Multimodal Engagement Analysis from Facial Videos in the Classroom

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Abstract—Student engagement is a key component of learning and teaching, resulting in a plethora of automated methods to measure it. Whereas most of the literature explores student engagement analysis using one-on-one computer-based learning often in the lab, we focus on using classroom instruction in authentic learning environments. We recorded audiovisual recordings of secondary school classses over a one and a half month period, acquired continuous engagement labeling per student (N=15) in repeated sessions, and explored computer vision methods to classify engagement levels from faces in the video. We learned deep embeddings for attentional and affective features by training Attention-Net for head pose estimation and Affect-Net for facial expression recognition using previously-collected large scale datasets (i.e., different from the classroom data). We used these deep represntations to train both shallow and deep engagement classifiers on our data, in individual and multiple channel settings and by considering temporal dependencies vs. static representations. The best performing engagement classifiers achieved student-independent AUCs of .620 and .720 for grades 8 and 12, respectively, with attention-based features outperforming affective features. We found that score-level fusion either improved the engagement classifiers or was on par with the best performing modality. We also investigated the effect of personalization and found that using only 60 seconds of person-specific data, selected by margin uncertainty of the base classifier, yielded an average AUC improvement of .084. We discuss applications of our work for automating data analysis of classroom videos for research on student engagement and instruction pedagogy, but not for evaluative purposes.

Index Terms—Affective computing, computer vision, educational technology, nonverbal behaviour understanding.

1 Introduction

When are students are engaged in learning during class? What is the relationship between student engagement and the content and the quality of the learning material? And, how is student engagement related to learning outcomes and long-term learning goals? These research questions and more have drawn the interest of scientists from educational sciences, psychology, and similar fields to investigate student engagement during learning. We advance this research using computational methods.

To begin our investigation of student engagement, we must first define the term engagement and contextualize its implications in the classroom setting. Several dictionaries share a similar definition for the term engagement; being engaged means "to involve oneself or become occupied; to participate" while engagement can be defined as "[being] actively committed". As it relates to human behavior, engagement is highly connected to commitment and involvement. Dictionary definitions aside, in educational contexts, student engagement has been the subject of research for the past three decades, including different attempts to define it [1].

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The definition by Fredricks et al. [2] is one of the most accepted ones and frequently used in education research. They define engagement as a multidimensional construct composed of three dimensions: *behavioral*, *cognitive*, and *emotional*. Those dimensions do not reflect isolated processes, but rather dynamically interrelated factors within an individual student. In the context of classroom and learning activities, behavioral engagement focuses on the act of participation and can include behaviors such as displaying attention and concentration, or asking questions. Emotional engagement encompasses affective reactions, such as a student's interest or boredom. Whereas aspects of behavioral and emotional engagement are typically externally observable, cognitive engagement incorporates less overt, internal cognitive processes such as psychological resource investments in learning and self-regulation [2]. Importantly, previous research has found positive correlations between aspects of student engagement and academic achievement, emphasizing its central role in classroom learning [3]. To put it differently, students' engagement during classroom instruction determines how much students learn, how well they develop intellectual skills, and how long they will persist in school [4]. Given its importance, in the present study, we aim to use affective computing techniques to measure student engagement in authentic classrooms based on visible indicators.

Two methods are proposed in affective computing literature to acquire engagement labels needed for supervised learning: 1) self-reports and 2) observer ratings. Self-reports are practical, relatively cheap, and easy to administer to a large sample, making them valuable for measurement of engagement and beyond [1]. Despite their value, self-reports have certain drawbacks, namely a dependence on

participant compliance and diligence [5]. Furthermore, self-reports can be used in two ways: after the lesson or multiple times as experience sampling. The former can lead to biases in retrospective recall, the latter risks disrupting the natural flow of instruction. To cause as little disruption as possible, self-reports administered in experience sampling studies have to be as short as possible, even though this comes with the risk that they might not adequately cover the construct under investigation (more details can be found in [6]).

External behavior observations are another useful assessment tool for student engagement and have a long tradition in education research, for example, to investigate determinants of classroom processes such as quality of instruction [7], teacher-student relationships (e.g., [8]), number of learning opportunities (e.g., [9]), and teacher's choice of practices (e.g., [10]). In general, observer ratings are systematic approaches that aim to identify and interpret certain behaviors [11]. Their deployment in large-scale studies is notably limited by the necessity of providing human raters with specialized training, the difficulty of acquiring reliable labeling, and the cost involved. Moreover, in contrast to many other computer vision applications, crowdsourcing is not a viable option to label student engagement collected in authentic classrooms due to privacy considerations and the specialized training required for raters.

Self-reports and external behavior observations pose a challenge for large samples of classrooms. A solution is to automatically estimate engagement using machine learning and computer vision. Automated methods have two main advantages: they are fast and they have the potential to increase the sample size of classroom studies. In the field of affective computing, initial studies aimed at estimating student engagement focused on computer-based learning [12], [13], [14] and intelligent tutor systems (ITS) [15]. From ITS log files, such as students' reaction times, errors, and performance [16], [17], [18], preferred modalities for engagement analyses shifted to video [12], [13], [19], audio, and physiological measures (i.e., galvanic skin response [20], [21], EEG [22], [23], heart rate [24]).

In computer-based learning settings, the availability of log data is an important asset [25]. Furthermore, vision-based features can be extracted reliably using webcams. In the classroom, on the contrary, log data is typically unavailable and using sensors for each student can render studies expensive, intrusive, and ultimately may affect student behaviors. Thus, a widely accepted practice in classrooms is to record the instruction with field cameras in the corners of the room. One drawback of this approach, however, is that audio and visual data is noisy and may be occluded, which is a challenge we address in the present work.

1.1 Contributions of the Study

Although automated engagement analysis is widely studied in computer-based settings such as intelligent tutors and educational games, to our knowledge this study is one of the first to perform video-based engagement classification in the classroom on a larger scale. In this paper, we review, in detail, engagement measurement studies in the field of affective computing. We then discuss the large-scale school study we conducted by collecting audio-visual recordings of classes during a one and half month period. Observer ratings of student engagement were acquired using an instrument previously validated in university-level seminars [26].

The current study's primary focus is to develop engagement classification from limited and unconstrained data where traditional face alignment and facial action unit estimation methods have largely failed. Following the definition by Fredricks et al. [2], we focus on behavioral and emotional aspects of student engagement as they have observable behavioral correlates [27]. Visual attention (subsequently referred to as attention) and affective expressions can thus provide useful cues into these two sub-components of engagement. Accordingly, we propose learning attention and affect features from two convolutional neural networks that we trained on head pose estimation and facial expression recognition as pretasks. In contrast to previous work that utilize handcrafted features in engagement analysis, the deep learning-based representations we propose work without precise facial alignment.Our engagement classification is performed using these learned feature embeddings. We also applied feature and score level fusion on these features. Beyond reporting baseline results using person-independent classification, we also investigated personalization to address intrapersonal variation in student (dis)engagement.

2 Related Work

In recent years, the use of automated methods in classroom behavior analysis and engagement estimation has been on the rise. The popularity of such methods is largely due to the availability of big data and the progress of artificial intelligence. Notably, developments in deep learning have yielded significant results in social signal processing problems [50], [51], [52], [53], including classroom and learning analytics [54], [55].

We can categorize the literature of automated engagement estimation based on the following criteria:

- learning situation (computer-enabled settings, classroom (traditional instruction vs. group-work, etc.)
- nonverbal features (various behavioral related to learning-related activities.)
- computational methodology (in both feature extraction and machine learning)
- final objectives (explanation [i.e., showing a statistical relation] vs. fully automated predictive system for psychologically valid measurements of engagement).

