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Article info

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Abstract
Academic stress is an emotion that students experience during their time at the university, sometimes causing physical and mental health effects. Because of the COVID-19 pandemic, universities worldwide have left the classroom to provide the method of teaching virtually, generating challenges, adaptations, and more stress in students. In this pilot study, a methodology for academic stress detection in engineering students at the University of Pamplona (Colombia) is proposed by developing and implementing an artificial electronic nose system and the galvanic skin response. For the study, the student’s stress state and characteristics were taken into account to make the data analysis where a set of measurements were acquired when the students were presenting a virtual exam. Likewise, for the non-stress state, a set of measurements were obtained in a relaxation state after the exam date.

To carry out the pre-processing and data processing from the measurements obtained previously by both systems, a set of algorithms developed in Python software were used to perform the data analysis. Linear Discriminant Analysis (LDA), K-Nearest Neighbors (K-NN), and Support Vector Machine (SVM) classification methods were applied for the data classification, where a 96% success rate of classification was obtained with the E-nose, and 100% classification was achieved by using the Galvanic Skin Response.

1. Introduction

Stress is one of the mental diseases currently in force. This malady seems to be unnoticed in society, but it affects many people worldwide in the XXI century. Most of the time, stress is focused on those places where people are exposed to various stimuli generated by modern life; however, it affects population centers such as universities [1]. Higher education is considered the most crucial period of human life because it involves changes in habits and lifestyle, troubles in adaptation, and the transition into the education system. According to research studies on this topic, the entry term and graduation of a student from an educational institution is often a learning experience linked with academic stress. This academic stress could be defined as the one produced parallel to the educational field. Stress is an adaptive and psychological systematic process that depends on the student [2]. Some authors have stated the principal source of stress in higher education students is the stressors that are the academic factors or stimulus from the organizational academic atmosphere that overwork and pressure students to provoke an unpleasant physical environment in the classroom. These stressors cause students to see the educational process as a threat or challenge, producing individual cognitive changes, physiological, psychological, and behavioral factors [3].

The COVID-19 pandemic and the virtual education challenges as a strategy to continue with the academic semester in universities in Colombia have generated some negative emotions in students such as anxiety, depression, and stress. Such factors may cause students unfavorable effects in their learning process and mental health because they have to take responsibility for their learning over [4]. This usually causes students to assimilate different responsibilities and cannot develop them properly because of the lack of adequate explanation from teachers, amount of homework, new methodologies adaptation, time management, lack of materials and electronic devices, for instance; a computer, internet, and others generate in students low performing, dropouts and large stress levels [5].

Some traditional methods based on psychometric survey applications are used for determining stress and anxiety [6]. The psychometric
survey test psychological and social aspects, including personality and abilities; however, the disadvantages of these methods are that people can give false answers that decrease their negative characteristics or increase their positives. These methodologies might be inaccurate or deceptive if they are not interpreted correctly. Some tests need much time because of the number of questions that sometimes might allow the answers to be fixed since participants often have to pick a response that does not fit with their personality [7]. Another way to measure stress is when the human body starts behavioral and physiological responses to emotional stress such as happiness, fear, anger, surprise, disgust, and other [8]. They cause the sympathetic nervous system to react to this stimulus and activate the adrenal medulla, which releases the generation of norepinephrine and subsequently the cortisol production (considered as a stress biomarker) from the adrenal cortex and adrenaline, causing an increase in blood pressure, heart rate, respiratory rate and activation of the sudoriferous through the secretion of sweat [9,10].

