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Emotion Metric Detection By Machine Learning For E-Learning System

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Abstract:
Online education became fully possible with the rapid growth in technological development. The quality assurance of e-learning system is a very important factor to consider in enhancing the learning 4.0. The student emotion detection is one from the most solution that helps optimize the e-learning process. The emotion detection is based on student facial expressions recognition. This method makes it possible for the teacher to know the concentration rate of their learners. In this paper, we proposed a new system that enables the teacher follow in real time the student's concentration. The concentration level is plotted in the teacher's screen. Student's facial detection parameters can help us measure the concentration rate of each learner. Our application can be used as a metric for student attention to enhance the pedagogical method. **It also ensure the teacher maintains the discipline needed for the smooth running of the remote classroom with the help of our alert agent which sends a signal message to the teacher each time there is malicious acts going on showing.** This application enables the teacher generate a detailed report of the learner's attention and concentration. This report will contain a classification of the student's concentration

level and the course section classification of the student concentration number. The result of this will help the teacher optimize their course contents.

Keywords: E-learning, Emotion metric, concentration level, machine learning

1. Introduction

With the current realities as a result of the ripple effects of COVID-19, the e-learning system became a solution for educational institutions world over. The online education is made available for students who are unable to go back to schools or attend lectures due to the interventions and safety measures such as physical-distancing and self-isolation policies put up by the government which was aimed stem the spread of the virus. The rapid growth in technological development and innovative inventions at the industrial level has facilitated the setting up of a fully functional online education system for both theoretical course and practical based courses, still providing the same services as the traditional face-to-face system but with an improved quality.

The concentration of the student during the online learning process is a very important factor to consider in enhancing the e-learning system. In fact, this level of concentration can present one of the most feedbacks that we can get from the learner. The concentration rate can be measured from the student emotion expression.

Emotions sometimes are revealed through facial expressions which involves the contraction of the facial muscles. We humans are extraordinarily good at expressing our emotions through facial expressions [1].

It is hypothetically believed that primates have developed a sophisticated set of facial muscles that now permits them convey emotions to anyone observing [2].

According to Duchenne et al in [3] these muscles are activated when creating a facial expression to convey an emotion such as: happiness, surprise, sadness, anger etc. The research by [4,5] focuses on other types of facial expression besides the six (6) basic facial expressions listed above. The twenty one (21) news distinct emotion categories have been defined by combining one basic component [6]. This study is based on muscle face movement to distinguish between the 21 categories defined.

Krithika.L et al in [7] proposed a metric that would detect negative component of student in the e-Learning environment based on head and eye movement. This application can provide a continuous feedback process to allow a teacher to improve the content of their course. Veena Mayya et al study the facial expression recognition by Deep Convolutional Neural Network (DCNN) in [8]. The proposed model analyzed the facial expression of person by using a single image.

The neural representation of facial emotion has been opined by [9,10,11]. According to these studies, emotion is invariant between persons and cultures. The neural patterns can be used to discriminate between emotion categories. Studies carried out by [12] revealed how facial expressions and their classification can be read.

To see that the gap in e-learning education is covered, we propose to develop a model that would enable the teacher measure in real-time the students' concentration based on remote face detection. This solution presents a student attention metric system that will enable the teacher to optimize their pedagogical method. This system will also provide the opportunity for a teacher to have an idea about the student attention in the online exam. Our system can also be used to generate report files containing the daily, weekly, and monthly reports of the students' concentration level according to user choice. The system developed in our paper will help the teacher make decisions on how best to enhance the course scenario and the practical work infrastructure. In our work, the concentration level of the learner can be obtained by the diagnoses of student face. In fact, this value can be estimated from the student eye, head movement, lips movement, color face variation and face muscle movement. This paper is composed of five sections. In the first part, we gave a background of our study, backing it up related works and added the values of the system. In the second part, we presented our solution that enables a teacher to enhance their online course and a remote practical work. In the third part, focused on the concentration level detection and we presented the concentration level equation. In the fourth part of our work, we focused on the experiment aspect of our solution and interpreted the result. The final section we concluded and made recommendations for further research in the frame of e-learning,systems.

2. Proposed Solution

E-learning is one from many ways international collaborations among universities is achieved. In fact, the virtual remote education system has proven to be beneficial to both teachers and the students. A student can comfortably study and graduate from any international university without physically being present in that particular country. The quality assurance of the e-learning is one of the most important solutions that allows us to optimize this system. Our proposed solution seeks to enhance online education system by detecting students' emotions in real-time. Our application is composed by two parts. The first part which is the student side must be installed on the learner's machine. This application will enable us to detect and analyze the student emotion based on his facial expression. The second one it is used in the teacher side. This module will collect information sent by the student machine, analyze the received information, and draw the learner level concentration on the teacher screen. Figure Fig.1 shows our application structure. To make our application operational in real-time, we divided the treatment information between student and teacher's machines. The extraction of the student expression will be done in the student machine. The interpretation and the final treatment will be insured by the teacher machine.