In addition to these points, another consideration is the use of sensors [56]. Whereas sensor-free measurements depend on educational systems' log files, sensor-based measurements use physical devices such as physiological sensors (i.e., EDA, EEG, heart rate sensors) and audiovisual recordings acquired from cameras and voice recorders. As our motivation is to measure engagement as seamlessly as possible without necessitating any expensive and intrusive sensors, we limit our scope to engagement analysis using only visual modalities. Table 1 summarizes the literature of automated engagement analysis across three domains: classroom, computer-based settings (including intelligent tutors and screen-based learning games), and human-human, human-robot interactions (HHI/HRI).

TABLE 1: Automated Engagement Analysis in Classroom, Computer-based Learning, Human-Human/Human-Robot Interaction (HHI/HRI) Settings

Reference	Setting	Behavioral Cues	Engagement Measurement	Predictive Models
[28]	classroom	head pose	observer reports	✓
[29], [30]	classroom	head pose, body motion	self-reports (in-class)	✗
[31], [32]	classroom	head pose, gaze, facial expressions, posture	observer reports	✓
[33]	classroom	gaze mapping (heads up/down)	–	✗
[34]	classroom	head pose, gaze, FACS action units	observer reports	✓
[35]	classroom	real-time monitoring system capable of extracting many behavioral features (i.e. smile detector, hand raising, head pose, speech analysis)	–	✗
[36]	classroom	monitoring system (head pose and gaze estimation)	–	✓
[37]	computer-based	FACS action units and ITS log features	observer ratings	✓
[38]	computer-based	FACS action units	self-reports (user engagement survey [39], NASA-TLX [40])	✓
[12]	computer-based	handcrafted features from faces	observer reports	✓
[19]	computer-based	FACS action units and appearance features	self-/observer reports (MW)	✓
[13]	computer-based	FACS action units and gross body movement	observer reports (BROMP [41])	✓
[42]	computer-based	Kinect Animation Units, facial appearance, heart rate estimated from face videos	self-reports (concurrent & retrospective)	✓
[43]	computer-based	facial appearance features	crowdsourcing	✓
[44]	computer-based	head pose and gaze direction	observer reports	✓
ELEA [45]	HHI	–	observer ratings	✗
RECOLA [46]	HHI	–	self-reports	✗
MHHRI [47]	HHI & HRI	audio, physiological, and first-person vision	self-reports	✓
[48], [49]	HRI	facial expressions, body pose, audio (in children's storrytelling and therapy with robots)	–	✓

2.1 Learning Analytics in the Classroom

Despite the popularity of computer-based learning technologies, Intelligent Tutor Systems (ITS), and Massive Online Open Courses (MOOC), traditional classroom-based learning is still the dominant setting for primary through tertiary education. The popularity of classroom-based learning is primarily due to the importance of sociological factors and collaboration throughout the learning process [57], [58]. For this reason, analytical tools in the classroom that measure students' learning-related behaviors and affective and cognitive engagement can play an essential role in research aiming to investigate and improve the efficiency of classroom-based learning.

Learning analytics methods in the classroom can include video cameras in the corner of the room, direct recordings of students' faces and upper bodies, and external audio recorders. The quality of audio-visual feature extraction, in general, is not as fine-grained as in computer-based situations where a webcam, 1-2 meters away, captures a student's behaviors. However, classroom analytics can provide more insight into student-teacher, student-learning material, and student-student interactions than focusing on individual students.

Bidwell and Fuchs [28] presumably proposed the first classroom monitoring system capable of analyzing student engagement. Although their technical report did not incorporate any quantitative results, they defined a general workflow for classroom analytics by using several color and Kinect depth-sensing cameras during a lesson in a third-grade classroom. Three observers attended the lesson and coded each student's behavior using a mobile device during 20 second intervals according to the following categories: appropriate (engaged, attentive, and transition) and inappropriate (non-productive, inappropriate, attention-seeking, resistant, and aggressive). Due to the limitations of only recording a single lesson and collecting highly imbalanced data, Bidwell and Fuchs used a Hidden Markov Model (HMM) to classify three categories (engaged, attentive, and transition) from head pose based gaze-target mappings.

A more recent classroom monitoring system was proposed by Raca and Dillenbourg [29]. Their study proposed the use of student's motion information during class and behavioral synchronization between neighboring students' feature representation to estimate student attention. In [30], they handcrafted several features such as eye contact (the percentage of time where faces are detected), amount of still time (where head pose does not change significantly for a period), and head travel (normalized head pose change). As ground truth labels of attention, Raca and Dillenbourg used self-reports that students completed in approximately 10-minute intervals. These features, together with a Support Vector Machines (SVM) classifier, performed up to the accuracy of 61.86% (Cohen's $\kappa = 0.30$) to predict 3-scale attention (low, medium, and high). Their seminal work showed that student attention can be automatically measured using visible behavioral cues. However, they used considerably long intervals (10 minutes) before self-reports were obtained. Moreover, they only employed attentional features (head pose and motion), and did not utilize any affective or behavioral nonverbal features.

Zalatelj and Kosir [31], [32] used a Kinect sensor and its commercial SDK to estimate body pose, facial expressions, and gaze. Subsequently, they computed behavioral cues (i.e., yawning, taking notes, etc.) from Kinect features and trained a bagged decision tree classifier to estimate observer-rated attention levels (low, medium, high). They also used manually-labeled behavioral features (i.e., writing, yawning, one's hand touching their head). They only ana-

lyzed a few minutes of video recording from datasets with 3 and 6 students, raising questions about generalizability. Additionally, the range of Kinect and similar depth sensors is around 0.4 to 5.45 meters [59], and the ideal range for their face alignment and body pose estimation is even less (i.e., Kinect One was used at 1.8 meters in [31]), suggesting that multiple sensors will be required in a typical classroom with 20-30 students, potentially introducing additional cost and device synchronization issues.

Thomas and Jayagopi [34] collected video recordings of 10 students in three 12-minute segments while they were listening to motivational video clips on YouTube. Three observers labeled the engagement of each student in 10-second intervals based on whether a student was looking towards the screen (teacher area), talking to a neighbor, or gazing in another direction. Their approach was to use head pose, gaze direction, and facial action unit features with SVM and logistic regression. The main limitation of this study was the limited data size and concerns with the engagement labeling methodology. Specifically, students can still be attending to the content in the audio despite looking elsewhere or taking notes.

Goldberg et al. [26] is the first study that utilizes a psychologically valid and comprehensive engagement rating system. Their continuous observer-based rating system combines Chi & Wylie's ICAP (Interactive, Constructive, Active, Passive) framework [60] and on-task/off-task behavior analysis [61]. Using attentional (head pose and gaze direction) and affective (FACS action unit intensities) sets of features with support vector regression, they predicted continuous observer-ratings and reported correlations between estimated engagement levels and self-reports collected at the end of 40-minute teaching units (N=52). They also found that behavioral synchrony with immediate neighbors improved the estimation of engagement.

One of the main objectives of learning analytics in the classroom is the reporting of students' estimated attention and engagement to teachers. For instance, Fujii et al. [33] estimated head-down (i.e., taking notes or reading learning material) and head-up (gazing at whiteboard/teacher area) behaviors for each student and depicted color-coded visualization to teachers with a synchronization rate of the classroom in terms of predicted classes, head-up and head-down. However, they tested the performance of the head-down/head-up detector on limited data (30 minutes of video recordings and 5 students) and reporting behavioral cues (looking at learning material or the teacher area) provides limited information on students' engagement levels leaves.

