Architecture for the identification of academic stress levels using Machine Learning and Internet of Things

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***Abstract*— Stress is a mental illness that causes serious health problems and even death when it is not detected and treated in time, although it positively and negatively influences many aspects of people's lives, studies show that it occurs more frequently in the academic life and generates a significant imbalance that occurs through various symptoms, whether physical, psychological or social, some of the most common symptoms are nausea, nervous spasms, depression, difficulty relaxing, lack of concentration among others, which causes that academic performance becomes deficient and negatively impacts the life project of the students, that is why, in this research, the architecture of a software module is proposed that allows identifying the stress level of university students through the use of Machine Learning, specifically Support Vector Machine (SVM) and the Internet of Things paradigm like non-invasive wearable devices.**

Keywords—Stress, Support Vector Machine, Academic environment.

I. Introduction

Stress is a mental disorder that, when not managed properly negatively influences the social, work and academic productivity of people, including manifestations of stress also affect physical health through diseases that, if not attended to in time cause death. In the academic field, according to studies carried out by UNAM, around 60% of university students in Mexico suffer from stress, which is reflected in the performance, behavior and general state of health of the students.

Academic stress is presented as a significant pressure that according to the assessment of each student, stimulates a stressful situation, and generates a series of symptoms that indicate that there is indeed an imbalance, some of the most common symptoms are trembling feet, nausea, nervous spasms, vomiting, sweating, restlessness, affective blockage, language alterations, among others. This instability pressures students to adapt to regain balance, however, when it is not possible to control the stressful situation, the body deteriorates and it provokes serious health problems. It is estimated that academic stress occurs more frequently when the students work and study, because to comply satisfactorily with both roles provokes demands that are complex and some students are not able to comply adequately, as well as, the interpersonal behavior to fit different situations.

Due to the great impact that academic stress generates in society, the need to contribute with a tool that allows to identify and to supervise the level of stress that the students present and thus finding strategies that benefit the quality of life and reduce the negative impact that hinders the academic development of students.

The paper is organized in follow sections: section II contains the summary of the works related to this research and the comparative analysis of the contributions and technologies that helped provide a solution to the problem; the section III presents the detailed description of the proposed architecture to provide a solution to the problem that was detected; the section IV describes a case study for stress detection is described and finally the section V presents the conclusion and future work.

II. Related Work

In this section, the works exposed are relevant, because contribute to the detection of stress through technological tools and these are closely related to a relationship with the present research.

A. Stress monitoring

In [1] a student stress monitoring framework was proposed that was based on IoT assisted by 5-layer fog clouds, the results showed that heart rate variability, skin conductance, head movement and eye blinking are the main parameters to determine the severity of stress. The authors in [2] focused on proposing an IoT system that efficiently detected a person's stress level and provided feedback that helped deal with stressors, the system consisted of a smartband module, chest strap, parameters such as electrodermal activity and heart rate were monitored in real time from the system. In [3] an IoT system for stress management of students was developed, which consisted of a mobile health application with relaxation content to minimize emotion and have an impact on reducing future stress, it was also composed of two elements: one that allowed the measurement of vital parameters to identify stress in students and the other for its control. In [4] the quality of life of athletes was analyzed to detect stress, prevent and control diseases and a real-time detection framework was proposed to analyze the stress level of a particular athlete, the proposed framework consisted of a hybrid classification technique called Multiple Output Regression with Deep Convolutional Neural Networks to analyze and identify various stress levels and their relationship to existing data.

B. Identification of stress parameters

In [5], the level of stress was detected using methods and techniques related to stress recognition devices that considered behavioral manifestation, physiological signal, physical features, emotional manifestation, facial expression, voice recognition, and others. In [6] the main objective was to identify parameters of the physical environment in a classroom and evaluate its influence on the concentration of students, the AdaBoostM1 algorithm was used to determine if students are concentrated in a class by the analysis of the values of these five attributes. In [7] an analysis of cognitive stress in students during the exam period through EEG biomarkers was carried out. The three brain waves such as theta, alpha, beta, the relative band energies, and the proportions of the EEG bands such as heart rate, neural activity, arousal index, vigilance index and arousal index, were considered cognitive performance attention resources extracted between the two mentioned conditions. In [8], the development of a remote stress detector system was proposed to measure the stress level of a person by reading the heartbeat, in addition Machine Learning was used to predict the patient's condition and the Internet of Things to communicate to the patient about their acute stress condition.

