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Emotion-Aware School Using Artificial Intelligence & Internet of Things

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Abstract— Modern educational institutions face the challenge of understanding and responding to the emotional states of students in real time. Traditional schooling approaches rely heavily on teacher observation, which is inherently subjective, scalable only to small groups, and limited to explicit behavioural cues. This research proposes an Emotion-Aware School System (EASS) that integrates Artificial Intelligence (AI) with Internet of Things (IoT) devices to continuously monitor, analyse, and respond to student emotional states across classroom and campus environments. The proposed system employs a Convolutional Neural Network (CNN)-based facial expression recognition model deployed on Raspberry Pi edge nodes. These nodes stream anonymised emotional classification outputs to a centralised Spring Boot backend, which aggregates real-time emotion data and surfaces actionable intelligence to teachers, counsellors, and administrators through a Flutter-based dashboard. The system recognises seven core emotional states — Happy, Sad, Angry, Fearful, Disgusted, Surprised, and Neutral — mapped to pedagogical intervention categories. Privacy is preserved through on-device inference; raw facial images are never transmitted over the network.

Keywords — Facial Expression Recognition, CNN, IoT Edge Computing, Emotion Detection, Student Well-being, Raspberry Pi, Flutter, Spring Boot, Educational Analytics, Privacy-Preserving AI

I. INTRODUCTION

Student emotional well-being is one of the most powerful predictors of academic engagement and long-term learning outcomes. Research in educational psychology consistently demonstrates that students in positive emotional states exhibit higher retention, better collaborative behaviour, and stronger motivation to engage with challenging material. Conversely, unaddressed negative emotional states — anxiety, sadness, and frustration — create cognitive interference that significantly impairs learning capacity.

Despite this established relationship, the majority of schools today lack any systematic mechanism for monitoring emotional climate. Teachers manage classrooms of 30 to 60 students simultaneously, making continuous emotional awareness of each learner practically impossible. School counsellors operate reactively, relying on referrals or visible crisis indicators rather than early identification of at-risk students.

The convergence of deep learning-based emotion recognition and low-cost IoT hardware creates a realistic opportunity to bridge this gap. This research presents the EASS comprising CNN-based emotion classifiers on Raspberry Pi edge nodes, an MQTT-based telemetry pipeline, a Spring Boot analytics backend with PostgreSQL, and a Flutter dashboard for teachers and counsellors.

II. LITERATURE REVIEW

Li and Deng (2020) conducted a comprehensive survey of deep learning approaches to Facial Expression Recognition, identifying CNN architectures as the dominant paradigm with over 89% accuracy on controlled datasets. They acknowledged a persistent gap between lab-validated performance and real-world deployment accuracy under variable lighting and partial occlusion. EASS addresses this through data augmentation and demographic-balanced training sets.

Gupta et al. (2021) proposed a student engagement detection framework using facial action unit analysis in e-learning environments. Their implementation was limited to online learning with individual webcam feeds and did not address multi-camera classroom orchestration. EASS extends their model to physical classrooms through distributed IoT edge nodes.

Shi et al. (2016) established the foundational edge computing architecture, demonstrating that latency-sensitive workloads benefit from inference at the network edge. Merenda et al. (2020) identified MobileNetV2 as preferred for embedded inference. EASS adopts MobileNetV2 with TensorFlow Lite as

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its on-device engine.

Al-Fuqaha et al. (2015) proposed MQTT as the preferred protocol for constrained IoT devices, forming the basis of the EASS telemetry architecture. Williamson (2020) identified absent consent mechanisms as primary ethical risks in school AI deployments, addressed in EASS through on-device inference and explicit consent workflows.

III. SYSTEM ARCHITECTURE

The EASS is designed as a four-layer distributed architecture with clearly defined responsibilities at each layer and standardised communication interfaces between them.

3.1 IoT Edge Layer (Raspberry Pi Nodes)

Each classroom is equipped with Raspberry Pi 4 devices and 8 MP camera modules running a TensorFlow Lite MobileNetV2 emotion classifier fine-tuned on FER2013, AffectNet, and custom school-environment data. The model accepts 48×48 greyscale face crops and outputs a probability distribution across seven emotion classes. Aggregate metadata is published to the MQTT broker over TLS every 10 seconds. No facial images leave the device.

3.2 Telemetry Broker (MQTT + Redis)

An Eclipse Mosquitto MQTT broker receives emotion telemetry at QoS Level 1. A lightweight consumer enqueues events into a Redis-backed processing queue, decoupling ingestion throughput from backend latency and absorbing burst volumes during lesson transitions.

3.3 Backend Service (Spring Boot + PostgreSQL)

The Spring Boot backend exposes 42 REST API endpoints across five modules: Device Registration, Real-Time Emotion Stream, Classroom Analytics, Counsellor Referral Management, and Report Generation. It computes the Emotional Comfort Index (ECI) — a normalised score from the weighted distribution of positive, neutral, and negative emotions. JWT tokens with role-scoped claims govern all API access.

3.4 Flutter Dashboard

The Flutter dashboard serves three roles from a single codebase. Teachers access live Classroom View with real-time ECI and alerts. Counsellors access the Student Well-being Module with longitudinal trends. Administrators access school-wide sentiment heatmaps and device health monitoring.

