Affect-driven Engagement Measurement from Videos

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Abstract—In education and intervention programs, person’s engagement has been identified as a major factor in successful program completion. Automatic measurement of person’s engagement provides useful information for instructors to meet program objectives and individualize program delivery. In this paper, we present a novel approach for video-based engagement measurement in virtual learning programs. We propose to use affect states, continuous values of valence and arousal extracted from consecutive video frames, along with a new latent affective feature vector and behavioral features for engagement measurement. Deep learning-based temporal, and traditional machine-learning-based non-temporal models are trained and validated on frame-level, and video-level features, respectively. In addition to the conventional centralized learning, we also implement the proposed method in a decentralized federated learning setting and study the effect of model personalization in engagement measurement. We evaluated the performance of the proposed method on the only two publicly available video engagement measurement datasets, DAiSEE and EmotiW, containing videos of students in online learning programs. Our experiments show a state-of-the-art engagement level classification accuracy of 63.3% and correctly classifying disengagement videos in the DAiSEE dataset and a regression mean squared error of 0.0673 on the EmotiW dataset. Our ablation study shows the effectiveness of incorporating affect states in engagement measurement. We interpret the findings from the experimental results based on psychology concepts in the field of engagement.

Index Terms—Engagement Measurement, Engagement Detection, Affect States, Temporal Convolutional Network.

1 INTRODUCTION

Online services, such as virtual education, tele-medicine, and tele-rehabilitation offer many advantages compared to their traditional in-person counterparts; being more accessible, economical, and personalizable. These online services make it possible for students to complete their courses \(^1\) and patients to receive the necessary care and health support \(^2\) remotely. However, they also bring other types of challenges. For instance, in an online classroom setting, it becomes very difficult for the tutor to assess the students’ engagement in the material being taught \(^3\). For a clinician, it is important to assess the engagement of patients in virtual intervention programs, as the lack of engagement is one of the most influential barriers to program completion \(^4\). Therefore, from the view of the instructor of an online program, it is important to automatically measure the engagement level of the participants to provide them real-time feedback and take necessary actions to engage them to maximize their program’s objectives.

Various modalities have been used for automatic engagement measurement in virtual settings, including person’s image \(^5\), \(^6\), video \(^7\), audio \(^8\), Electrocardiogram (ECG) \(^9\), and pressure sensors \(^10\). Video cameras/webcams are mostly used in virtual programs; thus, they have been extensively used in assessing engagement in these programs. Video cameras/webcams offer a cheaper, ubiquitous and unobtrusive alternative to other sensing modalities. Therefore, majority of the recent works on objective engagement measurement in online programs and human-computer interaction are based on the visual data of participants acquired by cameras and using computer-vision techniques \(^11\), \(^12\).

The computer-vision-based approaches for engagement measurement are categorized into image-based and video-based approaches. The former approach measures engagement based on single images \(^5\) or single frames extracted from videos \(^6\). A major limitation of this approach is that it only utilizes spatial information from single frames, whereas engagement is a spatio-temporal state that takes place over time \(^13\). Another challenge with the frame-based approach is that annotation is needed for each frame \(^14\), which is an arduous task in practice. The latter approach is to measure engagement from videos instead of using single frames. In this case, one label is needed after each video segment. Fewer annotations are required in this case; however, the measurement problem is more challenging due to the coarse labeling.

The video-based engagement measurement approaches can be categorized into end-to-end and feature-based approaches. In the end-to-end approaches, consecutive raw frames of video are fed to variants of Convolutional Neural Networks (CNNs) (many times followed by temporal neural networks) to output the level of engagement \(^15\). In feature-based approaches, handcrafted features, as indicators of engagement, are extracted from video frames and analyzed by temporal neural networks or machine-learning methods to output the engagement level \(^16\), \(^17\). Various features have been used in the previous feature-based approaches including behavioral features such as eye gaze, head pose, and body pose. Despite the psychological evidence for the effectiveness of affect states in person’s engagement \(^15\), \(^18\), \(^19\), none of the previous computer-vision-based approaches have utilized these important features for engagement measurement. In this paper, we propose a novel

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feature-based approach for engagement measurement from videos using affect states, along with a new latent affective feature vector based on transfer learning, and behavioral features. These features are analyzed using different temporal neural networks and machine-learning algorithms to output person’s engagement in videos. Our main contributions are as follows:

- We use affect states including continuous values of person's valence and arousal, and present a new latent affective feature using a pre-trained model on the AffectNet dataset, along with behavioral features for video-based engagement measurement. We jointly train different models on the above features using frame-level, video-level, and clip-level architectures.
- We conduct extensive experiments on two publicly available video datasets for engagement level classification and regression, focusing on studying the impact of affect states in engagement measurement. In these experiments, we compare the proposed method with several end-to-end and feature-based engagement measurement approaches.
- We implement the proposed engagement measurement method in a Federated Learning (FL) setting, and study the effect of model personalization on engagement measurement.

The paper is structured as follows. Section 2 describes what engagement is and which type of engagement will be explored in this paper. Section 3 describes related works on video-based engagement measurement. In Section 4, the proposed pathway for affect-driven video-based engagement measurement is presented. Section 5 describes experimental settings and results on the proposed methodology. In the end, Section 6 presents our conclusions and directions for future works.