In a similar vein, two recent studies [35], [36] developed smart classroom monitoring systems. Whereas Anh et al. [36] mapped gaze directions to three areas (board/teacher, table/notebook, and other directions) and visualized the distribution on a dashboard, Ahuja et al. [35] integrated various nonverbal features in their smart classroom, EduSense. These features included the state-of-the-art methods in face detection and alignment, body pose estimation, hand raise detection, and active speaker detection. [35] presented a technical analysis of real-time classroom monitoring systems, including the speed and latency of the system and their algorithms' performance. However, they did not report on student engagement. Even though nonverbal features are essential to understand engagement, they are not easy for a teacher to interpret on their own.

In summary, computer vision-based classroom analytics studies though emerging are still limited. The sample sizes are small and the majority do not estimate attention or engagement levels. Besides, for studies that estimate student attention/engagement, there are some concerns about the validity of the engagement labels.

2.2 Engagement Estimation in Computer-based Learning

Computer-based learning situations are more restricted than classroom situations because they only contain student-technology interactions. These studies generally capture video and audio from 1 to 2 meters away, resulting in better quality data for feature extraction methods. Furthermore, introducing an intervention during learning is more straightforward than in the classroom setting. For these reasons, automated engagement estimation is more prevalent in computer-based situations, for example when students' play an educational game, engage in reading comprehension or writing tasks, or learns with ITSs [see [25], [56] for a review].

One study that predicted the level of engagement in computer-based settings (during which the participants perform a cognitive training task) was conducted by Whitehill et al. [12]. They used appearance-based facial features (Box filters, Gabor filters, CERT FACS features) and estimated levels of engagement using several classifiers such as GentleBoost, SVM, and multinomial logistic regression. They developed a manual rating system (4-scales) and annotated the video recordings at 60-sec or 10-sec intervals. The accuracy of their classifiers varied between 36-60%.

In a similar computer-based setting, Monkarasi et al. [42] estimated engagement using Kinect face tracker ANimation Unit (ANU) features, LBP-TOP, and heart rate (estimated from videos of the face) features during a writing task. They used concurrent self-reports (every 2-minutes during the writing task) and retrospective self-reports after the participants finished the task. Both self-reports showed high correlation ($r = 0.82, p \leq 0.001$), and the engagement classification (low/high) achieved an AUC of .758 and .733 using concurrent and retrospective labels, respectively. Bosch et al. [13] used estimated FACS action units as features and predicted observer annotations [41] using different classifiers (Bayes Net, Updateable Naive Bayes, Logistic Regression, AdaBoost, Classification via Clustering, and LogitBoost). Six variables they predicted according to [41] are boredom, confusion, delight, engagement, frustration, and off-task. Engagement classification performed an AUC of .679 and 64% of accuracy.

Mind wandering (MW) is an important attentional component of engagement, defined as an attentional shift from task-related to task-unrelated thoughts [62] and is consistently linked with negative performance in learning tasks [63]. The availability of automated methods to detect MW can reveal this covert aspect of engagement. The use of visual modalities, particularly face videos, to detect MW is preferable to eye gaze [64] and physiological signals [65], which necessitate specialized sensors, Stewart et al. [66]

is the first study that used visual modality, facial action units and body motions to detect MW. They recorded facial videos while the participants watched a narrative film for 35 minutes. Each participant self-reported MW by pressing a key through the video screening. Facial action unit features and classifiers including logistic regression, naive Bayes, and support vector machines could spot MW in a person-independent setting with F_1 score of .390. Later, [67] showed the generalizability of MW detection when trained and tested on different tasks (reading scientific text and watching a narrative film). Bosch et al. [68] showed the applicability of video-based MW detection in a classroom study (N=135) while learning from an intelligent tutor system.

2.3 Human-Human and Human-Robot Interactions (HHI/HRI)

Another line of work is the attention analysis in human-human interactions (e.g., in group work) and in human-robot interactions. For example, Sanches-Cortes et al. [45] developed an audiovisual corpus of groups of four who engaged in a survival task and focused on estimating group performance, apparent personality, and perceived leadership and dominance. Similarly, Rinvegal et al. [46] used a survival task during remote collaboration using audio, video, and physiological signals as well as self-reported engagement. However, although survival tasks can be useful to measure group interactions, they do not represent typical learning situations, which is the current focus.

Looking into more recent studies, Celiktutan et al. [47] collected an audiovisual dataset during human-human and human-robot interactions using first-person cameras. They acquired self-/acquaintance-assessed personality and self-reported engagement labels. However, limitations include the size of the dataset and interactions wherein one participant or robot asks predefined questions. Another application in human-robot interactions is autism therapy for children [48], [69] and child-robot interactions (a dialogic storytelling task) [49], [70]. The measurement of engagement during children's storytelling or autism therapy is more obvious and, in these settings, it is comparably easier to differentiate between engaged and disengaged behaviors than it is in schools where most pupils learn to hide their disengagement. Despite the lack of expert-labeling criteria, these studies adopt a continuous engagement labeling approach and deep Q learning to actively sample training data and personalize models with limited data.

To summarize, the literature in attention and engagement analysis is centered on computer-based learning settings as well as human-human and human-robot interactions. Collecting data for automated analysis in those domains is comparably more convenient than in the classroom. However, the impact of schools and classroom instruction exceeds the scope of these applications and, moreover, plays a crucial role in every student's life. Therefore, research on analyzing attention and engagement in the classroom is of high importance and may benefit from novel analytic approaches. Existing classroom-based studies are very limited in terms of data size. They were mostly conducted on university-level courses or on a small number of participants (mainly to test computer vision systems). While Raca and Dillenbourg [30] conducted the most comprehensive attention monitoring study in the classroom and, showed the applicability of these technologies in a school setting, their study lacked expert-labeled attention/engagement measures and predictive learning models on a larger scale. We build off this existing work and extend it further in the current study.

3 Data Collection for Automated Engagement Estimation in the Classroom

The study was conducted during regular lessons at a secondary school in Germany over a one and a half month period. The ethics committee from the Faculty of Economics and Social Sciences of the University of Tübingen approved our study procedures (Approval #A2.5.4-097_aa), and all teachers and parents provided written consent for their students to be videotaped. Students who did not consent to being videotaped attended a parallel session covering the same instructional content.

3.1 Participants

We collected audio-visual recordings of 47 classes from 5^{th} to 12^{th} grades, resulting in 128 participants overall. Each participant attended more than one class (3.84 on average). Therefore, the total number of samples across grades was over 360. The collection of labelled data for developing and benchmarking automated methods is time consuming. Thus, we identified a sub-sample of students based on their occurrence and visibility in multiple video recordings resulting in 15 students from grade 8 (N=7) and grade 12 (N=8) in our analysis. Each participant appeared five times on average and the total number of samples in our data is 75. Classes cover a wide range of subjects, including Mathematics, Chemistry, Physics, IMP (**I**nformatics, **M**athematics, **P**hysics), History, Latin, French, German, and English.

