The Attention of Students in Online Education

Using Head Pose Techniques to Detect Attention in Videoconferencing Platforms: A Case Study

https://doi.org/10.3991/ijet.v17i22.34241

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Abstract—The level of attention of students who receive classes through videoconferencing platforms is troubling. Different throughout an entire lecture, the instructor can perceive the participants' behavior, while in an online class, it is difficult to determine if they are attentive to the instructions given. An innovative method that helps solve this problem is the use of computer vision algorithms, with methods such as face detection, facial landmarks, face recognition, and head pose detection based on deep learning networks. In this paper, a neural network was trained using facial landmarks to estimate head position and thus attention levels. The model was applied in five classes using different videoconferencing platforms in the Intelligent Systems subject of a private university in Ecuador. Some limitations, such as lighting and video quality, affected the level of accuracy. The number of registered participants was 12, of which between 30% and 80% attended. The maximum level of attention detected was 91.9%, while the minimum level was 86.6%. This case study proves that the head position detection function employed by many videoconferencing platforms is a useful parameter that aids the instructor in this type of context.

Keywords—attention level, head detection, intelligent systems, computer vision, online education, videoconferencing platforms

1 Introduction

Experimental models have been used to conduct substantial research on the topic of attention in the classroom. Moraine et al. [1] mentioned a very elementary concept that the brain uses to control attention and behavior, this idea is called *executive function*. With a wide variety of these executive functions, *attention* is an essential instrument for the student when he begins to learn. Several publications that evaluate attentional models are available, including the test of the five digits [2], Attentional Network Test ANT [3], and the test of attention D2 [4].

The work of [5] proposes different teaching methods in the classroom and measures the students' moments of attention and inattention. The students could press a button each time they experienced a period of inattention. Other research uses technology as support in this task. Ro et al. [6] indicates the relationship between the human face and attention, this occurs when the individual pays attention to a certain phenomenon or event that interests him. Langton and Bruce [7] state that facial stimuli such as the position of the head and eyes indicate attention to a particular scene, primarily if eye tracking is performed, the attention of that individual can be captured [8].

The position of the head is the most important factor in determining attention in all situations where it is impossible to see someone's iris of the eyes [9]. The findings of the study on higher education students' interest in online learning are provided in that context. The model supported by the instructor in the classroom is also evaluated by a variety of studies relating to the application of computer vision algorithms in the detection of the head and face. The definition of online and distance learning, as well as some relevant studies, are provided here.

1.1 Online education

Interaction plays a fundamental role in online education; in this context some factors affect a student's academic performance. In an online class, the teacher and students interact with each other. The communication between the teacher and the student can be face to face through video chat or video conferencing [10]. In this context, some factors affect a student's academic performance such as previous grades, motivation, attention, and participation [11], especially when it comes to online classes where keeping the student's attention for several hours is everything a challenge.

However, many students may develop problems related to inattention in class. The attention of students in the classroom is crucial in online learning environments where face-to-face interaction is limited. Assessing the attention of students is the main point to improve both instructing and learning [12]. Kainat et al. [13] declared that attention is core for effective learning, but analyzing attention is a complex task.

Wali et al. [14] mentioned that technology plays an important role in facilitation of learning and teaching in a classroom environment. With the integration of technology in classes, is possible to provide online resources in higher education context. During these last years with the COVID-19 pandemic, universities have had to adopt educational platforms that, in addition to integrating resources such as videos, forums, chats, and interactive documents, facilitate synchronous meetings through video, allowing the continuity of the student-professor encounter.

Currently, technological advances allow the analysis of student access records to the resources used in classes, to obtain monitoring variables to measure the attention of students during their interaction with learning materials (for example, lectures in the classroom) and thus take corrective measures to improve student attention in the classroom.

1.2 Related work

This section presents studies related to the detection of student attention in the classroom and other variables involved, such as participation and concentration. For example, Chen et al. [15] propose a method for automatically estimating attention through facial feature points using machine learning algorithms. Authors use face detection and face alignment algorithms to capture landmarks on students' faces in classroom videos and introduce face reference information to constrain landmarks and extract feature sets. Leng et al. [16], propose a face detection algorithm based on Yolo v5, which detects the left and right head turn, head up or head down and facial expression by face images; classifies the head posture according to the left and right head turn and head up or head down, and then judges its concentration degree by combining with the detection classification of facial expression.

