

# ALEBk: Feasibility Study of Attention Level Estimation via Blink Detection applied to e-Learning

**Roberto Daza, Daniel DeAlcala, Aythami Morales, Ruben Tolosana, Ruth Cobos, Julian Fierrez**

School of Engineering, Autonomous University of Madrid

{roberto.daza, daniel.dealcala, aythami.morales, ruben.tolosana, ruth.cobos, julian.fierrez}@uam.es

## Abstract

This work presents a feasibility study of remote attention level estimation based on eye blink frequency. We first propose an eye blink detection system based on Convolutional Neural Networks (CNNs), very competitive with respect to related works. Using this detector, we experimentally evaluate the relationship between the eye blink rate and the attention level of students captured during online sessions. The experimental framework is carried out using a public multimodal database for eye blink detection and attention level estimation called mEBAL, which comprises data from 38 students and multiple acquisition sensors, in particular, *i*) an electroencephalogram (EEG) band which provides the time signals coming from the student's cognitive information, and *ii*) RGB and NIR cameras to capture the students face gestures. The results achieved suggest an inverse correlation between the eye blink frequency and the attention level. This relation is used in our proposed method called ALEBk for estimating the attention level as the inverse of the eye blink frequency. Our results open a new research line to introduce this technology for attention level estimation on future e-learning platforms, among other applications of this kind of behavioral biometrics based on face analysis.

## INTRODUCTION

During the last decades, e-learning and virtual education platforms have had a period of high growth (Chen 2018), becoming an essential part in the academic strategy of most important higher education institutions in the world.

Although e-learning presents many advantages (Bowers and Kumar 2015), it also hands over certain challenges compared to the traditional face-to-face education. One of the most important aspects is the absence of a direct contact between teachers and students. As a result, recent e-learning platforms (Hernandez-Ortega et al. 2020a) allow to incorporate novel technologies to estimate different factors such as the attention level (Daza et al. 2020), the heart rate (Hernandez-Ortega et al. 2020b), the emotional state (Shen, Wang, and Shen 2009), and the gaze and head pose (Asteriadis et al. 2009).

Among these behavioral modalities, the estimation of the student attention level is especially interesting for e-learning

platforms (Peng et al. 2020). This information could be used, for example, to: *i*) adapt dynamically the environment and content (Fierrez et al. 2018a; Nappi, Ricciardi, and Tistarelli 2018) based on the attention level of the user, and *ii*) improve the educational materials and resources with a posterior analysis of the e-learning sessions, e.g. detecting the most appropriate types of contents for a specific student and adapting the general information to her (Fierrez-Aguilar et al. 2005a,b).

On the other hand, since the 70s, several studies have analyzed the relationship between the eye blink rate and the cognitive activity of the person such as the attention level (Bagley and Manelis 1979; K. Holland and Tarlow 1972). These studies suggest that lower eye blink rates can be associated to high attention periods while higher eye blink rates are related to lower attention levels. Consequently, eye blink detection can be a very useful tool to estimate the students attention level and for improving e-learning platforms. However, the potential use of automatic eye blink detectors to infer the attention level of users has not been evaluated in realistic scenarios. The existing studies are limited to initial qualitative analyses that suggest the correlation between signals (Daza et al. 2020). Furthermore, eye blink detection can be used for fraud/cheating/lies detection as the eye blink rate decreases when cognitive demand increases (Mann, Vrij, and Bull 2002).

Eye blink detection methods can be classified into two main groups: *i*) Image-based approaches: in this case the methods classify each individual frame as *opened*, *closed*, or the degree of eye closure (Anas, Henriquez, and Matuszewski 2017; Remeseiro, Fernández, and Lira 2015). *ii*) Video-based: these approaches consider the temporal information obtained from the entire sequence of frames (Soukupová and Cech 2016; Hu et al. 2019).