C. Sensors for stress detection

Authors in [9], used wearable sensors for data collection and machine learning algorithms to predict stress level, found that stress level is detected by some physiological measures such as heart rate, heart rate variability of heart rate and skin conductance, while the Support Vector Machine, Random Forest and K-Nearest Neighbor algorithms are more effective for classification. In [10] a model for the detection of mental stress states using sensor-based biological signals was presented, a multilevel deep neural network with hierarchical network learning capabilities was proposed convolution neuron, to combine high-level features and classify stress states. The authors in [11], identified stress in early stages based on five conditions with data obtained through IoT sensors. To obtain the pattern of stress detection, data from sensors such as the Galvanic Skin Response Sensor and the Electrocardiogram were collected. The dataset was then categorized with different classification algorithms such as Decision Tree, Support Vector Machine, and deep learning algorithms. The [12] showed that stress is detected through different physiological indicators, so a method was proposed to identify the state of stress of a person based on changes in skin conductance, skin temperature skin and heart rate variability. A wearable device that combined different sensors was implemented and the measurements taken by these sensors were analyzed in real time through a cloud-based artificial intelligence implementation to determine the user's stress level. In the analysis of the research presented, various solutions related to stress detection are found, however, there are some shortcomings in these solutions to specifically address academic stress, such as: (a) some works examine stress in a general way; (b) they are based solely on identifying when a person suffers from stress but not the level that they present; (c) they contemplate the same physiological responses for the detection of stress, that is, they do not propose new correlations to provide a more assertive response. Some significant improvements in these deficiencies are: (a) the development of a module specifically to identify academic stress; (b) the use of artificial intelligence techniques and non-invasive wearable devices to discover the value of new stress-related biomarkers; (c) the automatic classification of a student's stress level, according to the information extracted from the devices, corresponding to the user.

Table 1 shows a comparative analysis of the five most relevant works, in order to visualize the most notable similarities and differences.

TABLE I. COMPARATIVE ANALYSIS OF WORKS AND RESEARCH RELATED TO THE IDENTIFICATION OF STRESS.

Work research	**Problem**	**Contribution**	**Technology**
Verma and Sood 2019 [1]	Lack of a method to calculate stress parameters in students.	5-layer fog cloud-assisted IoT-based stress monitoring framework.	Classification algorithms, Kinect 3D, body area sensors Amazon EC2, WEKA 3.7.
Uzelac, Gligoric, and Krco 2015 [6]	Lack or loss of concentration of students during classes.	Identification of parameters of the physical environment in a classroom and evaluation of its influence on the concentration of students.	WEKA toolkit, AdaBoostM1 algorithm.
Gedam and Paul 2020 [9]	Stress is one of the main causes that lead to major chronic health disorders.	Analysis of stress detection approaches using sensors for data collection and machine learning algorithms.	Artificial Intelligence Algorithms: Support vector machine, Random Forest and K-Nearest Neighbor.
Rajendran, Jayalalitha, and Adalarasu 2021 [4]	Stress in college students increases due to academic problems and causes physical illness and mental illness.	Analysis and evaluation of cognitive stress and anxiety in students during the exam period using EEG biomarkers.	Methods: EEG, ECG and objective measurement, Perceived Stress Scale (PSS), classification algorithms: Naive bayes, Random Forest, linear regression and Support Vector Machine.
Zainudin et al. 2021 [11]	Stress weakens the immune system and has strong correlations	Stress detection system that uses heart rate as a parameter.	Machine learning algorithms, Internet of things

	with terminal illness, heart disease, and cancer.		