In a research study conducted about this topic, electronic devices to measure stress in diverse environments such as social networking usage [11], builders [12], dentists [13–15], and higher education teachers were used. Another method was applied from the physiological patient signals in which electrocardiogram (ECG) [16,17], ECG characteristics, for example heart rate (HR) [18,19], electroencephalogram (EEG) [20,21], electrodermal activity (EDA) [22,23], electromyogram (EMG) [24,25], breathing [26,27], blood volume pulse (BVP) [28], skin temperature [29,30] the pupil diameter [31,32], thermal photographs [33], etcetera, which also were implemented. Cortisol in biofluids and the Volatile Organic Compounds (VOCs) emitted by the skin seem to be practical and useful markers for the detection of emotional stress events [34,35]; nevertheless, nowadays, there are no investigations about the application of electronic devices for the parameter measurements related to stress in academic settings. In this research study, two methods based on emotional sweating were applied. The emotional sweating behavior is generated when there is a reaction to a sensory stimulus as stress leads to superficial skin sweating focused on the palms of the hands, sole of the feet, forehead, and armpits [36]. The first method measurements were based on the finger’s electrodermal activity where a Grove 1.2 GSR sensor from “Seeed Studio” company was implemented. On the other hand, for measuring the skin conductivity in all students, the Grove sensor was used following these conditions: relaxation state and stress state generated during the development of a virtual exam, based on the principle that the value of electrical conductance will depend on sweating. Therefore, by increasing the stress level perceived, the sweating increases resulting in a skin electrical resistance reduction. Otherwise, if the student is relaxed, perspiration decreases; therefore, the skin resistance increases [37].

The second method proposed was based on VOCs detection method since it is a non-invasive technique widely used in medicine for diseases and disorders inquiry [38,39], VOCs method is developed through breath analysis, urine, sweat, and other bio-fluids. This way, if a sick person presents changes in VOCs pattern, a difference from a healthy individual is established. As mentioned above and taking advantage of the biological information about sweat, where many compounds from the human sweat (in which more than 500 are volatiles) have been distributed of some sudoriparous glands of the skin, the VOCs profiles are different in the body regions [35] and affect an individual odor. When an event is interpreted as threatening by an individual, it provokes behavioral responses such as facial expressions and physiological responses that generate body odors. Those responses may have a distinctive quality indicating VOCs olfactory roles that can exist and be associated with human emotions [41,42].

For determining the VOCs profiles associated with academic stress, an electronic nose system was designed and implemented. The electronic nose is composed of a gas sensor array with overlapping sensitives, a data acquisition card, data pre-processing methods, and processing software for data analysis [43]. One of the few studies conducted for the stress detections is the investigation carried out by García-Cortes in which they described an Electronic Nose for the detection of stress biomarkers such as cortisol and adrenaline [44].

Different algorithms such as pattern recognition method and machine learning technique were used for data processing. During this process, the free software Python version 3.8 with the “Scikit learn” library version 0.23 was implemented [45]. On the other hand, the SISCO inventory of academic stress as a validation technique was applied. This technique has been used in different studies in which validation tests, reliability, and statistical and psychometric analysis were carried out and support its applicability in the academic field [46,47]. The SISCO inventory is structured in 31 items that identify if the intervieewee is a candidate to answer the list, determine the level of academic stress intensity, and recognize the environmental demands valued as a stressful stimulus [48]. During the year 2020 and due to the pandemic, different studies have been carried out to study the student’s stress because of COVID-19.

Therefore, several studies were conducted on related methods about online learning [49], stress and anxiety during confinement [50], and another recent research on the perception of stress in students in virtual classrooms [51]. Additionally, other methods have currently been disclosed to determine the consequences of stress in students from the stressors related to COVID-19 and their mental health concerns [52–54].

For the stress detection in academic contexts during the pandemic, it is necessary to make the research question to answer the problem of stress detection in students. Is it possible to detect stress in engineering students through electronic devices such as Electronic Nose and GSR during the COVID-19 pandemic?

