Near Real-time Stress Prediction for Patients with Disturbed Allostatic Load

William da Rosa Fröhlich[1], Sandro José Rigo[1], Marta Bez[2]

[1] University of Vale do Rio dos Sinos - UNISINOS University

[2]FEEVALE University

william_r_f@hotmail.com, rigo@unisinos.br, martabez@feevale.br

Abstract. *Stress is one relevant cause of diseases nowadays, and prolonged exposure to stress can cause a disturbance in the allostatic load. Alternatives have been sought to deal with this situation and verify the impact of this allostatic load disorder. Wearable sensors are an option for automatically identifying acute stress since they can measure signs such as electrocardiogram, heart rate, electroencephalogram, electromyogram, or galvanic skin response. All these signals have intrinsic characteristics in a normal state and change if associated with stress occurrence. The literature presents Machine Learning Approaches and Deep Learning Models as alternatives to pattern detection in physiological signals. Nevertheless, we identify a gap regarding the allostatic load impact identification and the real-time classification when using these models. this article aims to acquire data in stress induction experiments in clinical and non-clinical patients, train a machine learning model, and, in sequence, carry out a new experiment to evaluate the classification in near real-time. The classification experiment presented results with accuracy above 92.72%. When it comes to real-time classification experiments we obtained an accuracy of 78.93%. Evaluating participants in experiments divided into clinical and non-clinical groups, a decrease of 5% in precision was identified. Based on the results obtained, we verified that the allostatic load can present challenges for real-time stress classification.*

1. Introduction

Stress is a serious challenge as a public health problem associated with several diseases. Stress tends to generate impacts on the most varied areas of our lives, as reported by [Farias et al. 2011] and [Can et al. 2019]. Due to this issue, currently, several researchers seek ways to identify stress, as a way to monitor and present an intervention proposal as soon as possible. Closely related to stress detection, a point that has been studied in the psychological area recently is the influence of allostatic load on the behavior of the signals of individuals.

[Corrigan et al. 2021] highlight the use of Heart Rate Variability (HRV) as a way to monitor stress and allostatic load. The allostatic load consists of metabolic energy composed of biological measures. It captures the dysregulation of multiple physiological systems due to chronic exposure to stress [Guidi et al. 2021] [Wang et al. 2022]. Heart Rate Variability decreases in response to a stressful situation, whether physically or cognitively. They observed that HRV recovery is usually slow in response to higher-magnitude stressors. They also conclude that people with allostatic load disorder usually have a lower standardization HRV response. The authors [Corrigan et al. 2021] emphasize that further studies are needed to further the usefulness of HRV in assessing allostatic load and other physiological signs.

As an alternative to broad support this integration and evaluation of physiological signs, we have observed the use of the Internet of Things (IoT) and Artificial Intelligence (AI). According to [Mbunge et al. 2021], smart healthcare systems comprise the IoT, AI, cloud computing, wearables, and electronic medical records (EMR). The IoT applied to the hospital context offers the best solutions for patient follow-up, intelligent medical records, device integration, and improved diagnostics. These integrated devices aim to improve health systems, speed up diagnoses, and facilitate patient follow-up [Mukati et al. 2021].

[Iqbal et al. 2021] explain that wearable sensors are devices that allow the acquisition of physiological signals through small and practical devices that do not need to be attached to large equipment or inserted into the body. [Sharma et al. 2021] highlights the importance of wearable sensors in facilitating patient follow-up. Through wearables, we can follow in a non-intrusive way different biosignals, biomarkers, and even hormones. Wearables are an alternative to streamline hospital routines, in which the health professional needs to access the participants for frequent measurements of their vital signs. In addition, the measurement process of some signals may vary depending on the professional who performs the measurement, something that does not occur with continuous monitoring [Costa et al. 2018].

this article aims to describe stress induction experiments using a new architecture for signals acquisition to evaluate the impact of allostatic load on predicting stress in patients with disturbed allostatic load. The architecture comprises a single-board computer (SBC) and a wearable sensor. It allows the acquisition of physiological data and the composition of a dataset, including performing pattern prediction in almost real-time in cases with a trained machine learning model.