The main contributions of this work are:

- To the best of our knowledge, we present the first feasibility study of attention level estimation based on blink frequency detection (see Fig. 1).
- A novel architecture for blink detection based on Convolutional Neural Networks (CNN). This architecture has been trained using the largest public blink database up to the date.
- Our blink detector has been evaluated over a public eye

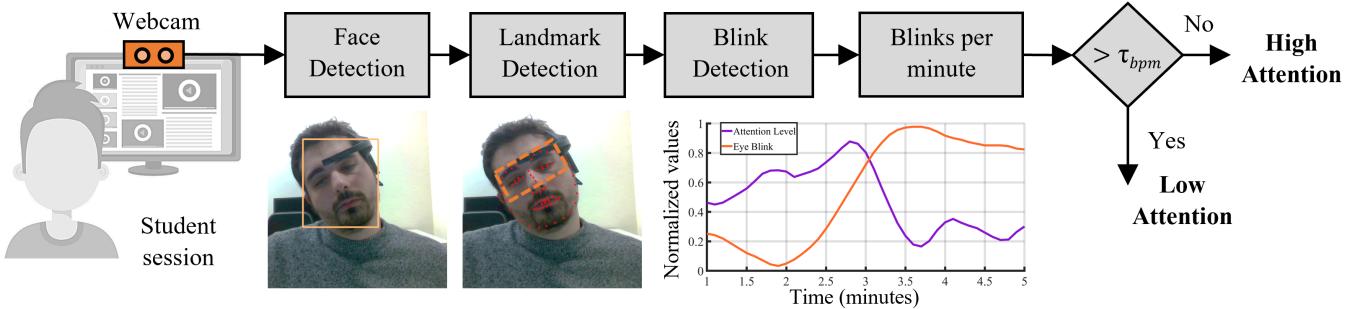


Figure 1: Architecture of the proposed attention level estimation approach based on blink frequency detection.

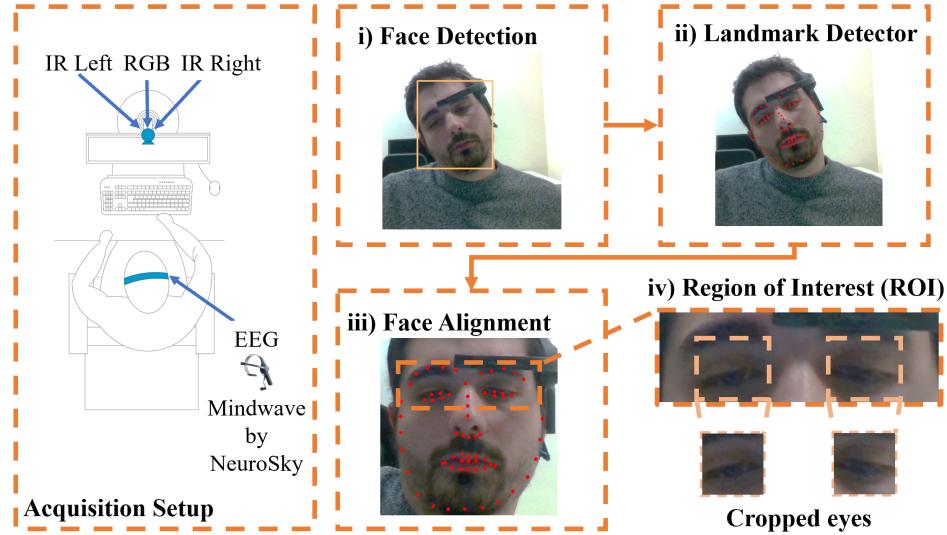


Figure 2: On the left side it is shown the acquisition setup used on mEBAL. On the right it is shown the pipeline of the proposed approach for the localization of the region of interest: Face Detection, Landmark Detection, Face Alignment, and ROI Extraction.

blink database (Hu et al. 2019), considering *in-the-wild* scenarios. Our experiments suggest that it is possible to detect high and low attention periods with a moderate accuracy around 74%.

The rest of the paper is organized as follows: Section 2 presents the materials and methods, including the databases and the proposed blink detection approach. Section 3 shows the experiments and results. Finally, remarks and future work are drawn in Section 4.

## MATERIALS AND METHODS

### Database for Attention Level Estimation: mEBAL

In this work the mEBAL database<sup>1</sup> is employed (Daza et al. 2020). This database was acquired with an experimental e-learning platform for remote education assessment called edBB (Hernandez-Ortega et al. 2020a). Students had to perform different tasks including an enrollment form, logic questions, and visual questions for an average total duration

of 23 minutes. mEBAL comprises data acquired from multiple channels including cameras and cognitive signals. Regarding the task of eye blink detection, mEBAL comprises 6,000 samples (3,000 blinks and 3,000 no-blanks) from 38 different students. Each eye blink sample is composed of 19 frames with 3 cameras (2 NIR cameras and 1 RGB camera). This database is 8 times larger than related public eye blink databases.