2. Materials and methods

2.1. Measurements protocol and participants selection

A group of 25 volunteer students from the Faculty of Engineering and Architecture of the University of Pamplona – Colombia, participated in this research, signing an informed consent to contribute to the study. Among the 25 students, 7 were women, and 18 were men between 18 and 30 years. Besides, each of the volunteers reported being healthy, non-smokers, not diagnosing any psychological disorder, and not suffering from underlying diseases. In the measurement collection, the participants abstained from drinking carbonated and alcoholic beverages, medications, engaging in sexual activity, consuming smelling foods (for example garlic, onion, and asparagus), and exercising excessively the previous day. Additionally, they were instructed not to use lotion, sunscreen, creams, makeup, and others. For the stressful state, the samples were collected while the students were preparing virtual exams. For the state of relaxation, the samples were gathered once the students finished the exams of the different subjects enrolled in their academic semester between March and June 2020. It should be noted, and despite the quarantine and curfew in Pamplona city due to COVID-19, it was possible to acquire a set of measurements to perform the tests.

Physiological measurements were taken at participant’s residences, following the necessary safety measures such as overalls, face masks, and disposable gloves. Table 1 illustrates the number of samples taken by each device, where all measurements were arranged by age and each student’s status.

2.2. Galvanic skin response

The galvanic skin response is the measurement of the continuous variation in the skin’s electrical characteristics, such as electrical conductivity, which is affected by the human body sweating. The galvanic skin response measurement is based on the fact that the skin resistance changes depending on the sweat gland’s activation level of the skin during the perspiration process. The sweating of the human body is...
MOX sensors were used in this study. Gas sensors are based on metal oxide (MOX) semiconductors, photodetection detectors, biosensors, nanotechnology, etc. [56], where the skin conductance and vice-versa. That reaction allows skin conductance increases, causing greater perspiration, which leads to an increase in the sympathetic branch of the ANS is overstimulated, the sweat gland response controlled by the Autonomic Nervous System (ANS). When the sympathetic branch of the ANS is overstimulated, the sweat gland response increases, causing greater perspiration, which leads to an increase in skin conductance and vice-versa. That reaction allows skin conductance to be used as a measurement of the response of the human sympathetic nervous system [55]. The GSR signal was measured by placing the device electrodes on the index finger and the middle finger of the patient’s non-dominant hand during a measurement time of 5 min (Fig. 1). The patient was asked not to move his/her fingers or touch the electrodes with the other hand.

2.3. Electronic nose system

2.3.1. Design

The electronic nose system has a set of gas sensors combined with pattern recognition algorithms and artificial intelligence methods to classify the volatile organic compounds or marks. The most widely used gas sensors are based on metal oxide (MOX) semiconductors, photodetection detectors, biosensors, nanotechnology, etc. [56], where the MOX sensors were used in this study.

Fig. 2 shows the components that form the olfaction system: The gas sensor array developed for this purpose was connected to an Arduino Astar32U4 board with 8 analog inputs capacity and a 10-bit resolution. The chamber was built-in stainless steel with a dead volume of 20 mL, provided with a packaging that supplies airtightness and portability. The casing of the sensor chamber was provided with two orifices, one for the inlet and the other for the outlet, to evacuate the VOCs previously acquired from the skin. The sensor array is composed of 8 commercial chemical-resistive sensors manufactured by Hanwei and Figaro companies (see Table 2). The sensors were selected based on their overlapping sensibilities, gas target to be detected, and different characteristics to acquire the most significant amount of information from the spectrum of volatile compounds measured during the analytes absorption and desorption process. Each of the sensors was powered with a 5 VDC power supply and load resistances of 1 kΩ, which was used to obtain a satisfactory response when making the measurements. Furthermore, the sensor heaters were also powered individually with the same power supply to stimulate the active layer to detect the VOCs. The power consumption of the sensor array was 1 A approximately which was supplied through the power supply described above.