Findings from literature shows that teachers were not able to maintain the discipline needed in remote classrooms like what is generally seen in the traditional face-to-face system of education.

Our application enables a teacher to ensure the discipline needed for the smooth running of the remote classroom. Let's take in the case of an examination; if there is any malicious act going on, our system will automatically scan and capture the facial expression of that student at that particular moment, backing it up with a message signal that would be sent to the teacher by the alert agent indicating that a malicious act has occurred and the necessary disciplinary action will be taken immediately.

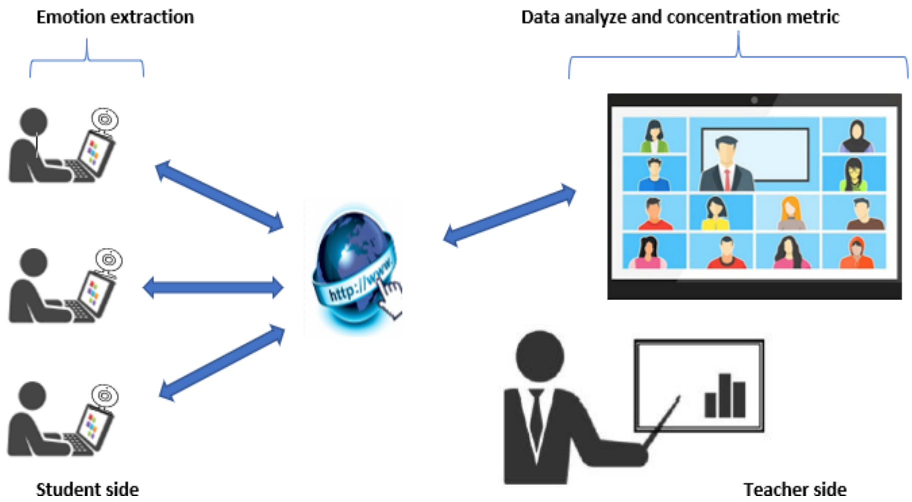

Fig.1: Emotion metric application structure

3. Concentration Level Detection

The emotion detection in our work is based on the learner's facial expression. The concentration level is dependent on multiple facial parameters. For our study, we will use the eye movement, head movement, lip, and facial muscle of our students. We developed a machine learning that helped us to create concentration card identity for each learner. Using that, we will find the best facial expression that able us decide if these students are concentrating or not. Using this machine, we can define a list of parameters dependent which is on the concentrate state of learner during the online learning process. After which we would then detect the emotion facial expression and then make a comparison between the real-time detected parameters and the saved values formed by our machine learning for each student. The result of this comparison will allow us to measure the concentration rate of our student.

This method enabled us to solve the problem of the student facial expression between various students; this is because each student has their own facial expression. The machine learning with the help neural network process helps avoid the complexity of the facial interest region. To authenticate our results, we suggest that teachers should introduce gaming education in their e-learning.

The concentration level and interest of most students will increase when playing a game dedicated for education. We can start our courses by asking the students some questions and providing a reward for the fastest respondent. Student will be more attracted to be the classroom winner. These two proposed methods will enable our machine learning to optimize the concentration card identity content.

The concentration level C_i for the ith student can be expressed by the following equation:

$$C_i = \sum_{i=1}^{6} \frac{a_i Emotion_i}{6} \qquad (1)$$

Where a_i is the coefficient of the ith of the ith emotion and $Emotion_i$ is the rate of one of the lists [happiness, surprise, sadness, anger, disgust, neutral].

Our goal is to estimate the a_i coefficients for each student. This coefficient will be estimated by experimental method in the next section.

4. Experiments and Results

In this section, we will find the relationship between the learner's emotion and the concentration level. This relationship will able us estimates the a_i for each student using experimental method. To enhance our parameters, we used three methods that enabled our student concentrate more.

The first one is based on learning game. The student is more attracted to learning by playing games. Our game allows the student make a geostationary satellite. The student can choose the velocity to launch the satellite in the space. The launched satellite can have three possibilities according to their speed. The satellite can be placed in the orbit, return to the earth, or leave completely the earth.

The second method is easy based. Students will be allowed to do an easy exercise and the winner of the activity will be announced. By doing so, everyone would be interested to be the classroom winner.