In Table 1, the comparison of the problem, the contribution and the technology that helped provide an adequate solution to the problem that was presented was made, these works focused on the identification of parameters related to stress and the various approaches where it occurs; A similarity they have is that most used artificial intelligence algorithms for stress detection and obtained favorable results, however, they do not specify the classification of the level of stress that occurs in students, a key element that is intended to be developed in this investigation proposal, through the use of a non-invasive wearable device for brain perception to find new biomarkers and the correlations they have with the existing ones to achieve the classification of the stress level in students efficiently.

III. Architecture Design

This section describes as a proposal the development of a module that allows the identification of the stress levels in university students through a Support Vector Machine (SVM) classification algorithm and wearables devices.

The proposed module will be used the values provided by the wearable device in order to identify the stress levels using the SVM supervised learning classification algorithm and the biomarkers of stress. The Figure 1, shows the architecture of the solution.

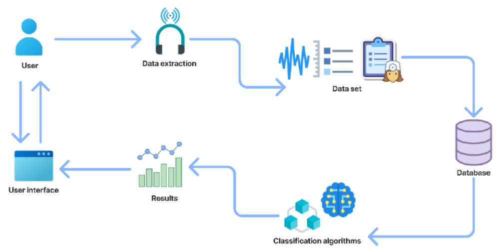

Fig. 1. Architecture for the academic stress detection module.

A. *Description of the architecture*

- **User:** It is the student who provides the values corresponding to the biomarkers, through the use of a cerebral perception headband.
- **Data extraction:** It is an information retrieval process, which is done to process the data further or transfer it to another storage repository. In this stage of the architecture, the data corresponding to the previously selected biomarkers are extracted, obtained from the wearable device that is used, in this case it is a brain perception headband that emits the value of brain waves corresponding to the user.
- **Dataset:** It contains a pool of values originated by a set of signals emitted by the wearable device used (Muse® headband).
- **Database:** The database contains the information of the biomarkers corresponding to the university students. It is responsible for persistence of data that will be subdued to the classification processing to identify the stress levels.
- **Classification algorithms:** It refers to a grouping procedure of a series of values according to a criterion, generally similarity. It occupies the data set that was previously stored in the database, to train and learn to perform the classification. In this case, this component use the SVM for carry out such classification.
- **Results:** It component is responsible of integrate ant maintaining the connection among all the variables is shown according to the value of the biomarkers and the resulting information that establishes which classification group corresponds (low or high stress level). Furthermore, this component displays the user the informations in tabular format, as well charts that facilitate the interpretation of results.
- **User interface:** It is closely related with the results componente. Since it is the means by the users interacts with the module. Through this, the information can be captured, charged and visualizase that module requires for its operation and make known to the users the get results after make the process of stress levels classification process.

The architecture of the module begins when the user puts on the wearable device, which is a brain perception headband, which will extract information about brain activity, heart rate, body movements and breathing, then that information has to be concentrated in a set of data . which will be later stored in a database management system, so that with the help of Artificial Intelligence classification algorithms the ideal correlation is found in the values that allow identifying the level of stress presented by the user.

Finally, the results will be consulted at any time, through the use of the web application that will be developed to identify stress levels in university students.

IV. Case Study

For this work, we used a case of study that describes the importance of the research and the impact it has on the field of study are presented.

A. *Case description*

A university student whose personal data is omitted is in the period of partial evaluations, given that he has an overload of academic responsibilities, he presents a series of symptoms and other diverse behaviors with which it can be deduced that he spends most of his time stressed. Some of the symptoms detected are the following:

1) *Physical*
   - General discomfort
   - Exhaustion
   - Nervousness
   - Excessive sweating
   - Stomachache
2) *Psychological*
   - Difficulty in solving problems
   - Episodes of insomnia
   - Dissatisfaction
   - Negativity
3) *Stress factors*

- Academic evaluations
- Excess of academic responsibilities
- Limited time to get the work done
- Lack of understanding of a specific topic

Due to this, he is under stress treatment, however, his psychologist requires an analysis of the stress levels to which he is subjected every day. Therefore, the following unknowns arise:

1) *How could the student measure their stress levels?*
2) *How could the specialist analyze the student's stress biomarkers to support her treatment?*

The use of the architecture proposed in this research is an alternative solution to solve the questions raised above.