2 What is Engagement?

In this section, different theoretical, methodological categorizations, and conceptualizations of engagement are briefly described, followed by brief discussion on the engagement in virtual learning settings and human-computer interaction which will be explored in this paper.

Dobrian et al. [23] describe engagement as a proxy for involvement and interaction. Sinatra et al. defined “grain size” for engagement, the level at which engagement is conceptualized, observed, and measured [18]. The grain size ranges from macro-level to micro-level. The macro-level engagement is related to groups of people, such as engagement of employees of an organization in a particular project, engagement of a group of older adult patients in a rehabilitation program, and engagement of students in a classroom, school, or community. The micro-level engagement links with individual’s engagement in the moment, task, or activity [18]. Measurement at the micro-level may use physiological and psychological indices of engagement such as blink rate [24], head pose [16], heart rate [25], and mind-wandering analysis [26].

The grain size of engagement analysis can also be considered as a continuum comprising context-oriented, person-in-context, and person-oriented engagement [18]. The macro-level and micro-level engagement are equivalent to the context-oriented, and person-oriented engagement, respectively, and the person-in-context lies in between. The person-in-context engagement can be measured by observations of person’s interactions with a particular contextual environment, e.g., reading a web page or participating in an online classroom. Except for the person-oriented engagement, for measuring the two other parts of the continuum, knowledge about context is required, e.g., the lesson being taught to the students in a virtual classroom [27], or the information about rehabilitation consulting material being given to a patient and the severity of disease of the patient in a virtual rehabilitation session [19], or audio and the topic of conversations in an audio-video communication [8].

In the person-oriented engagement, the focus is on the behavioral, affective, and cognitive states of the person in the moment of interaction [13]. It is not stable over time and best captured with physiological and psychological measures at fine-grained time scales, from seconds to minutes [13].

- Behavioral engagement involves general on-task behavior and paid attention at the surface level [13], [18], [19]. The indicators of behavioral engagement, in the moment of interaction, include eye contact, blink rate, and body pose.
- Affective engagement is defined as the affective and emotional reactions of the person to the content [28]. Its indicators are activating versus deactivating and positive versus negative emotions [29]. Activating emotions are associated with engagement [18]. While both positive and negative emotions can facilitate engagement and attention, research has shown an advantage for positive emotions over negative ones in upholding engagement [29].
- Cognitive engagement pertains to the psychological investment and effort allocation of the person to deeply understand the context materials [18]. To measure the cognitive engagement, information such as person’s speech should be processed to recognize the level of person’s comprehension of the context [8]. Contrary to the behavioral and affective engagements, measuring cognitive engagement requires knowledge about context materials.

Understanding of a person’s engagement in a specific context depends on the knowledge about the person and the context. From data analysis perspective, it depends on the data modalities available to analyze. In this paper, the focus is on video-based engagement measurement. The only data modality is video, without audio, and with no knowledge about the context. Therefore, we propose new methods for automatic person-oriented engagement measurement by analyzing behavioral and affective states of the person at the moment of participation in an online program.

3 Literature Review

Over the recent years, extensive research efforts have been devoted to automate engagement measurement [11], [12]. Different modalities of data are used to measure the level
of engagement [12], including RGB video [15], [17], audio [8], ECG data [9], pressure sensor data [10], heart rate data [25], and user-input data [12], [25]. In this section, we study previous works on RGB video-based engagement measurement. In these approaches, computer-vision, machine-learning, and deep-learning algorithms are used to analyze videos and output the engagement level of the person in the video. Video-based engagement measurement approaches can be categorized into end-to-end and feature-based approaches.

3.1 End-to-End Video Engagement Measurement

In end-to-end video engagement measurement approaches, no hand-crafted features are extracted from videos. The raw frames of videos are fed to a deep CNN (or its variant) classifier, or regressor to output an ordinal class, or a continuous value corresponding to the engagement level of the person in the video.

Gupta et al. [15] introduced the DAiSEE dataset for video-based engagement measurement (described in Section 5) and established benchmark results using different end-to-end convolutional video-classification techniques. They used the InceptionNet, C3D, and Long-term Recurrent Convolutional Network (LRCN) [30] and achieved 46.4%, 56.1%, and 57.9% engagement level classification accuracy, respectively. Geng et al. [31] utilized the C3D classifier along with the focal loss to develop an end-to-end model to classify the level of engagement in the DAiSEE dataset and achieved 56.2% accuracy. Zhang et al. [32] proposed a modified version of the Inflated 3D-CNN (I3D) along with the weighted cross-entropy loss to classify the level of engagement in the DAiSEE dataset, and achieved 52.4% accuracy.

Liao et al. [7] proposed Deep Facial Spatio-Temporal Network (DFSTN) for students’ engagement measurement in online learning. Their model for engagement measurement contains two modules, a pre-trained ResNet-50 is used for extracting spatial features from faces, and a Long Short-Term Memory (LSTM) with global attention for generating an attentional hidden state. They evaluated their method on the DAiSEE dataset and achieved a classification accuracy of 58.84%. They also evaluated their method on the EmotiW dataset (described in Section 5) and achieved a regression Mean Squared Error (MSE) of 0.0736.