The third one is based on a dedicated satisfactory questionnaire addressed to the student. This can go a long way helping the student express their challenges concerning the course content and their comprehension rate. This method will help us in confirming the results obtained by the previously methods.

Our application combines the results obtained in the three steps above to estimate the coefficient emotion of each student. Due to COVID-19 our High Institute of Applied Mathematics and Computer Science in Kairouan decided to adopt the learning blinded system. This decision gave us the opportunity to test our system.
Our application has been tested with different students who participated in online courses both at masters and license (undergraduate) levels. We have 20 students in master's level that followed the network system course remotely and 20 students that attended an online course in satellite network. Each student attended 14 seances for one hour and 30 minutes. Each student has been invited to install our student application which will help us in getting the learner emotion.
The figure Fig.2 shows the student's emotion detected in the learning process of our application.

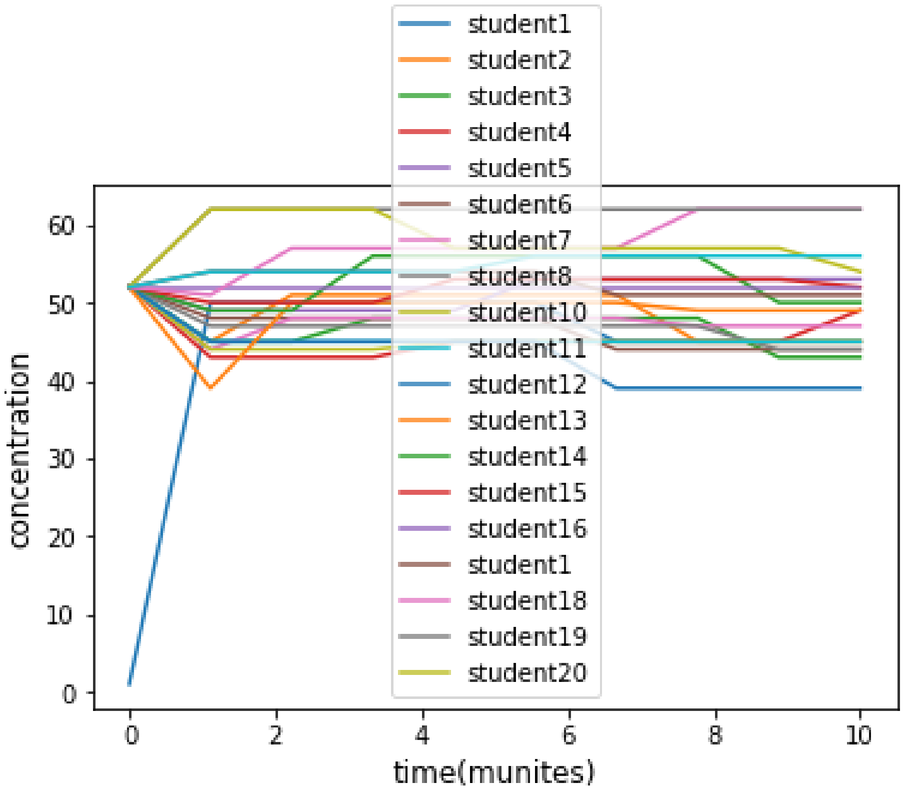

Fig. 2 Student concentration

According to the figure Fig. 2 and equation (1), we estimated the coefficient emotion for each student. The parameters are illustrated in the table Tab.1. below:

Emotion coefficients	a_1	a_2	a_3	a_4	a_5	a_6
Student 1	3.445	2.333	1.733	0.473	0.121	0.231
Student 2	3.552	2.154	1.855	0.435	0.152	0.223
Student 3	3.122	2.147	1.803	0.48	0.166	0.253
Student 4	3.145	2.123	1.737	0.495	0.178	0.233
Student 5	4.123	3.321	1.833	0.463	0.111	0.221
Student 6	4.158	2.896	1.775	0.545	0.192	0.283
Student 7	3.145	2.789	1.703	0.583	0.196	0.252
Student 8	3.152	2.456	1.822	0.552	0.159	0.226
Student 9	2.997	2.133	1.736	0.579	0.191	0.281
Student 10	3.147	2.554	1.756	0.436	0.175	0.254
Student 11	3.985	2.114	1.825	0.589	0.196	0.273
Student 12	3.149	2.565	1.698	0.577	0.173	0.293
Student 13	3.189	2.489	1.766	0.573	0.223	0.214
Student 14	3.178	2.154	1.812	0.435	0.154	0.225
Student 15	4.011	3.121	1.741	0.523	0.152	0.223
Student 16	4.811	2.145	1.852	0.585	0.141	0.299
Student 17	3.557	2.786	1.829	0.525	0.123	0.231
Student 18	3.256	2.145	1.777	0.435	0.157	0.239
Student 19	3.633	2.789	1.843	0.522	0.165	0.243
Student 20	3.966	2.369	1.811	0.425	0.145	0.232

Tab.1: Student’s emotion coefficients

After forming the identity emotion for each student, we can now test our solution to detect the concentration rate of our learners.

