Engagement Recognition using Deep Learning and Facial Expression

Omid Mohamad Nezami, Len Hamey, Deborah Richards, and Mark Dras
Macquarie University, Sydney, NSW, Australia
omid.mohamad-nezami@hdr.mq.edu.au, {len.hamey,deborah.richards,mark.dras}@mq.edu.au

Abstract

Engagement is a key indicator of the quality of learning experience, and one that plays a major role in developing intelligent educational interfaces. Any such interface requires the ability to recognize the level of engagement in order to respond appropriately; however, there is very little existing data to learn from, and new data is expensive and difficult to acquire. This paper presents a deep learning model to improve engagement recognition from face images captured ‘in the wild’ that overcomes the data sparsity challenge by pre-training on readily available basic facial expression data, before training on specialised engagement data. In the first of two steps, a facial expression recognition model is trained to provide a rich face representation using deep learning. In the second step, we use the model’s weights to initialize our deep learning based model to recognize engagement; we term this the Transfer model. We train the model on our new engagement recognition (ER) dataset with 4627 engaged and disengaged samples. We find that the Transfer model outperforms effective deep learning architectures that we apply for the first time to engagement recognition, as well as approaches using histogram of oriented gradients and support vector machines.

1. Introduction

Engagement is a significant aspect of human-technology interactions and is defined differently for a variety of applications such as search engines, online gaming platforms, and mobile health applications [28]. According to Monkaresi et al. [25], most definitions describe engagement as attentional and emotional involvement in a task.

This paper deals with engagement during learning via technology. Investigating engagement is vital for designing intelligent educational interfaces in different learning settings including educational games, massively open online courses (MOOCs), and intelligent tutoring systems (ITSs). For instance, if students feel frustrated and become disengaged (see disengaged samples in Figure 1), the system should intervene in order to bring them back to the learning process. However, if students are engaged and enjoying their tasks (see engaged samples in Figure 1), they should not be interrupted even if they are making some mistakes [19]. In order for the learning system to adapt the learning setting and provide proper responses to students, we first need to automatically measure engagement. This can be done by, for example, using context performance [1], facial expression [35] and heart rate [25] data.

This paper aims at quantifying and characterizing engagement using facial expressions extracted from images ‘in the wild’. In this domain, engagement detection models usually use typical facial features which are designed for general purposes, such as Gabor features [35], histogram of oriented gradients [18] and facial action units [4]. To the best of the authors’ knowledge, there is no work in the literature investigating the design of specific and high-level features for engagement. Therefore, providing a rich engagement representation model to distinguish engaged and disengaged samples remains an open problem (Challenge 1). Training such a rich model requires a large amount of data which means extensive effort, time, and expense would be required for collecting and annotating data due to the complexities [3] and ambiguities [28] of the engagement concept (Challenge 2).

To address the aforementioned challenges, we design a deep learning model which includes two essential steps: basic facial expression recognition, and engagement recognition. In the first step, a convolutional neural network (CNN) is trained on the dataset of the Facial Expression Recognition Challenge 2013 (FER-2013) to provide a rich facial representation model, achieving state-of-the-art performance. In the next step, the model is applied to initialize our engagement recognition model, designed using a separate CNN, learned on our newly collected dataset in the engagement recognition domain. As a solution to Challenge 1, we train a deep learning-based model that provides our
representation model specifically for engagement recognition. As a solution to Challenge 2, we use the FER-2013 dataset, which is around eight times larger than our collected dataset, as external data to pre-train our engagement recognition model and compensate for the shortage of engagement data. The contributions of this work are three-fold:

- To the authors’ knowledge, the work in this paper is the first time a rich face representation model has been used to capture basic facial expressions and initialize an engagement recognition model, resulting in positive outcomes. This shows the effectiveness of applying basic facial expression data in order to recognize engagement.

- We have collected a new dataset we call the Engagement Recognition (ER) dataset to facilitate research on engagement recognition from face images. To handle the complexity and ambiguity of engagement concept, our data is annotated in two steps, separating the behavioral and emotional dimensions of engagement. The final engagement label in the ER dataset is the combination of the two dimensions.

- To the authors’ knowledge, this is the first study which models engagement using deep learning techniques. The proposed model outperforms an extensive range of baseline approaches on the ER dataset.