2.3.2. Measurement protocol

Fig. 3 shows the scheme for the VOC’s extraction emitted from the skin, specifically on the forehead. The patient is in contact with a metal funnel placed on his/her forehead, as shown in Figs. 3 and 4. Valve 1 allows or prevents the opening of VOCs emitted by the patient to the gas sensor array. The funnel is held by the student for five minutes, which is an experimentally estimated time to accumulate the maximum amount of compounds in the funnel since the gases take the entire volume of the container. At this stage, the pressure is applied with the funnel on the student’s forehead to avoid the compounds being leaked outside. Then, after 3 min, and from the funnel’s location on the patient, a vacuum pump is activated to purge the gas chamber with air keeping valve 2 opened and valve 1 closed. The purging process helps to clean the piping loop and the gas sensor chamber. After two minutes of purging, valve 1 is opened and valve 2 is closed since it allows the path of the volatile compounds into the measurement chamber for 2 min. At the end of these two minutes, valve 1 is closed, and valve 2 is opened, again to clean the measurement chamber and the compounds that may have been trapped. This process is done in ambient air. Finally, after this time, the vacuum pump is turned off, and it is prepared to repeat the test once again. As mentioned above, the data acquisition was performed with an Arduino Astar32U4 board connected to a laptop with a graphical interface designed to monitor the gas sensor’s behavior in real-time, apart from saving all signals obtained from each sensor in. txt files.

2.4. Processing methods

2.4.1. Linear discriminant analysis (LDA)

LDA is a supervised classification method that performs a selection of independent or predictor variables that allow differentiating groups and select which of the variables may achieve the highest classification among the groups on the data set. It gives a quantitative answer to the level of discrimination in which a subject or object belongs to one group.

| N° | Label | Age | Semester | Samples in relaxed state | Samples in stressful state |
|----|-------|-----|----------|--------------------------|----------------------------|
| 1  | A     | 22  | 8        | 3                        | 1                          |
| 2  | B     | 25  | 4        | 3                        | 1                          |
| 3  | C     | 19  | 5        | 3                        | 1                          |
| 4  | D     | 18  | 1        | 4                        | 1                          |
| 5  | E     | 25  | 10       | 4                        | 1                          |
| 6  | F     | 24  | 10       | 3                        | 1                          |
| 7  | G     | 23  | 9        | 4                        | 1                          |
| 8  | H     | 21  | 7        | 5                        | 1                          |
| 9  | I     | 20  | 7        | 5                        | 1                          |
| 10 | J     | 24  | 9        | 6                        | 1                          |
| 11 | K     | 27  | 10       | 3                        | 1                          |
| 12 | L     | 21  | 9        | 4                        | 1                          |
| 13 | M     | 26  | 5        | 5                        | 1                          |
| 14 | N     | 24  | 7        | 5                        | 1                          |
| 15 | O     | 23  | 6        | 5                        | 1                          |
| 16 | P     | 24  | 10       | 5                        | 1                          |
| 17 | Q     | 23  | 10       | 5                        | 1                          |
| 18 | R     | 23  | 5        | 5                        | 1                          |
| 19 | S     | 30  | 10       | 5                        | 1                          |
| 20 | T     | 24  | 9        | 5                        | 1                          |
| 21 | U     | 23  | 10       | 5                        | 1                          |
| 22 | V     | 23  | 7        | 5                        | 1                          |
| 23 | W     | 24  | 9        | 5                        | 1                          |
| 24 | X     | 20  | 8        | 5                        | 1                          |
| 25 | Y     | 22  | 9        | 5                        | 1                          |

Table 1 Information about the number of samples and patient labeling.

Fig. 1. Sensor GSR, a) electrode location, b) Electronic card y c) electrodes.
or another. Because of these characteristics, this technique is considered a dependency and classification test. Its operation is similar to the logistic regression analysis method, although the previous one only works with quantitative variables. From the application of discriminant analysis, the discriminant function equation is obtained. This equation represents the linear combination of canonical variables (also known as predictive variables). The maximum number of discriminant functions that can be achieved is equal to the minimum number between the variables and the number of groups minus one. In Eq. 1, the coefficient discrimination $a_j$ represents the weighting coefficients of the predictive variables, which show the level of contribution of each variable in the discriminant function. Likewise, covariation present in the predictive variables influences the result of the discriminant coefficients [57,58].

$$Y = a_0 + a_1 \times X_1 + a_2 \times X_2 + \ldots + a_p \times X_p$$

(1)

Where $X$ are the independent variables, $a_0$ is the constant and $a_1\text{--}a_p$ are the discrimination coefficients.