B. Data acquisition and export

Information is obtained from the Muse® brain perception headband (SCR_014418) [13], which is a meditation tool that focuses on real-time feedback of brain activity, heart rate, breathing, and body movements.

1) *Mind:* allows to detect Delta, Theta, Alpha, Beta and Gamma (EEG) brain waves.
2) *Heart:* allows you to tune the performance of the heart rate (PPG + Pulse Oximetry).
3) *Breath:* Provides breath rate performance (PPG + Gyroscope).
4) *Body:* Provides information about body posture (Accelerometer).

The Muse® headband consists of five sensors which are calibrated to be able to detect the signals and provide the corresponding feedback. The Figure 2 shows how the signal quality of the following sensors is checked:

- TP9 - Left ear
- AF7 - Left forehead
- AF8 - Right forehead
- TP10 - Right ear
- AUXR - Right Auxiliary

Fig. 2. Signal quality of headband sensors.

Currently there is no way to access the raw data through the Muse Direct portal, however, Mind Monitor® [14] was alternatively tested, a through discrete frequency spectrogram: raw and absolute, it also allows visualize the effect of gravity on the headband, values corresponding to the accelerometer and gyroscope. The frequency spectra corresponding to each of the signals are:

- Delta(δ) 1-4Hz
- Theta(θ) 4-8Hz
- Alfa(α) 7.5-13Hz
- Beta(β) 13-30Hz
- Gamma(γ) 30-44Hz

The EEG PSD values read by the sensors are usually in the range {-1:+1}.

The Figure 3 shows the values of absolute brain waves, that is, based on the logarithm of the power spectral density (PSD) of the EEG data for each of the signals, while the Figure 4 shows the values of discrete frequencies on a logarithmic scale, these are calculated using a fast Fourier transform (FFT) of the RAW data, with a hamming window.

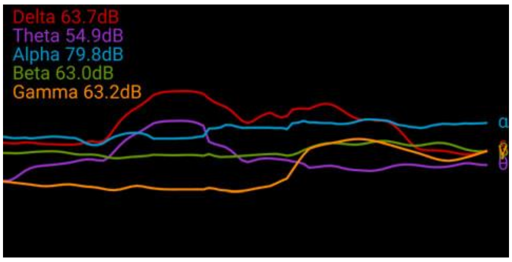

Fig. 3. Absolute frequency brainwave values.

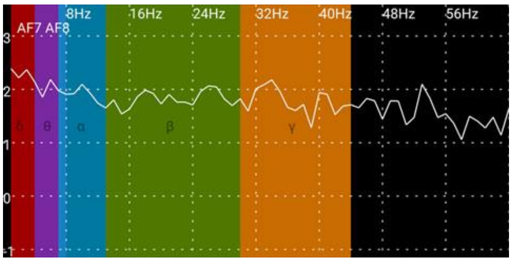

Fig. 4. Discrete frequency brainwave values.

Finally, the Figure 5 shows how the signals from the sensors are read through Mind Monitor® when a university student uses the Muse® headband.

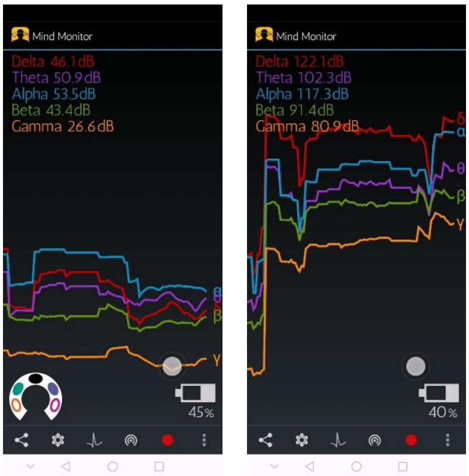

Fig. 5. Brainwave reading of a student wearing the headband.

Data from each session can be transmitted directly to an OSC data receiver and is also recorded by default in plain text CSV (Comma Separated Values) format, recording approximately every second. The following data is logged: Absolute, Raw, Right AUX, Accelerometer, Gyroscope, Headset On, HSI (Horseshoe Indicator/Sensor Connectivity), Marker button presses.

