Real-time Biofeedback System for Interactive Learning using Wearables and IoT

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Abstract

This work presents a real-time biofeedback tool that uses wearables and Internet of Things (IoT) for applications in education. Using wearables (electroencephalography helmet, smart bands) and a Raspberry Pi, signals were integrated in real-time. Moreover, a three-class random forest (RF) classification machine learning (ML) algorithm, based on the aforementioned signals, which predicted a student's mental fatigue (none, moderate and extreme fatigue) with 92.69% average correct classification percentage using 5-fold cross-validation (CV). The system can evaluate a student's performance under different learning modalities, in addition, it can show different content types to students, depending on the professor's necessities. In the current work, vehicle signals were integrated for teaching automotive engineering.

Keywords
Biometrics, machine learning, IoT, wearable sensors

1. Introduction

Education needs to adapt constantly, hence a variety of trustworthy evaluation and teaching methods need to be employed. A recent option is the use of biometrics as a biofeedback tool that works as an intelligent system for students, as well as teachers, to improve their respective learning performance.

Biometrics is the use of biological measurements related to the human body, one of the oldest biometrics being used are fingerprints, since they have been used on forensics with the purpose of identifying an individual, as each fingerprint is unique (NarayanMohanty and Sikka 2021). On the other hand, recent methods extract biometrics, such as vein biometrics, further used on the financial industry to authenticate financial transactions (Mohsin et al. 2020).

Moving back to education, multiple efforts have been made to implement them, advances range from its basic form as biometric scanners such as fingerprints or face recognition (Leaton, 2018) to access facilities or as a payment method within the campus, done via companies as identiMetrics and IDconnect (Garg et al. 2018). Other studies use neuroimaging techniques such as functional magnetic resonance imaging (fMRI), that helps in the visualization of the current set of exercises a student is doing (Anderson et al. 2010).

Both of the previously mentioned cases represent opposites sides regarding pricing and dependency of biometrics. The current study aims for a middle point, a variety of wearables devices that can extract physiological signals such as: electroencephalogram (EEG), electrocardiogram (ECG), and many others, these devices have an accessible price while still offering great resolution to reliably evaluate an individual.

As it was previously stated, education needs to innovate in order to deliver a modern and fulfilling learning experience to its students. This demands new metrics that are highly related to the student's cognition when exposed to different teaching methods, which then lead to the creation of a database that could be further analyzed to deliver high quality lectures for the best learning experience by each student, based on their biometrics.

The previous scenario can be achieved via an integrated system that considers multiple biometrics in order to create advanced metrics, further used to evaluate teaching techniques and methods. This would provide a holistic perspective that uses reliable procedures to collect the corresponding data, as well as interpreting it using Machine Learning (ML) models. The collection of these data is then delivered in an easy-to-use platform for a teacher, in sought of giving perspicuity to the teacher in question of their respective students' state.

Further exploring education's field, the current study focuses on smart classes using Internet of Things (IoT) devices, with the purpose of gathering quantitative biofeedback that could be further used as a metric by both lecturer and student in hopes of creating a more cohesive, learning environment.

The aim is to create an integrated framework of biometric devices with the capability to improve performance of a student's learning during education. The development uses multiple biometric devices that gather biometrics from the student, in order to deliver an accurate prediction about the student’s level of mental fatigue that wears the wireless devices, which is further uploaded to a created web application to track the student’s performance.

The system was already tested via a student using the integrated system while exposed to a video lecture, which is used by Tec de Monterrey's Automotive Engineering subject. A future module would also be integrated, which gathers signals from a moving vehicle, so students can get an interactive approach on learning the subject.

By using these biometric signals, the system in question was capable enough of providing the user feedback about their respective fatigue level.

1.1 Objectives

As far as the authors know, currently there is not an integrated system which generates reliable, quantitative data as a metric of a student's performance. This is the objective of the project, to create an interactive application that uses student's biometrics to further create a report used by the teacher or the student itself, so to improve learning via using the right activities and assessments that are less fatiguing to a student in question.