The experiments were approved by the ethics committee and carried out by psychology professionals. As a way of evaluating the experiments, the participants of the experiments are classified into two groups, clinical and non-clinical. Clinical participants have some psychological support for treatment and, therefore, some impact on the allostatic load. Non-clinical participants are those who do not have any psychological follow-up or previous diagnosis. We performed the stress induction experiment to compose the dataset of physiological patterns and evaluate the results. The next step involved data processing and training of the machine learning model. After training the model, we performed a new round of experiments to evaluate the prediction in near real-time.

According to the allostatic load theory [Corrigan et al. 2021], people with some mental disorders may present different behavior in stressful situations. Furthermore, clinical people may not feel anything in a stressful situation. Alternatively, after starting a stressful situation, they can take more time to return to a normal state or even not return. This was one of our motivations in this article since, as verified in the literature, few works have evaluated the impact of allostatic load on patients. Therefore, our work has as its main differential to evaluate the impact of allostatic load on stress classification in near real-time.

The article is organized as follows. Section 2 presents the main works developed with a focus on pattern detection using AI. Section 3 describes the Material and methods. Section 4 presents details on the experiments and evaluates the results. Section 5 presents the conclusion and future work.

2. Related Works

Several works have shown good results in pattern detection using AI, either machine learning or deep learning. A challenge still widely faced is the detection of stress due to several factors [Corrigan et al. 2021], [Mbunge et al. 2021], and [Alanazi 2022]. Among the main challenges that arise from the use of AI for stress detection is the difficulty of differentiating stress from other anomalies in physiological signals, such as increased heart rate and sweating due to physical activity [Guidi et al. 2021] [Wang et al. 2022]. [de Souza et al. 2022] presents research that developed a new pipeline for stress prediction based on data collected from wearable devices. The authors have used the WESAD dataset for the experiments obtaining 86% accuracy in three classes: baseline, stress, and amusement. Moreover, when the experiment uses only the categories stress or not, the accuracy goes up to 96.5%.

[Ali et al. 2021] elaborated a work for integrating wearable sensors and social networking for data collecting. The authors defend the efficiency of healthcare monitoring. The developed system classifies patients' health status using physiological data, such as blood pressure (BP), diabetes, social networking data, and drug review. They obtained an accuracy of about 79 % and 89 %, using only Long Short-Term Memory (LSTM). Moreover, 90 % to 94 % combine LSTM and ontologies. The authors performed experiments with CNN (70 %), MLP (80 %), SVM (73 %), and Fuzzy Logic (83 %). The PhysioNet MIMIC-II dataset got an accuracy of 88 % with this dataset applied to training.

[Hammad et al. 2022] developed a work that uses deep learning models (DLMs) of convolutional (CNN) and long-term convolutional neural networks (ConvLSTM) to identify and detect arrhythmia for IoT applications. The authors provided Electrocardiogram (ECG) signals in a 2D format to the model. The search yielded results for four different datasets, the MIT-BIH dataset having an accuracy of 97%, the compressed MIT-BIH dataset yielding 98%, the PhysioNet 2016 dataset yielding 94%, and the PhysioNet 2018 dataset reached 91%. They got all these results using CNN.

3. Materials and Methods

This section will describe the materials and methods used in this article. We initially described the architecture used in the stress induction experiments (Subsection 3.1). The sequence describes the protocol used in the experiment (Subsection 3.2), a protocol elaborated by the health professionals responsible for the experiment. In the third subsection (3.3) we present a brief account of the experiment participants. Next, in subsection 3.4 we present the process of data preparation and model training. Finally, we present the stress induction process for classification in near real-time (Subsection 3.5).

3.1. Architecture ATHENA I

For the stress induction experiments, we used the ATHENA I architecture. ATHENA I is acronymous of Architecture for Healthcare reinforced by Artificial Intelligence. This architecture aims to acquire, process, store, and classify physiological signals. The architecture is characterized by flexibility, as it focuses on the possibility of replacing the devices that make up the architecture. The architecture's functionalities are distributed in blocks to allow the distribution of tasks of the architecture into many devices.

The architecture comprises a set of components responsible for interacting with external devices and generating pattern identification. The architecture uses the wearable sensor BITalino Model PsychoBIT, which measures the external device data in the acquisition component. The wearable generates the signals and sends them via Bluetooth to a Single-board Computer (SBC), a Raspberry Pi 4, Model B + chosen due its processing power. The next step involves the processing component dedicated to filtering and processing data. This step is essential to remove noise and obtain the signal in the desired format. After the data processing, the architecture stores the data based on information defined by the user. The storage can occur in two ways. First, as soon as the architecture reads the text file, it stores the data without filtering or processing directly in comma-separated values (CSV) files. Then, the architecture store the processed data in a database.