C. Analysis of data

For the analysis of this case study, a data set was used that contains the biomarkers provided by the wearable device, cortisol levels were included because it is released to modify the internal environment during times of stress [15], although the levels of cortisol can vary, the data used for this case were obtained from studies validated in the literature and by a health specialist, the gender and age of the students are also considered. The graph in Figure 6 shows the histogram corresponding to the variables of the data set.

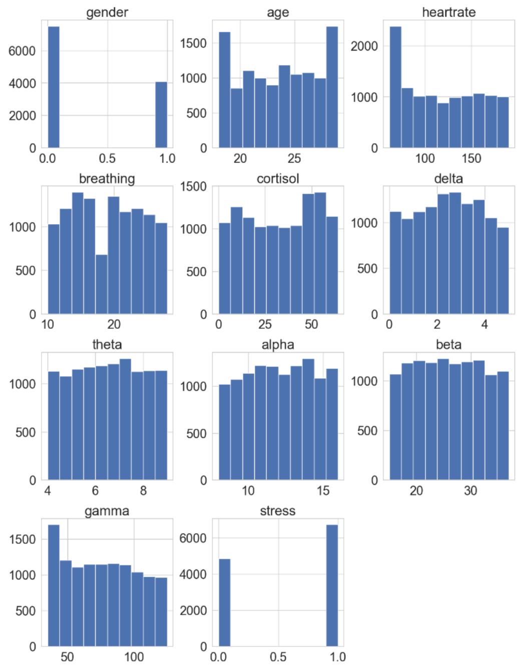

Fig. 6. *Histogram of data distribution.*

The graph in Figure 7 shows the number of observations in the data set for each of the containers, where 0 is low stress level and 1 is high stress level.

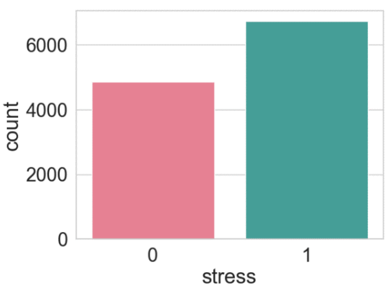

Fig. 7. *Containers corresponding to low and high stress level.*

There is a clear difference between the gender of the students in reference to stress, in most cases women are more prone to this condition. The graph in Figure 8 shows the values corresponding to the number of students who suffer from stress and the gender to which they belong, where 0 is female and 1 is male, subsequently, the graph in Figure 9 shows the values corresponding to the students who suffer from stress and the age at which they suffer from it.

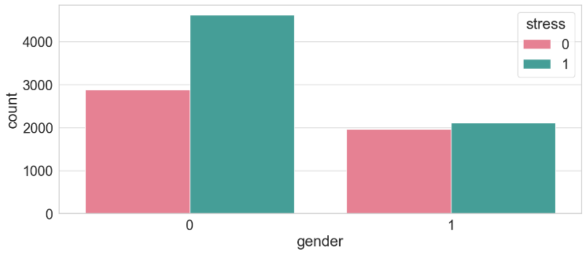

Fig. 8. *Affectation of stress for men and women.*

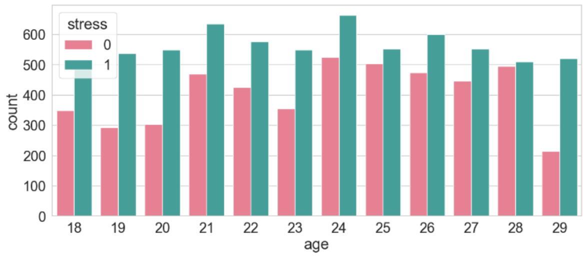

Fig. 9. *Suffering from stress according to the age of the students.*

The graph in Figure 10 shows the total population of students, grouped according to gender and stress level, obtaining the following results:

- 38.43% female students suffering from low stress.
- 61.57% female students who suffer from a lot of stress.
- 48.28% male students suffering from low stress.
- 51.72% male students with high stress.