The results of our application are given in the figure Fig3.

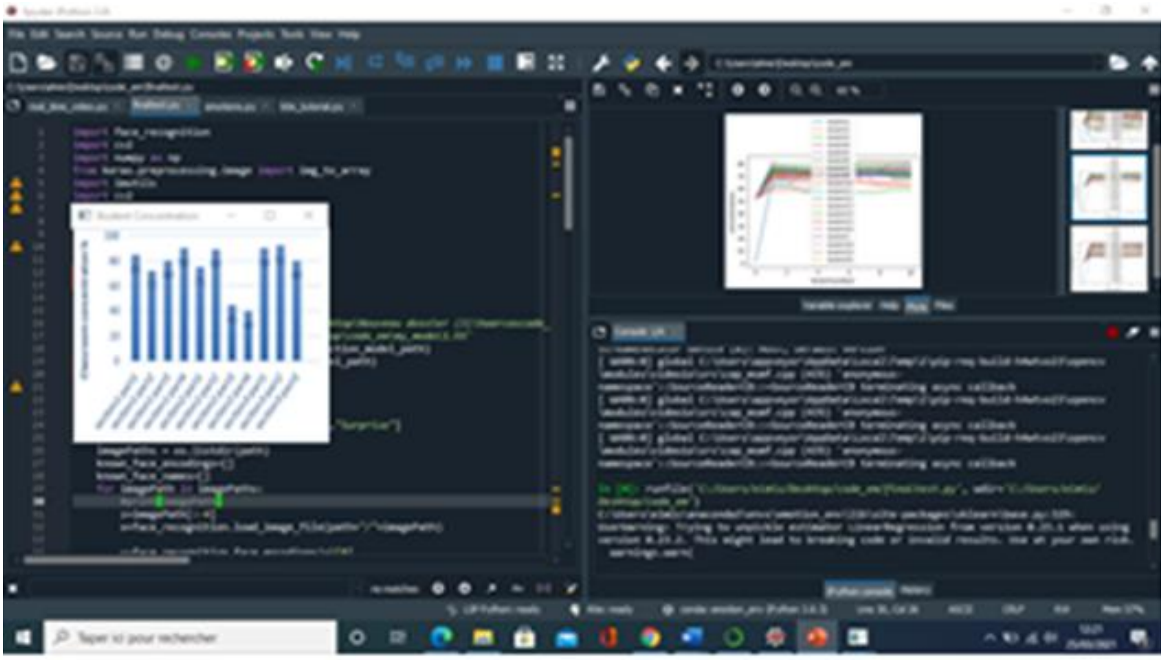

Fig. 3 Example of our metric application

According to the result obtained during the first semester which was from 28 September 2020 to 15 January 2021, the majority of the students were motivated to be concentrated when we informed them that metric concentration detection will be implemented in our courses and the teachers can fellow and see the results in real time.

With our application teacher will now be able to:

- Know the recent updates on a courses,
- Fellow up the students concentration in real time,
- Enhance courses scenario and contents,
- Notify students who have less concentrate in real time,
- Motivate student to be more concentrated,
- Make the learning process more attractive for the learner,
- Generate a weekly and monthly concentration report of students,
- Classify each student based on their concentration level.

The percentage of the students' concentration in the classroom is illustrated in the Fig. 4 below. From the results obtained we can clearly see that there is every need to enhance the course content and change the course scenario in section 2 – part 3 which is at 45% and section 2 – part 4 which is at 40% based on the fact that it fell below 50% of the classroom concentration as compared to other sections.

