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Non-invasive monitoring with Ballistocardiographic sensors for sleep management

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Abstract—Sleep has an important impact on people’s daily lives. A successful methodology for monitoring sleep is Polysomnography (PSG). This is an accurate and reliable approach but, unfortunately, very invasive. PSG uses expensive sensors that must be positioned by experts, what, in practice, makes its adoption only viable in hospital setups. Therefore, there is a demand for better non-invasive alternatives, such as Ballistocardiography (BCG). BCG uses cheaper sensors, easy to install and ideal for domestic use. This allows its integration in solutions that manage sleep, using mobile apps not only for presenting valuable information to users but may also for acting on the environment, through actuators, such as sound.

This work uses this principle to help users to wake up smoothly. Sleep monitoring is performed with Murata SCA11H BCG external sensors. Low-pass filters have been implemented, using a sliding exponential average, for all metrics. The Random Forest algorithm was then selected for sleep phase classification, that presented the best performance when using the Weka exploration tool for learning methods. With the implemented model, it has been proved that four sleep phases are predicted. It was then possible to define a strategy for avoiding waking up alarms to be fired during deep sleep. It consists on the analysis 15 minutes prior to the alarm and, when deep sleep is detected, a relaxing sound is played.

This work demonstrated that non-invasive sleep monitoring can be used to actuate on, and improve, the user environment, in a home setup with cheap sensors.

Index Terms—Ballistocardiography, Sleep Monitoring, Sleep prediction.

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I. INTRODUCTION

The work explored here focuses on rest management, through sleep monitoring. In particular it contributes to solve the problem of reliable sleep monitoring and actuation at home, without using invasive methods.

In short, the most used methodologies in this area are PSG and BCG. The PSG monitoring method is the most reliable, but it is invasive, expensive and requires a specialist to identify the phases during sleep time. Therefore, BCG should be the method to be used, for non-invasive setups that can be easily deployed at home, with no need for hospital support or specialists in the identification of sleep phases. [20] [19]

BCG is the most recently developed method, and it is somehow supported on PSG. It reads different metrics, by using sensors such as accelerometers and gyroscopes. In order to obtain enough precision for a reliable sleep monitoring, this metrics must be compared with PSG classification carried out by specialists.

The main objective for the work presented here is to monitor sleep through external non-invasive sensors and to act accordingly on the environment. An integration proposal and the mobile application "GoToBed", presented here, has been developed as a means to achieve this goal.

Section II surveys different sleep monitoring approaches and some known applications in the area.

Section III presents our integration proposal and application. This uses an external BCG sensor, selected because of its price and easy handling by end users, both in terms of configuration and calibration. Low pass filters are proposed for the data obtained from those sensors. Only then a classification of sleep stages and actuation on the environment is possible. In order to avoid a startle and sudden wake-up response, that necessarily happens when on deep sleep, the actuation aims to induce users to move to the light sleep phase. For this, a smooth sound is played prior to the alarm.

Section IV presents configuration options for the filters and a performance comparison of different classification learning methods and how they can be used for sleep prediction on this proposal.

Conclusions are presented in Section V

II. LITERATURE REVISION

A. PSG versus BCG

PSG is an intrusive, expensive and complex method for analysing sleep. It is only suitable for continuous short-term measurements. This sleep monitoring and analysis is performed by highly specialized technicians and doctors in a laboratory setting. This measurement requires the use of numerous sensors. The PSG features 18 channels for measuring various types of signal. Among them, 6 electrodes to measure brain activity with the support of a Electroencephalography (EEG) procedure, 2 electrodes to measure eye movements using the Electro-oculography (EOG) method, 2 electrodes to measure the tension of the mandibular musculature through

the Electromyography (EMG), 3 electrodes to measure cardiac function with the Electrocardiography (ECG) and, finally, chest and abdomen belts to measure respiratory effort. [26] [22] Thus, it has become important to find new ways to monitor sleep in a more effective, inexpensive, both in a continuous way and in the long run. Consequently, methods based on Balistocardiography (BCG) have emerged, which have an increasing potential in the analysis of sleep.