In addition, mEBAL includes cognitive signals from an electroencephalogram (EEG) headset by NeuroSky<sup>2</sup>, which measures the power spectrum density on 5 channels of electroencephalographic information ( $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $\delta$ ,  $\theta$ ). More specifically, the EEG data obtained are used to measure the voltage signals produced by synaptic excitations of the pyramidal cells dendrites in the top layer of the brain cortex (Li et al. 2009). The signals intensity is produced mainly by the number of neurons and fibers that are fired synchronously and it needs thousands/millions to be able to record information (Hall and Hall 2020).

<sup>1</sup><https://github.com/BiDALab/mEBAL>

<sup>2</sup><https://store.neurosky.com/pages/mindwave>

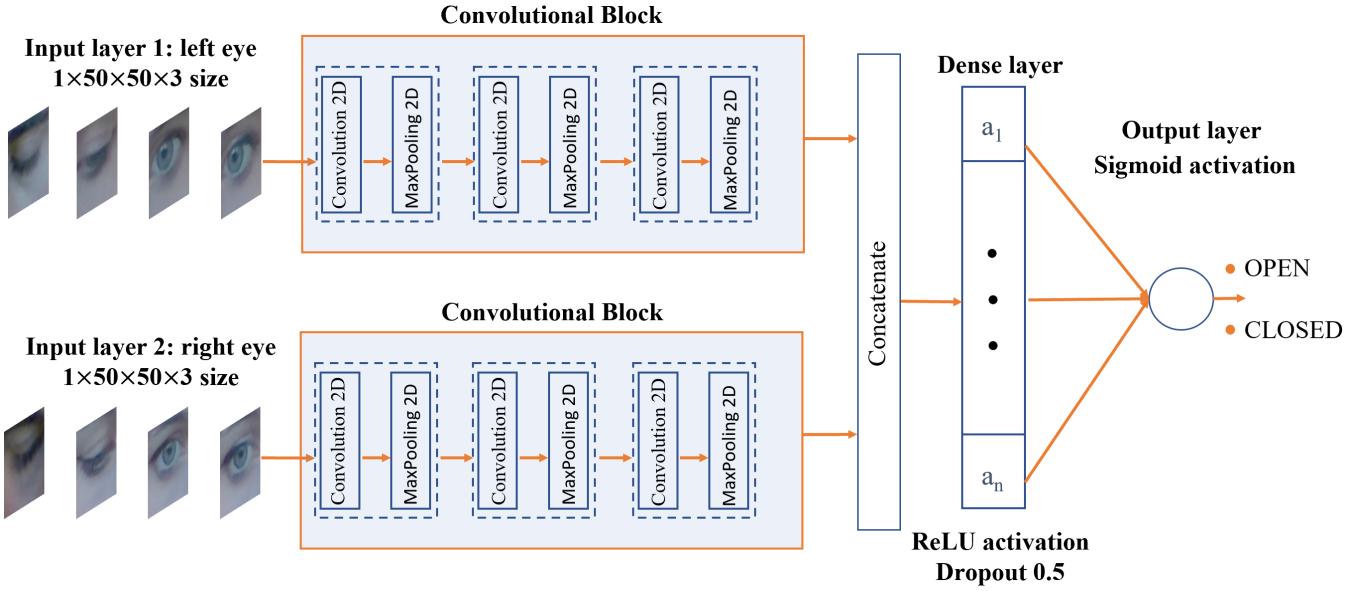


Figure 3: Architecture of the proposed CNN eye blink detector based on two convolutional blocks (one for each eye).

EEG information is considered one of the most important, effective, and objective measures in estimating the attention level (Chen and Wang 2018; Li et al. 2011), since these signals are sensitive to the mental effort and cognitive work, which varies significantly between activities like learning, lying, perception, stress, etc. The resulting EEG information consists of 5 signals in different frequency ranges. Previous studies in the neurology field have carried out extensive research on EEG signals and their relationship with intellectual and cognitive activities (Hall and Hall 2020; Lin and Kao 2018; Chen, Wang, and Yu 2017; Li et al. 2009), proving that EEG signals are rich in cognitive information.