The architecture has two operation possibilities, the Offline Mode and the Online Mode. The first one refers to the mode used for the dataset acquisition. This option is valuable whether the user does not have a dataset. In these cases, the user can use the architecture to compose a dataset following some specific acquisition protocol. This mode is used also to perform the machine learning model training, after the composition of the dataset. The second operating mode is the Online mode. In this mode, the architecture must have a Machine Learning (ML) or Deep Learning (DL) model previously loaded. The data stored by the storage block is sent to the prediction block and analyzed; if the architecture classifies the sign as altered, it sends an alert message. However, if it evaluates the signal as regular, the architecture continues to operate normally.

3.2. Protocol

The protocol developed for this experiment is based on inducing stress based on negative thoughts. All the experiments received the permission of the ethics committee (CAAE number 40555420.0.0000.5344), and psychologists conducted the experiments. We carried out experiments with two participant groups, clinical and non-clinical. Clinical participants are those who have some prior psychological monitoring by psychologists. Non-clinical participants are those who have no previous follow-up or diagnosis. The first stage of the protocol is the coupling of the wearable sensor. We decided to place the electrodes at the beginning of the experiment for the participants would get used to using the sensors. In the next step, participants filled in sociodemographic and relevant data for inclusion in the model as the social context and physiological information.

After completing the sociodemographic data, the pre-stress meditation process begins, in which the participant remains looking at a white screen, oriented to try not to think about anything specific. The participant remains that way for five minutes. After completing the five pre-stress minutes, the white screen changes to a screen with the phrase ”Think about a recent situation that has made you distressed or upset ...”(Figure 1). In this stage, the induction of stress occurs through negative thinking. The participant spends one minute thinking about the current situation that has made him go through some unpleasant moments.

Figura 1. Photos of the participants during the stress induction experiment with the sensors placed

After completing this minute of stress induction, the screen returns to a white screen, in which the participant again tries to ward off any thinking, constituting a post-stress stage. In this stage, as in pre-stress, it occurs for 5 minutes to return to a neutral state. When completing the period time of the post-stress stage, the participant performs a self-report. He explains what he thought and what was the feeling he felt during the process.

3.3. Participants

We have performed the initial experiments with 27 participants, 12 non-clinical and 15 clinical cases. Of these 27 participants, 66.67% of the participants were women ages 18 and 38. Male participants represent 33.33%, aged between 19 and 38 years. In this second round of experiments, we performed 20 acquisitions; eight participants were clinical and twelve non-clinical participants. Male participants represent 25% of the second experiment, the remainder comprising women between 19 and 38 years old. Of the analyzed participants, seven were in the first experiment, and 13 we acquired for the first time.

3.4. Machine Learning Training

In the preparation of the data, we first separate the ranges of values used in training, and then we apply the windowing technique to reinforce the characteristics of the data. This step has relevance because it is crucial for proper training that all categories provide the same amount of data. The dataset has 13 minutes of acquisition for each participant.

Removing these values from the first and last minutes, we have 11 minutes of data, of which the initial 5 minutes refer to pre-stress, 1 minute to stress, and the last 5 minutes to post-stress. We defined that the data we would use for pre-and post-stress would be the third minute because, in an evaluation carried out, these points correspond better to the objective of the classifier step. In other words, of the 11 minutes acquired in the experiment, we selected the third, sixth, and ninth minutes. Thus, the data we used during the AI experiment comprises 3 minutes of acquisition per participant, with 27 participants.

The windowing process aims to reinforce the characteristics of physiological signals. For this, the data, after going through the filtering process, are arranged into matrices. Each column is a signal, and the lines represent its instant in time. As seen in Figure

2, we split the data into 600 ms windows, and windowing occurs by overlapping these windows by sliding one over the other. For example, the first window occurs from 0 ms to 600 ms, so we relocate these selected data to the new dataset. The second window has an overlapping of 50%. This overlapping of 50% means that the window advances 300 ms, thus forming a time window of 300 ms to 600 ms. We relocate this second window again into the new dataset, repeating 300 ms of data. This technique tends to reinforce the characteristics of the trained data. This process repeats for the entire dataset.