Dewan et al. [33], [34], [35] modified the original four-level video engagement annotations in the DAiSEE dataset and defined two and three-level engagement measurement problems based on the labels of other emotional states in the DAiSEE dataset (described in Section 5). They also changed the video engagement measurement problem in the DAiSEE dataset to an image engagement measurement problem and performed their experiments on 1800 images extracted from videos in the DAiSEE dataset. They used 2D-CNN to classify extracted face regions from images into two or three levels of engagement. The authors in [33], [34], [35] have altered the original video engagement measurement to image engagement measurement problem. Therefore, their reported accuracy would be hard to verify for generalization of results and their methods working with images cannot be compared to other works on the DAiSEE dataset that use videos.

More recently, Abedi and Khan [36] proposed a hybrid neural network architecture by combining Residual Network (ResNet) and Temporal Convolutional Network (TCN) [37] for end-to-end engagement measurement (ResNet + TCN). The 2D ResNet extracts spatial features from consecutive video frames, and the TCN analyzes the temporal changes in video frames to measure the level of engagement. They improved state-of-the-art engagement classification accuracy on the DAiSEE dataset to 63.9%.

3.2 Feature-based Video Engagement Measurement

Different from the end-to-end approaches, in feature-based approaches, first, multi-modal handcrafted features are extracted from videos, and then the features are fed to a classifier or regressor to output engagement [6], [7], [8], [10], [11], [12], [16], [17], [38], [39], [40], [41], [42], [43], [44], [45]. Table 1 summarizes the literature of feature-based video engagement measurement approaches focusing on their features, machine-learning models, and datasets.

As can be seen in Table 1, in some of the previous methods, conventional computer-vision features such as box filter, Gabor [6], or LBP-TOP [43] are used for engagement measurement. In some other methods [8], [16], for extracting facial embedding features, a CNN, containing convolutional layers, followed by fully-connected layers, is trained on a face recognition or facial expression recognition dataset. Then, the output of the convolutional layers in the pre-trained model is used as the facial embedding features. In most of the previous methods, facial action units (AU), eye movement, gaze direction, and head pose features are extracted using OpenFace [45], or body pose features are extracted using OpenPose [47]. Using combinations of these feature extraction techniques, various features are extracted and concatenated to construct a feature vector for each video frame.

Two types of models are used for performing classification (C) or regression (R), sequential (Seq.) and non-sequential (Non.). In sequential models, e.g., LSTM, each feature vector, corresponding to each video frame, is considered as one time step of the model. The model is trained on consecutive feature vectors to analyze the temporal changes in the consecutive frames and output the engagement. In non-sequential models, e.g., Support Vector Machine (SVM), after extracting feature vectors from consecutive video frames, one single feature vector is constructed for the entire video using different functionals, e.g., mean, and standard deviation. Then the model is trained on video-level feature vectors to output the engagement.

Late fusion and early fusion techniques were used in the previous feature-based engagement measurement approaches to handle different feature modalities. Late fusion requires the construction of independent models each being trained on one feature modality. For instance, Wu et al. [44] trained four models independently, using face and gaze features, body pose features, LBP-TOP features, and C3D features. Then they used weighted summation of the outputs of four models to output the final engagement level. In the early fusion approach, features of different modalities are simply concatenated to create a single feature vector to be fed to a single model to output engagement. For
TABLE 1
Feature-based video engagement measurement approaches, their features, fusion techniques, classification (C) or regression (R), sequential (Seq.) or non-sequential (Non.) models, and the datasets they used.

| Ref. | Features | Fusion | Model | C/R | Seq./Non. | Dataset |
|------|----------|--------|-------|-----|-----------|---------|
| [6]  | box filter, Gabor, AU late GentleBoost, SVM, logistic regression | C, R | Non. | HBCU [6]| |
| [38] | gaze direction, AU, head pose early GRU | R | Seq. | EmotiW [17]| |
| [17] | gaze direction, eye location, head pose early LSTM | R | Seq. | EmotiW [17]| |
| [39] | gaze direction, head pose, AU early TCN | R | Seq. | EmotiW [17]| |
| [40] | gaze direction, eye location, head pose, AU early LSTM | C | Seq. | DAiSEE [15]| |
| [41] | body pose, facial embedding, eye features, speech features early logistic regression | C | Non. | EMDC [41]| |
| [42] | facial embedding, speech features early fully-connected neural network | R | Non. | RECOLA [14]| |
| [16] | gaze direction, blink rate, head pose, facial embedding early AdaBoost, SVM, KNN, Random Forest, RNN | C | Seq., Non. | FaceEngage [16]| |
| [43] | facial landmark, AU, optical flow, head pose late SVM, KNN, Random Forest | C, R | Seq., Non. | USC [42]| |
| [44] | LBP-TOP - fully-connected neural network | R | Non. | EmotiW [17]| |
| [45] | gaze direction, head pose, body pose, facial embedding, C3D late LSTM, GRU | R | Seq. | EmotiW [17]| |
| [46] | gaze direction, head pose, AU, C3D late neural Turing machine | C | Non. | DAiSEE [15]| |
| proposed | valence, arousal, latent affective features, blink rate, gaze direction, and head pose joint, early LSTM, TCN, fully-connected neural network, SVM, and Random Forest | C, R | Seq., Non. | DAiSEE [15], EmotiW [17]| |

instance, Niu et al. [38], concatenated gaze, AU, and head pose features to create one feature vector for each video clip and fed the feature vectors to a Gated Recurrent Unit (GRU) to output the engagement.

