Engagement Intensity Prediction with Facial Behavior Features

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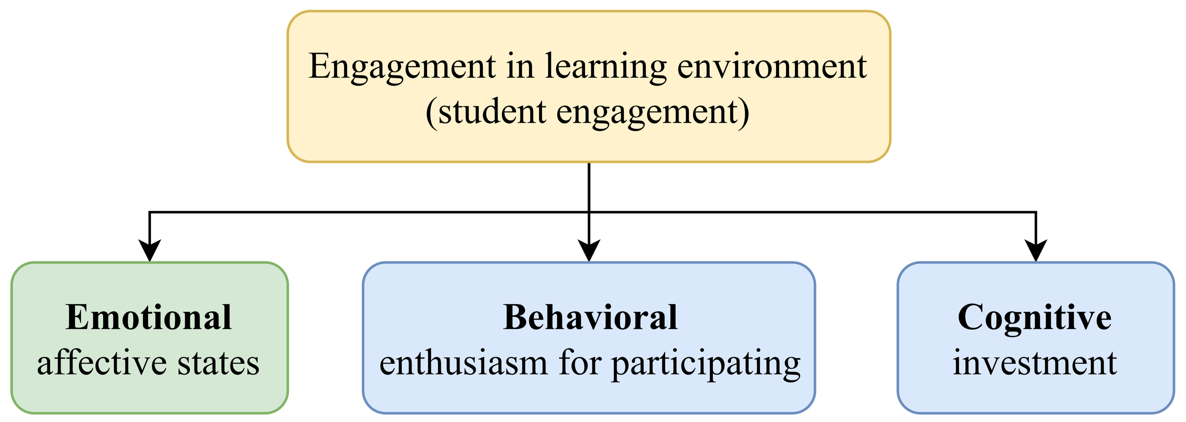
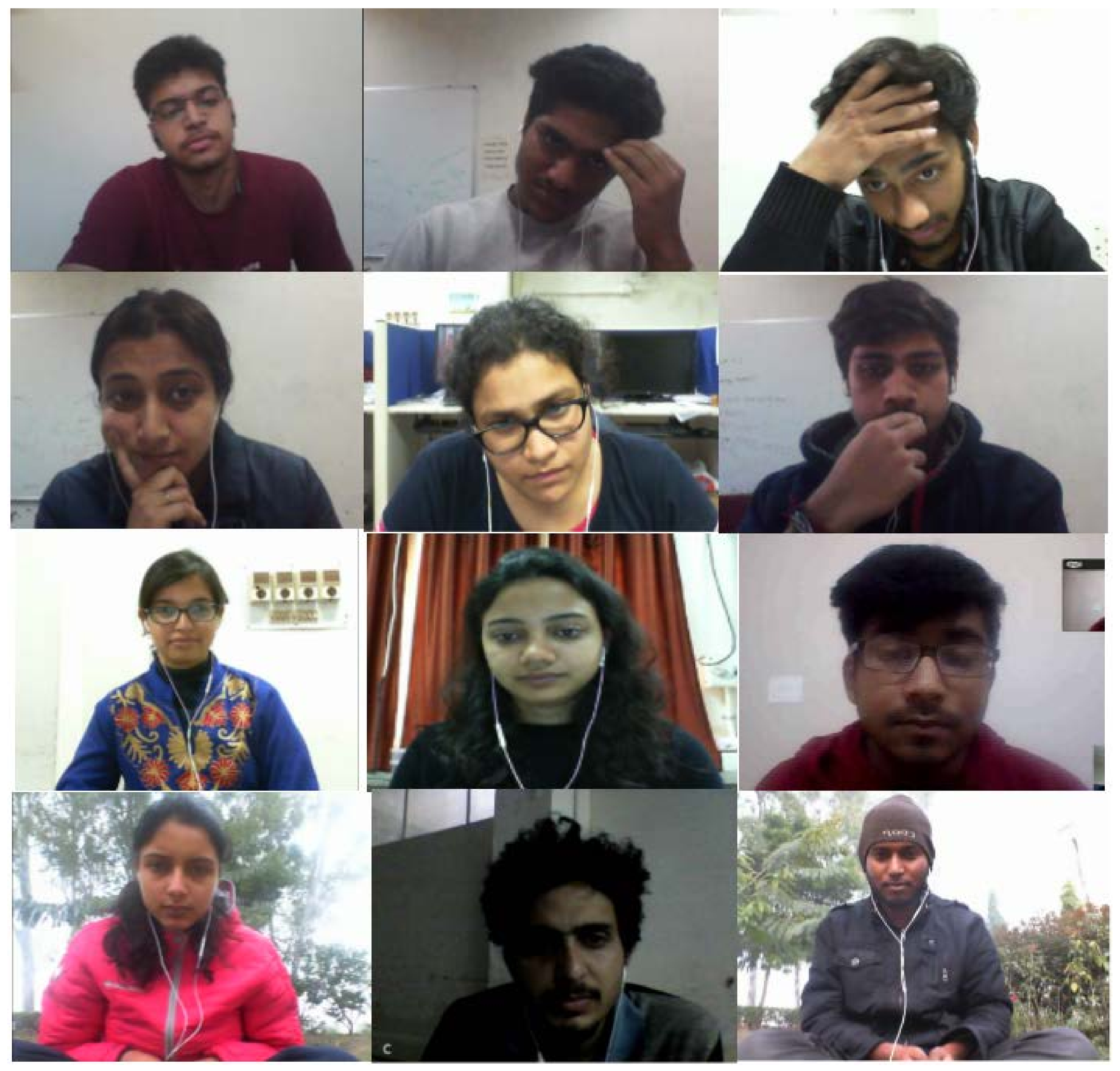
Introduction