2. Related Work

2.1. Facial Expression Recognition

As a form of non-verbal communication, facial expressions convey attitudes, affects, and intentions of people. They are the result of movements of muscles and facial features [11]. Study of facial expressions was started more than a century ago by Charles Darwin [10], leading to a large body of work in recognizing basic facial expressions [11, 51]. Much of the work uses a framework of six ‘universal’ emotions [9]: sadness, happiness, fear, anger, surprise and disgust, with a further neutral category.

Facial expression recognition (FER) using deep learning based methods has been successful in automatically recognizing facial expressions in images [15, 23, 24, 30, 37, 38, 39]. These approaches learn hierarchical structures from low- to high-level feature representations thanks to the complex, multi-layered architectures of neural networks. Kahou et al. [17] applied convolutional neural networks (CNNs) to recognize facial expressions and won the 2013 Emotion Recognition in the Wild Challenge. Another CNN model, followed by a linear support vector machine, was trained to recognize facial expressions by Tang et al. [34]; this won the 2013 FER challenge [12]. In FER tasks, CNNs can be also applied for feature extraction and transfer learning. For instance, Kahou et al. [16] applied CNNs for extracting visual features accompanied by audio features in a multi-modal data representation. Nezami et al. [27] used a CNN model to recognize facial expressions, where the learned representation is used in an image captioning model: the model embedded the recognized facial expressions to generate more human-like captions for images including human faces. Yu et al. [37] employed a CNN model that was pre-trained on the FER-2013 dataset [12] and fine-tuned on the Static Facial Expression in the Wild (SFEW) dataset [8]. They applied a face detection method to detect faces and remove noise in their target data samples. Mollahosseini et al. [24] trained CNN models across different well-known FER datasets to enhance the generalizability of recognizing facial expressions. They applied face registration processes to extract and align faces to achieve better performance. Kim et al. [20] measured the impact of combining registered and unregistered face samples on FER recognition tasks. They used the unregistered samples when the facial landmarks of the samples were not detectable. Zhang et al. [38] applied CNNs to capture spatial information from video frames. The spatial information was combined with temporal information to recognize facial expressions. Pramerdorfer et al. [29] employed a combination of modern deep architectures such as VGGnet [32] on the FER-2013 dataset. They also achieved the state-of-the-art result on FER-2013 dataset.

2.2. Engagement Recognition

Engagement can be detected in three different time scales: the entire video of a learning session, 10-second video clips, and static images. In the first category, Grafsgaard et al. [13] studied the relation between facial action units (AUs) and engagement in learning contexts. They col-
lected videos of web-based learning sessions between students and tutors. After finishing the sessions, they requested each student to fill in an engagement survey to annotate the student’s engagement for the entire session of learning. Their work also used linear regression methods to detect different levels of engagement. However, this approach does not characterize engagement in fine-grained time intervals which would be required for making an adaptive educational interface.

As an attempt to solve this issue, using 10-second video clips, Whitehill [35] applied linear SVMs and Gabor features, as the best approach in this work, to classify four engagement levels: not engaged at all, nominally engaged, engaged in task, and very engaged. In this work, the dataset includes 10-second captured video annotated into four levels of engagement by observers, who are analyzing the videos. Monkaresi et al. [25] used heart rate features in addition to facial features to detect engagement. They used Kinect SDK’s face tracking engine to extract facial features and WEKA (a classification toolbox) to classify the features into engaged or not engaged classes. They annotated their dataset, including 10-second videos, using self-reported data collected from students during and after their tasks. In the wild condition, Bosch et al. [4] detected engagement by AUs and Bayesian classifiers. The generalizability of the model was also investigated across different times, days, ethnicities and genders [5]. Furthermore, in interacting with intelligent tutoring systems (ITSs), engagement was investigated based on a personalized model including appearance and context features [1]. Engagement was also considered in learning with massively open online courses (MOOCs) as an e-learning environment [7]. In such settings, data are usually annotated by observing video clips or filling self-reports. However, the engagement levels of students can change during 10-second video clips, so assigning a label to the entire clip is difficult and sometimes inaccurate.