While there is psychological evidence for the big influence of affect states on engagement [13], [18], [19], [48], [49], none of the previous methods utilized affect states as the features in engagement measurement. In the next section, we will present a new approach for video engagement measurement using affect states along with latent affective features, blink rate, eye gaze, and head pose features. We use sequential and non-sequential models for engagement level classification and regression.

4 AFFECT-DRIVEN PERSON-ORIENTED VIDEO ENGAGEMENT MEASUREMENT

According to the discussion in Section 2, the focus in the person-oriented engagement is on the behavioral, affective, and cognitive states of the person in the moment of interaction at fine-grained time scales, from seconds to minutes [13]. The indicators of affective engagement are activating versus deactivating and positive versus negative emotions [29]. While research has shown an advantage for positive emotions over negative in promoting engagement [29], theoretically, both positive and negative emotions can further lead to the activation of engagement [29]. Therefore, dissimilar to Guhan et al. [8], the engagement cannot directly be inferred from high values of positive or activating emotions. Furthermore, it has been shown that, due to their abrupt changes, six basic emotions, anger, disgust, fear, joy, sadness, and surprise cannot directly be used as reliable indicators of affective engagement [15].

Woolf et al. [48] discretize the affective and behavioral states of persons into eight categories, and defined persons’ desirability for learning, based on positivity or negativity of valence and arousal in the circumplex model of affect [51] (see Figure 1), and on-task or off-task behavior. In the circumplex model of affect, the positive, and negative values of valence correspond to positive, and negative emotions, respectively, and the positive, and negative values of arousal correspond to activating, and deactivating emotions, respectively.

Fig. 1. The circumplex model of affect [51]. The positive, and negative values of valence correspond to positive, and negative emotions, respectively, and the positive, and negative values of arousal correspond to activating, and deactivating emotions, respectively.
person-oriented engagement measurement approach. We train neural network models on affect and behavioral features extracted from videos to automatically infer the engagement level based on affect and behavioral states of the person in the video.

4.1 Feature extraction

Toisoul et al. [20] proposed a deep neural network architecture, EmoFAN, to analyze facial affect in naturalistic conditions improving state-of-the-art in emotion recognition, valence and arousal estimation, and facial landmark detection. Their proposed architecture, depicted in Figure 2, is comprised of one 2D convolution followed by two hourglass networks [52] with skip connections trailed by five 2D convolutions and two fully-connected layers. The second hourglass outputs the facial landmarks that are used in an attention mechanism for the following 2D convolutions.

Affect features: The continuous values of valence and arousal obtained from the output of the pre-trained EmoFAN [20] (Figure 2) on the AffectNet dataset [21] are used as the affect features.

Latent affective features: The pre-trained EmoFAN [20] on AffectNet [21] is used for latent affective feature extraction. The output of the final 2D convolution (Figure 2), a 256-dimensional feature vector, is used as the latent affective features. This feature vector contains latent information about facial landmarks and facial emotions.

Behavioral features: The behavioral states of the person in the video, on-task/off-task behavior, are characterized by features extracted from person’s eye and head movements.

Ranti et al. [24] demonstrated that blink rate patterns provide a reliable measure of person’s engagement with visual content. They implied that eye blinks are withdrawn at precise moments in time so as to minimize the loss of visual information that occurs during a blink. Probabilistically, the more important the visual information is to the person, the more likely he or she will be to withdraw blinking. We consider blink rate as the first behavioral feature. The intensity of facial Action AU45 indicates how closed the eyes are [46]. Therefore, a single blink with the successive states of opening-closing-opening appears as a peak in time-series AU45 intensity traces [16]. The intensity of AU45 in consecutive video frames is considered as the first behavioral features.

It has been shown that a highly engaged person who is focused on visual content tends to be more static in his/her eye and head movements and eye gaze direction, and vice versa [16], [27]. In addition, in the case of high engagement, the person’s eye gaze direction is towards visual content. Accordingly, inspired by previous research [6], [7], [8], [10], [11], [12], [16], [17], [38], [39], [40], [41], [42], [43], [44], [45], eye location, head pose, and eye gaze direction in consecutive video frames are considered as other informative behavioral features.

The features described above are extracted from each video frame and considered as the frame-level features including:

- 2-element affect features (continuous values of valence and arousal),
- 256-element latent affective features, and
- 9-element behavioral features (eye-closure intensity, x and y components of eye gaze direction w.r.t. the camera, x, y, and z components of head location w.r.t. the camera; pitch, yaw, and roll as head pose [46]).

4.2 Predictive Modeling

Frame-level modeling: Figure 3 shows the structure of the proposed architecture for frame-level engagement measurement from video. Latent affective features, followed by a fully-connected neural network, affect features, and
Fig. 3. The proposed frame-level architecture for engagement measurement from video. Latent affective features, followed by a fully-connected neural network, affect features, and behavioral features are concatenated to construct one feature vector for each frame of the input video. The feature vector extracted from each video frame is considered as one time step of a TCN. The TCN analyzes the sequences of feature vectors, and a fully-connected layer at the final time-step of the TCN outputs the engagement level of the person in the video.

