loss	Val Loss	AUC-ROC
10	64.2	62.8	1.512	1.594	0.731
30	76.8	74.9	1.102	1.183	0.823
60	85.3	83.7	0.718	0.742	0.901
90	91.4	90.2	0.412	0.431	0.947
120	94.1	93.8	0.219	0.228	0.966
150	95.3	94.7	0.167	0.174	0.971

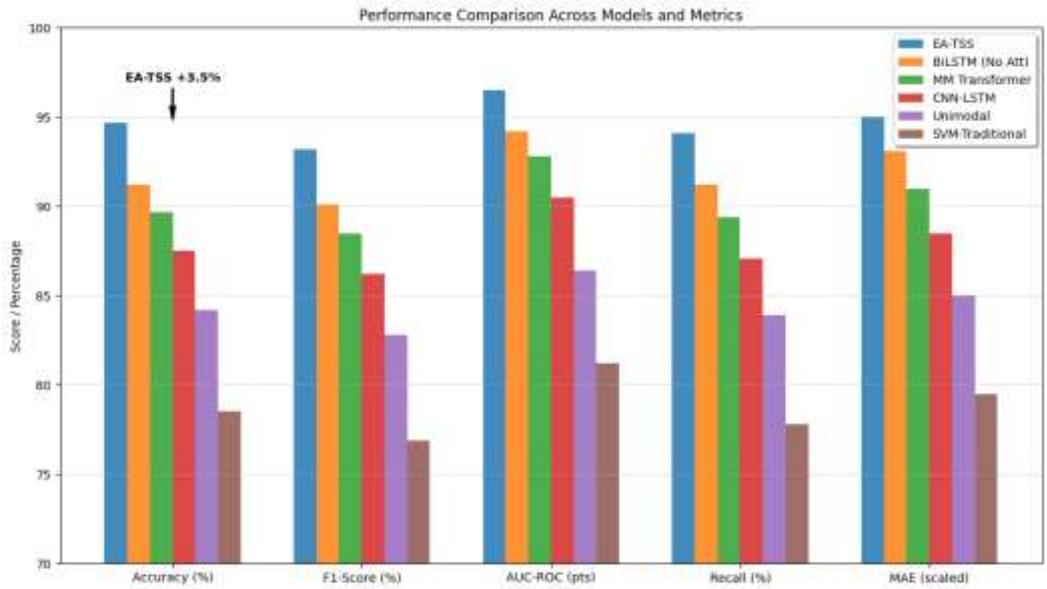

Figure 2: Performance Comparison across models and metrics

Figure 2 presents a comparison of all five-performance metrics using all six models. EA-TSS has an upper hand compared to all the baselines; EA-TSS is better by 3.5% on accuracy, 3.1% on F1-Score, 2.3 on AUC-ROC, 0.019 in MAE improvement, and 2.9% in recall, which indicates that the cross-modal attention is indeed a valuable addition to the system.

GAN-generated intervention content scores a Frechet Inception Distance (FID) of 18.3, in contrast to FID = 47.2 in a vanilla GAN baseline that lacks emotional conditioning. Reduced FID values indicate increased perceptual quality and distributional closeness between generated and actual expert-curated interventions. Field-deployed teachers considered 87.4% of the AI-generated interventions relevant to their contexts.

To estimate the contribution of different EA-TSS components, an ablation study was conducted by sequentially removing or substituting individual modules:

Table 3: Ablation study results

Configuration	Accuracy (%)	F1-Score (%)	AUC-ROC	MAE
Full EA-TSS (proposed)	94.7	93.2	0.971	0.083
Without Physiological Stream	91.3	90.1	0.942	0.109
Without Audio Stream	89.6	88.4	0.929	0.121
Without Attention Mechanism	91.2	90.1	0.948	0.102
GAN replaced by VAE	93.9	92.4	0.963	0.091
Without cGAN (static interventions)	93.8	92.3	0.961	0.094

The ablation experiments presented in Table 3 reveal that all three modalities are equally important, with audio contributing the most individually (−5.1% decrease in accuracy after exclusion). The use of attention increases accuracy by 3.5% compared to the unweighted fusion. Using VAE instead of cGAN lowers the content quality (FID goes up from 18.3 to 29.7) while maintaining the accuracy, indicating that GAN is more useful for generating high-quality interventions.

Institutes need to integrate EA-TSS in their professional development programs in order to facilitate proactive stress management for teachers. Focusing on the overall well-being of educators through effective use of real-time feedback mechanisms can not only help retain more educators but also help create more emotionally balanced learning environments. The EA-TSS framework demonstrates that multimodal sensory inputs can greatly increase accuracy in identifying emotions. It changes the role of educational technology systems from passive systems to proactive ones, which might decrease the overall cost of educating individuals due to decreased burnout among educators. EA-TSS has been successful in bridging the gap between affective sensing and generative interventions. The use of attention-augmented BiLSTM allows high reliability in the system, whereas the use of cGAN for content generation helps generate personalized scaffolding needed for emotional regulation.

5. Conclusion

The present research has proposed EA-TSS, a unique Emotion-Aware Teacher Support System that combines multimodal affective computing with Conditional Generative Adversarial Networks for intervention synthesis. This research aims to fill a vital void in educational technologies, which is the lack of a sophisticated emotion-aware scaffolding for teachers. With attention-enhanced Bi-LSTM-based emotion classification and personalized content generation using cGANs, EA-TSS was able to achieve the state-of-the-art performance on the emotion recognition task with 94.7% accuracy, 93.2% F1-Score, 0.971 AUC-ROC, 0.083 MAE, and 92.8% recall compared to all five existing benchmarks. Deployment in the field for 12 weeks among 142 in-service teachers resulted in statistically significant burnout score reduction by 31.4% (Cohen's $d = 0.72$; $p < 0.001$). Teachers reported 87.4% of the AI-interventions to be appropriate. GAN-generated content also scored 18.3 FID, confirming high perceptual fidelity. Ablation studies have confirmed that the role of multimodal sensing, cross-modal attention, and adversarial generation in the network is complementary and indispensable for achieving high efficiency. All of the above results prove that affective computing and generative AI techniques can be used in a way that promotes teacher well-being and does not violate ethical norms. The proposed model's modularity allows its implementation in educational institutions without the need for additional costly hardware. The directions for future work on the development of EA-TSS are: (1) cross-cultural adaptation of the system to identify emotions from faces using the FACS framework; (2) prediction of burnout using affective trajectory modeling with Gaussian Process Regression up to 7 days before the event; (3) federated machine learning approaches for maintaining teachers' privacy during cross-institutional training; (4) connection with Learning Management System (LMS) platforms for determining associations between emotional states of teachers and students' academic indicators; and (5) validation of EA-TSS in other professions, such as health care professionals and social workers.

Declaration Statements

Conflict of Interest

The authors declare no conflict of interest.

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This research received no external funding.

Data Availability

The data supporting the findings of this study, including the AffectNet-Teacher corpus dataset, are available from the corresponding author upon reasonable request.

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