The system has also opportunity to utilize the other biometric systems (Hexiwear and Empatica) in further experiments to add new features of interest to the interactive platform. As for the current project, only EEG signals provided by the OpenBCI were used, as these electroencephalographic signals are highly correlated with mental fatigue.

2. Literature Review

Many research has been made using single biometric devices to validate its effectiveness on predicting and gathering relevant cognitive features, such as: stress, mental fatigue, attention to a given task. These features might be used in an interactive IoT environment to support constant monitoring, and so improve student’s learning experience.

Research on biometric wearables show their reliability: Empatica on detecting convulsive seizures (Regalia et al. 2019), and Raspberry Pi with Hexiwear to develop a cloud-based IoT framework (Mocnej et al. 2021).

On cognitive features, EEG signals are used to evaluate the student's level of meditation (Xu and Zhong 2018) and attention (Brawner and Avelino 2016), further combined with an audio signal to increase the level of attention (Sun and Yeh 2017). Thermal infrared imaging can also obtain students' level of attention within a smart classroom (Kim

2019), and ECG features such as Hearth Rate Variability (HRV) can identify stress conditions (Zhou et al. 2021), which performed best when combined with electromyogram (EMG) features (Pourmohammadi and Maleki 2020).

These biometrics can then be used to solve learning-related issues such as assessments loads, which affect students' mental health, as negative emotions related to stress and anxiety deteriorate learning (Wass et al. 2020). Monitoring of biometrics in the classroom can create new learning ways, as direct feedback to students with an appropriate implementation of teaching methods, improve learning pace and retention (Gruzelier et al. 2014).

In essence, validation of biometrics and cognitive features has been well stablished, with some studies even explored their relationship to student's performance. Although there is scarce research when using IoT to interconnect in real-time, multiple biometric devices, and combined with cloud services to create interactive environments in education, with the purpose on fostering new learning methods and so leverage education based on biometrics.

3. Methods

The current study focuses on smart classes using wearable sensors and IoT devices, with the purpose of providing quantitative biofeedback to both lecturer and student in hopes of creating a more cohesive, learning environment. The aim is to create an integrated framework of biometric devices that has the capability of improving a student's performance during learning, by providing biofeedback.

Wireless devices attached to the student gather biometrics (EEG, heart rate, temperature), to deliver an accurate prediction about their mental fatigue, further uploaded to a web application to track the performance of a student.

The system is composed on four key modules:

1. Data Acquisition (OpenBCI, Empatica, Hexiwear).
2. Data Integration (Raspberry Pi, ML Model).
3. IoT and Web Server (Backend, Frontend).
4. Interactive Visualization for Students (Geotab, Google Street View), which is specific for the current study, however, can be modified depending on the learning content.

The methodological proposal is presented in Figure 1; the workflow starts on the left-side with the user interacting with the biometric devices connected to a single Raspberry Pi 4 Model B, where wearables' data are processed and sent to the ML model created using R and Python, which predicts mental fatigue based on a previously trained model.

All these data are further sent to the Django designed backend, which is able to interconnect with the web application created using Angular and hosted in Google Firebase, and so the user can visualize and interact with its biometric data and cognitive features in real-time.

Meanwhile, using an IoT approach, the biometric data is stored in cloud storage using Heroku, so that the user can further visualize their past biometrics' recordings and respective level of mental fatigue level in a given session.

An additional Geotab device (vehicle-related features reading sensor) and Google Street View were combined to further implement the system when the student learns about a specific subject (in this case, automotive engineering).

These last components represent the interactive feature of the system, as they present information to the students, and are included because the system was first implemented an automotive engineering course. It is important to note that this system is flexible, thus allowing the inclusion of different biometric devices, ML models and learning content.