- Engagement prediction in the Wild (EW), a sub challenges in the 7th Emotion Recognition in the Wild 2019 Grand Challenge (EmotiW), *predicts the engagement intensity* of a subject in a video which recorder while the subject is watching and educational video (MOOC) [1].



- Kaur et al. [2] described EW dataset with some examples of frames of the video as the above figure, top to bottom rows show engagement intensity level: [0 (low) - 3 (high)].
- Our method achieved the best result, a mean square error of 0.0597, with three fundamental steps:
  1. Feature Extraction.
  2. Predict the engagement intensity for each type of feature with two different models.
  3. Fusion the results of each type.

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https://github.com/th2l/SML_EW_EmotiW2019

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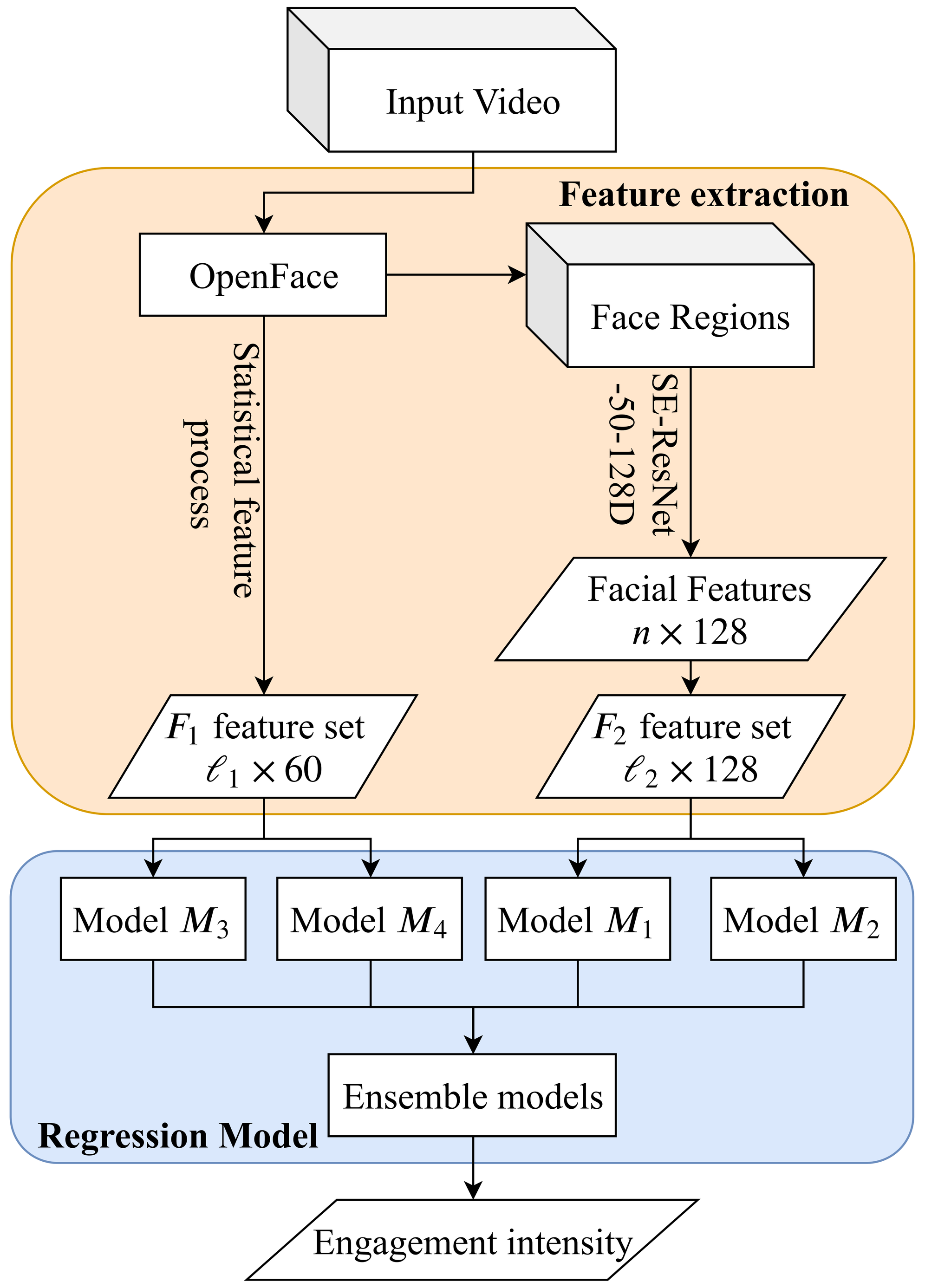
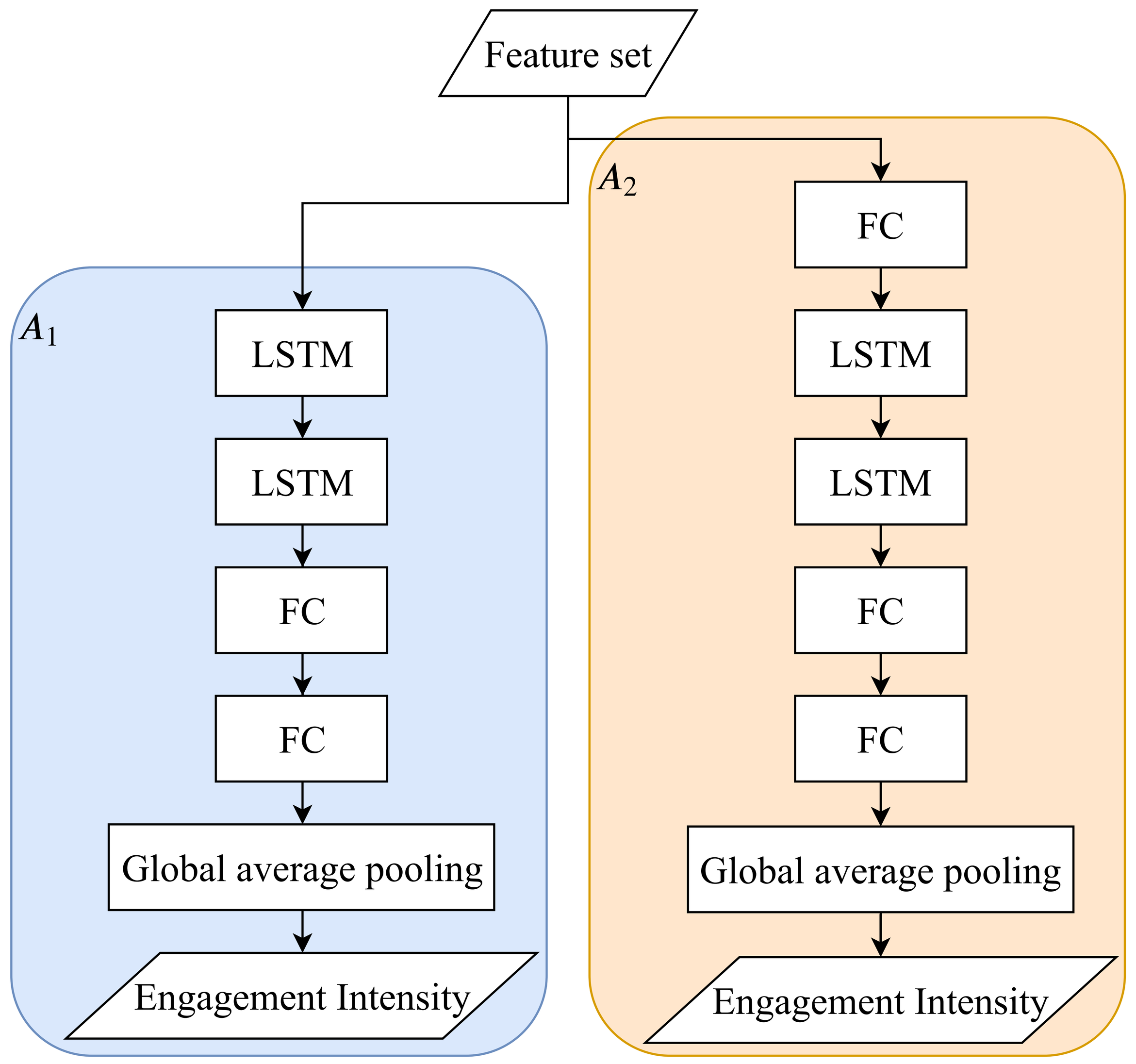
Architecture

