A Technological Monitoring Architecture for Academics' Mental and Physical Health

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Abstract. *Educational institutions are moving to a hybrid model that allows onsite and online classes. Students and teachers must adapt to these changes in the teaching and learning routine, leading them to stress and anxiety moments. This work proposes an architecture to assist academics in detecting these stressful moments during daily activities. The proposal uses smart bands, machine learning algorithms, and a smartphone app for environment monitoring. The evaluation was conducted by collecting real data from heart rate spikes and enriching it using the location information to send recommendations. The results show that it is possible to identify stressful moments by respecting the academics' environment by monitoring their routine.*

1. Introduction

The COVID-19 pandemic brought several changes to the population's daily lives and how some professionals act. Changes concerning interaction, work performance, and activities are examples of changes [Hamdan et al. 2021, Vaziri et al. 2020]. However, some activities had a quick adaption that allowed them to be carried out safely [Carroll and Conboy 2020]. This adaptation was also necessary for education, where teachers and students had to implement and adapt themselves to a fast digital transformation in the educational process (facilitated by technologies such as Zoom, Cisco Webex, Google Class, Panopto, etc.) [Pakhomova et al. 2021, Lima and Maciel 2021].

In 2022, most higher education classes came back from remote to face-to-face teaching. However, some educational institutions chose a hybrid model, in which students can follow classes in person (on-site) or remotely (online) [Bülow 2022, Leite et al. 2021, Kastornova and Gerova 2021, Li et al. 2021]. All these possibilities and routine changes affect the physical health of students and teachers, impacting their mental health [Chaturvedi et al. 2021, Hall et al. 2021, Pitanga et al. 2020].

It is interesting to notice those effects on students and teachers who, despite still being able to have classes in a hybrid model, still need to adapt themselves to this new routine, which can lead them to stress and anxiety moments [Souza et al. 2020]. Some studies point to the negative impact that levels of stress and anxiety of educational agents (students and teachers) can have on academic achievement [Pascoe et al. 2019, Gustems-Carnicer et al. 2019]. Positive thoughts and emotions can help students have better aca-

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demic performance. On the other hand, negative emotions make knowledge difficult and harm the student during the teaching and learning process [REIS et al. 2021].

Helping students and teachers monitor stress and anxiety levels can benefit their mental health and teaching and learning. From a technological perspective, we can analyze, through environment sensors, smart bands, and smartwatches, the signals captured, such as heart rate, to determine moments of stress and anxiety during teachers' and students' day [Silva et al. 2019, Misra et al. 2000]. The relationship between heart rate patterns and anxiety can be found in several studies over the years [Gorman and Sloan 2000]. Therefore, using it can be highly effective, non-invasive, and with great potential for analyzing education agents' physical and mental health without crossing the boundaries between health and computing specialists. Furthermore, environmental sensor data related to the agents' location enriches body sensors' information and enable more accurate and assertive analyses regarding the collected data. In this way, we encompass the profile and context spectra in personalized treatment using both information combined.

Based on the above context, this paper proposes an event-driven architecture to identify stress and anxiety moments during an academic routine. The architecture uses smart band sensor data to understand behavioral variation and mental and physical problem signs. Being a less invasive solution, it also uses environmental sensor data for the educational agents to inform which locations they would like to be monitored. Therefore, as a contribution, we can point out the mix between the areas of computing in education and health that can bring great results to the teaching and learning process.

The study followed four main steps: (i) literature reviewing; (ii) a proposal specification with a well-defined and concise architecture to ensure the fulfillment of the desired purpose of monitoring and assisting students and teachers; (iii) studies conducted with real-world data from body sensors and location to observe the proposal's feasibility; and (iv) the analysis of the results to verify improvements, problems, and adaptation of technologies.

The literature review includes a study to understand the state of the art in real-time monitoring solutions and the collection and processing of sensor data. We rely on the Fog-Cloud paradigm [Verma and Sood 2018] and the Lambda Architecture [Kiran et al. 2015] concepts to design a system to collect and monitor users in sensor data streams. Our approach comprises an architecture able to support (i) a large amount of data generated by sensors, (ii) methods to process the raw data in the fog before sending the enriched data to the cloud, and (iii) the use of machine learning methods to extract knowledge from data and to highlight changing standards of students and teachers that are being monitored. We evaluated the proposed architecture through a feasibility study where data generated by sensors were sent to the system, and machine learning methods were used to identify the students' emotional moments.