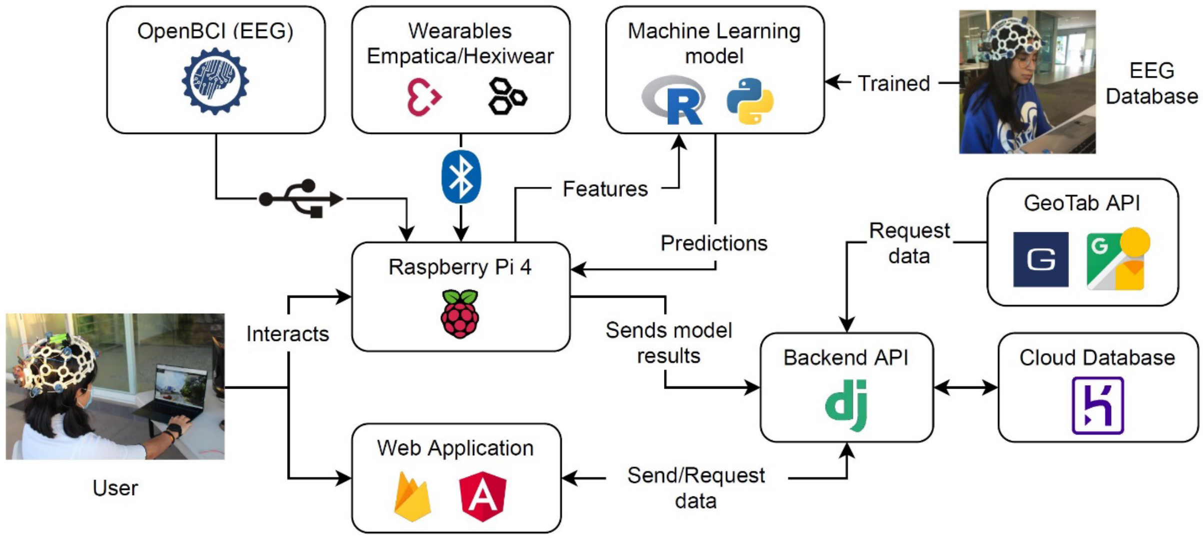

Figure 1. Flow diagram of the overall integration within the multiple modules involved in the process.

The Raspberry Pi was a central module, as it connected with the biometric devices in Table 1 and posted all its data to a web server, using Python 3.8. This device is the world's third best-selling general-purpose computer, after personal computers (PCs) and Macs (Fletcher and Mura 2019). Resembles a small computer that runs Raspbian OS, which is a Linux-based operating system, and thus its versatile, portable, cost effective, and powerful.

Table 1. IoT devices' general description, connection to the central module and features generated.

Device	Description	Connection	Features
Empatica E4	Smart bracelet, measures acceleration, blood volume pulse (BVP), electrodermal activity (EDA) and skin temperature.	Lab Stream Layer (LSL) module using Python, able to interact with the "E4 streaming server" Windows app (Empatica Inc. 2021).	ECG-related features can interpret if a subject is under stress, fatigue or relaxation period. EDA and BVP could be cross-checked to assess stress and fatigue.
Hexiwear	IoT smart device with sensors designed by the company MikroElektronika, to serve as a multipurpose device.	Bluetooth socket, data was acquired by each sensor's Universally Unique Identifier (UUID), and it was stored with Python.	Can be used as an accelerometer, magnetometer, gyroscope, and barometer, sensors employed: (HTU21D) Temperature, (MAX30101) Heart rate.
OpenBCI	Ultracortex "Mark IV" EEG headset, an open-source brain-computer helmet that record the brain's electrical activity.	*Brainflow*'s Python library to acquire, process and clean signals. Connected to the Raspberry using an USB dongle.	EEG band powers from 8-channel dry electrodes, following the 10-20 International System of Electrode Placement: FP2, FP1, C4, C3, P8, P7, O1, O2.