Peng et al. [17], explore methods to estimate students' engagement level from a series of facial and head movement behavior features describing the dynamic movement of eyes, head, and mouth from facial landmark extractions of video recorded when students were interacting with an online tutoring system. Then, the authors assessed their predictive value for engagement approximated by synchronized measurements from commercial EEG brainwave headsets worn by students.

In [18], an architecture for student attention detection is presented. The idea of this work is to estimate the student's state of attention at any time during the lecture based on the analysis of the student's facial and body expressions, such as body gesture classification, eye gaze estimation, and head pose estimation. The data used by this system are a stream of high-definition images encoded in video format provided by a camera. Likewise, a Multi-tasking Deep Neuro-Fuzzy Model (MDNFM) model for the accurate prediction of the attentiveness of the students in the classroom is proposed by Pandey et al. [19]. In this work, the images are acquired and transferred to the Capture, Transform and Flow (CTF) tool. Then, these images are preprocessed to make them suitable for face detection and activity monitoring. Authors apply the color models for face detection and propose a methodology to track the student's attention and so provide information to the teacher and the student.

Wenlong et al. [20], propose an evaluation algorithm of students' attention based on a face feature detection algorithm. The algorithm extracts the students' facial features in educational scenery, and then with the FSA-Net algorithm, they evaluate the posture of the head. Fatigue detection was performed by the degree of closure of students' eyes and mouth, and facial expression recognition was performed by the SCN network.

Madsen et al. [21], measure the synchronization of eye movements while preserving the privacy of the student. In this study, the authors show that attentive students have similar eye movements when watching instructional videos and that synchronization of eye movements is a good predictor of individual test scores on the material presented in the video.

However, other works that were also of interest for this study because they are related to factors that influence the student's attention are an analysis of students' role perceptions and their tendencies in classroom education using a visual inspection approach presented by Jiang [22]. The authors propose a multi-example learning student engagement assessment method based on a one-dimensional convolutional neural network. Head posture, eye gaze, eye-opening and closing states, and the most used facial movement units are used as visual features and others object detectors [23]. Jagadeesh and Baranidharan [24] develop a deep learning-oriented facial expression recognition (FER) of online learners from real-time videos to determine which facial physical behaviors are associated with emotional states and then to determine how these emotional states are related to student understanding. Li [25], present a visual analytics approach to facilitate the proctoring of online exams by analyzing the exam videos of each student recorded by a webcam and mouse movement data of the student. Authors detect and visualize suspected head and mouse movements of students in three levels of detail (Student List View, Question List View, Behavior View). Features that indicate suspected exam cheating behavior, including both abnormal head movements (e.g., abnormal head rotation, face disappearance from the screen) and mouse movements (e.g., copy and paste), were extracted.

2 Methods and materials

2.1 Sample

The study was conducted in two stages at a private university in Ecuador. The students who participated in the test are listed below.

- Stage A. In the winter of 2018, the course of Mathematical Foundations applied to the administrative area, the number of students who participated in the test was 25, and the age range is from 20 to 25 years old as explained by instructor A.
- Stage B. In the summer of 2021, in the Intelligent Systems course of the master's degree in Computer Science and Technology, the number of participants was 12, the age range is from 27 to 35 years old and explained by instructor B.

The first course was selected to obtain the data set and train the face detection model, while in the second course the attention detection model was implemented.

2.2 Data collection

The data (class recording) was gathered in various years ago using the knowledge from the early stages, as mentioned below. In the first dataset (2018), 12 sessions on various subjects from the mathematical foundations course were recorded. Each lesson goes for one hour. Each participant's face image was also taken to label, train, test, and assess the recognition model. It is important to remember that the goal of this set in 2018 was to train the online student service model for facial recognition in the classroom. The specifications and standards utilized in the creation of this model are shown in Table 1.

Table 1. Requirements and acceptance standards

Requirements	Acceptance Standards
Data face	It allows the capture of multiple images of the faces of the students and their processing for the dataset.
Training model	It allows the loading of the photographs and IDs of the dataset and the generation of a file with the properties of everyone.
Face recognition	It allows the detection of students with a success rate of at least 90%.
Registration of student data	It allows the recording of statistical data for later analysis and evaluation in the classroom.