The paper is organized as follows: In Section 2, the related work is presented; in Section 3, the proposal is discussed in detail; in Section 4, the studies carried out and the results obtained are presented, in addition to discussing them. Section 5 presents the final considerations as well as future works, and finally, in Section 6, some acknowledgments are considered.

2. Related Work

Disorders involving academics' mental health in the educational environment are a very expressive topic nowadays and frequently discussed in previous research. Given the solution complexity, we searched for works that discuss ways to identify students' and teachers' stress and anxiety levels, machine learning techniques to recognize academics' behavior, and alternatives to process the large volume of data generated by wearable devices.

An analysis in [Vitasari et al. 2010] establishes a significant relationship between students' anxiety levels and academic performance. Similarly, [Sohail 2013] shows an association between stress and the performance of medical students. These correlations are of concern because if these problems are experienced for long periods, they may show signs of worsening in students' mental health. In [Bamber and Morpeth 2018], the authors analyzed the effect of mindfulness meditation on controlling students' anxiety. They selected data from several published articles and performed a meta-analysis, which showed that the use of mindfulness meditation moderated anxiety levels. These studies collected data through forms, historical data, and interviews without using sensors to monitor and support students in real-time.

Other studies focus on the use of devices to monitor students. In [Melillo et al. 2011], a case study was conducted with 42 student volunteers to verify Heart Rate Variability (HRV) variation due to a real-life stressor. The authors indicate that it is possible to identify that the student is going through a moment of anxiety, but they do not present alternatives for students to get out of this state. The research of [Silva et al. 2019] proposes a model that uses wearable sensors for monitoring and managing students' emotions. The authors present recommendations for students but do not verify their location or whether the student wants to be monitored or not. [Hasanbasic et al. 2019] presents an experiment using wearable sensors to recognize students' stress levels. These studies indicate that it is possible to monitor students' anxiety levels using body sensors. However, they do not use data from the environment, being this goal a contribution of our proposal enabling the students to define which locations they want to be monitored.

The collected data must be processed using pattern recognition techniques to recognize academics' behavior. Several well-founded machine learning techniques in the literature have proven to be effective. For example, classification algorithms such as KNearest Neighbor (KNN) and Support Vector Machines (SVM) are used to identify the patterns in the stress degrees of the students [Hasanbasic et al. 2019]. Similarly, [Priya et al. 2020] uses machine learning algorithms to determine the experiment participants' different degrees of anxiety, depression, and stress.

Performing data collection, processing, and visualization from multiple users simultaneously is not a trivial task. For this reason, the solution presented in this paper employs an operation based on the Fog-Cloud paradigm [Munir et al. 2017] and uses the strategies and concepts presented in the lambda architecture [Kiran et al. 2015]. Such gimmicks have already proven to support the large data volume received from users and do not affect the processing and delivery of information [Verma and Sood 2018].

Our work proposes to detect changes in users' behavior and even prevent the intensification of their stress and anxiety levels. We do this by monitoring the educational agents' health status, using location sensors for contextual information, and wearable sensors to collect the body data. With the system properly deployed, its ultimate goal is to provide recommendations and notifications to these users to reduce their stress and anxiety levels, enabling them to reach better academic achievement. Through the user's contextual information, the system can provide appropriate real-time notifications to the student or teacher. In [Silva et al. 2019], a methodology for executing such notifications is established.

3. Helping students in stress and anxiety control

Considering body and location data, we collect academics' data in different scenarios and contexts. We provide a specific predictive model for each academic that enriches information about their profile and context. With this, we highlight anxiety and stress moments and recommend some action to revert these situations, such as doing physical activities to reduce tension in the long term. All types of activities and possible actions for recommendation are based on other research works [Zaccaro et al. 2018, Silva et al. 2019, Carter et al. 2021].

Since students and teachers perform many daily activities, we assume that some environments are specific for academic activities, leisure, physical activities, etc. Therefore, some locations may not be of academic interest to be monitored. In this way, we must assist academics by considering environmental and wearable sensor data.

Figure 1 provides an overview of the proposed architecture with its layers and workflow. We base the design on a Lambda architecture [Kiran et al. 2015], taking advantage of both 'batch' and 'stream-processing' methods with a hybrid approach.