Data posting was done via an Application Programming Interface (API) described in Section 5.2, and so the Raspberry converted all Comma-Separated Values (CSV) files into JavaScript Object Notation (JSON) files. With the purpose of making the web application faster and more efficient, as JSON files are lighter. The posted information:

- Hexiwear: User's temperature and heart rate fluctuations through time.
- Brainflow: Power Spectral Density (PSD), and power ratios for all EEG channels.
- Machine Learning Algorithm: Level of mental fatigue, based on model's prediction.

Moreover, a telematics provider that connects vehicles and provide web-based analytics was developed using Geotab and Google Street View. The data used for the current study was obtained setting up multiple devices in buses, then the images of them driving across a street were extracted via an API connection to Geotab's Software Development Kit (SDK). Using Python, the following functions were used:

- LogRecord: Required the vehicle's ID and the timeframe desired, returned the position and velocity of the vehicle according to the date and time specified.
- FuelUpEvent: Obtained the current fuel's consumption data.

The aforementioned data is then saved as a JSON file and sent to the sever to further display it. Furthermore, using the latitude and longitude, an image of the vehicle's location was created using Google Street View API. With the purpose of identifying a person's mental fatigue level at a certain speed and fuel's consumption.

4. Data Collection

The data used was obtained during a past study (Ramírez-Moreno et al 2021), it is composed of: a set of EEG signals acquired via an 8-channel OpenBCI, by placing dry electrodes on the head of a subject; and mental fatigue classifications according to the 3-class (No, Moderate and Extreme Fatigue) Fatigue Assessment Scale (FAS), assessed by their official self-answered questionnaire (Spanish version) taken before recording EEG, this was applied to 17 healthy subjects with mean age of 22 years and standard deviation of ± 3 years (8 male, 9 female).

The dataset consisted on a five-minute EEG recording, composed by: 30 seconds measurement of Eyes Closed (EC), 30 seconds of Eyes Open (EO), and 4 minutes of an Auditory Oddball task to elicit P300 waveforms. The Auditory Oddball task consists in two stimuli with different intensity, in this case the stimuli were two tones with different frequency: baseline and oddball, and so the baseline tone is repeated more frequently that the oddball. The system then evokes the P300 waveform when the oddball sound is presented, on the other hand, first minute is used as a calibration step to normalize signals according to each subject’s signals.

The collected EEG signals are related to emotional states on different frequency band powers, so a band-pass filter was first applied to remove noise, then, the power of each signal was calculated using the Fast Fourier Transform (FTT). Lastly, a spectral analysis classified each signal using the following band power ranges: Delta δ (1–4 Hz); Theta θ (4–7 Hz); Alpha α (8–12 Hz); Beta β (13–29 Hz); and Gamma γ (30–50 Hz), calculated using PSD. These resulting features were normalized using the following Equation 1:

$$x_{norm} = \frac{x - \mu}{\mu} \tag{1}$$

Where $\boldsymbol{x_{norm}}$ represents the normalized band power and μ, the mean of a given band power and subject, from the 30 seconds EO recording. For data pre-processing: outliers were removed from the normalized data so that every value lied within $\mathbf{-10 \leq x \leq 10}$ range. Class imbalance was present, as 66% percent of total classes were "Moderate Fatigue", so a random over-sampler method was applied, so that each class had an equal 33% representation of the total data (as three levels were employed).

Moreover, a set of combined features in the form of power ratios within the same EEG channel (such as: $\boldsymbol{\frac{\gamma}{\beta}}$ P7), were added. Considering that there are 5 band powers and 8 EEG channels, 40 base features were power bands, and 160 EEG Power Ratios. The resulting 200 features were reduced to 8 most significant features, to reduce model's complexity for real-time predictions. A hybrid feature selection method was developed to accomplish the task, which combined importance from both Random Forest (RF) and Multivariate Adaptive Regression Splines (MARS).