The resulting discriminant Eq. (1) will be optimized as it provides a classification rule that decreases classification errors and explains more of the variability between groups [59].

2.4.2. K-NN (K-Nearest Neighbors)

The K-NN algorithm is applied in pattern recognition for data classification. It is famous for its simplicity and low error rate. The algorithm principle is: if most of the $k$ samples similar to a query point $q_i$ in the space function belong to a specific category, then a verdict may be that the query point $q_i$ falls into this category. The distance can measure similarity in features. A dataset must contain the labels and must be shown at the beginning of the algorithm. Then, for a query of $q_i$ data, whose label is unknown and presented by a vector in the feature space, the algorithm calculates the distances between it and each point in the data set. After ordering the results of the calculated distances, the decision of the class label of the test point $q_i$ is based on the label of the $k$ closest points in the dataset. Each point in a d-dimensional space might be expressed as a d-coordinate vector [60], as:

$$p = (p_1, p_2, \ldots, p_d)$$

(2)

The distance between two points in the multidimensional feature
space can be defined in many ways. The use of Euclidean distance is one of the most used methods for sample classification, and the equation is given by:

$$d(p, q) = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2}$$

(3)

2.4.3. SVM (support vector machine)

An SVM establishes a decision surface between two or more different classes in an input dataset. When used to classify only one category, the support vector’s information defines a decision boundary that encompasses the entire learning dataset, regardless of the information that corresponds to data outside the boundary generated. The information is mapped using a linear kernel defined in the algorithm to a larger space, in which it intends to make an optimal separation between each of the classes using a border function. The border function can return to the input space, and it allows the information corresponding to each of the categories to be separated, resulting in a grouping [56]. In different situations, the SVMs have performed very well for data classification, better than conventional machine learning methods such as neural networks, and they have been used in scientific fields as useful tools for solving classification problems of various datasets. SVM modeling is remarkably optimized as it is not necessary to have all the points in the dataset to find a solution when defining the decision surface [61,62].

2.5. Implementation of SISCO inventory

SISCO inventory is a technique extensively used to determine students’ academic stress levels. It is a self-administered instrument, and it is possible to carry out its filling collectively or individually; no more than 10 min are needed to provide a solution. It is configured by 31 items that are categorized as follows: 1 filter item that, in dichotomous terms, allows determining whether the respondent is eligible to reply to inventory. An item on a “Likert scale” with five quantitative values identifies the academic stress level intensity. Additionally, 8 items allow identifying how often the demands of the respondents environment are considered as stressors stimuli, 15 items that serve to determine how often symptoms or reactions to stress stimulus occur, and finally 6 items that show how often the respondent uses the coping strategies defined in the test [46]. It was applied virtually to each of the participants by trained staff from the University of Pamplona psychology program. This method was used to validate the results obtained with the devices mentioned above.

3. Results and discussion

3.1. GSR responses

Fig. 5 illustrates the GSR sensor response through two means to the same patient during a state of relaxation a) and during a state of stress b). As shown in the figures, the measured variable of the sensors is obtained in volts. The signals were acquired for 5 min with a sampling rate (10 samples per second), allowing us to obtain a significant difference between the two responses, and also allowing an exact classification of the measurements.

3.1.1. Data processing with GSR

The “StandardScaler” function used by the library of Phyton software was applied to the set of measurements acquired from the GSR device before implementing the Linear Discriminant Analysis algorithm with Python. Fig. 6(a) and (b) in 3D show the dispersion of measurements made from the factors resulting from the LDA algorithm, it is observed that the algorithm classified each of the two classes in the dataset. The LDA factors were used as data testing and validation for the SVM algorithm, which was later implemented with a linear kernel and using the k-fold cross-validation method with k = 5. On the other hand, a graphical representation of the algorithm’s response was made from the hyperplane distance regarding each measure.