Fig. 4. The proposed video-level architecture for engagement measurement from video. First, affect and behavioral features are extracted from consecutive video frames. Then, for each video, a single video-level feature vector is constructed by calculating affect and behavioral features functionals. A fully-connected neural network outputs the engagement level of the person in the video.

behavioral features are concatenated to construct one feature vector for each video frame. The feature vector extracted from each video frame is considered as one time step of a dilated TCN [37]. The TCN analyzes the sequences of feature vectors, and the final time-step of the TCN, trailed by a fully-connected layer, outputs the engagement level of the person in the video. The fully-connected neural network after latent affective features is jointly trained along with the TCN and the final fully-connected layer. The fully-connected neural network after latent affective features is trained to reduce the dimensionality of the latent affective features before being concatenated with the affect and behavioral features. 

**Video-level modeling:** Figure 4 shows the structure of the proposed video-level approach for engagement measurement from video. Firstly, affect and behavioral features, described in Section 4.1, are extracted from consecutive video frames. Then, for each video, a 37-element video-level feature vector is created as follows.

- 4 features: the mean and standard deviation of valence and arousal values over consecutive video frames,
- 1 feature: the blink rate, derived by counting the number of peaks above a certain threshold divided by the number of frames in the AU45 intensity time series extracted from the input video,
- 8 features: the mean and standard deviation of the velocity and acceleration of x and y components of eye gaze direction,
- 12 features: the mean and standard deviation of the velocity and acceleration of x, y, and z components of eye gaze direction, and
- 12 features: the mean and standard deviation of the velocity and acceleration of head’s pitch, yaw, and roll.

According to Figure 4, the 4 affect and 33 behavioral features are concatenated to create the video-level feature vector as the input to the fully-connected neural network. As will be described in Section 5, in addition to the fully-connected neural network, other machine-learning models are also experimented.

5 Experimental Results

In this section, the performance of the proposed engagement measurement approach is evaluated compared to the previous feature-based and end-to-end methods. The classification and regression results on two publicly available video engagement datasets are reported. The ablation study of different feature sets is studied, and the effectiveness of affect states in engagement measurement is investigated. Finally, the implementation results of the proposed engagement measurement approach in a FL setting and model personalization is presented.
5.1 Datasets

The performance of the proposed method is evaluated on the only two publicly available video-only engagement datasets, DAiSEE [15] and EmotiW [17].

DAiSEE: The DAiSEE dataset [15] contains 9,068 videos captured from 112 persons in online courses. The videos were annotated by four states of persons while watching online courses, boredom, confusion, frustration, and engagement. Each state is in one of the four levels (ordinal classes), level 0 (very low), 1 (low), 2 (high), and 3 (very high). In this paper, the focus is only on the engagement level classification. The length, frame rate, and resolution of the videos are 10 seconds, 30 frames per second (fps), and 640 × 480 pixels. Table 2 shows the distribution of samples in different classes, and the number of persons, in train, validation, and test sets of the DAiSEE dataset [15].

| level (class) | train | validation | test |
|--------------|-------|------------|------|
| 0            | 743   | 239        | 419  |
| 1            | 2,130 | 1,430      | 839  |
| 2            | 2,617 | 813        | 822  |
| 3            | 2,394 | 450        | 814  |
| total        | 5,674 | 2,142      | 1,156|

EmotiW: The EmotiW dataset has been released in the student engagement measurement sub-challenge of the Emotion Recognition in the Wild (EmotiW) Challenge [17]. It contains videos of 78 persons in online classroom setting. The total number of videos is 262, including 148 training, 48 validation, and 67 test videos. The videos are at a resolution of 640 × 480 pixels and 30 fps. The lengths of the videos are around 5 minutes. The engagement levels of each video are divided into four values 0, 0.33, 0.66, and 1, where 0, and 1 indicate that the person is completely disengaged, and highly engaged, respectively. In this sub-challenge, the engagement measurement has been defined as a regression problem, and only training and validation sets are publicly available. We use the training, and validation sets for training, and validating the proposed method, respectively. The distribution of samples in this dataset is also imbalanced, Table 3.

| level | train | validation | test |
|-------|-------|------------|------|
| 0.00  | 6     | 4          |      |
| 0.33  | 75    | 10         |      |
| 0.66  | 79    | 19         |      |
| 1.00  | 28    | 15         |      |
| total | 148   | 48         |      |

5.2 Experimental Setting

The frame-level behavioral features, described in Section 4.1, are extracted by the OpenFace [46]. The OpenFace also outputs the extracted face regions from video frames. The extracted face regions of size 256 × 256 are fed to the pre-trained EmoFAN [20] on AffectNet [21] for extracting affect and latent affective features (see Section 4.1).

In the frame-level architecture in Figure 3, the fully-connected neural network after the latent affective features (see Section 4.1), are analyzed by a two-layer unidirectional LSTM with 37 × 128 and 128 × 64 neurons. The output of this fully-connected neural network, a 32-element reduced dimension latent affective feature vector, is concatenated with affect and behavioral features to generate a 43 (32 + 2 + 9)-element feature vector for each video frame and each time-step of the TCN. The parameters of the TCN, giving the best results, are as follows, 8, 128, 16, and 0.25 for the number of levels, number of hidden units, kernel size, and dropout [37]. At the final time step of the TCN, a fully-connected layer with 4 output neurons is used for 4-class classification (in the DAiSEE dataset). For comparison, in addition to the TCN, a two-layer unidirectional LSTM with 43 × 128 and 128 × 64 layers, followed by a fully-connected layer at its final time step with 64 × 4 neurons is used for 4-class classification.