In the third category, HOG features and SVMs have been applied to classify static images according to three levels of engagement: not engaged, nominally engaged and very engaged [18]. This work is based on the experimental results of whitehill et al. [35] in preparing engagement samples. Whitehill et al. [35] showed that engagement patterns are mostly recorded in static images. Bosch et al. [4] also confirmed that video clips could not provide extra information because they reported similar performances using different lengths of video clips in detecting engagement. The dataset of Kamath et al. [18] includes static images annotated into the three levels of engagement using crowdsourcing platforms. However, competitive performances are not reported in this category.

We focus on this third category, static images, in this work. In order to detecting engagement from images, we need an effective data annotation procedure and engagement recognition model. To do this, we collected a new dataset annotated by Psychology students, who can potentially better recognize the psychological phenomena of engagement, because of the complexity of analyzing student engagement. To assist them with recognition, brief training was provided prior to commencing the task and delivered in a consistent manner via online examples and descriptions. We did not use crowdsourced labels, resulting in less effective outcomes, similar to the work of Kamath et al. [18] to annotate our dataset. We also captured more effective labels by following an annotation process to simplify the engagement concept into the behavioral and the emotional dimensions. We requested annotators to label the dimensions for each image and make the overall annotation label by combining these. Our aim is for this dataset to be useful to other researchers interested in detecting engagement from images. Given this dataset, we introduce a novel model to recognize engagement using deep learning. Our model includes two important phases. First, we train a deep model to recognize basic facial expressions. Second, the model is applied to initialize the weights of our engagement recognition model trained using our newly collected dataset.

3. Facial Expression Recognition from Face Images

3.1. Facial Expression Recognition Dataset

To recognize facial expressions, the facial expression recognition 2013 (FER-2013) dataset [12] is used. The dataset includes examples ‘in the wild’, which are labeled happiness, anger, sadness, surprise, fear, disgust, and neutral. It contains 35,887 samples (28,709 for the training set, 3589 for the public test set and 3589 for the private test set), collected by the Google search API. The samples are in grayscale at the size of 48-by-48 pixels (Figure 2).

We split the training set into two parts after removing 11 completely black samples: 3589 for validating and 25,109 for training our facial expression recognition model. To compare with related work [20, 29, 37], we do not use the public test set for training or validation, but use the private test set for performance evaluation of our facial expression recognition model.

3.2. Facial Expression Recognition using Deep Learning

We train the VGG-B model [32], using the FER-2013 dataset, with one less Convolutional (Conv.) block as shown in Figure 3. This results in eight Conv. and three fully connected layers. We also have a max pooling layer after each Conv. block with stride 2. We normalize each FER-2013 example so that the sample has a mean 0.0 and a norm 100.0 [34]. Moreover, for each pixel position, the pixel values are...
normalized to mean 0.0 and standard-deviation 1.0 using all FER-2013 training samples. Our model has similar performance with the work of Pramerdorfer et al. [29] generating state-of-the-art on FER-2013 dataset. The model’s output layer (softmax layer) consists of seven neurons, corresponding to the categorical distribution probabilities over the facial expression classes in FER-2013. In the next section, we use the model’s weights as an initial step to train our engagement recognition model to recognize engaged and disengaged samples.

4. Engagement Recognition from Face Images

4.1. Engagement Recognition Dataset

Data Collection To recognize engagement from face images, we construct a new dataset that we call the Engagement Recognition (ER) dataset. The data samples are extracted from videos of students, who are learning scientific knowledge and research skills using a virtual world named Omosa [14]. Samples are taken at a fixed rate instead of random selections, making our dataset samples representative, spread across both subjects and time. In the interaction with Omosa, the goal of students is to determine why a certain animal kind is dying out by talking to characters, observing the animals and collecting relevant information (Figure 4 (top)). After collecting notes and evidence, students are required to complete a workbook (Figure 4 (bottom)).

The videos of students were captured from our studies in two public secondary schools involving twenty students (11 girls and 9 boys) from Years 9 and 10 (aged 14–16), whose parents agreed to their participation in our ethics-approved studies. We collected the videos from twenty individual sessions of students recorded at 20 frames per second (fps), resulting in twenty videos and totalling around 20 hours.

After extracting video samples, we applied a convolutional neural network (CNN) based face detection algorithm [21] to select samples including detectable faces. The face detection algorithm cannot detect faces in a small numbers of samples (less than 1%) due to their high face occlusion (Figure 5). We removed the occluded samples from the ER dataset.