Fig. 6(c) illustrates the scatter plot, where a 100 % success rate of classification was achieved, whereas the Receiver Operating Characteristic (ROC) and Area Under Curve (AUC) graphical representation were made from the classifier results (see Figure (d)).

3.2. E-nose responses

Fig. 7 illustrates the measures (a), (c), and (e), which correspond to three samples that were taken from a patient in a relaxation state, and measures b), (d), and (f) show the behavior of the sensors in three samples taken during the presentation of a midterm exam regarding the state of stress. As observed in the measurements with the sensors, it was possible to visually check the signal evolution in the measurements made corresponding to a stress state and a relaxation state. On the other hand, it is shown that the measured variable of the sensors is in volts, and the patients condition is determined with this amplitude. Therefore, that state can be classified through artificial intelligence algorithms or pattern recognition methods. Additionally, the horizontal axis represents the signal acquisition time and the cleaning time of the sensors. Each Figure shows the gas sensors signals, which respond adequately to the skin’s volatile organic compounds emitted.

3.2.1. Data processing with E-nose

The processing and classification of gas sensor signals acquired during the relaxation and stress state measurements were done using the open-source Phyton, implementing the ‘Scikit-learn’ library in a similar way to GSR procedure, where all the processing functions used to belong to this library.

It is necessary to standardize the data to prevent large-scale responses from affecting the discrimination and classification algorithms. For this purpose, the “StandardScaler” statement belonging to the "processing" module was used; this instruction standardizes the data to be used by eliminating the mean and scaling to the unit’s variance.
Centering and scaling are independent in each function to calculate the most relevant statistics of samples in the dataset, i.e., the matrix with the gas sensor information. Dataset standardization is necessary for many machine learning estimators, which could respond negatively when the dataset’s individual characteristics do not resemble the standard data usually distributed, for example, with zero mean and unit variance.

After standardizing the data, the Linear Discriminating Analysis algorithm was applied, where Fig. 8 (a) and (b) show the graphs of the first components obtained by LDA containing 85% variance from the dataset. The 3D chart shows with green dots a relaxation state, and the red ones represent the samples taken in a state of stress.

The first classification algorithm implemented was K-NN with k = 5, Euclidean distance, using as training and testing data from the LDA algorithm. Fig. 8(c) shows the algorithm’s decision boundary, where the k-folds cross-validation method was used for training and validation with k=5, in d) the ROC curve of the model where 89% accuracy, 90% precision, and 89% sensitivity were achieved.

In this case, the LDA algorithm factors were used as training and testing data for the Support Vector Machine (SVM) algorithm with a linear kernel and using the k-folds cross-validation method with k = 5. In order to achieve a graphical representation of the algorithm response, the hyperplane distance of each sample was charted regarding the number of samples shown in Fig. 8(e).

Fig. 8(f) shows the receiver operating characteristics (ROC) chart, achieving 96% accuracy, 96% precision, and 95% sensitivity with this model.
3.3. SISCO statistical method analysis

Stress values or levels can be defined as the frequency or intensity in which the individual experiences the main symptoms of stress, stressful stimuli, and academic-oriented coping skills: the mild stress level going from 0 to 33 %, 34–66 % moderate, and finally for a deep stress level of 67–100 %. As for the scores obtained from students, after applying the SISCO inventory, those are found in Table 3.

The overall results allowed us to visualize that from 100 % of respondents, the 2% corresponds to 1 student who mildly perceived academic stress, 66 % corresponds to 16 students who perceived moderate academic stress, and 32 % corresponds to 8 students who perceived academic stress in-depth as shown in Fig. 9.