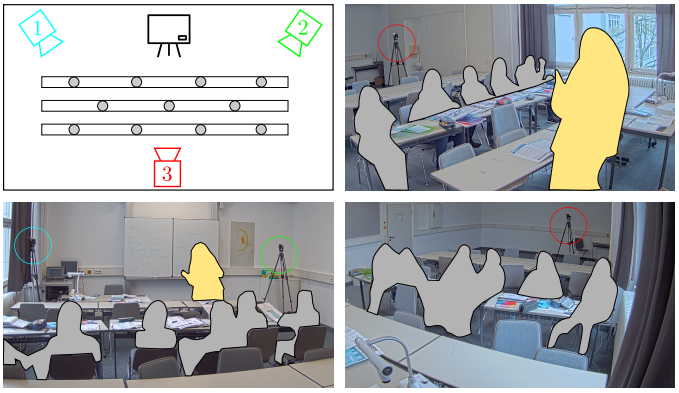

Fig. 1: Sample scene from the classroom. The synchronous cameras recorded the instruction simultaneously.

3.2 Procedure

Before classes on the first day, students filled out a questionnaire covering demographic information (age, gender) and individual differences (BFI-2 XS, 15 items; [71]). After each session, students completed another questionnaire

about their learning activities. Session recordings lasted between 30 and 90 minutes each. Video material during classes covered group work, individual work, and teacher-centered instruction. To best capture student attention on the instructor, we focused on teacher-centered components of the video (see Fig 1), extracting the main part of instruction time in intervals of 15 to 20 minutes from each recording. The intervals were manually annotated by human raters.

3.3 Self-Reported Learning Activities

After each session, we assessed students' involvement (four items, $\alpha = 0.73$; [72]), cognitive engagement (six items, $\alpha = 0.78$; [73]), and situational interest (six items, $\alpha = 0.92$; [74]) during the preceding instructional period.

3.4 Continuous Manual Annotation

To manually annotate students' observable behavior, we used a one-dimensional scale through the open software, CARMA [75], which enables continuous (1-second in our case) interpersonal behavior annotation via a joystick [76]. We combined the concept of on-task/off-task behavior [61], [77] with existing scales from the engagement literature. To define more fine-grained cues within the possible behavioral spectrum, **I**nteractive, **C**onstructive, **A**ctive, and **P**assive, we used the ICAP framework [60]. Thus, behaviors were annotated on a symmetric scale ranging from -2, indicating disturbing (i.e., interactive), off-task behavior, to +2, indicating highly engaged, interactive, on-task behavior (see Fig 2). Values closer to 0 indicated rather unobtrusive, passive behavior. Two raters annotated the sub-set of students in all videos in random order, with inter-rater reliability ICC(2,2) for each student being 0.77 on average (absolute agreement). For subsequent analysis, the mean across the two raters is calculated for every learner in every second.

The existing observational instruments often use time samplings of, for example, 20-s intervals or longer (e.g., in [78], [79], [80], [81]). However, classroom interactions are rather dynamic and students' behavior may change significantly within 20 seconds. To account for these changes and to capture the ground truth in a more fine-grained manner, we decided to acquire engagement labels per second. For more details about the manual annotation instrument, interested readers are referred to Goldberg et al. [26].

3.5 Preprocessing

For each video recording, we had three cameras as depicted in Figure 1. One camera was located in the rear part of the class covering the classroom and teacher and the other two cameras were placed on the left and right side of the teacher area (whiteboard) directed towards the class. We applied our computational pipeline to both the left and right camera and dynamically picked the stream where a particular student was more visible. Specifically, we used a single-stage face detector, RetinaFace [82], to detect all faces in the video streams. Subsequently, we picked several query face images that belonged to the students whose behaviors we intended to analyze. Instead of face tracking, we directly used those query images and extracted ArcFace embedding [83] for all face patches. By calculating the minimum cosine

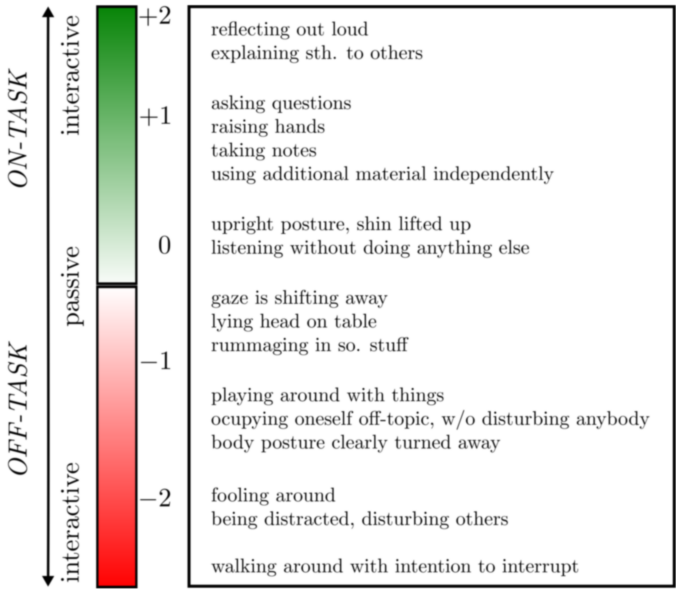

Fig. 2: Continuous scale of our manual rating instrument and visible behavioral indicators [26]

similarity between the query images and all faces, we created face tracklets for each student. Despite the challenges of occlusion and different camera angles, the face detection and recognition methods we employed could localize and recognize faces most of the time due to their training on large and unconstrained data sets. We used one-second (24 frames) continuous sequences where both face detection and recognition worked smoothly.

Table 2 shows the number of different day recordings per student and the total length of the data where preprocessing was successful. The total data length is 25,450 and 32,755 seconds for Grades 8 and 12, respectively. In total, we collected over 15 hours of recording in 30 sessions. Compared to other classroom-based studies, the line of work by Raca & Dillenbourg [30] used four classes in 9 sessions. Even though their study was on large-scale data, their attention analysis was based on 10-minute intervals and self-reports. Similarly, sample sizes of other engagement studies in the classroom are limited: three videos of 12-minute recordings in [34], 25 minutes of video recordings in [31], 4 minutes in [32].

In the continuous labeling scale, values denoting disengagement were rarely observed and the labels were often imbalanced. Thus, we followed the previous works that discretized the continuous scale into three groups: low [-2, 0.35], medium (0.35, 0.65], and high engagement (0.65, 2.0]. Figure 3 depicts the continuous and discrete distribution of labels in grades 8 and 12.

4 Methodology

4.1 Problem Statement

To classify students' engagement level, we used video recordings of classes. Formally, we employed sequences $\mathcal{S} = \{I_1, I_2, \cdots I_N\}$ where $n = 1, \cdots, N$ denotes the time intervals of a second (24-frames). Using any of the modalities, we extracted feature vectors from each sequence

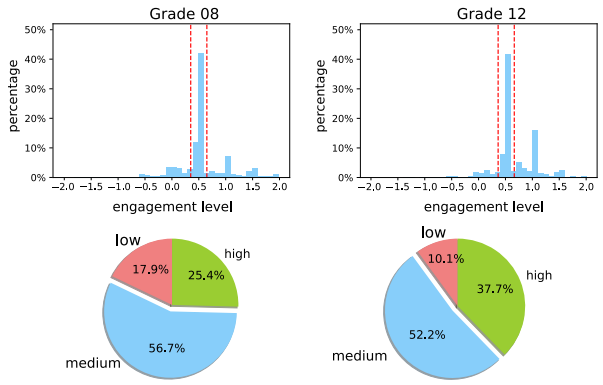

Fig. 3: The distribution of engagement labels in Grade 8 and 12. Pie charts show the percentage of quantized labels according to continuous labelling.