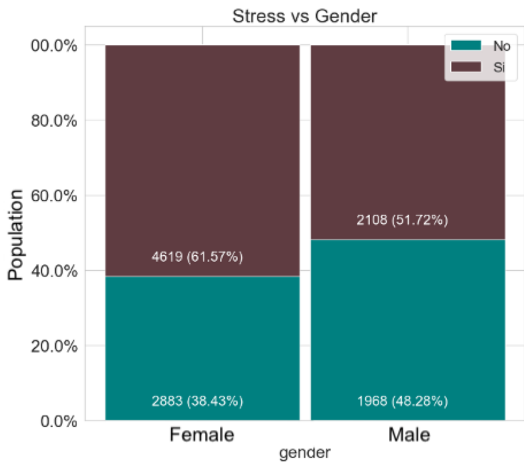

Fig. 10. *Student groups of men and women with low and high stress*

Subsequently, the validation of the data set was carried out, selecting the best characteristics, the results obtained during this process are shown in the Figure 11.

	Feature	Importance_score
0	heartrate	18.332233
1	cortisol	12.488816
2	gamma	12.466640
3	delta	11.231065
4	alpha	10.331609
5	theta	9.759965
6	beta	9.583267
7	breathing	6.713871
8	age	6.658285
9	gender	2.434250

Fig. 11. List of importance of the best values for the classification.

Finally, the set was divided into test and training data to evaluate the Support Vector Machine classification algorithm, where the following results were obtained, which are shown in Figures 12 and 13.

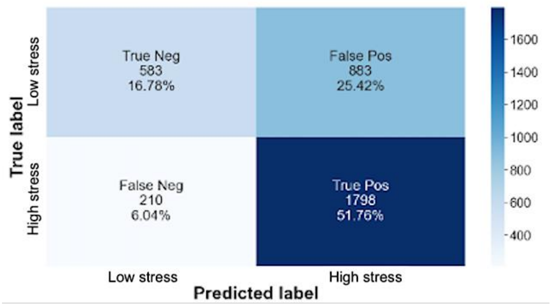

Fig. 12. Support Vector Machine confusion matrix.

Interpretation of the confusion matrix:

- *True Neg:* Correct classification, 16.78% students suffer low stress.
- *False Pos:* classification error, 25.42% students suffer from low stress and were classified with high stress.
- *False Neg:* classification error, 6.04% students suffer from high stress and were classified with low stress.
- *True Pos:* Correct classification 51.76% students suffer high stress.

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Classification report data
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              precision    recall  f1-score   support

 Low stress        0.74      0.40      0.52      1466
High stress        0.67      0.90      0.77      2008

    accuracy                           0.69      3474
   macro avg       0.70      0.65      0.64      3474
weighted avg       0.70      0.69      0.66      3474

Accuracy score: 0.69
Precision score: 0.67
Recall score: 0.90
f1 score: 0.77
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Fig. 13. Ranking metrics for Support Vector Machine.

V. Conclusions and Future Work

Stress is the psychological and physiological response to situations that involve a demand for adaptation in the body of people, this condition attributes positive links as long as it is controlled properly, otherwise, it becomes problems that affect the health of people and many aspects of your life. In the academic field, stress affects the well-being of students, their academic performance and even their general state of health, which in most cases prevents them from performing satisfactorily and fulfilling the competencies they have established. During the analysis, it was observed that there are multiple investigations that contemplate techniques and physiological variables that allow stress to be identified, through sensors or clinical studies, however, research focused on stress in the academic field lacks methods and tools that facilitate identification and classification of the stress levels that a student presents, therefore, there is a need to invest and know methods that allow identifying stress to help reduce the negative impact on the life project of the students. In consideration of the exposed problem, it seeks to help identify the level of academic stress, by creating a module that, with the help of a headband of brain perception, identifies through the user's data, what level of stress a student presents, It is also necessary to identify the causes that provoke it, since stress is associated with the development of some diseases or risk factors for health, so achieving the identification of stress and its causes will favor taking preventive measures and treating the discomforts related to this ailment.