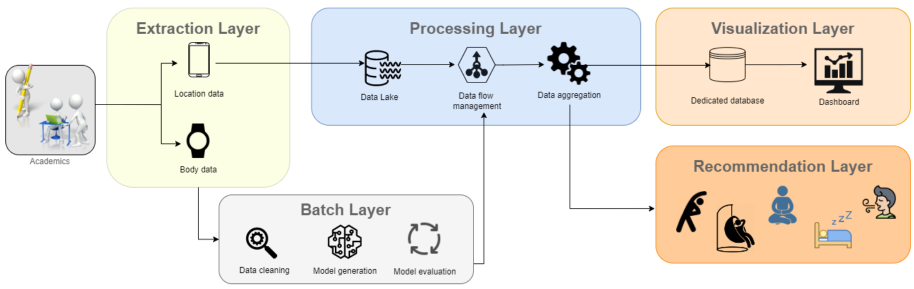

Figure 1. The proposed architecture with its major components and workflow.

The **extraction layer** is responsible for extracting the data needed for the system process. This layer uses two types of sensors: location sensors that collect the academic's location data for contextualization and wearable sensors that monitor heart rate data. Location data are sent to a database whose operation follows the concepts of a *Data Lake*, ensuring that no data is lost and that they are always available for queries. Body data are sent to the **batch layer**, whose operation is carried out asynchronously. Its main task is to carry out the entire process of cleaning, modeling, and classifying the academics' body data to be sent back to the main processing stream.

One important element to highlight is the efficiency and modularity achieved by the system using lambda architecture concepts. As treating and evaluating the body data requires a considerable computational cost, performing it online in the system would lead to data congestion and a general delay. The implementation of the lambda architecture solves this issue by separating the processing flows into a *batch* and a *speed layer*. The batch layer has the function of doing all the arduous computation and storing the generated results so that they are already available for the speed layer to use. The speed layer is responsible for detecting new data entries and providing an appropriate response in the shortest possible time, using the previously generated information in the batch layer. This process happens by sending information for both the batch and speed layers. The speed layer only needs to use previously generated models to offer quick and consistent feedback in almost real-time.

The **processing layer** is responsible for ensuring the availability of recorded information, defining the data processing flow, and performing the necessary transformations to extract the most relevant decision-making answers. It is important to clarify that this layer performs such processing functions because we already have the transformed data, ensuring that future queries are faster. The first step performed by this layer is to request the location data stored in the Data Lake. The data is periodically requested for updated evaluations. The next step aims to collect the data corresponding to the behavior of the student or teacher. This information is obtained through machine learning classification methods performed separately from the system in the batch layer. Finally, the academics' behavior and location data are combined so that we generate more expressive information.

At the end of the process performed by the previous layer, we have a database with enriched data appropriately stored and ready to be consulted. In this way, the **visualization layer** is responsible for making the appropriate queries on this specialized database and generating the visualizations that serve as a guide for monitoring the academics' activities and detecting irregular patterns in their behavior. In addition, interactive dashboards generate visualizations that can be accessed by students and teachers externally from anywhere with the appropriate credentials.

The graphics and information on the dashboard are regularly updated, constantly checking to see if new data has been provided. We created visualizations to show more relevant information to users, focusing on body and location data. For example, students and teachers can see their heart frequency in a specific location. This way, the dashboards highlight patterns in their behavior in which stress or anxiety contexts are detected. It is worth mentioning that if the users do not set up locations where they want to be monitored, our solution will not collect their body data.

Finally, the **recommendation layer** is responsible for presenting the resources to students through the features defined in the previous steps. Our system makes two types of recommendations: *immediate activities* (Brain Breaks, diaphragmatic breathing, progressive muscle relaxation, and positive self-talk) [Zaccaro et al. 2018], and *preventive activities* (physical activities, meditation, outdoor relaxation, seeking medical help) [Carter et al. 2021]. So, depending on the students' location, we can recommend meditation to reduce these harmful states, contributing to the progress of their performance.

In this way, the proposal architecture configures a great opportunity to help students and teachers. By sending suggestions to them, it is possible to reduce stress moments and these occurrences. Consequently, the proposal helps mental health and performance in the educational field since students tend to be more relaxed for exams, presentations, and daily academic activities.

4. Evaluation

Due to the proposed study's complexity and scope in treating data, we must consider different possibilities to evaluate it. When dealing with data from body sensors, we must capture it for analysis regarding the feasibility of possible models and ways to reach a viable solution to the problem addressed. So it's necessary to conduct a meticulous study of each captured signal used as input variables for the machine learning model. We should analyze each one to check for correlations, missing data, patterns, and intrinsic knowledge about the data [Klein and Lehner 2009].