The aforementioned method starts with a RF classification model that computed the Mean Decrease Impurity (MDI), measured by the Gini index in Equation 2. Where $\boldsymbol{f_i}$ represents the frequency of label $\boldsymbol{i}$ at a node, while $\boldsymbol{C}$ are the possible labels (No, Moderate and Extreme Fatigue). The computed metric then reflects the reduction of the index, which represents the number of splits in a tree that used that feature, the more it is used on splits of a given binary decision tree, it then means that is more determinant to separate each class.

$$Gini = \sum_{i=1}^{C} f_i(1 - f_i) \tag{2}$$

Using the RF metric, the best 50 features were selected and fitted into a MARS model using the *earth* R package (Milborrow 2018), to capture non-linear relationships. The decrease of Residual Sum of Squares (RSS) (Equation 3) of each feature was calculated via a Leave-One-Out (LOO) approach, removing each feature and computing the difference on the RSS, the results were normalized to relative importance, where 100 is the biggest decrease (best).

$$RSS = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{3}$$

Given that RF is a boosted-based method, it depends on randomness, and so an average approach was taken to better generalize, which consisted on running 20 iterations with different seeds. For each iteration, features where reduced to the best 10 features according to the MARS model, then both MDI and RSS were computed. Each feature's importance was summed and normalized by their maximum value, displayed in Table 2, features are ordered according to RSS, the determinant metric.

5. Results and Discussion

5.1 Numerical Results

Using features' importance in Table 2, features with $\leq$ 30 normalized decrease in RSS were removed, and so only the best 8 features with the greatest RSS were selected, which are 6 band powers and 2 ratio powers.

Table 2. Feature selection using decrease in RSS and Mean Decrease Impurity (MDI).

Feature	MARS (RSS)	RF (MDI)	Feature	MARS (RSS)	RF (MDI)
θ (O1)	100.00000	62.04875	δ (FP2)	51.3624	63.51241
θ (C4)	87.56760	52.23073	δ / γ (O2)	41.53791	52.94083
β (P7)	82.80721	100.00000	θ (FP2)	29.02988	23.06057
β (P8)	74.26629	73.19926	δ / β (P8)	26.46342	14.35046
δ / γ (P8)	56.99946	48.53941	δ (P8)	23.53160	11.45306
β (FP1)	56.29914	37.63690	β (C4)	21.46678	40.13383

To evaluate the ML models created using the given best features, accuracy (Equation 4) was used as an evaluation metric, which is considered as the average correct classification percentage.

$$Accuracy\ (\%) = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} * 100 \tag{4}$$

Using the aforementioned best features, 5 different ML algorithms were used to generate 5 different ML models: Random Forest (RF); radial-kernel Support Vector Machine (svmRadial); Gradient Boosted Machines (GBM); Classification and Regression Trees (CART); and Linear Discriminant Analysis (LDA). To generalize and validate results, 20 random splits with an 80:20 split ratio (80% training and 20% testing) were created, for each split, models were trained using training dataset and 5-fold cross-validations to obtain the best model, afterwards tested on the testing dataset to obtain its accuracy. After the splits, minimum, average and maximum accuracies were obtained.

Based on the average accuracy obtained using a multiple seeds approach, results are displayed in Table 3. Which shows that RF was superior (92.69%), followed by svmRadial (76.29%) and GBM (76.07%), lastly, CART (55.52%) and LDA (55.64%). For the best model (RF), maximum accuracy was 93.56% and minimum accuracy 91.74%, which serve as confidence intervals for the created, chosen model.

Table 3. Testing accuracy using 80:20 split on balanced dataset with 5-fold cross-validation.

Model	Minimum Accuracy (%)	Average Accuracy (%)	Maximum Accuracy (%)
RF	91.74384	92.69576	93.56949
svmRadial	74.78683	76.29217	77.74977
GBM	74.56579	76.07552	77.53790
CART	53.79128	55.52461	57.24792
LDA	52.17807	53.91520	55.64522

5.2 Graphical Results

The final integration of the entire modules within a single Raspberry Pi, provided an astounding tool that yields a complete report on body biometrics, including the brain (OpenBCI) and body (Empatica, Hexiwear). A picture of the final, integrated system is displayed in Figure 2: The participant on the left picture is using the three wearables, while using the Interactive Visualization, created using Google Street View and Geotab. On the other hand, a researcher on the right picture is visualizing the data inflow that is being generated, further uploaded to the created web server.