3.5 End-to-End Data Flow

The Raspberry Pi captures frames at 5 fps, detects faces, and runs on-device classification. Results are published every 10 seconds. The backend updates the ECI, triggers alerts, and persists records. The Flutter dashboard polls every 15 seconds and receives Firebase Cloud Messaging push notifications for critical alerts.

IV.IMPLEMENTATION & TECHNICAL COMPLEXITY

4.1 On-Device Emotion Classification

The TensorFlow Lite model was fine-tuned for 30 epochs on 87,000 labelled images. Post-quantisation model size is 4.2 MB, enabling inference at approximately 12 fps on the Raspberry Pi 4. BlazeFace achieves sub-20 ms face detection latency, keeping the total inference pipeline within 100 ms per frame.

4.2 Privacy-Preserving Architecture

Raw facial images never leave the edge device. Only the aggregated emotion count vector (seven integers) is transmitted as MQTT payload, eliminating central storage of student biometric images while preserving sufficient signal for meaningful classroom analytics.

4.3 Emotional Comfort Index (ECI)

ECI weights: Happy/Surprised = +1.0; Neutral = 0.0; Sad/Fearful = −0.7; Angry/Disgusted = −1.0. Normalised to 0–100: below 40 triggers counsellor alerts; 40–70 flags teacher awareness; above 70 indicates a positive environment. Weights are configurable by administrators.

4.4 Multi-Role JWT Security

Teacher tokens grant access to assigned classroom emotion data only. Counsellor tokens grant individual student longitudinal data. Administrator tokens grant school-wide aggregated analytics. Parent tokens grant only their registered child's trend. Spring Security filter chains enforce these boundaries at the controller level.

4.5 Alerting and Threshold Engine

Alerts are triggered when ECI drops below the configured threshold for two consecutive polling windows, when a single emotion class exceeds 60% of the classroom distribution, or when a student's negative emotion trend exceeds a configurable standard deviation from their rolling baseline.

V.RESULTS & ANALYSIS

The system was evaluated through a four-week pilot across three classrooms at a private school in Pune:

- Emotion Classification Accuracy: 83.7% weighted accuracy; highest on Happy (91.2%), lowest on Disgusted (71.4%).
- End-to-End Latency: 134 ms from frame capture to MQTT delivery; 2.3 s to dashboard update.
- ECI Correlation: Pearson r = 0.71 between ECI scores and teacher-reported engagement across 120 sessions.
- Alert Precision: 29 of 37 counsellor alerts (78.4%) confirmed as warranting follow-up.
- Device Stability: 97.8% uptime across 28 continuous operational days.
- Parent Engagement: 84% of surveyed parents found weekly emotion trend reports useful.

Table 1: Comparison with Existing Approaches

Feature	Traditional	Proposed EASS
Real-Time Monitoring	Not available	15-second refresh
Privacy	N/A	On-device inference
Scalability	Manual observation	Multi-camera, multi-room
Proactive Alerts	None	Configurable thresholds
Parent Visibility	Report cards only	Emotion trend reports
Hardware Cost	N/A	< ₹12,000 per classroom

VI.ADVANTAGES

- Privacy-by-design: on-device inference eliminates transmission and central storage of student facial images.
- Real-time ECI enables immediate pedagogical adjustments in response to detected negative classroom sentiment.
- Proactive counsellor alerting converts reactive support into early identification before crises escalate.
- Low-cost Raspberry Pi hardware keeps per-classroom deployment under ₹12,000.
- Configurable ECI weights and alert thresholds allow administrators to adapt the system without code changes.
- Role-scoped access ensures sensitive emotional information reaches only authorised staff.

VII.LIMITATIONS

- Accuracy degrades under poor lighting, facial occlusion (e.g., masks), and extreme head pose angles.
- Observed facial expressions may not reflect internal emotional states for students who mask emotions.
- Individual student tracking across frames requires opt-in configurations; defaults are classroom-aggregate.
- Continuous classroom camera operation requires clear consent and school policy frameworks.
- Pilot limited to three classrooms and four weeks, constraining generalisability across age groups and cultures.

VIII.CONCLUSION

This research designed and implemented an Emotion-Aware School System integrating AI-based facial expression recognition with IoT edge computing to deliver real-time emotional intelligence to teachers, counsellors, and administrators. The system achieves 83.7% emotion classification accuracy, sub-150 ms end-to-end latency, and r= 0.71 correlation between the ECI and teacher-assessed engagement using commodity hardware and open-source frameworks.

The four-layer architecture establishes a scalable, modular foundation for school emotional intelligence systems. The pilot results demonstrate meaningful potential: 78.4% of system-generated counsellor alerts warranted follow-up, showing that automated early warning can meaningfully supplement counselling staff observational capacity.

IX.FUTURE WORK

- Integration of multi-modal emotion signals — speech tone and physiological wearable data — for improved robustness.
- Longitudinal ML models learning individual student baselines for personalised anomaly detection.

- Automated curriculum adaptation module suggesting pedagogical changes based on real-time ECI.
- Federated learning to improve model accuracy across schools without centralising student data.
- India-specific facial expression dataset covering diverse demographics and school lighting conditions.

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