However, we must consider some factors to enrich the body sensor data with information about the academics' location within their home environment. First, we must study how to collect such information in the least intrusive way. In addition, analyzing possible interference, data format, storage techniques, and environment discrimination in detail is paramount for developing the research. Thus, it is possible to see two significant aspects: (i) the collection and analysis of data from body sensors and (ii) the use of data obtained from the academics' location.

4.1. Location Data Study

We conducted tests to monitor students and teachers in their environments and implemented the system to obtain continuous and consistent observations of their activities over time. So, we set up the location of some classrooms at the university, and students involved in the evaluation set up the location data in specific parts of their homes. Later, we analyzed whether the data received by the sensors corresponded to displacement in the demarcated areas. So, data about academics' location (classrooms and home environments) can be enriched for a more detailed analysis following the research project scope.

The proposed system was deployed and tested using containers created through the Docker platform [Anderson 2015] on a dedicated server. In addition, the visual IoT device flow deployment tool *Node-RED* was used for the collection of the location data as well as for the flow management of processing the received data and storing the generated information. The data collection was scheduled to run at 1-minute intervals.

The location sensor was deployed using a smartphone app (FIND3[1]), while for the wearable sensor, a *SmartBand* was used. For the creation of the *DataLake* a *SQLite3* relational database was used and the dedicated database of the visualization layer was implemented using a *Postgres* relational database. Requests for the data stored in the *DataLake* are made through a *Web API*. In addition, the dashboard for the visualizations was created using the analysis and monitoring tool *Grafana*.

It is worth noting that the location data is not collected as a *GPS* information but with the use of categorical identifications of previously classified locations. Furthermore, although the system can continuously receive and process the data, they are not necessarily sent to the system at the exact moment they are measured. Instead, it is only required that the instant the measurement was taken be registered.

As aforementioned, the measurement requests made by the location sensor are executed periodically, and this periodicity can be adjusted according to the observed needs. However, it is important to emphasize that the categorical values returned by the sensor

[1]https://www.internalpositioning.com/doc/tracking_your_phone.md

need to be previously specified by the user so we can avoid erroneous measurements. As said before, the academics must register the location for the monitoring. This is done through classification training, where the sensor captures data from *WiFi* and *Bluetooth* wave frequencies to be used for training the area. This training must take place for at least 30 minutes over the selected location for the sensor to make accurate measurements.

As the location data are categorical, students and teachers must make the appropriate classifications with the sensor in the environment to perform the measurements. We did a technical report to help them with this configuration. The dashboard consists of three main panels: a representative image of the environments with the sensors of the most recent measurements taken in each place, a state transition panel showing a timeline of the people's movement through the environment, and a table with all the measurements taken so far. The data visualization is also periodically updated to present the most recent possible data. Figure 2 shows how the dashboard and its panels work.

In addition, it is necessary to emphasize that measurements taken at unspecified locations are not recorded or considered, respecting academics' privacy. For example, suppose that a measurement has been taken on the balcony of the user's home (Figure 2). Since it has not been previously classified, the system will consider that the user is in an unknown location or does not want to be monitored at that moment, which would be a different situation if the user is in the living room. Additionally, it was defined that if the measurement confidence probability is less than 50%, it is assumed that the user's location is unknown. This way, we can make observations with greater reliability of the information presented. The treated data is then registered in the Postgres database to be consulted in Grafana for the dashboard creation.

Data returned from the Data Lake are the variables used for monitoring the academics' location. These variables by themselves are proposed to be sufficient for user location monitoring. We collected data from the teacher's office and three classrooms in the academic environment. From the home environment, 112 entries were recorded in the cloud database throughout the experiment, where 64 correspond to the user's bedroom, 23 to the kitchen, and 15 to the living room. The remaining 10 entries correspond to unknown locations.