Each video goes through OpenFace [3] to extract face region, facial landmark and gaze direction. We divide the video sequence v into ℓ segments $s_1, s_2, \vdots, s_\ell$ with $|s_i \cup s_{i+1}| = 0.5$ and $|s_i| = |s_{i+1}|, i = \overline{1, \ell-1}$.

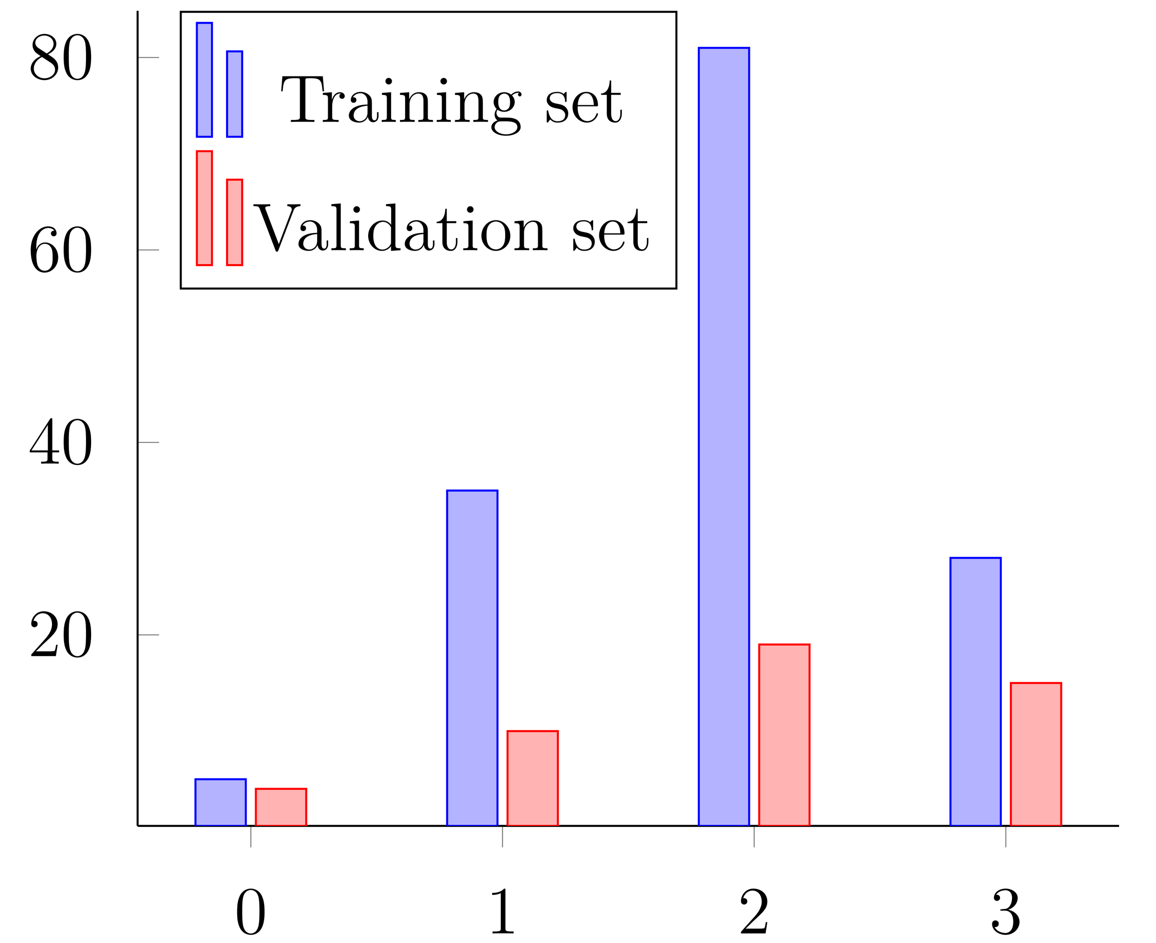


We explore two feature sets: F_1 - eye gaze and head pose features, F_2 - facial features from SE-ResNet [4]. Each feature set is classified by two networks A_1, A_2.