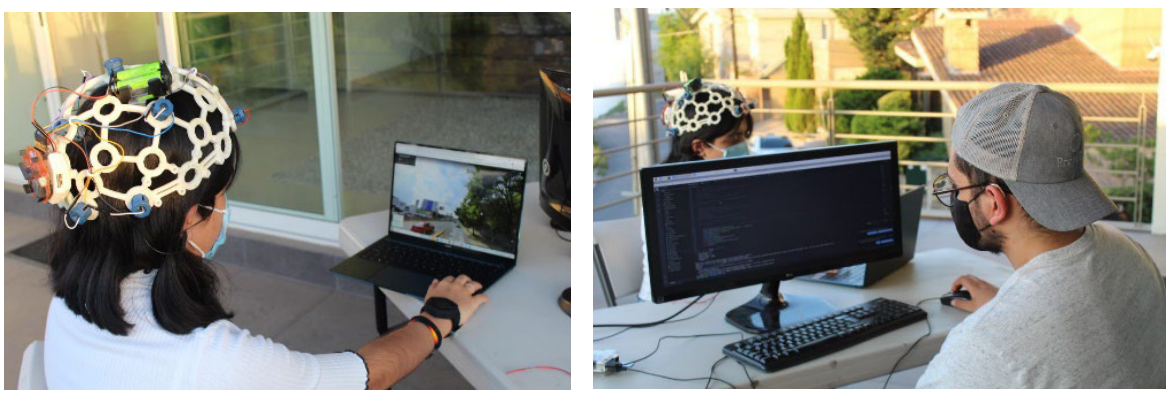

Figure 2. (Left) A participant using the created interactive environment and biometric devices, (Right) Data acquired during the experiment is sent to another PC wirelessly for visualization and analysis.

Moreover, a web application based on microservices was developed for this study, the architecture consisted of back-end and front-end. The back-end was developed in Django to create a Representational State Transfer (REST) API that manages user's requests, further hosted on Heroku as a service. On the other hand, the front-end module was developed in Angular (Google's front-end framework) and used Nebular to create a simple but elegant User Interface (UI), further hosted on Google Firebase, an example of feature visualization is shown in Figure 3.

The web application interconnects the results of multiple biometric devices (OpenBCI, Hexiwear and Empatica) on a single Firebase App that also uses Geotab to provide an interactive UI. Biometrics are injected into a ML algorithm to predict the level of mental fatigue that the user has during a session and uploads it to cloud storage in order to inspect and contrast the performance of a student during multiple sessions, using the developed infrastructure.