Data Annotation We designed custom annotation software to request annotators to independently label 100 samples each. The samples are randomly selected from our collected data and are displayed in different orders for different annotators. Each sample is annotated by at least six annotators. Following ethics approval, we recruited undergraduate Psychology students to undertake the annotation task, who received course credit for their participation.

\[ \kappa = 0.59 \]

\[ \text{Fleiss' kappa of the six annotators is 0.59, indicating a high inter-} \]

\[ \text{coder agreement} \]
Before starting the annotation process, annotators were provided with definitions of behavioral and emotional dimensions of engagement, which are defined in the following paragraphs, inspired by the work of Aslan et al. [2].

**Behavioral dimension:**
- **On-Task:** The student is looking towards the screen or looking down to the keyboard below the screen.
- **Off-Task:** The student is looking everywhere else or eyes completely closed, or head turned away.
- **Can’t Decide:** If you cannot decide on the behavioral state.

**Emotional dimension:**
- **Satisfied:** If the student is not having any emotional problems during the learning task. This can include all positive states of the student from being neutral to being excited during the learning task.
- **Confused:** If the student is getting confused during the learning task. In some cases, this state might include some other negative states such as frustration.
- **Bored:** If the student is feeling bored during the learning task.
- **Can’t Decide:** If you cannot decide on the emotional state.

During the annotation process, we show each data sample followed by two questions indicating the engagement’s dimensions. The behavioral dimension can be chosen among on-task, off-task, and can’t decide options and the emotional dimension can be selected among satisfied, confused, bored, and can’t decide options. In each annotation phase, annotators have access to the definitions to label each dimension. A sample of the annotation software is shown in Figure 6. In the next step, each sample is categorized as engaged or disengaged by combining the dimensions’ labels (Table 1). For example, if a particular annotator labels an image as on-task and satisfied, the category for this image from this annotator is engaged. Then, for each image we use the majority of the engaged and disengaged labels to specify the final overall annotation.

If a sample receives the label of can’t decide more than twice (either for the emotional or behavioral dimensions) from different annotators, it is removed from ER dataset. Labeling this kind of sample is a difficult task for annotators, notwithstanding the good level of agreement that was achieved, and finding solutions to reduce the difficulty remains as a future direction of our work.

Using this approach, we have created the ER dataset consisting of 4627 annotated examples including 2290 engaged and 2337 disengaged.

![Figure 6. An example of our annotation software where the annotator is requested to specify the behavioral and emotional dimensions of the displayed sample.](image)

| Behavioral | Emotional | Engagement |
|------------|-----------|------------|
| On-task    | Satisfied | Engaged    |
| On-task    | Confused  | Engaged    |
| Off-task   | Satisfied | Disengaged |
| Off-task   | Confused  | Disengaged |

Table 1. The adapted relationship between the behavioral and emotional dimensions from Woolf et al. [36] and Aslan et al. [2].

![Figure 7. Randomly selected examples of ER dataset including engaged and disengaged samples.](image)

**Dataset Preparation** We apply the CNN based face detection algorithm to detect the face of each ER sample. If there is more than one face in a sample, we choose the face with the biggest size. Then, the face is transformed to grayscale and resized into 48-by-48 pixels, which is an effective resolution for engagement detection [35]. Figure 7 shows some examples of the ER dataset. We split the ER dataset into training (3224), validation (715), and testing (688) sets, which are subject-independent (the samples in these three sets are from different subjects). Table 1 demonstrates the statistics of these three sets.
| State        | Total | Train | Valid | Test |
|--------------|-------|-------|-------|------|
| Engaged      | 2290  | 1589  | 392   | 309  |
| Disengaged   | 2337  | 1635  | 323   | 379  |
| Total        | 4627  | 3224  | 715   | 688  |

Table 2. The statistics of ER dataset and its partitions.

4.2. Engagement Recognition

The deep learning architecture we will use is a Convolutional Neural Network (CNN). We define two of these as baselines, one designed architecture and one that is similar to VGGNet [32]. The key model of interest in this paper is a version of the latter baseline that incorporates facial expression recognition. For completeness, we also include another baseline that is not based on deep learning, but rather uses classical machine learning with histogram of oriented gradients (HOG) features [6].