Experiment & Results

EW dataset in EmotiW 2019 contains 4 engagement levels: *disengaged* (DE, 0), *barely engaged* (BE, 1), *engaged* (E,2) and *highly engaged* (HE, 3) with a highly unbalanced.



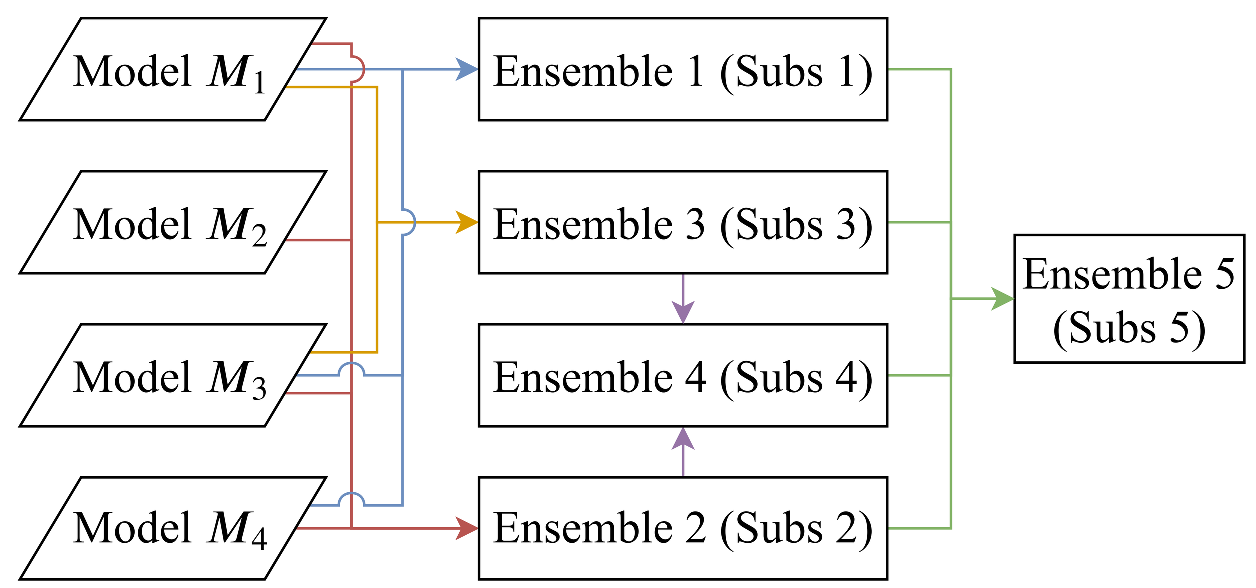
We empirically selected $\ell_1 = 15$ and $\ell_2 = 21$ which are the number of segments for F_1 and F_2, respectively. Dimensions, the output shape of FC, LSTM layers in A_1, A_2 are summarized in the table below.

Input	Model	Network	Dimension
F_1	M_3	A_1	$\ell_1 \times [128, 128, 128, 128, 1]$
F_1	M_4	A_2	$\ell_1 \times [100, 128, 128, 48, 128, 1]$
F_2	M_1	A_1	$\ell_2 \times [64, 128, 64, 128, 1]$
F_2	M_2	A_2	$\ell_2 \times [64, 64, 128, 48, 64, 1]$

Our ensemble models based on two techniques: Support Vector Regression (SVR) with RBF kernel and the following equation

$$V_{fused} = \sum_{k=1}^{m} \alpha_k V_k, \quad \text{w.r.t} \quad \sum_{k=1}^{m} \alpha_k = 1 \qquad (1)$$

where V_k denotes the output of model k. The following figure describe the progress of our fusion to achieve final model.



Experiment & Results

Subs	Test$_{\text{MSE}}$ DE	BE	E	HE	Overall
Yang et. al. [5]	-	-	-	-	0.0626
Niu et. al. [6]	-	-	-	-	0.0724
Thomas et. al. [7]	-	-	-	-	0.0792
Chang et. al. [8]	-	-	-	-	0.0813
Ensemble 1	0.3342	0.0834	**0.0133**	0.0660	0.0787
Ensemble 2	0.3289	0.1087	0.0270	**0.0353**	0.0911
Ensemble 3	0.2686	0.0644	0.0231	0.0640	0.0696
Ensemble 4	**0.2204**	0.0405	0.0320	0.1022	0.0628
Ensemble 5	0.2461	**0.0297**	0.0224	0.1378	**0.0597**

Reference

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