Five sessions covering a variety of subjects from the Intelligent Systems course were recorded for the second dataset (2021). Classes were held online using platforms like Teams, Zoom, and Google Meet in 2021 due to the pandemic (Covid-19). The class had a total of 12 people registered, but only 10 could be connected. All the sessions were recorded, therefore the teacher had to put the video to the school's learning site because of the low level of participation from all the students [26]. Information on the platforms utilized in the online course is shown in Table 2.

Table 2. Video conferencing software platforms

Classroom	Platforms	Description
Class_1	ZOOM	Participants: 5 Video dimension: 1280 × 720 px Lighting conditions: Good
Class_2	ZOOM	Participants: 10 Video dimension: 1280 × 720 px Lighting conditions: Poor
Class_3	Google Meet	Participants: 4 Video dimension: 1920 × 1080 px Lighting conditions: Good
Class_4	Microsoft Teams	Participants: 10 Video dimension: 1280 × 720 px Lighting conditions: Good
Class_5	Microsoft Teams	Participants: 9 Video dimension: 1280 × 720 px Lighting conditions: Good

2.3 Evaluation metrics

The following equations are typically used to assess the model's performance [27]:

$$Precison = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F1 = 2 * \frac{Precision \times recall}{precision + recall} \tag{3}$$

Where *TP* is the number of true positives, *TN* means the number of true negatives, *FP* represents the number of false positives and *FN* signifies the number of false negatives. Recall and accuracy are the most widely used metrics and are evaluated in most investigations.

2.4 Procedure

Implementing artificial vision algorithms like face detection, facial reference point detection, facial recognition, and head position determination is the first step in determining a student's attention level. According to related works, estimating the head's position is a good alternative to completing this task given that detecting the eye's iris posed issues when various online platforms were first introduced. When a face is in front of the camera, face identification appears to be a simple operation, and it sometimes is. However, the difficulty arises when the face is viewed from multiple angles.

To train the model we used the set of scenario A, the traditional algorithms used were LBP Faces and Eigenfaces [28]. The metrics used to evaluate these algorithms are based on [27]. The average obtained in the evaluation metrics for LPB Faces was the *accuracy* of 83%, *recall* with 91%, and *F1-score* with a value of 87%. While for the Eigenfaces algorithm, the *accuracy* is 91%, *recall* 98%, and the *F1-score* with a value of 94%. Although these algorithms have significant value in accuracy and recall metrics, they are sensitive to lighting change, even more so in online classes through different videoconference platforms (see Table 2). As a result of the disadvantage of traditional algorithms, it was decided to use deep neural network models. Figure 1 presents the general process to detect the level of attention in class.

