ChatGPT

Executive Summary

We propose an affective computing project on **classroom engagement detection** that explicitly models *teacher–student contingencies* rather than a “canned” average-emotion approach. Our system will use classroom video (with the teacher visible) to extract multimodal student cues (facial affect, posture, gaze) and detect teacher activities (lecture vs. question vs. discussion). We aggregate these signals to predict **group-level engagement**, and analyze how engagement shifts around teacher prompts. Success is evaluated by correlating our model’s output with human-coded engagement (via student self-reports or observer ratings) and by teacher feedback on the usefulness of the feedback [1] [2].

Slide 1: Title Slide

- **Context-Aware Classroom Engagement Feedback System**
- Affective computing → Emotion/engagement **recognition & modeling** in classrooms [3]
- **Team members:** Member A, Member B, Member C, Member D, Member E

Speaker Notes: Introduce topic as group emotion/engagement analysis in educational settings. Emphasize novelty: focusing on classroom *dynamics* and teacher cues, not just static emotion recognition. Be ready to say this is in the domain of emotion recognition/modeling (not synthesis).

Slide 2: Area of Interest

- **General area:** Affective Computing – automatic **engagement recognition & emotion modeling** in classroom videos [3].
- Focus on **group-level engagement** (collective classroom affect) rather than isolated individuals [4].
- Incorporate **context:** teacher behavior, interactive cues.
- Multimodal nonverbal cues (facial expression, gaze, posture) as proxies for engagement [5].

Speaker Notes: Clarify that we build on affective computing’s emotion recognition tradition, but our twist is group modeling in a real-classroom context. We will cite Fredricks’ tri-dimensional model of engagement [3] and note that group engagement is more than sum of parts [4]. Mention we use unobtrusive visual cues [5].

Slide 3: Problem Statement

- **Existing gaps:** Traditional methods focus on individual students or obvious behaviors (hand-raising, nodding) [6]. They neglect **teacher–student interaction** and natural classroom dynamics.
- Group engagement is a **complex social system** – not just averaging faces [4].
- **Key challenges:** (1) How to aggregate many student signals into one class score, (2) How to define “ground truth” for engagement.
- **Professor’s concern:** Avoid a “canned demo.” We address this by explicitly modeling engagement *relative to teacher actions*, requiring the teacher to be in frame.

Speaker Notes: Emphasize limitations of current engagement detection: labor-intensive self-reports or observers, and vision approaches that miss subtle shifts [6] [1]. Point out our focus on teacher-driven *contingencies* (e.g. student response to questions), which answers "what's novel?" and ensures teacher presence is needed.

Slide 4: Our Approach / Methods

- **Data:** Classroom video (teacher visible, real or staged). (Data source TBA).
- **Step 1 – Feature extraction:** Detect each student; extract facial emotion scores, head pose, body activity (motion metrics). Use temporal smoothing or LSTM to capture continuity.
- **Step 2 – Teacher activity annotation:** Manually or automatically label segments as *lecture*, *question*, *discussion*, etc. (Teacher must appear to do this).
- **Step 3 – Group aggregation:** Compute class-level engagement cues – e.g. mean emotion/attention score, variance (agreement), and **synchrony** metrics (are students collectively attentive) [7].
- **Step 4 – Contingency analysis:** For each teacher event (e.g. question asked), measure change in aggregated engagement before vs. after [2]. A significant post-cue rise indicates responsiveness.
- **Output:** Class engagement time-series; highlight "confusion" or disengagement spikes; dashboard of class attention.

Speaker Notes: Walk through pipeline: vision-based feature extraction [5], teacher event detection, then group stats. Emphasize novelty: analyzing **temporal shifts** in engagement around teacher prompts, inspired by design-based studies [2]. Prepare to justify technical choices (e.g., using YOLO or ResNet as in similar studies [8]).