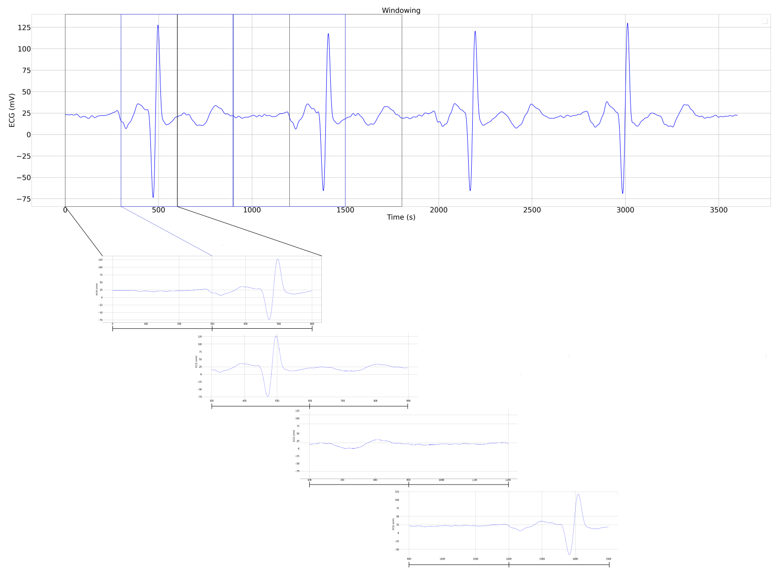


Figura 2. Example of Data Windowing Technique

We performed a series of ML experiments using five different classification algorithms. Among the algorithms used, we can mention Decision Tree (FDT), k-near neighbors (kNN), Random forest (RF), Ada Boost, and Multilayer Perceptron (MLP). Furthermore, it is essential to evaluate broadly the results obtained. In the evaluation step, we used the accuracy, precision, F1, and Recall metrics. In addition to the beforementioned metrics, we also used the confusion matrix to assess how the model classified the data. Moreover, we use a cross-evaluation method to evaluate the possible overfitting. We selected the kFold method for the cross-evaluation.

3.5. Near Real-time Detection

To evaluate the real-time detection, we performed additional experiments for stress induction. The new experiments followed the same inducting stress protocol (described in Subsection 3.2). The experiment's first step is placing the wearable electrodes on the participant, after which the participant fills in the sociodemographic data. As in the first experiment, we instructed the participant to remain relaxed for 5 minutes. After this period, we again instruct the participant to think about a situation that has recently made him/her distressed or upset to acquire the stress stage. After 1 minute, we instruct the participant to return to their normal state; this step lasts 5 minutes.

After carrying out the experiments, we analyzed the data obtained. The developed code considers the start of the experiment and, according to the time, evaluates whether the architecture classified the signals correctly. Finally, we performed new training and classification experiments using Machine Learning for the data from both stress induction experiments. Again, we conducted the experiments using the algorithms Decision Tree, kNN, Random Forest, Ada Boost, and Multilayer Perceptron.

4. Results and Discussion

In this section, we will present the results obtained in the experiments and discuss the results evaluating some points analyzed. We performed a series of Machine Learning training experiments evaluating classification approaches and exploring the results with the acquired dataset. In subsection 4.1, we present the experiments with static data. The first experiment includes all participants classified into three classes. Predicted classes were pre-stress, stress, and post-stress. The second and third experiments divided the dataset into non-clinical and clinical participants using the same three classes. Subsection 4.2 described experiments with the trained model used for classification approaches for real-time acquired data. These acquired data were also used in a new training experiment, described in subsection 4.3.

4.1. Machine Learning Model training

We separated the results obtained in the Machine Learning experiments according to the set of participants used and the type of classification. In the experiment with all participants classifying three classes, predicted classes were pre-stress, stress, and post-stress. The results verified (Table 1) the Decision Tree (DT) and Random Forest (RF) classification algorithms stand out, with results above 90%. Algorithms tested, such as kNN and Ada Boost, showed regular results in the range of 60%.

Tabela 1. Results from all participants - First Experiment — Classes: Pre-stress, Stress, and Post-stress

Algorithm	Accuracy	F1	Precision	Recall	kFold
DT	90.522	90.521	90.521	90.522	86.341
kNN	72.046	72.075	72.136	72.046	69.992
RF	92.720	92.724	92.725	92.725	89.697
Ada Boost	57.605	57.279	57.273	57.605	58.042
MLP	33.551	18.173	33.357	33.551	33.806

Another way to evaluate the values obtained in training is by using confusion matrices. We selected the algorithm Random Forest Classifier with three classes for this verification. In Figure 3, we can observe the predicted values in each class in percentage terms using the DT algorithm.