For all the models, every sample of the ER dataset is normalized so that it has a zero mean and a norm equal to 100. Furthermore, for each pixel location, the pixel values are normalized to mean zero and standard deviation one using all ER training data.

**HOG+SVM** We trained a method using the histogram of oriented gradients (HOG) features extracted from ER samples and a linear support vector machine (SVM), which we call the HOG+SVM **MODEL**. The model is similar to that of Kamath et al. [18] for recognizing engagement from static images and is used as a baseline model in this work. HOG [6] applies gradient directions or edge orientations to express objects in local regions of images. For example, in facial expression recognition tasks, HOG features can represent the forehead’s wrinkling by horizontal edges. A linear SVM is usually used to classify HOG features. In our work, $C$, determining the misclassification rate of training samples against the objective function of SVM, is fine-tuned, using the validation set of the ER dataset, to the value of 0.1.

**Convolutional Neural Network** We use the training and validation sets of the ER dataset to train a Convolutional Neural Networks (CNNs) for this task from scratch (the **CNN MODEL**); this constitutes another of the baseline models in this paper. The model’s architecture is shown in Figure 3. The model contains two convolutional (Conv.) layers, followed by two max pooling (Max.) layers with stride 2, and two fully connected (FC) layers. A rectified linear unit (ReLU) activation function [26] is applied after all Conv. and FC layers. The last step of the CNN model includes a softmax layer, followed by a cross-entropy loss, which consists of two neurons indicating engaged and disengaged classes. To overcome model over-fitting, we apply a dropout layer [33] after every Conv. and hidden FC layer. Local response normalization [22] is used after the first Conv. layer. As the optimizer algorithm, stochastic gradient descent with mini-batching and a momentum of 0.9 is used. Using Equation 1, the learning rate ($a_t$) at step $t$ is decayed by the rate ($r$) of 0.8 in the decay step ($s$) of 500. The total number of iterations from the beginning of the training phase is global step ($g$).

$$a_t = a_{t-1} \times r^\frac{g}{s}$$

5. Experiments

5.1. Evaluation Metrics and Testing

In this paper, the performance of all models are reported on the both validation and test splits of the ER dataset. We use three performance metrics including classification accuracy, F1 measure and the area under the ROC (receiver operating characteristics) curve (AUC). In this work, classification accuracy specifies the number of positive (engaged) and negative (disengaged) samples which are correctly classified and are divided by all testing samples (Equation 2).

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$
Figure 8. The architecture of the CNN Model. We denote convolutional, max-pooling, and fully-connected layers with “Conv”, “Max”, and “FC”, respectively.

Figure 9. The architecture of the VGGnet model.

Figure 10. Our facial expression recognition model on FER-2013 dataset (left). The Transfer model on ER dataset (right).

where $TP$, $TN$, $FP$, and $FN$ are true positive, true negative, false positive, and false negative, respectively. F1 measure is calculated using Equation 3:

$$F1 = 2 \times \frac{p \times r}{p + r}$$

where $p$ is precision defined as $\frac{TP}{TP + FP}$ and $r$ is recall defined as $\frac{TP}{TP + FN}$. AUC is a popular metric in engagement recognition task [4, 25, 35]; it is an unbiased assessment of the area under the ROC curve. An AUC score of 0.5 corresponds to chance performance by the classifier, and AUC 1.0 represents the best possible result.

5.2. Implementation Details

In the training phase, for data augmentation, input examples are randomly flipped along their width and cropped to 48-by-48 pixels (after applying zero-padding because the samples were already in this size). Furthermore, they are randomly rotated by a specific max angle. We set learning rate for the VGG NET model to 0.001 and for other models to 0.002. The batch size is set to 32 for the TRANSFER model and 28 for other models. The best model on the validation set is used to estimate the performance on the test partition of the ER dataset for all models in this work.