$\mathbf{x} = \{x_1, x_2, \cdots x_N\}$ with $\mathbf{x} \in \mathcal{R}^{\mathcal{T} \times M \times D_m}$. The 24-frame feature sequences are associated with engagement label $y = \{0, 1, 2\}$. When training engagement classifiers (except for LSTM models), we used the middle frame as a training sample. To predict the engagement labels, we used either the majority voting of all 24-frame predictions or a single prediction in a temporal learning model.

TABLE 2: The number of classes and the total duration of recording where face detection was successful (in seconds) per each student.

Grade 8							
student	**S4**	**S7**	**S8**	**S11**	**S13**	**S14**	**S16**
#class	2	7	7	3	6	4	6
seconds	836	5450	5309	2269	4404	2674	4508
Grade 12							
student	S1	S2	S3	S4	S5	S6	S7	S8
#class	9	8	3	3	4	3	6	4
seconds	6363	6695	2662	2708	4219	2605	3844	3659

4.2 Feature Representation

In most of the classes, students were listening to the teacher instead of speaking. Due to occlusion of the students' upper bodies in many of the recordings, nonverbal features such as speech and body pose were not always available. However, faces were usually visible and computationally faster and more reliable to detect. Consequently, our analysis depends on preprocessed faces as described in 3.5.

Motivated by the fact that engagement is a multidimensional construct, we can extract two different sets of information from face images: attentional and emotional features. There are several studies in the literature that used available face processing tools such as OpenFace [84] for engagement estimation [44], [48].

The main drawback of this approach, however, is that it depends on very accurate face alignment. In the classroom, camera distance from students varies between 2-10 meters, and this reduces image quality and eventually leads to poor facial keypoint localization. When we processed the classroom data using OpenFace [84], it could only process approximately 30-40% of a student face in a class with high confidence. Furthermore, even though facial action unit-based approaches provide valuable information on affect, they almost always anticipate nearly frontal images. Considering these issues, we extracted affect features based on categorical facial expression recognition and attention features based on head pose estimation without depending on 68-point facial landmarks.

Figure 4 shows the feature learning method for affect and attention. In the affect branch (Affect-Net), we used one of the most unconstrained and large-scale affect datasets, AffectNet [85], which is a a ResNet-50 network trained using softmax cross entropy loss to predict categorical models of affect (seven discrete facial expressions): neutral, happy, sad, surprise, fear, disgust, and anger. The training set of AffectNet was composed of 23,901 images, whereas the validation set had 3,500 images. We aligned all face images using five facial keypoints that were estimated by the face detector [82] and aligned by similarity transform to the size of 224×224. The training was done using an SGD solver with an initial learning rate of 0.1 (decayed ten times in each 30 epochs) for 100 epochs. The best accuracy on the validation set reached 58.37%. This performance is comparable to the [85]'s benchmark 58% and state-of-the-art methods that used pyramid super resolution and label smoothing [86], and knowledge distillation [87], improved up to 60.68%, and 60.60% by using additional training data. We used the feature activations of the layer before the last fully connected layer of the AffectNet model for affect embedding.

We used another ResNet-50 backbone (Attention-Net) to learn attention features. By adopting the approach in [88], we trained the network on 300W-LP [89] to estimate head pose jointly by softmax classification on discretized values and mean squared loss on continuous values. The combined

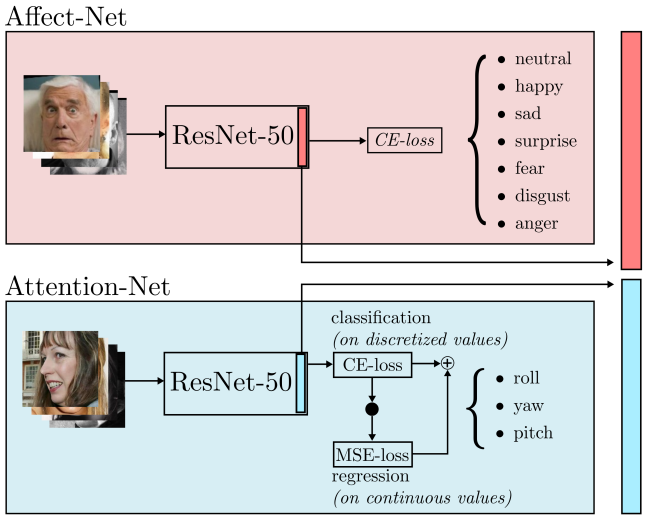

Fig. 4: Feature learning for affect and attention. Two ResNet-50 backbones are separately trained for facial expression recognition and head pose estimation. The learned features will be used subsequently for engagement estimation on classroom data.

loss function is as follows:

$$\mathcal{L}_{Att.Net} = H(y, \hat{y}) + \alpha \cdot MSE(y, \hat{y}) \quad (1)$$

where H is the cross-entropy term on discretized values and MSE is the mean squared error term on continuous values. The output of the network is head pose angles: roll, yaw, and pitch. MSE loss is applied on continuous values (regression), cross-entropy is on discretized values (classification), and both terms were jointly optimized during the training. Among different settings in [88], we picked $\alpha = 1$, and trained the ResNet-50 model on the synthetically expanded 300W-LP dataset. It performed a mean angular error of 7.36 on the AFLW2000 dataset [89].

The advantage of the CNN-based approach for head pose estimation is that it is more robust than Perspective n-Point (PnP)-based methods that find correspondence between estimated facial keypoints on image and their corresponding 3D locations in an anthropological face model [88]. In challenging cases where those methods fail, CNN-based methods can return satisfactory predictions and, more importantly, map the inputs in a continuous low-dimensional embedding according to poses. We do not use either estimated head pose or facial expressions. We are only interested in the learning embedding feature representation to use as attentional or affective features.

We also experimented with different convolutional neural network architectures and the relation between facial expression recognition and engagement classification. These results supports how these auxiliary tasks and engagement classification are aligned with one another. The details of Attention-Net/Affect-Net training procedure are provided in the supplementary material.

As the training corpus is very large and contains various challenging situations in both Affect-Net and Attention-Net branches, these methods learn robust features. Compared to the handcrafted appearance features such as Local Binary Patterns or Gabor filters, deep embeddings can be extracted without precise alignment and are extendable by training with new DNN architectures on more data. We trained Attention-Net and Affect-Net representations on head pose estimation (300W-LP) and facial expression (AffectNet) datasets. To avoid overfitting due to the limited number of subjects represented in the classroom data, we did not perform any fine-tuning on student engagement data.

4.3 Engagement Classification

We trained several classifiers on affective and attention features. Frame-based classifiers were trained on the middle frame of each 1-second sequence to avoid redundant training samples when all frames were used. In the test phase, we retrieved predictions for all 1-second (24 frame) sequences and applied majority voting. The shallow classifiers that we used included Support Vector Machine (SVM), and Random Forests (RF). All model training and dimensionality reduction was conducted in a person-independent manner where an individual participants' data could be either in the training or test fold, but not in both. Considering the behavioral differences between grades, we separately build seperate models for grades 8 and 12.

For SVMs, we tested linear and radial basis function (rbf) kernels. Training SVM-based models with a large number of instances and features (i.e., 2048-dimensional features and 20-25K training samples) posed computational challenges. Thus, before training SVM models, we applied Principal Component Analysis (PCA) and used the top 48 components that explain 99% of the variance in the training set. Principal components were calculated in training sets separately and we applied the same transformation to the test set in order to preserve person-independence. For RF, we used feature embeddings directly without dimension reduction.