Besides, from the official SDK of NeuroSky, the EEG band provides: the attention level, the **meditation level**, and the temporal sequence with the eye blink strength. These parameters are estimated from the  $\delta$  ( $< 4\text{ Hz}$ ),  $\theta$  (4-8 Hz),  $\alpha$  (8-13 Hz),  $\beta$  (13-30 Hz), and  $\gamma$  ( $> 30\text{ Hz}$ ) signals. The attention and meditation attributes have a value ranging from 0 to 100. The sampling rate of the band is 1 Hz.

We used the EEG headset to capture the cognitive activity of the student and the ground truth of the eye blinks. We first consider the EEG-estimated eye blinks as candidates for ground truth. Then, a posterior human intervention discards false positives. The remaining eye blinks are considered as a high-quality ground truth.

### Blink Detection Approach

We propose an automatic eye blink detector based on Convolutional Neural Networks. It has been trained combining the visible (RGB) and near infrared (NIR) spectrum. Note that NIR images have only been used during training. In the inference phase the images used are exclusively acquired from the RGB camera (webcam). The eye blink detector is characterized by two main phases: localization of the region of interest and eye blink detection.

**Region of Interest Localization:** Fig. 2 shows our proposed approach for the localization of the region of interest. This approach has four phases: *i*) face detection, *ii*) landmark detection, *iii*) face alignment, and *iv*) eye cropping.

For the face detection we consider the RetinaFace Detector (Deng et al. 2020). Two popular landmark detectors were evaluated based on the iBUG 300-W dataset (Sagonas et al. 2016) and Convolutional Pose Machines (CPM) (Dong et al. 2018). Our initial experiments over the mEBAL dataset showed a superior performance of the detector based on CPM with improvements around a 2% of detection accuracy. The dlib library is used to make the face alignment. The face alignment serves to normalize the face pose. We apply a normalization trying to have eyes on a horizontal line (Tome et al. 2015). The bounding boxes of the eyes are cropped for both eyes using the detected landmarks (Tome et al. 2013). The resulting cropped regions are resized to images of  $50 \times 50 \times 3$ .

**Eye Blink Detection:** Fig. 3 shows the architecture proposed for the eye blink detector. The architecture is inspired in the popular VGG16 neural network model (Simonyan and Zisserman 2014), considering two parallel CNNs trained from scratch (one for each eye). The architecture has two input layers of  $50 \times 50 \times 3$  size. Each input layer is connected with a convolutional block. All convolutional blocks have the same architecture consisting of 3 convolutional layers with ReLU activation (32/32/64 filters of size  $3 \times 3$ ), and 3 max pooling layers between them. The output of the first and second convolutional blocks are concatenated. Finally, we consider a dense layer of 64 units with ReLU activation, and the final output layer with one unit (sigmoid activation). In addition, dropout (0.5) is used to reduce overfitting. The batch size is set up to 32. Adam optimizer is considered with default parameters (0.001 learning rate). The network

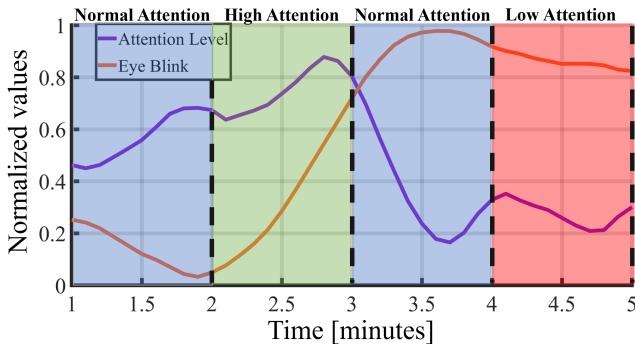


Figure 4: Normalized Attention Level and Eye Blink rate obtained by the NeuroSky headset. We classify each minute according to three different categories of attention: high, low, and normal attention. The signals show the inverse relationship between attention level and blink rate.

is trained as a binary classifier (open or closed eyes) using two input images (cropped left eye and cropped right eye) to make the decision. **We use mEBAL to train the network with the eye blinks of the RGB and NIRs cameras.**