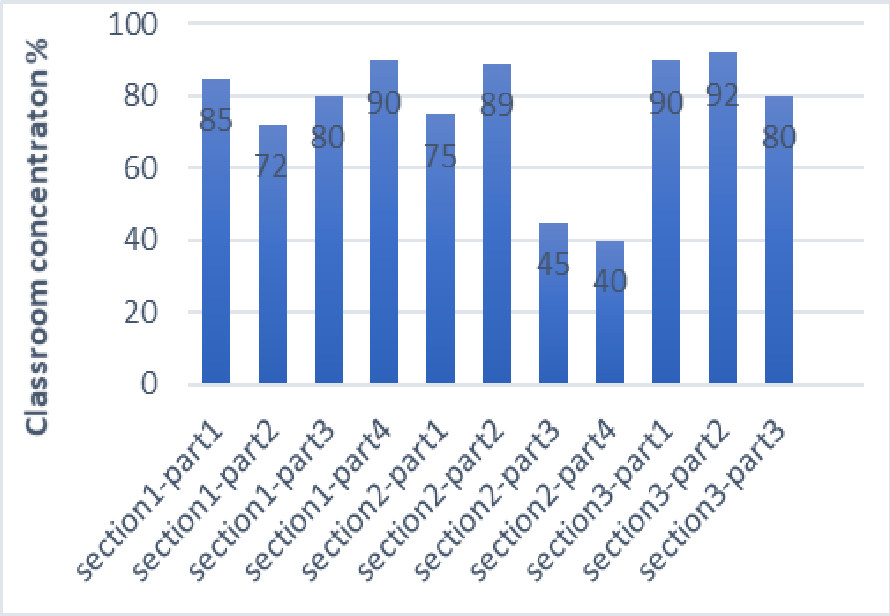

Fig.4 Percentages of students concentrate

In other to enhance our application, we integrated our reporting tool which was developed under the e-LIVES project. The integration of e-Learning and the remote lab into educational systems will go a long way in solving the problems faced by the educational sector, as it plays a vital role towards enhancing quality learning and making the learning process a fun-filled one. The system is a tool that enables the data collection of detailed reports of the students and teachers on their level of satisfaction concerning remote practical works and online education [13].

This reporting tool interface is illustrated in Fig. 5. Our reporting tool has detailed information of their responses, ranging from their response, average in percentage and the total number of respondents. Under the responses table, 57% (8) of the respondents totally agreed, 29% (4) agreed and only 14% (2) disagreed; this implies that 86% of the respondents are satisfied while 14% are unsatisfied with remote practical works and online education.

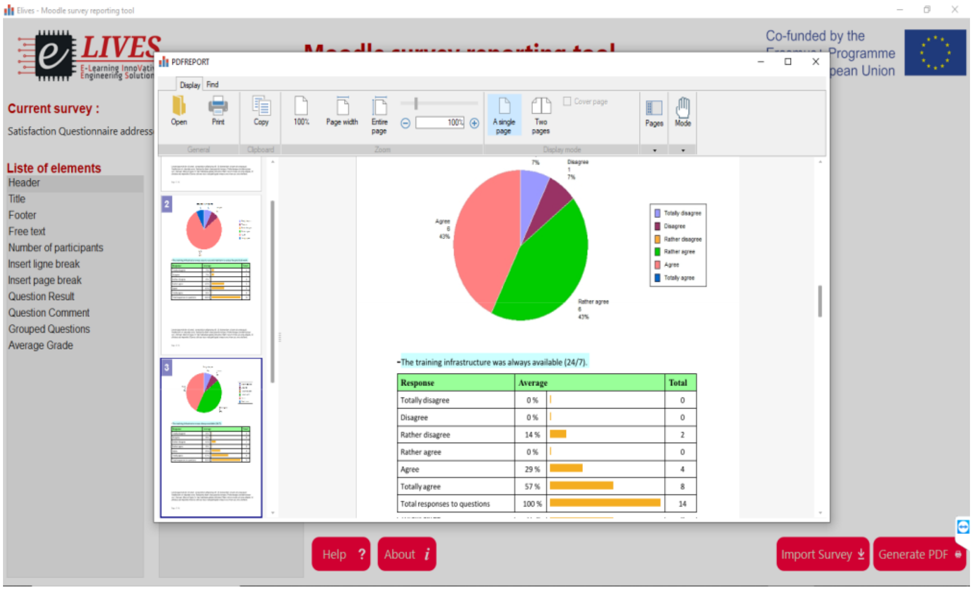

Fig.5 Reporting tool interface

5. Conclusion

Due to world situation create by COVID-19; the e-learning system became a necessity to ensure the education continuity. In face-to-face system, a teacher can follow up on their students and have information about their concentrations. But in online system teachers do not idea of the concentrations rate of their learners. In this paper, we proposed and test a metric solution that can enable teachers know the concentration rate of their students in real time. This application is very helpful to those in the academic sector to enhance their course and to look for a very good methodology for online teaching. Our solution enables us to generate a comprehensive report file that contains statistics and classification of student concentration.

In our future work, we will try to enhance the detection of student facial expression. We will also try to apply our results in large number courses and for big number of students. We will also test our solution for a remote lab system and manufacturing process.

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