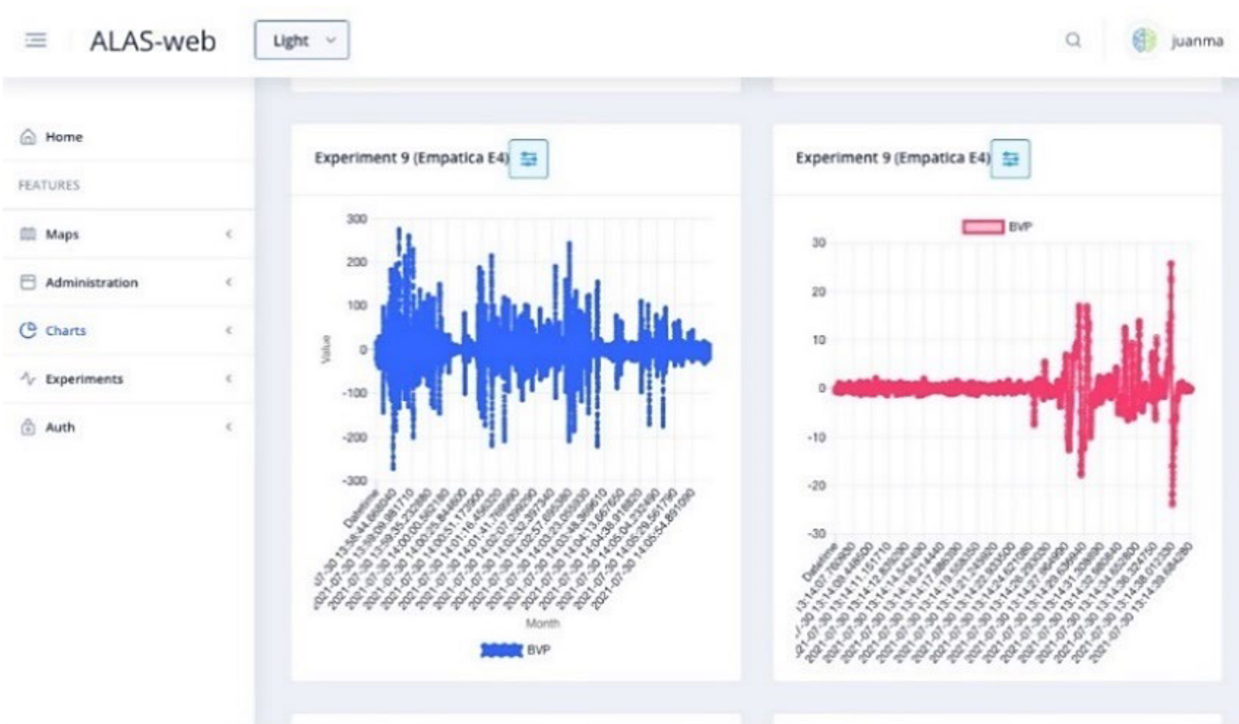

Figure 3. Screenshot of the web application created, where the Blood Volume Pulse (BVP) of two takes from a participant is shown on two different plots.

5.3 Proposed Improvements

The tool can be further improved with additional biometrics and ML models, in order to gather additional features and metrics, which are related with students' learning rate and attention, these features are hard to find using traditional, non-technological techniques, such as the mental fatigue level.

Moreover, testing was done with students exposed to a video lecture used by Tecnologico de Monterrey's Automotive Engineering subject (Ramírez-Moreno et al. 2020). The lecture included Geotab as an interactive environment that integrates the signals of a vehicle moving across the streets. With every lecture, a biometrics' dataset was obtained, which was further used to predict the student's mental fatigue level in real-time.

5.4 Validation

Although the accuracy of the RF model was already acquired using multiple seeds, random 80:20 splits and 5-fold cross-validations, an additional validation technique was used. Such validation consisted of training the RF model on the whole labeled recordings, and then be tested on another different dataset, which consisted of 16 different students. In this new dataset, the FAS questionnaire was applied to students, and then underwent two five-minute EEG recordings: one at the beginning of a class, and another one after (1.5-hour) the class. The trained RF model was then used to predict the mental fatigue levels after the lecture and were compared to the "real" ones obtained from the FAS.

Each mental fatigue classes' prevalence is in Figure 4; where it seems clear that there was a reduction on the number of samples that were categorized as "No Fatigue" after the class, which is then related to an increase of the number of samples in "Moderate Fatigue" category. While the third classification, "Extreme Fatigue", remained similar before and after the test, with a very slight decrease after the class. Although these results refer to data obtained from a different dataset, it provides validation to the created model, as it was successfully capable of generalizing and predicting on a completely new dataset, and thus predicting the expected trend (students experiencing more mental fatigue as compared to their baseline) on an unknown (to the model) dataset.