**Attention Level Estimation:** Our target is to analyze the relation between the eye blink rate and the cognitive activity in a remote education environment. Based on the literature discussed in previous sections, we expect to notice an inverse relationship between the eye blink rate and the level of attention. For the analysis done in this work, and as indicated previously, we use the data included in mEBAL, more specifically the attention levels captured by the EEG band and the eye blinks detected. First, for each user we synchronize the attention and eye blink signals. Then, we calculate the average attention level per minute and the eye blink rate as bpm (blinks per minute). **Both, the attention level and the blink rate are obtained by the EEG headset and they will be used as ground-truth for the experiments.** Fig. 4 shows the normalized values of the attention signal and blink rate for a 5-minutes session. Instead of trying to predict the exact value of the attention or the eye blink rate per second, we argue that it is possible to predict high/low sustained levels of attention over some time using exclusively the images captured by the webcam.

Fig. 5 shows the Probability Density Function (PDF) of the attention levels provided by the SDK of the NeuroSky band considering all the students and sessions of the database. Most of the time, the attention level remains in a mean value around 50%. The main aim of our experimental framework is to detect periods of high and low attention levels, and therefore, we consider three different groups: high attention (attention higher than a threshold  $\tau_H$ ), low attention (attention lower than a threshold  $\tau_L$ ), and normal attention (attention in between). For the experiments conducted here we define two symmetric thresholds with  $\tau_H = 100 - \tau_L$  and  $\tau_L = \mu - \Delta$ . Where  $\mu$  is the average of the attention level ( $\mu = 47.27$  in the mEBAL dataset) and  $\Delta$  is a variable that controls how far with respect to the mean attention we position the low and high attention thresholds

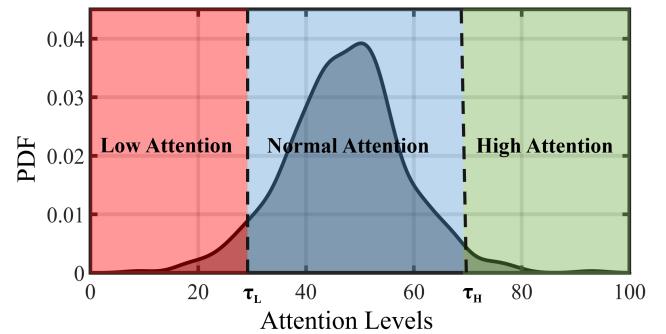


Figure 5: Probability Density Function of the attention levels provided by the SDK of the NeuroSky band in the mEBAL database.

(see Fig. 5.) According to these two thresholds, we have estimated the attention level (High-Normal-Low) of the students for periods of 1 minute (without overlap). In total we have 660 values of attention level (660 minutes) and the corresponding images from the webcam. These images served to estimate the blink rate using the detector proposed in the previous Section. Then, we experimentally establish a blink rate threshold  $\tau_{bpm}$  (see next Section). When the value of the estimated blink rate is above  $\tau_{bpm}$ , the attention level is classified as low. When the value of the estimated blink rate is below  $\tau_{bpm}$ , the attention level is classified as high.

## EXPERIMENTS AND RESULTS

### Eye Blink Detection Results

First of all, we evaluate the performance of the proposed eye blink detector. The evaluation is performed with two databases: mEBAL (Daza et al. 2020) and HUST-LEBW benchmark (Hu et al. 2019). **The mEBAL database is used to train our blink detector and considers a controlled environment, while the HUST-LEBW dataset is obtained in an unconstrained environment. The evaluation on HUST-LEBW allows to evaluate the generalization ability of the proposed eye blink detector to unseen scenarios (Gonzalez-Sosa et al. 2018; Proen  a et al. 2018).**

The evaluation in mEBAL is performed with a leave-one-out cross validation protocol. We leave out one user for testing and we train using the remaining users. We repeated the process for all users in the database. The decision threshold was fixed to the point in which the False Positive and False Negative rates in blink detection are equal. Our eye blink detector gets a 96.16% of accuracy for a total 1,094,400 images ( $9,600 \times 19 \times 2 \times 3$ ).