For DNN's, we trained a Multi-Layer Perceptron (MLP) instead of retraining the entire representation up to the first layers of the ResNet-50 architecture. Even though the data subset that we acquired for manual annotation and used in our analysis is over 15 hours, we still faced a problem of a limited number of participants and restricted context of in-class learning. Thus, training a network from scratch would result in overfitting and the failure to recall previously learned features from a larger set of participants that may be useful for modeling engagement. We used two-layer MLPs (one for AffetcNet and another for AttentionNet features), each with an input layer of 2048 neurons and a hidden layer of 128 neurons. Training was done in mini-batches of 256 using soft-max cross-entropy loss and a SGD solver with a learning rate of 0.001. In each trial, we kept a random 10% of the training data as a validation set for early stopping. As with the SVM models, we applied majority voting on individual frames to acquire the prediction for 1-second sequences.

In addition to those approaches, we used a recurrent neural network model, long short-term memory (LSTM) [90], to learn temporal patterns in the data.

We provided 2048-length Attention-Net or Affect-Net embeddings as input to a two-layer LSTM network with a hidden layer size of 128. The output of the LSTM network on the last time step was fed to a fully connected layer of 64 neurons, and the entire model was trained using softmax cross-entropy loss and Adam solver [91] with a learning rate of 0.001. All LSTM models are trained for 5 epochs.

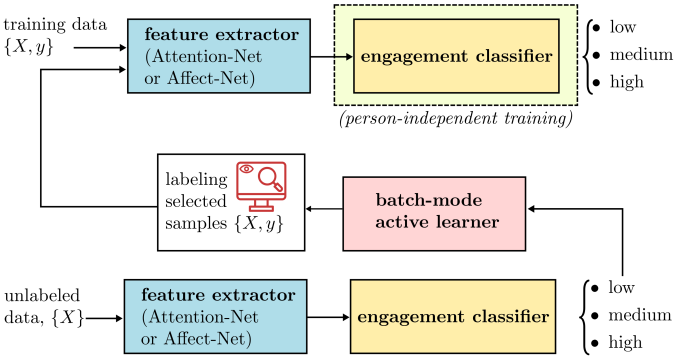

Fig. 5: Batch-mode Active Learning for Personalized Engagement Classification (The initial network is the engagement classifier trained in a person-independent manner and the weights of the feature extractors are kept frozen during all experiments).

4.4 Personalization of Engagement Classifiers

Because engagement and disengagement during instruction can differ significantly from one student to another, engagement classifiers could benefit from personalization. Typically, traditional active learning algorithms propose a single instance to label at a time. This may result in a longer waiting period for the expert labeler during the personalization phase of the engagement classifier. In contrast, we assume the labeler starts from an engagement classifier trained in a person-independent manner and labels a set of instances. For SVM-based classifiers, engagement probability can be calculated via Platt scaling whereas the mean predicted class probabilities of the trees can be used in Random Forests. MLP and LSTM classifiers provide an engagement probability output because they were trained with softmax cross-entropy loss. We used these probabilities as an uncertainty score for unlabeled instances.

In order to investigate the effect of personalization with a small amount of data, we utilize the margin uncertainty principle that considers the samples with the smallest margin between the first and second to be most likely class probabilities. These samples can be considered more difficult, and labeling them helps define a better separation among the engagement levels. The margin uncertainty rule can be written as follows (REF):

$$x^*_{marg} = \arg\min_x \left[P_{M_{init}}(\hat{y_1} \mid x) - P_{M_{init}}(\hat{y_2} \mid x) \right] \quad (2)$$

where $\hat{y} = P_{M_{init}}(\hat{y} \mid x)$ is the prediction with highest posterior probability, $\hat{y_1}$ and $\hat{y_2}$ are first and second most likely predictions.

Figure 5 depicts our personalization framework using batch-mode active learning. As there is no additional training in the deep embedding part (Attention-Net and Affect-Net), training time is not increased. Only a small batch of unlabeled data is sent to the "oracle" in each episode, and the classifier part is retrained. Instead of updates with a single instance, we sampled a small batch of unlabeled images to label, removed them from the pool, and retrained the initial model iteratively. In this way, each personalization step is applied on a day or a week of recording, and a batch is composed of the most qualitative samples to adapt the existing engagement classifier on a specific subject.

5 Results

As indicated above, we performed engagement classification experiments separately in grades 8 and 12 because visual engagement across grades can vary. With the exception of the test subject, every student in every grade was used for training and the same experiment was repeated for each test student, modality (affect vs. attention), and grade. Table 3 shows the performance of various classifiers using Attention-Net and Affect-Net features. We used weighted Area Under the ROC Curve as a performance measure in the three-level engagement classification task since it measures the performance of a classifier at different thresholds. Furthermore, it is more attune to class imbalances than to metrics such as accuracy.

Engagement classification. AUCs in general ranged from X to Y with a mean of Z, which reflect an improvement from chance AUC of 0.5. The best performing unimodal classifiers used attention features and a RF in grade 8 (AUC of 0.62) and an LSTM for Grade 12 (AUC of .72).

When visual indicators were compared, Attention-Net features yielded .01 to .03 better AUC than Affect-Net for Grade 8. On the other hand, the margin between the average AUCs of Grade 12 students is more notable; attention-net features performed .08-.11 better than Affect-Net features in Grade 12. This may be related to the easy distraction, movement, and increased gaze drifts characteristic of students in both grades. As a result, attention features are more effective than affect features in engagement classification.

Another comparison is the type of classifier used to examine engagement. In our experiments, linear SVM classifiers had the lowest perforance (.03 to .06 lower AUCs). However, there were no explicit performance differences among SVM with rbf kernel, RF, and MLP classifiers across both grades and feature sets. We would expect deep learning-based methods, MLP for instance, to better model engagement than shallow classifiers, but it was comparable to RF and SVM-rbf. This may be due to the limited sample size of the data, the multifaceted aspect of learning problems, and imbalances in feature and label distribution. As we transfer feature representations of engagement from similar tasks and large-scale corpus, better feature representations facilitate engagement classification, and the margin among the classifiers is not wide.

Looking into DNN-based classifiers, the use of temporal information negligably improved the performance of MLP only in the settings of Affect-Net/Grade 8 (+.013 in AUC) and Attention-Net/Grade 12 (+.018 in AUC). The limited improvement of LSTMs may be due to the short time window (24-frame) over one second. We adopted this approach to match the continuous engagement labeling method which generated engagement labels per second, which we deemed suitable to provide real-time feedback for applications deployed in a school setting.

Besides the average AUC performance of different feature sets and grades, there are interpersonal variations classification accuracy. In particular, affective classifiers performed better for some students whereas attention features were better for others.

We tested different fusion strategies using RF engagement classifiers. For feature level fusion, different feature embeddings were concatenated to train a single engagement classifier. Score level fusion averaged the probability outputs of two separate classifiers trained on Affect-Net and Attention-Net representations. Table 4 shows the performance of feature-level and score-level fusion for grade 8 and 12. For grade 8, both fusion strategies yielded comparable improvement, +.012-.013 over the best modality (Attention-Net). On the other hand, score level fusion in grade 12 was on par with the unimodal attention classifier, whereas feature-level fusion was much lower.

Reviewing the overall results, and when considering the difficulty of interpreting a student's level of engagement using only facial videos, these results are moderate. This is notable given that the criteria for the manual annotation of engagement (as depicted in Figure 2) were not directly related to gaze direction or facial expression.

Personalized models. We selected RF classifiers for the

TABLE 3: Performance Comparison of Engagement Classifiers on Classroom Data using Attention-Net and Affect-Net Features and Different Classifiers.