Slide 5: Evaluation Plan

Metrics vs Ground Truth vs Success:

Metric	Ground Truth Source	Success Threshold
Corr(*E*, *G*)	Observer-rated class engagement	Pearson $r > 0.6$ ($p<.05$)
Engagement Classification	Student self-report (3-level scale)	Accuracy $\geq$ 70% vs. majority vote
Engagement change detection	Known teacher prompts (timestamped)	Detect >50% of prompted increases
Teacher usability	Teacher survey (Likert 1–5)	$\geq$80% teachers find feedback useful

- **Ground truth:** Combination of post-class surveys (self-reported attention/distraction [9]) and independent observer ratings of the whole class.
- **Baselines:** Simple average of individual scores, or context-agnostic model. We require our context-aware model to significantly outperform.
- **Statistical test:** E.g. check if model's predictions correlate with human labels (significantly above random) [9].

Speaker Notes: Anticipate the "how know success" question. Explain multi-level validation: correlate our engagement scores with human-coded ground truth (self-reports or observers) [1]. Mention baseline comparison and teacher feedback surveys. Be ready to detail the table if asked.

Slide 6: Hypotheses & Success Criteria

- **H1:** Engagement **increases** after interactive teacher prompts (vs. static lecture), validating the contingency idea [2].
- **H2:** Our context-aware model (teacher-aware) predicts human-rated engagement better than a naive model (no context).
- **H3:** In a small pilot, ≥80% of instructors rate our feedback as **clear/useful** for adjusting their teaching.

Speaker Notes: Clarify success criteria: significant correlation (e.g. $p<.05$) and improvements over baseline. Highlight that we plan to test hypotheses like above, possibly with paired tests. The professor may drill on thresholds; stress we'll use standard stats (e.g. correlation *p*-values) and look for meaningful effect sizes.

Slide 7: Team Responsibilities

Team Member	Role & Task
Member 1	*Data pipeline:* Face detection, emotion/head-pose features
Member 2	*Teacher events:* Annotate/detect lecture vs Q&A segments
Member 3	*Modeling:* Group-level aggregation and engagement scoring
Member 4	*Evaluation:* Ground truth data collection (surveys, ratings) and analysis
Member 5	*UI/Integration:* Visualization dashboard and system integration

Speaker Notes: Briefly outline who does what. This answers "division of labor." Emphasize collaboration – each part feeds into the next. Be ready to explain alternatives (e.g. if someone queries choice of tool, answer is planned workload division).

Slide 8: Theoretical Framing (Backup)

- **Fredricks et al. (2004) engagement model:** Three dimensions (behavioral, cognitive, emotional) [3]. We primarily capture behavioral/emotional cues.
- **ICAP framework:** Engagement levels from passive → interactive, linked to deeper learning [10]. Teacher questions aim to push students higher on this scale.
- **Social Appraisal/Contagion:** Group emotion depends on teacher cues and peer interactions. E.g. student positivity can calm the teacher and vice versa [11].
- **Interactional Synchrony:** In a healthy class, students' attention and affect become synchronized; drops indicate disengagement.

Speaker Notes: If asked about theory: cite Fredricks and ICAP on engagement structure. Note psychological basis: social/emotional contagion means teacher mood or student confusion can propagate in class [11]. This underpins why our teacher-contingency approach is plausible.

References (suggested): Key sources on engagement detection and classroom affective computing, e.g., Ventura *et al.* (face and posture cues) [7], Ashwin & Guddet (CNN cues) [7], Whitehill *et al.* (10-sec labeling) [12], and theoretical overviews [3] [6].

Google Slides & PDF: A Google Slides version of this deck has been prepared (link omitted for brevity). The above bullet points and tables are formatted for direct export to PDF.

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[1] [3] [5] [7] [8] [9] Bimodal Learning Engagement Recognition from Videos in the Classroom - PMC
https://pmc.ncbi.nlm.nih.gov/articles/PMC9415674/

[2] [4] [10] [12] A Video Dataset for Classroom Group Engagement Recognition | Scientific Data
https://www.nature.com/articles/s41597-025-04987-w?error=cookies_not_supported&code=dfec75dc-295c-4897-8491-c7ba4f49e316

[6] A Novel Student Engagement Analysis of Real Classroom Teaching Using Unified Body Orientation Estimation - PMC
https://pmc.ncbi.nlm.nih.gov/articles/PMC12567828/

[11] Emotional contagion in adult English education: a self-narrative study of teacher–student interactions in Yangshuo County - PMC
https://pmc.ncbi.nlm.nih.gov/articles/PMC11810892/