HUST-LEBW is very different from mEBAL. It is an unbalanced database that includes only 381 blink and 292 no-blink samples. Each sample comprises 13 frames. We process each image with the eye blink detector proposed. We get a score for each pair of eyes. We have 13 scores obtained for each sequence of frames (one per frame), the minimum is selected to represent the sample score (minimum scores are more important in the sequence because they are closed eyes candidates). As in the mEBAL evaluation, we fixed the

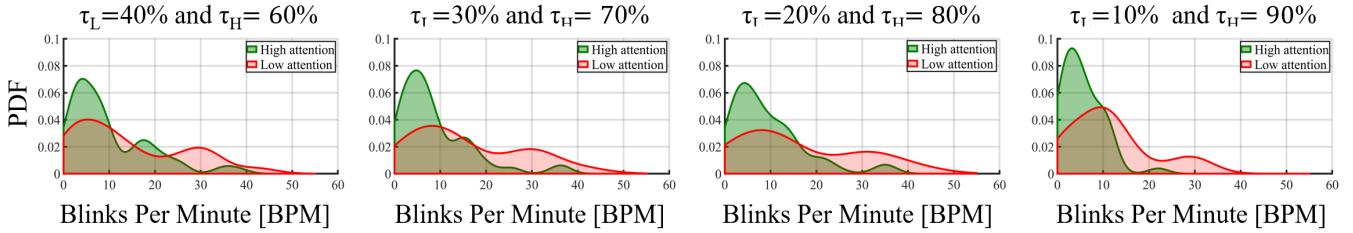


Figure 6: Probability density function of eye blinks per minute during high and low attention periods (4 different values of  $\tau_L$ ).

Table 1: Eye Blink detection results on HUST-LEBW dataset. Methods: A=(Morris, Blenkhorn, and Zaidi 2002), B=(Chau and Betke 2005), C=(Tabrizi and Zoroofi 2008), D=(Drutarovsky and Fogelton 2014), E=(Soukupová and Cech 2016), F=(Hu et al. 2019), G=(Daza et al. 2020).

<b>Method</b>	<b>Eye</b>	<b>Recall</b>	<b>Precision</b>	<b>F1</b>
A	Left	0.0164	0.6667	0.0320
	Right	0.0159	<b>1.0000</b>	0.0313
B	Left	0.0164	<b>1.0000</b>	0.0323
	Right	0.0000	0.0000	0.0000
C	2 eyes	0.0714	0.4500	0.1233
D	Left	0.0574	0.4118	0.1007
	Right	0.0317	0.3077	0.0576
E	Left	0.3607	0.6471	0.4632
	Right	0.3016	0.5758	0.3958
F	Left	0.5410	0.8919	0.6735
	Right	0.4444	0.7671	0.5628
G	Left	0.9603	0.6080	0.7446
	Right	0.7950	0.7348	0.7637
<b>Proposed</b>	2 eyes	<b>0.9339</b>	0.7533	<b>0.8339</b>

threshold to the point in which the False Positive and False Negative rates in blink detection are equal. Table 1 shows the results obtained by our approach and the comparison with previous approaches evaluated over the same HUST-LEBW dataset (Chau and Betke 2005; Drutarovsky and Fogelton 2014; Hu et al. 2019; Morris, Blenkhorn, and Zaidi 2002; Soukupová and Cech 2016; Tabrizi and Zoroofi 2008; Daza et al. 2020). Our method outperforms state-of-the-art eye blink detection algorithms (in terms of F1 score) in an unconstrained environment, which is very different compared to the traditional e-learning environment. In addition, it is interesting to highlight that the proposed approach also outperforms our initial approach presented in (Daza et al. 2020). This is produced as both eyes are used as input, giving more information to the network and allowing to reduce the error due to head orientation, illumination, etc.