In another experiment, we divided the dataset into non-clinical and clinical participants using the three classes. This division aimed to identify whether any of these two sets impacted the trained values obtained. According to the allostatic load theory, we expected lower results with the clinical participant set. The experiment with non-clinical participants (Table 2) showed better values when compared to training values with all participants. The accuracy for DT and RF was above 93%.

Lastly, we carried out with clinical participants, and the values obtained were lower than non-clinical ones, according to Table 3. We expected this range of values,

Figura 3. Confusion Matrix Percentage Values of all participants — Classes: Pre-stress, Stress, and Post-stress

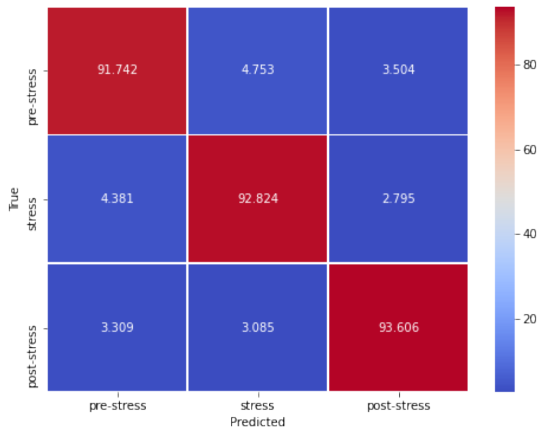


Tabela 2. Results of non-clinical participants - First Experiment — Classes: Pre-stress, Stress, and Post-stress

Algorithm	Accuracy	F1	Precision	Recall	kFold
DT	93.035	93.036	93.037	93.035	90.532
kNN	80.861	80.898	80.962	80.861	79.536
RF	94.564	94.564	94.564	94.564	92.845
Ada Boost	64.917	64.703	64.817	64.917	65.157
MLP	41.428	39.836	43.532	41.428	39.561

as the signals of clinical participants tend not to respond in a standard way in stressful situations. Therefore the model presents difficulties in classifying these individuals correctly. Even though the values obtained are lower than those of the previous experiments, the accuracy and precision values for Decision Tree and Random Forest remained above 90%.

Tabela 3. Results of clinical participants - First Experiment — Classes: Pre-stress, Stress, and Post-stress

Algorithm	Accuracy	F1	Precision	Recall	kFold
DT	90.081	90.081	90.083	90.081	86.547
kNN	70.276	70.289	70.322	70.276	68.407
RF	92.083	92.081	92.083	92.081	88.940
Ada Boost	60.140	59.986	60.071	60.140	59.046
MLP	36.344	30.248	35.039	36.344	34.242

4.2. Real-time Detection

In real-time detection experiments, we performed acquisitions with 20 participants; 8 participants were clinical and 12 non-clinical participants. Seven participants were in the first experiment, and 13 were acquired for the first time. For each 30-second data acquisition, the architecture generates a unique overall rating. For this unique classification to be generated, the architecture evaluated the signals in this period, classifying them from 300 ms windows. This generated ratings each 300 ms. These ratings are integrated to generate the overall rating for the period. In order to be classified as a given class, the values must be at least 70% of the classified results.

We can verify the classification accuracy values in the second stress induction experiment in Table 4. The Table presents the participant reference number in the first column, starting with the participants in the first stress-inducing experiment. The second column presents information about whether the participant is a clinical or non-clinical case. The third column highlights the data if the participant is new to the experiment or if he is participating again in the experiment. Finally, in the fourth column, we have the accuracy value obtained for each participant.