Classifier	**AUROC**			
	Grade-8		Grade-12	
	Attention-Net	*Affect-Net*	*Attention-Net*	*Affect-Net*
SVM (linear)	.560 ± .05	.570 ± .06	.656 ± .09	.563 ± .06
SVM (rbf)	.603 ± .05	.604 ± .03	.697 ± .07	.595 ± .08
RF	.620 ± .04	.608 ± .03	.708 ± .05	.600 ± .09
MLP	.615 ± .05	.597 ± .03	.701 ± .06	.622 ± .05
LSTM	.603 ± .05	.610 ± .04	.719 ± .05	.612 ± .09

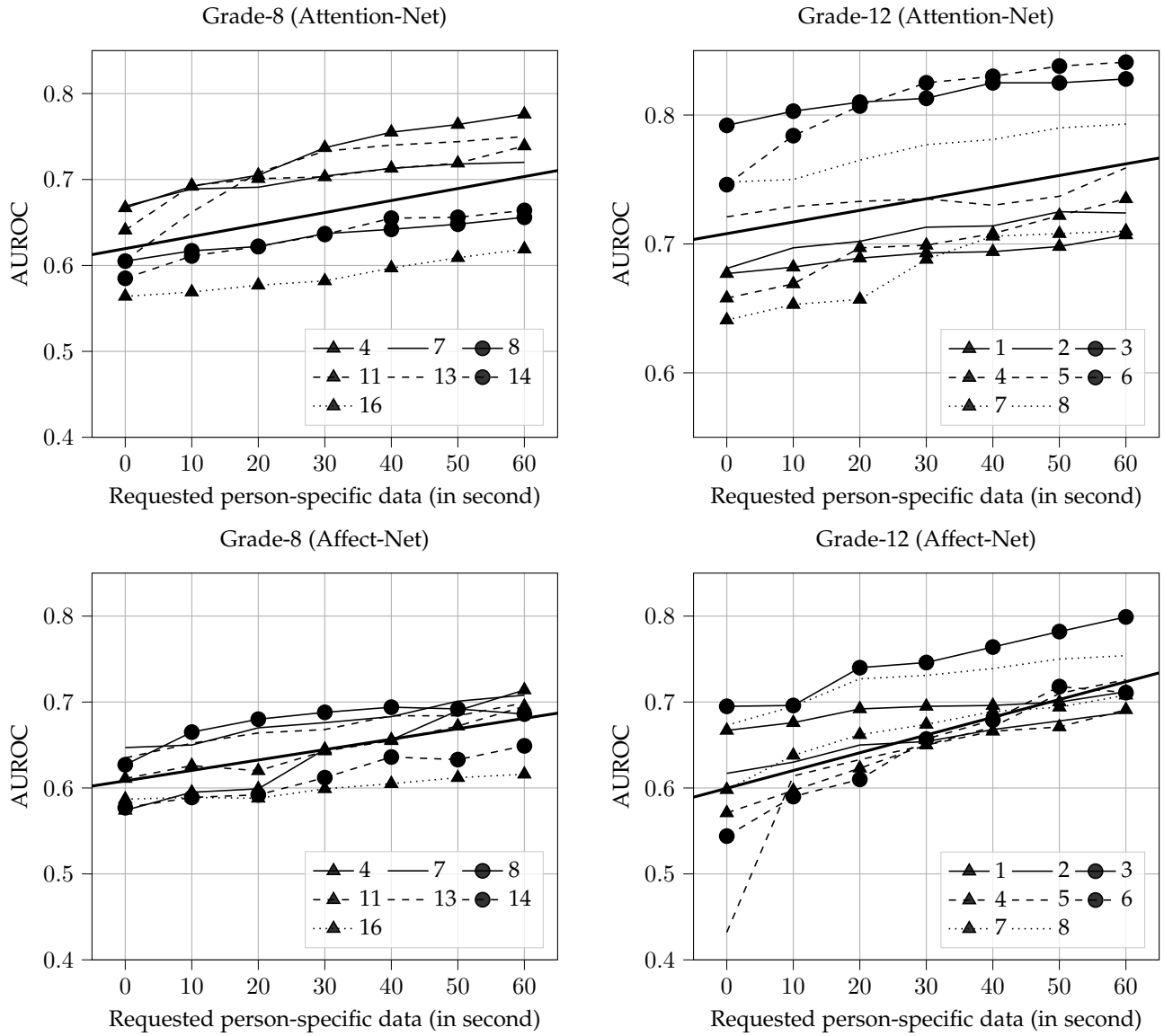

Fig. 6: The Effect of Personalization on Different Engagement Classifiers (All classifiers are based on RF. The legends show the corresponding AUC performance per student, and each thick line represents the overall trend of personalization.)

personalized models because of their successful performance in the above person-independent experiments and speed in training compared to the others. Recall that instead of directly training and testing on person-specific data, we started with person-independent models and adapted them based on small amounts of person-specific data in a simulated active learning setting. The number of samples from each student varied (as depicted in Table 2). Thus, we limited person-specific labels requested by the oracle to 60 seconds for each student.Specifically, starting with the model person-independent model, we sampled 60 samples using different sampling strategies, and compared ROC performance to initial performance. The 60 samples were acquired after 6 steps by selecting only 10 samples per

step, adapting the classifier with the new samples, and continuing to use the samples iteratively.

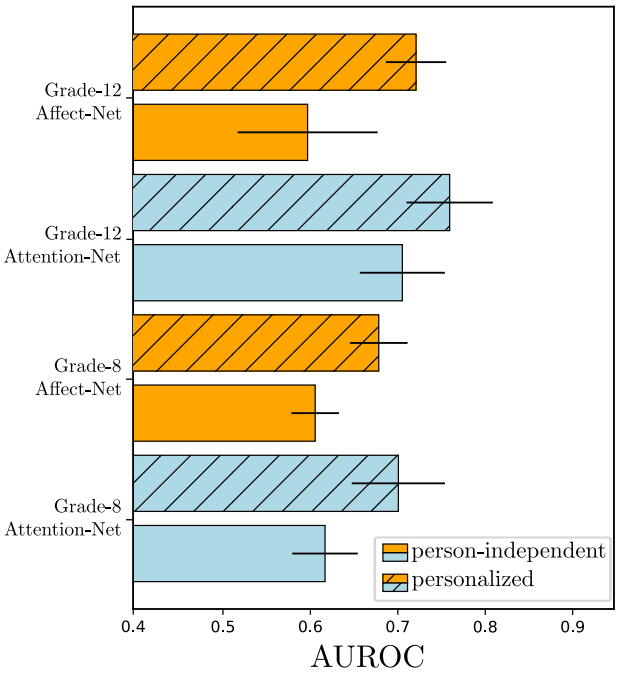

Fig. 7: The overall improvement of personalization in AUROC using Attention-Net and Affect-Net features in Grades 8 and 12.

The effect of personalization with RF engagement classifiers using Attention-Net and Affect-Net features in grades 8 and 12 is depicted in Figure 6 for each student individually.

TABLE 4: Performance Comparison of Different Fusion Strategies using Random Forest Classifiers.

Grade	Feature Set	Avg. AUROC
8	Attention-Net	.620
8	Affect-Net	.608
8	Feature-level Fusion	**.633**
8	Score-level Fusion	.632
12	Attention-Net	**.708**
12	Affect-Net	.600
12	Feature-level Fusion	.616
12	Score-level Fusion	.694

TABLE 5: Confusion Matrices for the Best Person-Independent and Personalized Models.