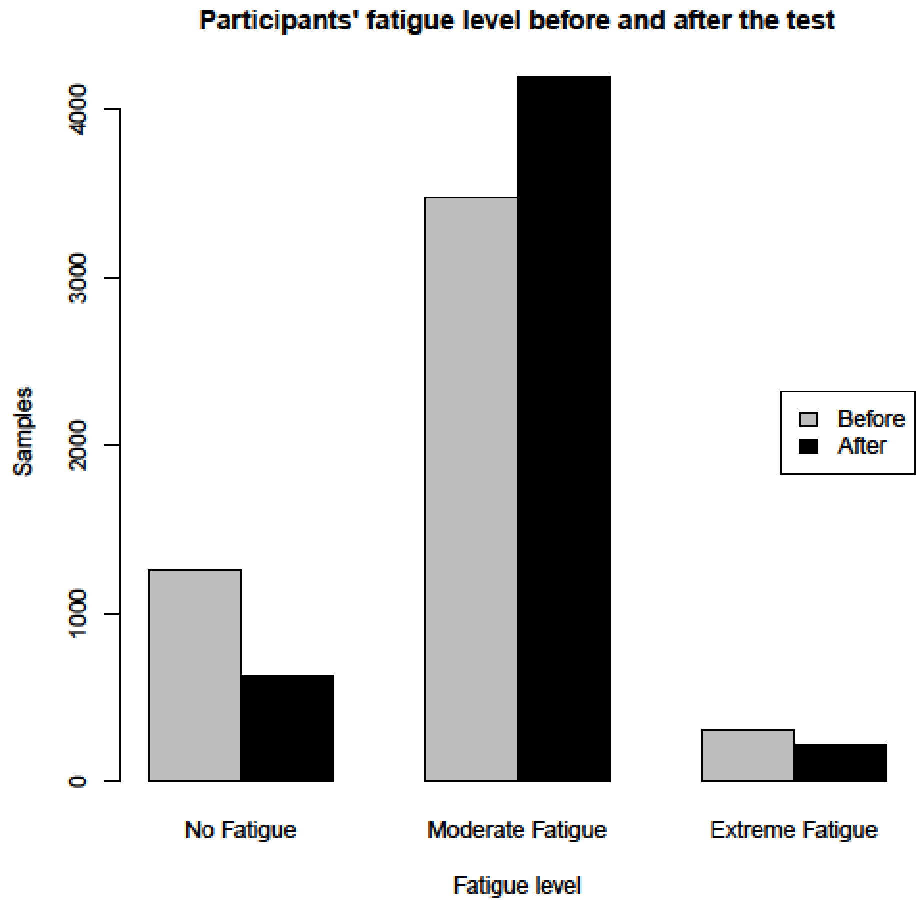

Figure 4. EEG pre-test data contained specific fatigue classifications given by a questionnaire answered by participants, used to train the final RF model. Afterwards, the model was used to predict fatigue level on the post-test EEG data, which had no true classifications given by participants.

6. Conclusion

The presented results only made use of the EEG signals provided by the OpenBCI to build the predictive models. However, the created system has the opportunity to use other biometric devices (Hexiwear and Empatica) in further experiments and so, add new features of interest into the predictive models.

The methodology followed within the study was concise and flexible, and it can be further escalated with additional biometrics, as well as algorithms that could enhance the created web application. Due to the current COVID-19 pandemic, the created system has yet to be tested on a larger scale with students in a classroom. Nonetheless, the current development has the potential to serve as a basis to further revolutionize the current traditional teaching. In the evaluated dataset, the system was able to predict that students were more fatigued by the end of the class, as more of them moved from the no fatigue to the moderate fatigue class, as it would be expected after a 1.5-hour lecture.

This type of systems might lead to the creation of new educational models. Such models would be developed based on the analysis of biometric signals of students during a class, thus providing a reliable validation. Both teaching and learning can be continuously improved, by analyzing the physiological variables of students during a class, to infer their mental and physical states. Then, educators would have the tools to perform adaptations and changes in their classes as a response to their students' reactions.

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