### Attention Level Estimation Results

Fig. 6 shows the probability density distributions of the blink frequency in terms of blinks per minute for high and low attention periods, considering four different thresholds  $\tau_L$  (from 40% to 10%). The results show that the overlap be-

Table 2: Attention level in terms of classification accuracy using the mEBAL database. We present results for 10 different values of  $\tau_L$  and  $\tau_H$ , considering the maximum accuracy and the accuracy obtained operational point where the False Positive and False Negative rates are equal (accuracy=1-EER).  $\tau_{bpm}$  = EER threshold

<b>Att. thresholds</b>	$\tau_L-\tau_H$	<b>max acc</b>	<b>acc=1-EER</b>	$\tau_{bpm}$
50%-50%		0.5611	0.5295	8.13
45%-55%		0.5680	0.5516	7.68
40%-60%		0.5974	0.5658	8.01
35%-65%		0.5843	0.5542	7.90
30%-70%		0.6585	0.6585	8.46
25%-75%		0.6092	0.6050	8.28
20%-80%		0.6368	0.6211	9.00
15%-85%		0.6479	0.6408	7.43
10%-90%		<b>0.7447</b>	<b>0.7021</b>	<b>7.10</b>
5%-95%		0.6458	0.5833	3.77

tween distributions is higher for the highest values of  $\tau_L$  (40%). Nevertheless, the separability between distributions improves when  $\tau_L$  decreases to 20% and 10%. As it has been theorized in previous studies, during the periods with high attention, the blink rate often has a lower frequency in comparison to low attention periods. However, during the periods with low attention the blink rate is more homogeneously distributed. These results suggest that high attention periods are easier to recognize than low attention periods.

Table 2 shows the classification accuracy of high and low attention periods for different values of  $\tau_L$ . The table shows the maximum accuracy and the accuracy for the operational point where the False Positive and False Negative rates are equal. The best results are obtained for the lowest values of  $\tau_L$  (10%). In other words, the periods of time with the highest and the lowest attention levels (i.e., extreme cases). For these cases, the blink frequency allows to correctly classify the 70.2% of the samples. Fig. 7 shows the False Acceptance Rate and the False Rejection Rate for this case ( $\tau_L = 10\%$ ). According to these results, we can observe a certain level of correlation between the level of attention and the eye blink frequency, which is coherent with the literature.

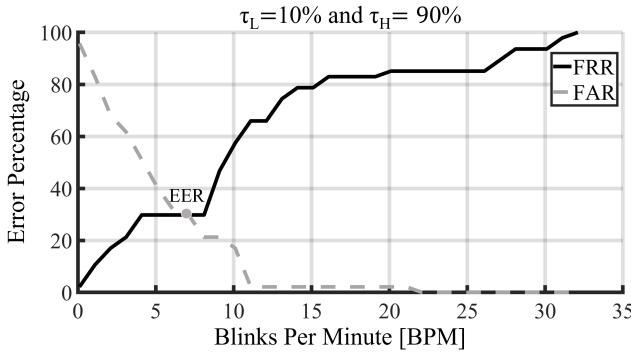


Figure 7: False Acceptance Rate (FAR) and False Rejection Rate (FRR) versus the blink rate (blinks per minute) for a value of  $\tau_L$  equal to 10%.

## CONCLUSIONS AND FUTURE WORKS

We proposed a novel Attention Level Estimation approach based on eye Blink frequency detection, coined ALEBk. Our method is based on a new eye blink detector based on a Convolutional Neural Network (CNN) that has been trained from scratch using RGB and NIR images from the mEBAL database<sup>3</sup>. We have evaluated our blink detection approach using two very different databases (mEBAL and HUST-LEBW). Our results have outperformed the state of the art, showing that the architecture presented in this paper can be used in real applications like remote education (Hernandez-Ortega et al. 2020a). Additionally, based on the studies that correlate the eye blink rate with the cognitive activity, we have analyzed the inverse relationship between the eye blink rate and the attention level in a remote education environment. Our experiments suggest that there is certain correlation between the attention levels and the eye blink rate. We have obtained ca. 74% of maximum accuracy in the detection of periods with high and low attention levels.

Future studies should explore other deep learning architectures based on Convolutional Long Short-Term Memory (ConvLSTM) neural networks or other architectures combining both short- and long-term information (Tolosana et al. 2021) to take advantage of the time dimension to better detect the blinking. Additionally, multimodal approaches (Fierrez 2006) based on other students behaviors apart from the eye blink frequency should be explored to improve the classification accuracy (Peng et al. 2020), including the rest of the inputs commonly considered in a remote e-learning session: keystroking (Morales et al. 2016b,a), mouse (Acien et al. 2020a), touchscreen interaction (Fierrez et al. 2018b), or other forms of human-computer interaction signals (Acien et al. 2020b).

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<sup>3</sup><https://github.com/BiDALab/mEBAL>

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