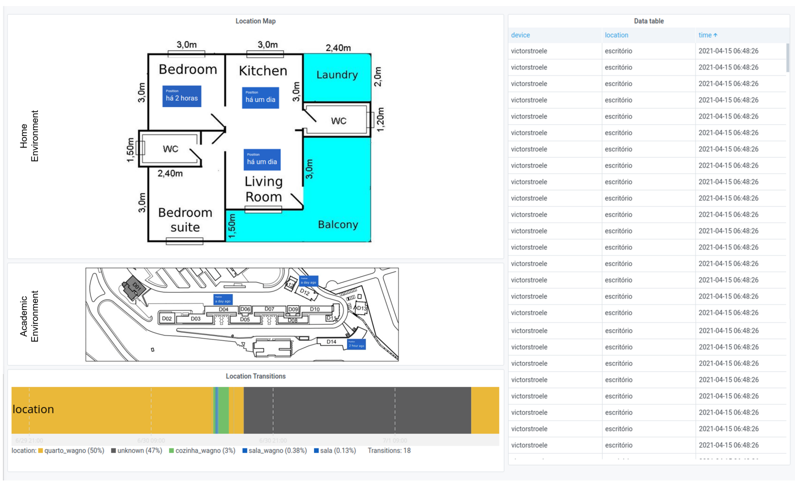

Figure 2. Dashboard preview image showing the user's locations monitoring panels (home and academical environments).

4.2. Body Sensors Data Study

For the behavioral monitoring of academics and the analysis of its impact on their health, a study with comprehensive data in the temporal aspect is necessary. It is required because we must understand each academic's behavior during a period so that the data are not at the mercy of particular situations in their routine.

Therefore, body data from a student covering a period from March 2021 to March 2022 were considered in this study. It is important to note that some data contains missing values due to the lack of wristband use and problems in sending the data. Thus, as they are concerned about the health of the student in question, no type of approach to fill in the missing data was adopted not to assume wrong information about his heart rate and other data related to his health. Data collection was done using a *Samsung* brand *smartband* which sends the collected data to the *Samsung Health* app, where they were exported to be processed by the architecture.

It is also worth highlighting a previous study carried out through the simulation of student body data during the execution of various tests with the *SIAFU* tool [Di iorio Silva et al. 2021]. This study was important to verify, through simulation, the relevance of body data and their changes and behaviors, considering the proposal's objective in that project. In this way, via simulation, we obtained a greater understanding of the information collected, enabling us to collect data from real users and analyze them with a more precise and assertive perspective.

The data collected from the smart band are related to the student's heart rate, pedometer, stress level, and blood oxygenation rates. The data concerning the heart rate is broken down into useful information in addition to his actual frequency. These are the Maximum, Minimum, and Measurement date/time heart frequency, which is collected and transferred to the application in one-hour intervals. In the entire database, we analyzed 6,304 measurement occurrences with a minimum recorded value of 55bpm and a maximum of 164bpm. Furthermore, an average of 78,5 bpm was identified with a standard deviation of 13,39. It is also worth noting that, for a better distribution visualization of values within the database, the values for the quartiles are: 69bpm for the first quartile, 77bpm for the median, and 85bpm for the third quartile. We enriched raw data by calculating the rate of increase and the acceleration of the rise in heart frequency to obtain more variables that seek to explain the variation in heart rate collected from the student.

4.2.1. Machine Learning Setup Study

Initially, we defined the explanatory variables based on the derivations made and the primary data collected by the smart band. As the initial idea of the proposal is to predict the frequency value and thus compare it with recent measured values, a new column was created that contains the subsequently measured frequency of the student in question. This new information column became the model's dependent variable for analysis, training, and prediction. We can use regression algorithms to compare the results expected by the machine learning techniques (predicted heart frequency) with the actual value collected (real heart frequency). Thus, it is possible to see if there is a significant difference in the interval between these values and point out peaks of stress or anxiety.

The algorithms *Support Vector Machines, Decision Trees, and K-Nearest Neighbors (KNN)* were used. In addition, tools provided by the *Scikit-Learn* Python library, such as *GridSearchCV* were also employed to search for the best parameters for each algorithm and obtain the best possible result from them. In this way, parameters for each algorithm are passed with each value that *GridSearchCV* must test. Therefore, an analysis with all possible combinations of parameters is studied to return the best combination found together with the cross-validation technique to avoid biasing the results. Furthermore, we developed a pre-processing step to scale the information, in addition to a data transformation task using *boxcox* to work with data closer to a normal distribution.

The machine learning algorithms reached good results, predicting reasonable values. In its vast majority of predictions, the model predicted values in a range of around 10 bpm (beats per minute) up and down. The results found for the *Decision Tree, KNN Regressor, Random Forest Regressor, and Gradient Boosting Regressor* algorithms were 46%, 45%, 45%, and 48%, using the *R^2 score* technique.