Method	Actual	Classified			Priors
(Grade 12)		*low*	*medium*	*high*	
Attention-Net, RF	*low*	.099	.442	.458	.101
	medium	.053	.735	.345	.522
	high	.075	.400	.525	.377
Attention-Net, RF	*low*	.185	.387	.429	.101
(personalized)	*high*	.027	.768	.205	.522
	high	.032	.360	.608	.377

As the amount of data per student varies, 60 samples correspond to different proportions of each person's data so we also report the requested (%) percent of samples.

Wtih the exception of one student (S4 in Grade 8), the amount of data was large enough, and the requested data (60 samples) corresponded to only 2-3% of all the data. The effect of personalization varied from .03 to .29 in terms of AUC improvements. Affect features had greater improvements after personalization for both grades. Overall, there was a 6.89% and 9.83% AUROC improvement for attention and affect features, respectively.

Table 5 shows the confusion matrices of the RF classifier using Attention-Net features in Grade 12 before and after personalization. Without personalization, high engagement was misclassified as medium (.400 and .360) engagement, and low engagement was misclassified as medium and high. This might be due to class imbalances since the majority are medium engagement (52.2%). Personalization improves engagement classification across the board.

In summary, our experiments in personalization yielded average AUC improvements of .084 using 60 seconds of personal data. The largest improvement, as depicted in Figure 7, was +.124 of AUC in Affect-Net features and RF classifier in Grade 12. Labeling 60 one-second samples picked from different parts of a video is more manageable than labeling the entire recording and takes only a few minutes for an expert annotator. In return for this effort, the performance gain was substantial for both feature sets and grades.

6 Discussion

We aimed to develop video-based models to detect engagement during learning in authentic classroom environments. We collected a large-scale classroom observation dataset along with observer ratings of student engagement for grades 8 and 12 (N=15). In contrast to previous works that used mainly handcrafted local (i.e., local binary patterns, Gabor filters) and precomputed features such as head pose or estimated facial action units, we used deep learning methods for feature extraction and a combination of shallow and deep classifiers. We discuss our main findings, limitations/future work, and applications and ethical implications below.

6.1 Main Findings

Our main findings are that: (1) attention-based features were more effective at predictive engagement than affect-related features; (2) fusion of affective- and attention- features led to small boosts in accuracy; (3) there were limited benefits to deep learning methods over shallow classifiers; (4) overall engagement could be classified with moderate accuracy in a person-independent setting from individual streams; (5) engagement classification was higher for grade 12 vs. grade 8; and (6) even a small amount of person-specific data could considerably enhance classification accuracy.

Our engagement models relied on observer-ratings, so it is important to compare their alignment with students' own self-reported assessments of engagement. Our data collection at the school was completed after one and a

half month's time, and students completed questionnaires measuring involvement [72], situational interest [74], and cognitive engagement [73] at the end of each teaching unit. The relationship between manually annotated engagement levels and these self-reported instruments is reported in Table 6.

TABLE 6: The relationship between manual annotations and post-test items. Values in square brackets indicate the 95% confidence interval for each correlation (* indicates $p < .05$, ** indicates $p < .01$).

	Grade 8		Grade 12	
Items	**All**	**1/3**	**All**	**1/3**
Involvement	0.26 [−.08, .55]	0.40 [−.12, .75]	-0.14 [−.42, .17]	-0.09 [−.47, .33]
Engagement	**.34*** [.01, .61]	**.62**** [.18, .85]	-0.07 [−.37, .24]	0.02 [−.39, .43]
Situational interest	**.35*** [.02, .62]	.44 [−.07, .77]	-0.01 [−.32, .30]	-0.05 [−.45, .37]

We found modest correlations among manual-annotated engagement and self-reported involvement, cognitive engagement, and situation interest (.26 to .62) in grade 8. Correlations were higher for the first 1/3 of the data compared to all the data. As we observed in our previous study [26], the self-report items were valid and showed strong and significant correlations with the same engagement annotation approach in undergraduate level courses. There were no correlations among manually-annotated engagement and self-reported measures for grade 12, suggesting that the link between expressive behavior as perceived by the raters and experience of emotions as reported by the students' was quite divergent for these older students.

6.2 Limitations and Future Work

From the technical perspective, the limited sample size is related to both technical constraints regarding the infrastructure in such field studies (e.g. the preparation of such a recording requires 20 minutes) and the manual effort associated with data annotations. Additionally, the presence of cameras can put pressure on students and cause their behavior to change when they know instruction is being recorded. Collecting a significant amount of audiovisual recordings from the same classes over the course of a school year as a longitudinal study could overcome some of these effects and allow researchers to investigate engagement in time.

Another limitation of this study is its focus on only the visible dimension of engagement. The detection of mind wandering through observation of students' facial expressions is a relevant emerging research topic. Combining automated methods to detect mind wandering with engagement analysis may yield a better understanding of students' affective and cognitive engagement.

Even though our study presents a step towards measuring facial representations in the classroom, it was not possible to learn them on the engagement data due to the limited sample size. The use of self-supervision and representation learning on unlabelled classroom data may result in better representations for engagement analysis in future work. Additionally, our models failed to detect low engagement, likely due to data skew. The distribution of continuous labeling was also highly imbalanced. To solve these issues, we propose collecting more data in uncontrolled environments or, in order to obtain additional low engagement samples, employing interventions to manipulate engagement.

Our study focused on particularly facial videos; however, speech features can also provide valuable information for engagement classification and complement visual modalities. We observed that the noisy capture from a distance makes the audio signal separation more challenging. Thus, recording audio by using separate voice recorders per desk synchronized by cameras would be the topic of future work including the use affective acoustic signal processing and even speech recognition and language processing.

6.3 Applications and Ethical Considerations

The reported results in this study suggest that engagement classifiers could be applied to automate data processing within the scope of classroom instruction research and also personalized using a small amount of data. Engagement models using the same feature extractor used here can be applied to many real-time students. Instead of recording videos, such a system only records behavioral data and helps increase the sample size for studies in classroom research. Data collection, storage, and privacy concerns are some of the significant issues that need to be addressed before large scale classroom studies can be conducted.

The use of these models outside of research settings is much more limited.and if used must be done in a privacy-preserving and ethical manner. In particular, our approach envisions, beyond anonymization [92], the immediate deletion of raw video recordings as part of the responsible use of the data. Instead, only aggregated information from the student group may be stored and individual-level scores discarded. As a result, the explicit mapping of a student's individual engagement scores and features can be avoided. Further improvement in the performance of engagement classification and a transition from student engagement to classroom-level analysis has the potential to make engagement analysis a more useful tool.

We are well aware that a potential application for engagement classifiers is a real-time classroom observation system such as [35]. Although such affective and cognitive interfaces summarizing engagement analytics as a teaching aid are growing in popularity, we strongly oppose any use of such solutions for real-world classroom monitoring for both ethical reasons and the lack of empirical data on possible negative side effects with regard to students' motivation and learning in such arrangements. As such, we explicitly do not advocate using these methods for any evaluative assessment of students' motivations/learning and instruction quality because of the moderate accuracy of the models, the focus on only sub-components of engagement, the fact that engagement was only annotated by raters and not cross-references with other sources of data, engagement levels might be due to external causes such as difficult family circumstances, students' engagement levels are not fully within the control of instructors, and for many other

purposes. To be blunt, using such tools for student and teacher evaluation and for any form of accountability would likely constitute a major ethical misuse of the technology. Importantly, advances in AI are needed to address the fairness, accountability, transparency, and bias of algorithms before being deployed in any application. In this context, only a continuous, reflective dialog with social stakeholders can lead to sustainable solutions.

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