5.3. Results

Overall Metrics We summarize the experimental results on the validation partition of the ER dataset in Table 3 and on the test partition of the ER dataset in Table 4. On the validation and test sets, the TRANSFER model substantially outperforms all baseline models using all evaluation metrics, showing the effectiveness of using a trained model on basic facial expression data to initialize an engagement recognition model. All deep models including CNN, VGGNET, and TRANSFER models perform better than the HOG+SVM method, showing the benefit of applying deep learning to recognize engagement. On the test set, the TRANSFER model achieves 72.38% classification accuracy, which outperforms VGGNET by 5%, and the CNN model by more than 6%; it is also 12.5% better than the HOG+SVM approach. The TRANSFER model achieved 73.90% F1 measure which is around 3% improvement compared to the deep baseline models and 6% better perfor-
### Table 3. The results of engagement subject independent models (%) on the validation set of ER dataset.

| Method      | Accuracy | F1   | AUC   |
|-------------|----------|------|-------|
| HOG+SVM     | 67.69    | 75.40| 65.50 |
| CNN         | 72.03    | 74.94| 71.56 |
| VGGNET      | 68.11    | 70.69| 67.85 |
| TRANSFER    | 77.76    | 81.18| 76.77 |

### Table 4. The results of engagement subject independent models (%) on the test set of ER dataset.

| Method      | Accuracy | F1   | AUC   |
|-------------|----------|------|-------|
| HOG+SVM     | 59.88    | 67.38| 62.87 |
| CNN         | 65.70    | 71.01| 68.27 |
| VGGNET      | 66.28    | 70.41| 68.41 |
| TRANSFER    | 72.38    | 73.90| 73.74 |

Performance than the HOG+SVM model. Using the AUC metric, as the most popular metric in engagement recognition tasks, the TRANSFER model achieves 73.74% which improves the CNN and VGGNET models by more than 5% and is around 10% better than the HOG+SVM method. There are similar improvements on the validation set.

### Confusion Matrices

We show the confusion matrices of the HOG+SVM, CNN, VGGNET, and TRANSFER models on the ER test set in Tables 5, 6, 7, and 8 respectively. The tables show the proportions of predicted classes with respect to the actual classes, allowing an examination of precision per class.

| actual | predicted |
|--------|-----------|
| Engaged| 92.23     |
| Disengaged| 7.77     |

Table 5. Confusion matrix for the HOG+SVM model (%).

| actual | predicted |
|--------|-----------|
| Engaged| 93.53     |
| Disengaged| 6.47     |

Table 6. Confusion matrix for the CNN model (%).

| actual | predicted |
|--------|-----------|
| Engaged| 89.32     |
| Disengaged| 10.68    |

Table 7. Confusion matrix for the VGGnet model (%).

| actual | predicted |
|--------|-----------|
| Engaged| 87.06     |
| Disengaged| 12.94    |

Table 8. Confusion matrix for the Transfer model (%).

### 6. Conclusion

Reliable models that can recognize engagement during a learning session, particularly in contexts where there is no instructor present, play a key role in allowing learning systems to intelligently adapt to facilitate the learner. There is a shortage of data for training systems to do this; the first contribution of the paper is a new dataset, labelled by annotators with expertise in psychology, that we hope will facilitate research on engagement recognition from visual data.

In this paper we have used this dataset to train models for the task of automatic engagement recognition ‘in the wild’, including for the first time deep learning models. The key contribution has been the development of a model that can address the shortage of engagement data to train a reliable deep learning model. This TRANSFER model has two key steps. First, we pre-train the model’s weights using basic facial expression data, of which is relatively abundant. Second, we train the model to produce a rich deep learning based representation for engagement, instead of commonly used features and classification methods in this domain. We have evaluated this model with respect to a comprehensive range of baseline models to demonstrate its effectiveness, and have shown that it leads to a considerable improvement against the baseline models using all standard evaluation metrics.
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Figure 11. Representative engaged (left) and disengaged (right) samples that are correctly classified using the TRANSFER model. Here, the label distribution across the engaged and disengaged classes is very different. This means that annotators can label these kinds of samples with less difficulties.
Figure 12. Engaged (left) and disengaged (right) examples that are correctly detected using the TRANSFER model. Here, labeling these kinds of examples is difficult for annotators. As shown, there is more visual likeness between engaged and disengaged examples compared to the previous samples.

Figure 13. These samples are wrongly predicted as engaged (left) and disengaged (right) using the TRANSFER model. The ground truth labels of the left samples are disengaged and the right samples are engaged. Here, labeling engaged or disengaged examples is also difficult for annotators which shows some challenging samples in engagement recognition tasks.