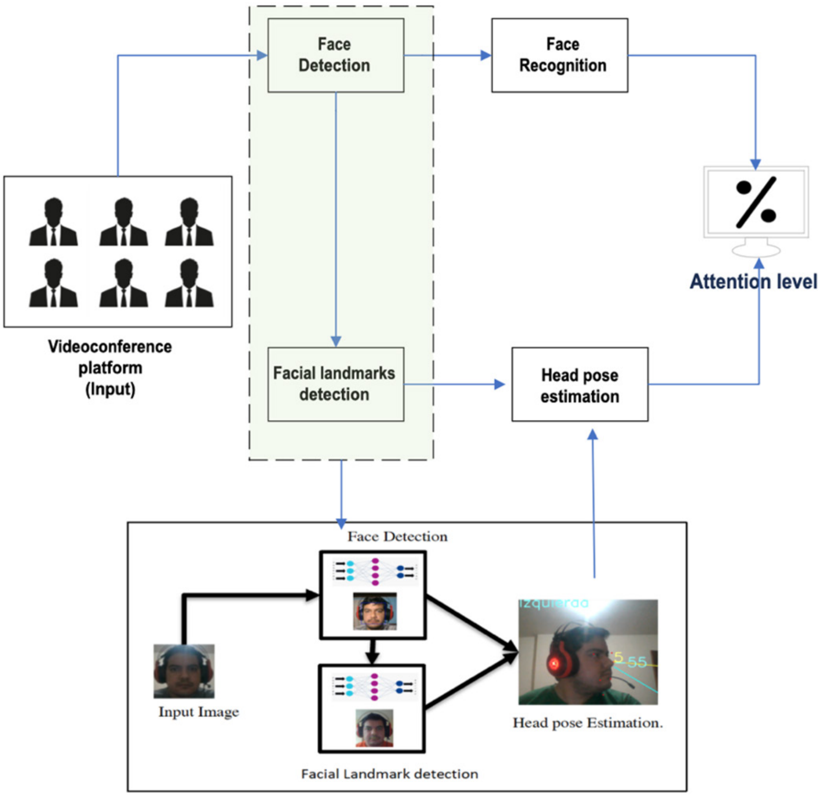

Fig. 1. General flowchart to detect the level of attention in class

- *Face detection:* In this step, the facial detector model based on Single Shot Detector (SSD) was used, it is a very fast detector [29].
- *Facial landmarks detection:* This process is defined to detect facial landmarks. This method uses the DLIB library, and the face feature point detection suggested in the work of [30].
- *Face recognition:* This process allows the face of the participant to be identified. This information is used to make statistical reports. The model used in this step is FaceNet [31].
- *Head pose estimation:* This process uses six facial reference points to estimate the position of the head [26], these are: the tip of the nose, the chin, the left and right corners of the lip, and finally the left corner of the left eye and the right corner of the right eye. These points are extracted from the work of [32].
- *Attention level detection:* No measure that determines the amount of attention using the head position was discovered in the literature review. Thus, the threshold of 48 degrees of the angle for the position of the head was established (algorithm implementation) for this case study based on tests performed in scenario A. Depending on how strict the model is, one can raise or lower the threshold value.

3 Results

The results analysis is limited to the online courses in which the case study's participants enrolled. Every student in every class has a tag called S_#, where # is the value, the system has assigned. The tests were created in the online classes listed in Table 2. It is important to understand that the model stores how frequently it recognizes a student's face in an online class; this information may be used to calculate their attention and distraction levels. In Figure 2, five students use the ZOOM platform to present themselves. The image is of high quality. The results of this exercise were as follows. The student with the highest level of attention is S_4 with a value of 98%, while S_5 has the lowest level of attention with a value of 82%.

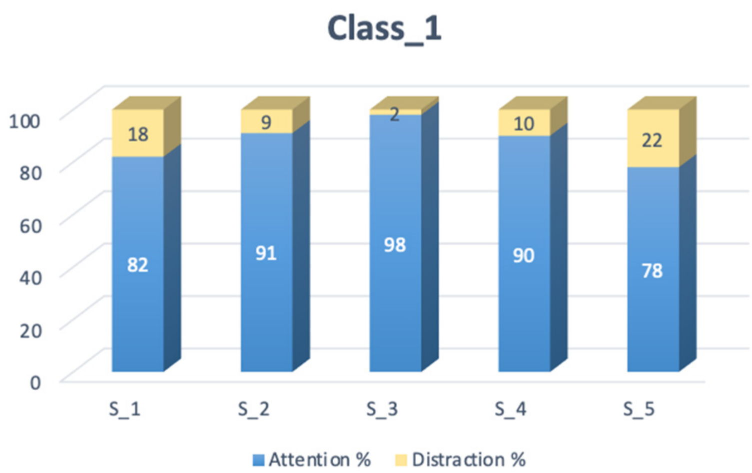

Fig. 2. Attention level – Class_1

Information from Class_2 is shown in Figure 3. 12 students used the Zoom platform to introduce themselves in this lesson. Although some students experienced lighting issues, the majority of students had acceptable image quality. Several students, including S_5, S_6, and S_9 with values of 98%, 97%, and 95% respectively, had high attention level percentages. S_4 is spending the least attention, at 83%.