BCG (Figura 1) is a method that does not require any type of intrusive measuring mechanism. As such, it has the potential to be an excellent tool to measure recovery and sleep quality for several use cases. A good night's sleep is important in the functioning of the heart or blood vessels, in mental well-being and in preventing some types of cancer. It may also help athletes to achieve good results, in terms of training and competition. Heart rate and breathing parameters also measure the condition of the autonomous nervous system and indicate many pathological conditions. Among them, the change in stroke volume as a measure of the condition of body fluid. [20] [19]

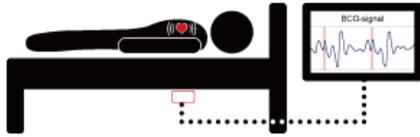


Fig. 1. BCG sleep monitoring process. [6]

B. Non-invasive monitoring & sleep management applications

We have identified some related applications in this area: Beddit [1], Sleep as Android [25], Pillow [23], Emfit QS [17], ZEEQ Smart Pillow by Rem-Fit [24], DREEM 2 [10]. We will compare them with this proposal ("GoToBed").

The most common way of actuating is through the use of sound coming from a mobile device or external actuator (ZEEQ), in order to wake the person. The Sleep as Android application features more types of actuators. Among them, captcha and intelligent light. The captcha aims to force the user to get out of bed in order to turn off the alarm.

Analysing Tables I and II, it can be concluded that for applications that have internal sensors, the cost is free: Pillow and Sleep As Android. Whereas, for applications that use external sensors, there is already an associated cost. This is the case for the applications Beddit, Emfit QS, ZEEQ Smart Pillow, DREEM 2 and "GoToBed" (proposal present in chapter 3), that have a cost of respectively 149, 299.98, 51.71, 428.10, and 168.45 euros. Thus, ZEEQ is the cheapest App and DREEM 2 the most expensive. This makes perfect sense, taking into account the methodologies by each of them. The BCG methodology is present in the Beddit, Emfit QS and "GoToBed" applications, but only the later supports WiFi. In turn, the SONAR and EEG methodologies are used respectively by App Sleep as Android and DREEM 2. Also,

there are differences, inherent to each application, on the way different types of data and audio are transferred and stored. Finally, as can be seen in the table I, applications run on different operating systems.

TABLE I
COMPARISON BETWEEN ALL APPLICATIONS REFERENCED AND ANALYZED THROUGHOUT THIS ARTICLE.

Applications	Operating system	Cost [euros]	Methodologies	Data and audio transfer
Beddit	IOS	149,00	BCG	Bluetooth
Sleep as Android	Android	0	SONAR	-
Pillow	IOS	0	-	-
Emfit QS	Web	299,98	BCG	Wifi Mobile data
ZEEQ Smart Pillow by Rem-Fit	Android IOS	51,71	-	Bluetooth
DREEM 2	Android IOS	428,10	EEG	Bluetooth Wifi
This Proposal "GoToBed"	Android	168,45	BCG	Wifi

TABLE II
COMPARISON BETWEEN SENSORS PRESENT IN ALL APPLICATIONS.

Applications	Sensor type	Sensors used
Beddit	External	Piezoelectric force sensor , capacitive touch, humidity and temperature
Sleep as Android	Internal (Device)	Ultrasonic sensor (SONAR), motion/position sensor (gyroscope and accelerometer) and passive infrared sensor
Pillow	Internal (Device)	Motion/position sensor (gyroscope and accelerometer)
Emfit QS	External	Ferroelectric sensors (Sheet quasi-piezoelectric, sensors band and cable)
ZEEQ Smart Pillow by Rem-Fit	External	Motion sensor (3-axis gyroscope)
DREEM 2	External	6 EEG sensors, accelerometer, pulse oximeter and sound level meter
This Proposal "GoToBed"	External	SCA10H sensor (accelerometer, gyroscope)

At the level of used sensors, identified in the Table II, both Beddit and Emfit QS have a sensor with a thin and soft structure. The Sleep as Android and Pillow applications fall under the same principles, that is, motion/position sensors (gyroscope and accelerometer). However, what distinguishes them is an ultrasonic sensor. On the other hand, the DREEM 2 application features six EEG sensors, which is why it is more expensive, and also includes an accelerometer, a pulse oximeter and a sound level meter. A pulse oximeter was developed to measure the heart rate and oxygen saturation

of the blood. [2] Finally, the proposal "GoToBed" features a Murata SCA10H chip with an accelerometer and a gyroscope sensor.