In the video-level architecture in Figure 4, the video-level affect and behavioral features are concatenated to create a 37-element feature vector for each video. A fully-connected neural network with three layers (37 × 128, 128 × 64, and 64 × 4 neurons) is used as the classification model. In addition to the fully-connected neural network, Support Vector Machine classifier with RBF kernel and Random Forest (RF) are also used for classification.

The EmotiW dataset contains videos of around 5-minute length. The videos are divided into 10-second clips with 50% overlap [39], and video-level features, described above, are extracted from each clip. The sequence of clip-level features are analyzed by a two-layer unidirectional LSTM with 37 × 128 and 128 × 64 layers, followed by a fully-connected layer at its final time step with 64 × 1 neurons for regression in the EmotiW dataset.

The evaluation metrics are classification accuracy and MSE for the regression task. The experiments were implemented in PyTorch [53] and Scikit-learn [54] on a server with 64 GB of RAM and NVIDIA TeslaP100 PCIe 12 GB GPU.

5.3 Results

Table 4 shows the engagement level classification accuracies on the test set of the DAiSEE dataset for the proposed frame-level and video-level approaches. As the ablation study, the results of different classifiers are reported using different feature sets. Table 5 shows the engagement level classification accuracies on the test set of the DAiSEE dataset for the previous approaches [36] (see Section 3). As can be seen in Table 4 and 5 the proposed frame-level approach, outperforms most of the previous approaches in Table 5 better than our previously published end-to-end ResNet + LSTM network and slightly worse than ResNet + TCN network [36] (see Section 3.1). According to Table 4 in the frame-level approach, using both LSTM and TCN, adding behavioral and affect features to the latent affective features improves the performance of the proposed method.
the accuracy. These results show the effectiveness of affect states in engagement measurement. The TCN, because of its superiority in modeling sequences of larger length and retaining memory of history in comparison to the LSTM, achieves higher accuracies. Correspondingly, in the video-level approaches in Table 4, adding affect features improves accuracy for all the classifiers, fully-connected neural network, SVM, and RF. In the video-level approaches, the RF achieves higher accuracies compared to the fully-connected neural network and SVM. However, video-level approaches perform worse than the frame-level approaches, highlighting the importance of temporal modelling of affective and behavioral features at a frame level in videos.

In another experiment, we replace the behavioral features in Fig. 3 with a ResNet (to extract 512-element feature vector from each video frame) followed by a fully-connected neural network (to reduce the dimensionality of the extracted feature vector to 32). In this way, a 66-element feature vector is extracted from each video frame (32 latent affective features and 32 ResNet features after dimensionality reduction, and 2 affect features). The ResNet, two fully-connected neural networks (after ResNet and after latent affective features), TCN, and the final fully-connected neural networks after TCN are jointly trained to output the level of engagement. As can be seen in Table 4, the accuracy of this setting, 60.8%, is lower than the accuracy of using handcrafted behavioral features along with latent affective features and affect states, 63.3%. This demonstrates the effectiveness of the handcrafted behavioral features in engagement measurement.

TABLE 4

| feature set              | model        | accuracy   |
|--------------------------|--------------|------------|
| latent affective         | LSTM         | 60.8%      |
| latent affective + behavioral | LSTM         | 62.1%      |
| latent affective + behavioral + affect | LSTM | 62.7%      |
| latent affective         | TCN          | 60.2%      |
| latent affective + behavioral | TCN         | 62.5%      |
| latent affective + behavioral + affect | TCN | 63.3%      |
| latent affective + ResNet + affect | TCN | 60.8%      |
| behavioral               | FC           | 55.1%      |
| behavioral + affect      | FC           | 55.5%      |
| behavioral + affect      | SVM          | 55.9%      |
| behavioral + affect      | SVM          | 55.2%      |
| behavioral               | RF           | 55.5%      |
| behavioral + affect      | RF           | 58.3%      |

According to Abedi and Khan [36] and Liao et al. [7], due to highly imbalanced data distribution (see Table 2), none of the previous approaches on the DAiSEE dataset (outlined in Table 5) are able to correctly classify samples in the minority class 1. While the total accuracy of video-level approaches is lower than frame-based approaches, the video-level approaches are more successful in classifying samples in the minority classes. Comparing Table 6(c) with (d), and (e) with (f) indicates that adding affect features improve the total classification accuracy, and specifically the classification of samples in the minority class 1.

TABLE 5

| method                              | accuracy |
|-------------------------------------|----------|
| C3D [15]                            | 48.1%    |
| C3D [34]                            | 52.4%    |
| C3D + LSTM [36]                     | 56.6%    |
| C3D with transfer learning [15]     | 57.8%    |
| LCN [15]                            | 57.9%    |
| DERN [14]                           | 58.8%    |
| C3D + TCN [36]                      | 59.9%    |
| ResNet + LSTM [36]                  | 61.5%    |
| ResNet + TCN [36]                   | 63.9%    |
| DERN [14]                           | 60.0%    |
| Neural Timing Machine [50]          | 61.3%    |