Figure 3 shows the heart rate and the values the machine learning model predicted. Values near the bottom-left corner give us low predicted and real heart frequency values. On the other hand, the middle-right region of the graph shows points where a frequency peak is noticed, being necessary to analyze it with caution. When students are in these situations, it is necessary to recommend some action to relieve stress and, consequently, lower their heart rate at that moment.

Also, we can see that algorithms such as Random Forest and Gradient Boosting managed to organize the data in a better-distributed way when we look at the general format in which the points are distributed along the axes. Thus, these stand out as the best candidates for model development.

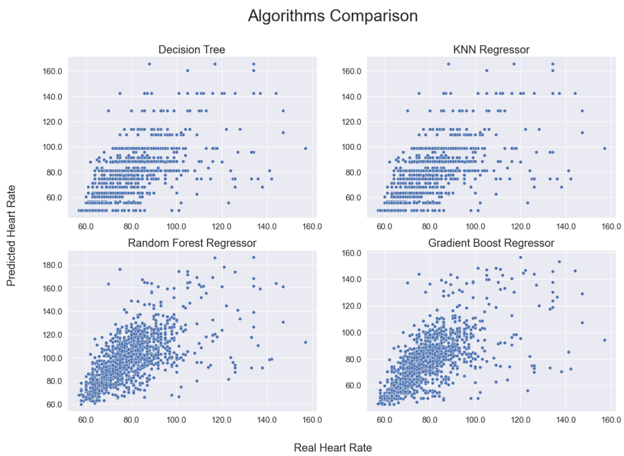

Figure 3. Algorithms comparison between the predicted and real heart rate

4.3. Stress and Anxiety notification Study

This study mainly analyzes how location and body sensor data can be integrated into a solution to ensure data enrichment and define environments and spaces where the user does not want to be bothered. Considering the trained models and the environment setup, when the system receives new data from academics (location and body data), it verifies if they want to be monitored in the current environment and recommend some action in case of stress and anxiety detection. In this study, we defined two types of notifications to be sent to students and teachers. One is related to immediate activities, and the other is related to preventive activities since both decrease their stress levels. Hence, it is up to users to choose which one best suits the environment in which they find themselves.

A sample of notification in this study occurred when the system recommended diaphragmatic breathing and Brain Breaks activities when the student was in the bedroom, and the models detected a high-stress level. Also, the system detected a persistent condition of nervousness and stress within the student's routine, with frequent anxiety peaks. Therefore, preventive activities were recommended to make such heart rate hikes less and less recurrent. In some cases, the student was in an unknown location, i.e., a location not defined as a valid environment to be monitored. In these cases, the system collected no heart rate and did not send recommendations.

Another notification sampling by the system occurred when the student entered the classroom configured to be monitored. The system detected the student's high heart rate and recommended a paused breath. However, the student gave us feedback and said he had just climbed a staircase and went straight to class. In this case, the student returned to their normal heart state after a period of rest, and the system did not need to send the recommendation. Therefore, it is interesting to emphasize and realize the vital role of location data in achieving the purpose of the idealized proposal. Through these, it is possible to promote a better accuracy of the moments of sending recommendations. The data collected and used in this paper is present in[2].

5. Final Remarks and Future Works

This work presented a proposal capable of helping teachers and students during remote classes. An architecture was designed to detect situations of stress and anxiety by using location monitoring and body sensor data. We used smartphone apps and smart bands to collect the data, and through machine learning algorithms, we identified stressful moments, enabling us to send recommendations to students and teachers. An evaluation was carried out using real data collected from a student, and its results show that the technologies and algorithms used are viable and promising.

Some limitations were found during this work, such as the data exported by the *Samsung Health* app has a granularity of hourly heart rate measurements. It is also worth highlighting issues involving computational resources for testing additional algorithms with more possibilities for their parameters. In future work, we will apply our solution to more students and teachers. Furthermore, new bracelets (*Wearfit 2.0*) have already been bought to obtain less granularity between measurements, giving us more control over the extraction data step. Also, we will use machines with greater processing power, improving the Machine Learning algorithms' performance even more. Finally, we will enhance the combined use of location and body data to improve the proposal's performance.

6. Acknowledgments

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[2]https://drive.google.com/drive/folders/1sv6ZS87fpJpyXEL2HtT3pcCYi176fztT?usp=sharing

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