With the information present in the Table II, it is also possible to analyse the maximum possible distance between the sensor and the user. Applications with internal sensors have a working distance of up to 100cm. On the other hand, the applications with BCG, that use external sensors and feature more precision, focus on smaller distances: 30cm for Beddit and Emfit, and 20 cm for "GoToBed". The distance for the ZEEQ and DREEM 2 applications is not critical, since they are using respectively cushion and headband integrated sensors.

III. MONITORING AND ACTUATION PROPOSAL

In this section the proposal integration and implementation are detailed, and all options are justified for the application development, including the external sensor to be used.

In Figure 2, the functional sequence diagram of the proposed integration and application is presented.

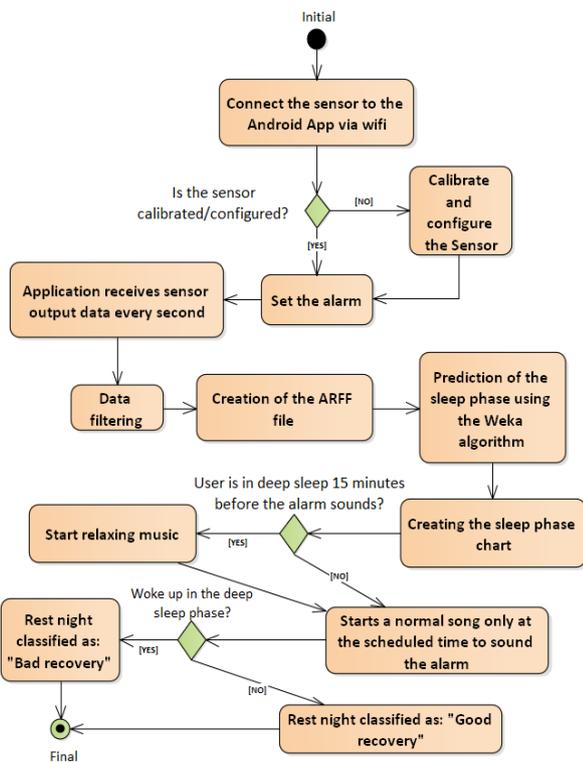


Fig. 2. Proposed functional sequence diagram for the application under study.

At first, the sensor is connected to the application via wifi. However, However, if the sensor has not been previously calibrated or configured, it is necessary to perform these operations. Then follows the phase where the desired action for this application is selected, such as, for example, an alarm for a smoother wake up. After this, the application starts the capturing process, where every second the output data from the sensor is read. All of this data is subject to a filtering process performed in real time. A ARFF file is then created with all the data previously filtered. With this file, it is possible

to make the prediction of the phases of sleep, by using the classification algorithm. In order to address the security issues, given the specificity of these personal medical and health data, no information is sent to de cloud, or stored outside the mobile device. Additionally, data that is no longer required is deleted.

Subsequently, a graph is created with all the identified phases of sleep. In this work, with this information, if the user is in deep sleep, 15 minutes before the alarm triggers, a relaxing music is played in advance. This type of music will last until the expected time to wake up or until the user is in a different state other than deep sleep. Otherwise, a normal alarm music starts, only at the time set in the alarm. Finally, if the person under study woke up in a state of deep sleep, the night rest is classified as a bad recovery. Whereas, if the person has not woken up in the state of deep sleep, the night of rest is classified as a good recovery.

This is done because there are different consequences when waking up during different sleep states. That is, for the deep sleep state a more relaxing sound is used, while, for all other states of sleep (light, REM and awake), the used sound is more intense. In short, this type of action aims to a calmer wake up in the deep sleep phase and to wake up more firmly in the other phases.

Figure 3 depicts the implementation of the proposal for the GoToBed application. The first phase is the monitoring, where the collection of data is performed through sensors.

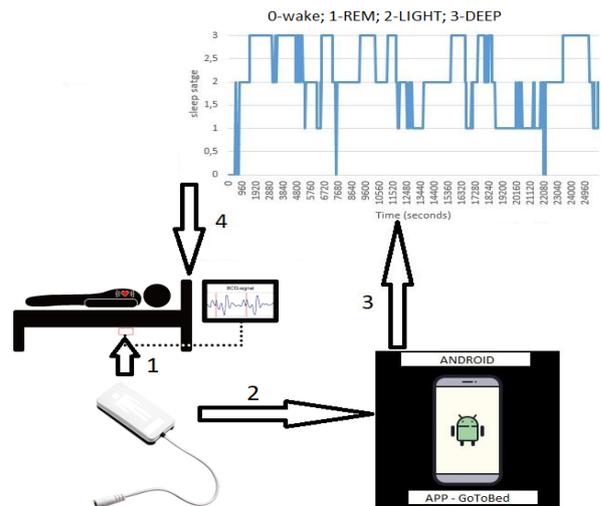


Fig. 3. Implementation of the proposal for the GoToBed application.