TABLE 6

| predicted labels | predicted labels | predicted labels |
|------------------|------------------|------------------|
| 0 0 0 4 3 1      | 0 0 0 4 3 1      | 0 0 0 2 2 0      |
| 1 0 0 64 20 2    | 1 0 0 62 22 2    | 1 0 15 42 27 2   |
| 2 0 0 616 266 2  | 2 0 0 623 259 2  | 2 0 4 674 204 2  |
| 3 0 0 290 574 2  | 3 0 0 339 475 2  | 3 0 388 426 2    |
|                  |                  |                  |
|                  |                  |                  |
|                  |                  |                  |

Figure 5 shows the importance of affect and behavioral features while using RF (achieving the best results between the video-level approaches) by checking their out-of-bag error [16]. This features importance ranking is consistent with evidence from psychology and physiology. (i) The first, and third indicative features in person-oriented engagement measurement are the mean values of arousal, and valence, respectively. It aligns with the findings in [19], indicating that affect states are highly correlated with desirability of content, concentration, satisfaction, excitement, and affective engagement. (ii) The second important feature is blink rate. It aligns with the research by Ranti et al. [24] showing that blink rate patterns provide a reliable measure of individual behavioral and cognitive engagement with visual content. (iii) The least important features are extracted from eye gaze direction. Research conducted by Sinatra et al. [18] shows that, to have high impact in engage-
Fig. 5. Features importance ranking of video-level features using Random Forest (see Section 5.3).

As can be observed in Figure 5(d), the behavioral features of the two videos in classes 2 and 3 are different from the video in class 1. Therefore, the behavioral features can differentiate between classes 2 and 3, and class 1. While the values of the behavioral features for the two videos in classes 2 and 3 are almost identical, according to Figure 5(e), the mean values of valence and arousal are different for these two videos. According to this example, the confusion matrices, and the accuracy and MSE results in Tables 4-7, affect features are necessary to differentiate between different levels of engagement.

### 5.5 Federated Engagement Measurement and Personalization

All the previous engagement measurement experiments in this section and in the previous works were performed in conventional centralized learning requiring sharing videos of persons from their local computers to a central server. In FL, model training is performed collaboratively, without sharing local data of persons to the server [22]. Figure 7. We follow the FL setting presented in [55] to implement federated engagement measurement. The training set in the DAiSEE dataset, containing the videos of 70 persons, is used to train an initial global model using the video-level behavioral and affect features and fully-connected neural network, described in Section 4.1 and 4.2. There are 20 persons in the test set of the DAiSEE dataset. 70% of videos of each person in the test set are used to participate in FL, while 30% are kept out to test the FL process. These 20 persons are considered as 20 clients participating in FL.

Following Figure 7 (i) the server sends the initialized global model to all clients. (ii) Each client update the global model using its local video data using local batches of size 4 and 10 local epochs, and (iii) sends its updated version of the global model to the server. (iv) The server, using federated averaging [22], aggregates all the received models to generate an updated version of the global model. The steps (i)-(iv) continue until the clients have new data to participate in FL. Finally, the server performs a final aggregation to generate the final aggregated global model as the output of the FL process. After generating the final aggregated global model, each client receives the FL’s output model, and performs one round of local training using its 70% data to generate a personalized model for the person corresponding to the client.

Figure 8 shows the engagement level classification accuracy of each client and totally, when applying the initial model (trained on the training set of the DAiSEE dataset) to the videos in the 30% of the test set. It also shows the results of FL, and the result of FL followed by personalization to the 30% of the test set. This 30% test set was kept out and has not participated in FL or personalization. As can be seen in Figure 8, FL slightly improves the classification accuracy for most of the persons. After personalizing the FL model, engagement level classification accuracies of most of the persons significantly improve. It aligns with the findings in [56] indicating that individual characteristics of persons in expressing engagement, their ages, races, and sexes may require distinct analysis. In the DAiSEE dataset, all persons are Indian students of almost the same age but of different

### 5.4 An Illustrative Example

Figure 6 shows 5 (of 300) frames of three different videos of one person in the DAiSEE dataset. The videos in (a), (b), and (c) are in low (1), high (2), and very high (3) levels of engagement. Figure 6(d), and (e) depict the behavioral, and affect video-level features of these three videos, respectively.

Table 7 shows the regression MSEs of applying different methods to the validation set in the EmotiW dataset. All the outlined methods in Table 7 are feature-based, described in Section 3.2. In the proposed clip-level method (see Section 5.2), adding the affect features to the behavioral features reduces MSE (second row of Table 7), showing the effectiveness of the affect states in engagement level regression. After adding affect features, the MSE of the proposed method is very close to [38] and [39].

| method | MSE  |
|--------|------|
| clip-level behavioral features + LSTM (proposed) | 0.0708 |
| clip-level (behavioral + affect) features + LSTM (proposed) | 0.0673 |
| eye and head-pose features + LSTM [17] | 0.1000 |
| DFSTN [7] | 0.0736 |
| body-pose features + LSTM [4] | 0.0791 |
| eye, head-pose, and AUs features + TCN [39] | 0.0655 |
| eye, head-pose, and AUs features + GRU [38] | 0.0671 |