As additional information, it is stated that the stressors perceived more frequently by the group of students who participated in the study according to the results obtained by the SISCO inventory were: evaluations of teachers (exams, essays, research papers, etc.), fear of getting wrong answers and overload of school tasks and jobs. Among the coping strategies, those with the most significant effect were: elaboration of a plan, execution of ideas, and defense of ideas without harming others.

Furthermore, throughout the tests conducted and according to the psychological analysis obtained by the consent reported in the study, the symptoms frequently presented by the students were concentration problems, sleep disorders (sleep difficulties or nightmares), inability to relax, anxiety and headaches. To a lesser extent, there are symptoms such as biting objects (chewing gum, erasers, among others), increased conflicts, and aggressive feelings.

As an important and novel finding in this study, we can highlight the excellent results that were obtained from the Electronic Nose composed of chemical sensors array to measure VOCs, since at present there are no studies where it has been shown that a device sensory perception system
specially developed to measure gases and with such characteristics is able to discriminate and classify samples acquired from the sweat of the forehead of students with symptoms of stress and relaxation state. Therefore, we can mention that with this system, a way is opened to explore the implementation of electronic noses to measure people’s mood.

On the other hand, we could confirm that one of the best methods to measure academic stress is through electronic devices using the GSR signal that is acquired by the response produced by the conductance of the skin, and it was determined that this type of device might be used easily, and the response is obtained in few minutes. Therefore, it should be mention that this study developed by using an E-nose system and a GSR response is perhaps the first of its type, as the COVID-19 pandemic has been around since early January 2020. Every country in the world has suffered the consequences of this pandemic; therefore, this study might be applied to every country globally.

Additionally, despite obtaining excellent results with the Electronic Nose and GSR signals, it is essential to mention that in the literature, there are several studies on the use of electronic devices such as ECG, EMG, among others [16]; Therefore, it is recommended to carry out a more detailed study on academic stress where the responses of the physiological signals obtained by students in different states should be identified to get a greater number of characteristic patterns of each of the electronic devices. This would be important to define or standardize the data processing methods that would be used for the different types of signals, both physiological and biological.

4. Conclusions

Using the E-nose and GSR sensor, it was possible to determine in a non-invasive way the state (stress or relaxation) in which the student was at the measurement’s time. Through physiological signals measurements acquired from instrumental systems, it was possible to determine student’s level of stress through a real situation and environment in which the student finished presenting an exam, achieving results that allowed excellent discrimination and classification of the dataset. Therefore, a midterm exam can be considered a prolonged and robust stress agent since students have on average 2 h to complete it.

With the electronic olfaction system methodology, the patient’s condition (stressed or unstressed) was detected, achieving a percentage
Despite the limited number of samples acquired in the study due to COVID-19 and the difficulty of being in direct contact with the students, it was possible to achieve promising results for further research. Therefore, a more significant set of measures is expected to be carried out, taking into account the patient’s characteristics or state more profoundly before testing with sensory equipment and psychological analyses.

This study generated excellent results by detecting stress on university student’s, and it was the first to be carried out in this area during the pandemic.

We can mention that the results and findings obtained with both GSR and E-nose systems open a broad range of possibilities for using this kind of device in different areas to identify or detect when a person can be suffering stress, for identifying other mood states, and diseases detection related to the malady.

Additionally, the GSR and E-nose systems might be promising tools that can be applied to validate and improve the psychometric survey test or psychological methods. They can also reduce some disadvantages or errors because people can give false answers and generate bad psychological results.

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CRediT authorship contribution statement
Cristhian Durán (CD): carried out the materials and methods selection to be applied with the samples collection. He also participated in the paragraphs alignment and drafted the manuscript. Jennifer Carrillo (JC): carried out the state of art about academic stress detection and she made the bibliography. Camilo Albarracín (CA): participated in the design and develop of the E-nose and GSR systems. He collected all measurements and applied the different processed methods in order to classify the data set.

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Declaration of Competing Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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