Tabela 4. Real-time Classification

Participant	Clinical	New Part.	Accuracy
Part. 01	No	No - 27	64.52
Part. 02	No	Yes	47.12
Part. 03	No	Yes	31.51
Part. 04	No	Yes	53.29
Part. 05	No	No - 2	73.67
Part. 06	No	Yes	52.32
Part. 07	No	No - 6	60.13
Part. 08	Yes	No - 15	71.52
Part. 09	Yes	No - 9	62.97
Part. 10	Yes	No - 18	78.93
Part. 11	Yes	Yes	61.51
Part. 12	Yes	Yes	38.63
Part. 13	No	Yes	21.78
Part. 14	No	Yes	46.31
Part. 15	No	No - 21	71.29
Part. 16	Yes	Yes	31.37
Part. 17	Yes	Yes	52.94
Part. 18	No	Yes	43.39
Part. 19	No	Yes	59.51
Part. 20	Yes	Yes	57.82

In the near real-time prediction experiment, we verified an accuracy trend of around 53.5 %, with the best results being 78.93 % and 73.67 % for clinical and non-clinical participants, respectively. We also verified a tendency for non-clinical participants to present better results in near real-time prediction compared to clinical participants, a result within the expected range considering the behavior of the allostatic load.

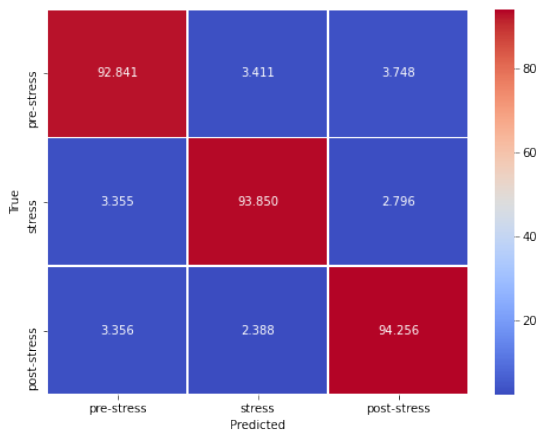
4.3. Machine Learning Model Update

After performing the second induction experiment, we performed new Machine Learning training to update the model with the additionally acquired data. The new experiments followed the previous approach, training the model using five different Machine Learning algorithms and comparing the values. Finally, we performed tests with all participants of both stress-inducing experiments using the three classes. Classes are pre-stress, stress, and post-stress. The verified results (Table 5) showed greater accuracy than previously presented. The results with the best accuracy remain Decision Tree and Random Forest, with 91% and 93% of correct answers, respectively. To evaluate the classified values, we can analyze Figure 4, which presents the confusion matrices for classification using Random Forests. Figure 4 the confusion matrix presents the classification for Pre-stress, Stress, and Post-stress.

Tabela 5. Results from all participants - Second Experiment — Classes: Pre-stress, Stress, and Post-stress

Algorithm	Accuracy	F1	Precision	Recall	kFold
DT	91.478	90.521	90.521	91.478	89.617
kNN	72.046	72.361	72.375	72.046	70.620
RF	93.648	93.648	93.649	93.648	91.761
Ada Boost	54.278	54.043	54.030	54.278	55.692
MLP	34.667	20.702	49.006	34.667	36.883

Figura 4. Confusion Matrix - Second Experiment - Classes: Pre-stress, Stress, and Post-stress



4.4. Results Analysis and Discussion

We justified the difference between the values obtained in the ML test experiments and the real-time detection experiments due to the participants in the first experiment not knowing what the experiment would be. In the second experiment, the participants who had participated in the first experiment no longer had the exact expectations, which could affect the classification result. In addition, there is a one-minute period before and after the stress induction, which tends to present more uncertain signals. In a new training of the model, this time adding the second experiment participants, the model showed a slight improvement in the classification, with values of 98,68% for binary classification and 93,64% for classification using three classes, both using the Random Forest algorithm.

The different values verified for clinical and non-clinical participants are also worth mentioning. If we compare the training model with the clinical and non-clinical participants, the values obtained with non-clinical participants were significantly better. However, the values are distributed accordingly with the allostatic load theory. We expected clinical participants to have slightly different physiological signal behavior than non-clinical people. Clinical participants tend to have a naturally higher (non-stress) baseline and do not return to baseline as quickly.

5. Conclusion

this article presented two experiments based on stress-inducting to evaluate the prediction of stress in near real-time for patients with disturbed allostatic load. We have used an architecture called ATHENA I to perform the acquisition, processing, storage, and classification of physiological signals supported by artificial intelligence. We carried out stress induction experiments conducted by psychology professionals. The ethics committee approved these experiments based on inducing stress through repetitive negative thinking.