As can be observed in Figure 6(d), the behavioral features of the two videos in classes 2 and 3 are different from the video in class 1. Therefore, the behavioral features can differentiate between classes 2 and 3, and class 1. While the values of the behavioral features for the two videos in classes 2 and 3 are almost identical, according to Figure 6(e), the mean values of valence and arousal are different for these two videos. According to this example, the confusion matrices, and the accuracy and MSE results in Tables 4-7, affect features are necessary to differentiate between different levels of engagement.
Fig. 6. An illustrative example for showing the importance of affect states in engagement measurement. 5 (of 300) frames of three different videos of one person in the DAiSEE dataset in classes (a) low, (b) high, and (c) very high levels of engagement, the video-level (d) behavioral features and (e) affect features of the three videos. In (a), the person does not look at the camera for a moment and behavioral features in (d) are totally different for this video compared to the videos in (b) and (c). However, the behavioral features for (b) and (c) are almost identical. According to (e), the affect features are different for (b) and (c) and are effective in differentiation between the videos in (b) and (c).

sexes. Here, model personalization improves engagement measurement as the global model is personalized for individual students with their specific sexes.

5.6 Discussion

The proposed method achieved superior performance compared to the previous feature-based and end-to-end methods (except ResNet + TCN [36]) on the DAiSEE dataset, especially in terms of classifying low levels of engagement. However, the overall classification accuracy on this dataset is still low. This can be due to the following two reasons. The first reason is the imbalanced data distribution, very small number of samples in low levels of engagement compared to the high levels of engagement. During training, with a conventional shuffled dataset, there will be many training batches containing no samples in low levels of engagement. We tried to mitigate this problem with a sampling strategy in which the samples of all classes were included in each batch. In this way, the model will be trained on the samples of all classes in each training iteration. The second reason is
the lack of context (e.g., students’ and tutors’ speech), their data of persons at the moment of interaction. Again, due to person-oriented engagement measurement using only video of students) was not available, the proposed method is a being taught, their progress in learning, and the speech context (e.g., the degree level of the students, the lessons video data. As any complementary information about the datasets (DAiSEE [15] and EmotiW [17]), containing only the only two publicly available engagement measurement (see Section 5.5).

Fig. 7. The block diagram of federated learning process for engagement measurement (see Section 5.5).

Fig. 8. Engagement level classification accuracy on the 30% of the test set of the DAiSEE dataset, using the pre-trained model on the training set (centralized learning), using output model of FL, and using the personalized models for individual persons. In this experiment, the video-level behavioral and affect features and the fully-connected neural network (described in Section 5.2) are used for classification (see Section 5.5).

the annotation problems in the DAiSEE dataset. According to our study on the videos in the DAiSEE dataset, there are annotation mistakes in this dataset. These mistakes are more obvious when comparing videos and annotations of one person in different classes, as it is discussed with examples by Liao et al. [7]. Obviously, the default reason for not achieving higher classification accuracy is the difficulty of this classification task, small differences between videos in different levels of engagement and the lack of any other type of data other than video.

6 Conclusion and Future Work

In this paper, we proposed a novel method for objective engagement measurement from videos of a person watching an online course. The experiments were performed on the only two publicly available engagement measurement datasets (DAiSEE [15] and EmotiW [17]), containing only video data. As any complementary information about the context (e.g., the degree level of the students, the lessons being taught, their progress in learning, and the speech of students) was not available, the proposed method is a person-oriented engagement measurement using only video data of persons at the moment of interaction. Again, due to the lack of context (e.g., students’ and tutors’ speech), their cognitive engagement could not be measured. Therefore, we were only able to measure affective and behavioral engagements based on visual indicators.

We used affect states, continuous values of valence and arousal extracted from consecutive video frames, along with a new latent affective feature vector and behavioral features for engagement measurement. We modeled these features in different settings and with different types of temporal and non-temporal models. The temporal (LSTM and TCN), and non-temporal (fully-connected neural network, SVM, and RF) models were trained and tested on frame-level, and video-level features, respectively. In another setting, for long videos in the EmotiW dataset, temporal models were trained and tested on clip-level features. The frame-level, and video-level approaches achieved superior performance in terms of classification accuracy, and correctly classifying disengaged videos in the DAiSEE dataset, respectively. Also, clip-level setting achieved very low regression MSE on the validation set of the EmotiW dataset. As the ablation study, we reported the results with and without using affect features. In the experiments in all settings, using affect features led to improvement in performance. In addition to centralized setting, we also implemented video-level approach in a FL setting and observed improvements in classification accuracy of the DAiSEE dataset, after FL and after model personalization for individuals. We explained different types of engagement and interpreted the results of our experiments based on psychology concepts in the field of engagement.

As future work, we plan to collect an audio-video dataset from patients in virtual rehabilitation sessions. We will extend the proposed video engagement measurement method to work in tandem with audio. We will incorporate audio data, and also context information (progress of patients in the rehabilitation program and rehabilitation program completion barriers) to measure engagement in a deeper level, e.g., cognitive and context-oriented engagement (see Section 2). In addition, we will explore approaches to measure affect states from audio and use them for engagement measurement. To avoid any mistakes in engagement labeling, as it was discussed in Section 5.6, we will use psychology-backed measures of engagement [13], [18], [19]. We will also explore an optimum time scale choice for labeling engagement in videos [13]. In all the existing engagement measurement datasets, disengagement samples are in the minority [14], [15], [16], [17], [27]. Therefore, in another direction of future research, we will explore detecting disengagement as an anomaly detection problem, and use autoencoders and contrastive learning [27] techniques to detect disengagement and the severity of disengagement.

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