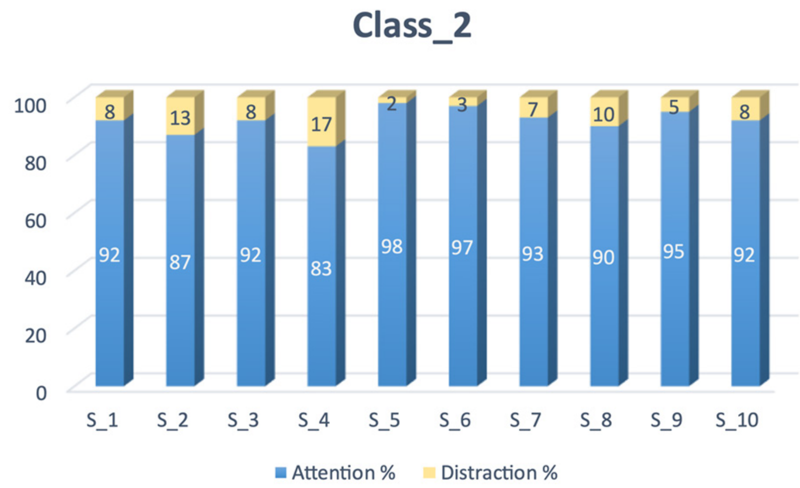

Fig. 3. Attention level – Class_2

Figure 4 shows information from Class_4. Here, 10 students attended using the Microsoft Teams platform. Students S_8 with a value of 97%, S_9 with 95%, and S_10 with 96% have the highest level of attention, while student S_1 with 84% have the lowest level of attention.

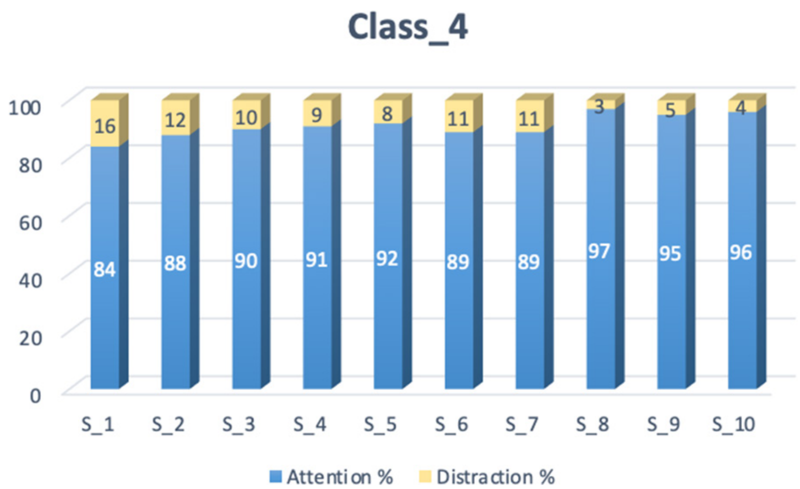

Fig. 4. Attention level – Class_4

The analysis of results is restricted to the online classes where the students of this case study participated. Table 3 presents the average level of attention and distraction using different videoconferencing platforms. Class_2, Class_4 and Class_1 have the highest values in attention with the values 91.9%, 91.1% and 87.8% respectively. It is also observed that Class_3 and Class_5 have the most disparate values in this report.

Table 3. Average attention level video conferencing software platforms

Classroom	Platforms	Attention %	Distraction %	Standard Deviation
Class_1	ZOOM	87.8	12.2	7.8
Class_2	ZOOM	91.9	8.1	4.4
Class_3	Google Meet	87.8	12.3	20.5
Class_4	Microsoft Teams	91.1	8.9	4.0
Class_5	Microsoft Teams	86.6	13.1	18.1

4 Conclusions

This paper has presented the use of technology in attention level in online education. Using computer vision techniques, as explained in [20], has made it possible to comply with the estimation of the position of the head as an alternative to detecting the level of attention. Some factors, such lighting intensity and image quality, can affect how attentive students are in classrooms using videoconferencing platforms. It is important to mention that if each student's illumination is poor, the only characteristic that matters is image quality. In this type of scenario, if both features perform well, the algorithm's accuracy may increase. Based on the investigations of [17] and [18], several techniques or processes were implemented to analyze attention on videoconference platforms. Some of these techniques include face detection, facial landmarks, face recognition, and head pose detection. (See Figure 1).

The results indicate that the distraction to some extent is related to students' attention level based on head movement features. In most cases, the students show a high level of attention with low distraction, which leads us suppose that in the zoom classes carried out in this study few distractors prevented keeping the students' attention in the learning process. In future work, we plan to use the head movement detection records to analyze student behavior and cope with tasks as a student performance prediction.

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Article submitted 2022-07-26. Resubmitted 2022-09-29. Final acceptance 2022-09-29. Final version published as submitted by the authors.