According to the results, we can highlight clinical participants' aspect impact on the machine learning model. When comparing the model training results with clinical and non-clinical participants, the obtained values with non-clinical participants were significantly better. Nonetheless, the values are distributed accordingly with expectations based on health literature [Corrigan et al. 2021], [Wang et al. 2022], [Guidi et al. 2021]. According to the allostatic load theory, clinical participants tend to behave differently toward physiological signals than non-clinical people. Clinical participants may have a naturally higher basal (non-stress) level. Alternatively, their physiological signal levels do not return to normal without intervention during a stressful situation.

We can also cite the results obtained with the real-time detection experiments. We performed experiments with 20 participants following the same protocol in the first experiment. Seven of these 20 participants were present in the first experiment, and we used their data to train the model. The average accuracy obtained in the experiments with all 20 participants was 52.33%. However, if we only analyze the participants in the first experiment, the average accuracy goes up to 69.00%. These results indicate the importance of adjusting the model for new participants' data, directly impacting the model's performance. Based on the results obtained, we can verify the allostatic load's impact on the model's generalization.

In future work, we intend to increase the number of participants to make the machine-learning model more robust and able to perform the prediction more efficiently. We assess the impact of participants with disorders on the load in groups with more participants. In addition, we will look for artificial intelligence techniques that can collaborate with our work, presenting a better performance for stress prediction.

Acknowledgement

We acknowledge Fapergs for supporting this article by means of Grant FAPERGS PQG, 5/2019.

Referências

Alanazi, A. (2022). Using machine learning for healthcare challenges and opportunities. *Informatics in Medicine Unlocked*, 30:100924.

Ali, F., El-Sappagh, S., Islam, S. M. R., Ali, A., Muhammad, A., Imran, M., and Kwak, K.-S. (2021). An intelligent healthcare monitoring framework using wearable sensors and social networking data. *Future Generation Computer Systems*, 114:23 – 43.

Can, Y. S., Arnrich, B., and Ersoya, C. (2019). Stress detection in daily life scenarios using smart phones and wearable sensors: A survey. *Journal of Biomedical Informatics*, 92.

Corrigan, S. L., Roberts, S., Warmington, S., Drain, J., and Main, L. C. (2021). Monitoring stress and allostatic load in first responders and tactical operators using heart rate variability: a systematic review. *BMC Public Health*, 21.

Costa, C. A. d., Pasluosta, C. F., Eskofier, B., Silva, D. B. d., and Righi, R. d. R. (2018). Internet of health things: Toward intelligent vital signs monitoring in hospital wards. *Artificial Intelligence In Medicine*, 89:61 – 69.

de Souza, A., Melchiades, M. B., Rigo, S. J., and Ramos, G. d. O. (2022). Mostress: a sequence model for stress classification. In *2022 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8.

Farias, S. M. d. C., Teixeira, O. L. d. C., Moreira, W., Aparecida, M., de Oliveira, F., and Pereira, M. O. (2011). Caracterização dos sintomas físicos de estresse na equipe de pronto atendimento. *Revista da Escola de Enfermagem da USP*, 45(3).

Guidi, J., Lucente, M., Sonino, N., and Fava, G. A. (2021). Allostatic load and its impact on health: A systematic review. *Psychother Psychosom*, 90(1):11 – 27.

Hammad, M., Abd El-Latif, A. A., Hussain, A., Abd El-Samie, F. E., Gupta, B. B., Ugail, H., and Sedik, A. (2022). Deep learning models for arrhythmia detection in iot healthcare applications. *Computers and Electrical Engineering*, 100:108011.

Iqbal, S. M. A., Mahgoub, I., Du, E., Leavitt, M. A., and Asghar, W. (2021). Advances in healthcare wearable devices. *Flexible Electronics*, 5(9).

Mbunge, E., Muchemwaa, B., Jiyane, S., and Batani, J. (2021). Sensors and healthcare 5.0: transformative shift in virtual care through emerging digital health technologies. *Global Health Journal*.

Mukati, N., Namdev, N., Dilip, R., Hemalatha, N., Dhiman, V., and Sahu, B. (2021). Healthcare assistance to covid-19 patient using internet of things (iot) enabled technologies. *Materials Today: Proceedings*.

Sharma, A., Badea, M., Tiwari, S., and Marty, J. L. (2021). Wearable biosensors: An alternative and practical approach in healthcare and disease monitoring. *Molecules*, 26(748).

Wang, S., Li, L. Z., Lu, Z., Li, S., and Rehkopf, D. (2022). Work schedule control and allostatic load biomarkers: Disparities between and within gender. *Social Indicators Research*, 163(3):1249–1267.