As future work, it is intended to improve the algorithm for a better classification and include more Artificial Intelligence algorithms, such as Random Forest, AdaBoost, K-Nearest Neighbor and assemblers for the identification of stress levels in students automatically, likewise, it is considered to add more stress-related biomarkers by extracting the information directly from the students.

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References

[1] P. Verma and S. K. Sood, “A comprehensive framework for student stress monitoring in fog-cloud IoT environment: m-health perspective,” Medical and Biological Engineering and Computing, vol. 57, no. 1, pp. 231–244, Jan. 2019, doi: 10.1007/s11517-018-1877-1.

[2] C. Sreedevi Uday and A. J. Jyotsna, “Detection of Stress using Wearable Sensors in IoT Platform,” pp. 1–7, 2018, doi: 10.1109/ICICCT.2018.8473010.

[3] B. Rodic-Trmcic, A. Labus, Z. Bogdanovic, M. Despotovic-Zrakic, and B. Radenkovic, “Development of an IoT system for students’ stress management,” Facta universitatis - series: Electronics and Energetics, vol. 31, no. 3, pp. 329–342, 2018, doi: 10.2298/fuee1803329r.

[4] N. Jin, X. Zhang, Z. Hou, I. Sanz-Prieto, and B. S. Mohammed, “IoT based psychological and physical stress evaluation in sportsmen using heart rate variability,” Aggression and Violent Behavior. Elsevier Ltd, 2021. doi: 10.1016/j.avb.2021.101587.

[5] G. Shanmugasundaram, S. Yazhini, E. Hemapratha, and S. Nithya, “A Comprehensive Review on Stress Detection Techniques,” 2019. doi: 10.1109/ICSCAN.2019.8878795.

[6] A. Uzelac, N. Gligoric, and S. Krco, “A comprehensive study of parameters in physical environment that impact students’ focus during lecture using Internet of Things,” Computers in Human Behavior, vol. 53, pp. 427–434, Jul. 2015, doi: 10.1016/j.chb.2015.07.023.

[7] V. G. Rajendran, S. Jayalalitha, and K. Adalarasu, “EEG Based Evaluation of Examination Stress and Test Anxiety Among College Students,” IRBM, 2021, doi: 10.1016/j.irbm.2021.06.011.

[8] P. Shekhar Pandey, “Machine Learning and IoT for Prediction and Detection of Stress,” 17th International Conference on Computational Science and Its Applications, pp. 1–5, 2017, doi: 10.1109/ICCSA.2017.8000018.

[9] S. Gedam and S. Paul, “Automatic Stress Detection Using Wearable Sensors and Machine Learning: A Review,” 2020. doi: 10.1109/ICCCNT49239.2020.9225692.

[10] A. Kumar, K. Sharma, and A. Sharma, “Hierarchical deep neural network for mental stress state detection using IoT based biomarkers,” Pattern Recognition Letters, vol. 145, pp. 81–87, May 2021, doi: 10.1016/j.patrec.2021.01.030.

[11] Z. Zainudin, S. Hasan, S. M. Shamsuddin, and S. Argawal, “Stress Detection using Machine Learning and Deep Learning,” in Journal of Physics: Conference Series, Aug. 2021, vol. 1997, no. 1. doi: 10.1088/1742-6596/1997/1/012019.

[12] A. Mustafa, M. Alahmed, B. Soudan, and A. Alhammadi, “Stress Detector System Using IoT and Artificial Intelligence,” 2020 Advances in Science and Engineering Technology International Conferences (ASET), 2020, doi: 10.1109/ASET48392.2020.9118345.

[13] Muse, “EEG-Powered Meditation & Sleep,” *Disponible: https://choosemuse.com/muse-app/*, 2022.

[14] James Clutterbuck, “Mind Monitor,” *https://mind-monitor.com/#page-top*.

[15] University of Sussex, “Response coherence in stress detection: Cortisol levels in stressed speakers predict human listeners’ voice-based judgments of stress,” *http://sro.sussex.ac.uk/id/eprint/74915/*.