The selection of the sensors to be used is critical and must necessarily contemplate the following requirements: a low price, free access to data, a number of sufficient and relevant metrics to achieve the objectives, and ease of use. Thus, we have opted for the Murata SCA11H chip that have sensors, that implement the BCG methodology, outputting several metrics for accelerometer and gyroscope sensors, and presents easy procedures that facilitate its installation, in particular its calibration, configuration and positioning. [7] [8] [5] With this sensor, it is possible to obtain all this type of information, in

particular the Heart rate (HR), Heart rate variability (HRV), Respiration rate (RR), Stroke volume (SV) and Signal strength (SS), which will be later explained, with a data acquisition rate down to 1 sample per second.

Then, the second phase involves connecting the application with the sensors via WiFi, in order to obtain the output data from the BCG sensors, every single second. The implemented application "GoToBed", installed on an Android mobile phone, was implemented using the Android Studio development tool.

Next, in the third phase, the application filters all these data and makes sleep predictions every 30 seconds. A lower period, down to 1s, would be possible, but no significant improvement is expected with this precision, with the inconvenience of having an increase in the processing cost.

Finally, in the fourth phase, the main objective of the application is achieved. This application acts in order to wake up the user in the lightest sleep phase. For this, an analysis is carried out 15 minutes before the scheduled time for the alarm. If this analysis results in the deep sleep phase detection, a relaxing music begins.

The use of data from the BCG SCA11H sensors is particularly critical for this proposal. Raw data is very noisy, particularly for higher frequencies, and a proper data processing is required. This has been achieved by using several filters, supported in the Equation 1. This equation represents a low-pass filter implementation, using a sliding exponential average. The k parameter is a filtering constant (between 0 and 1), $x(t)$ is the original value, that is, the current signal sample, $y(t-1)$ is the previously filtered value and, finally, $y(t)$ is the filtered value at time t . The higher the k , the more forgetful the filter is, that is, higher frequencies are more relevant, or in a different perspective the sensor is more reactive. [21]

$$y(t) = y(t-1) * (1 - k) + x(t) * k \quad (1)$$

HRFILT is calculated based on Equation 1 and measures heart rate (HR) filtering. The $x(t)$ matches HR(t) as the original value and $y(t-1)$ matches HRFILT(t-1) as the filtered value in the previous instant, as depicted to Equation 2. All remaining metrics have a similar treatment.

$$HRFILT(t) = HRFILT(t-1) * (1 - k) + HR(t) * k \quad (2)$$

HRVFILT is calculated using the relationship between the HF and LF components. To reduce the modulation caused by breathing, it is necessary to amplify the HRVFILT with the SVV. [21] By multiplying the HFHRV(t) by 10, obtained values are positioned around the value defined as the initial constant (equal to 8), as stated by Equation 3.

$$HRVFILT(t) = \frac{HFHRV(t) * 10}{LFHRV(t) * SVV(t)} \quad (3)$$

The choice for all initial values must be done automatically for each application user. To achieve this, the filtering process doesn't initiate immediately at boot time, that is, at instance zero seconds ($t = 0s$). In reality, the monitoring process waits

for a configured period, 5 minutes by default, so that it is possible to define the initial values for the person under study.

To better describe the processing of the various signals, figure 4 shows the dependencies between the expressions used in the data filtering process. The expressions marked in green obtain the final values (HRFILT, HRVFILT, dHRV, RRV, SVV and SSFILT) to be used for determining sleep phase. In order, the expression HRFILT depends on the value of HR, the expression HFHRV depends on HRV, the expression RRFILT depends on the RR, the expression SVFILT depends on the SV, the expression SSFILT depends on the SS. The expression LFHRV depends on HRFILT and HR, the expression RRV depends on RRFILT and RR, the expression SVV depends on SVFILT and SV. HRVFILT, on the other hand, depends on LFHRV, HFHRV and SVV and, finally, dHRV depends on HRVFILT.

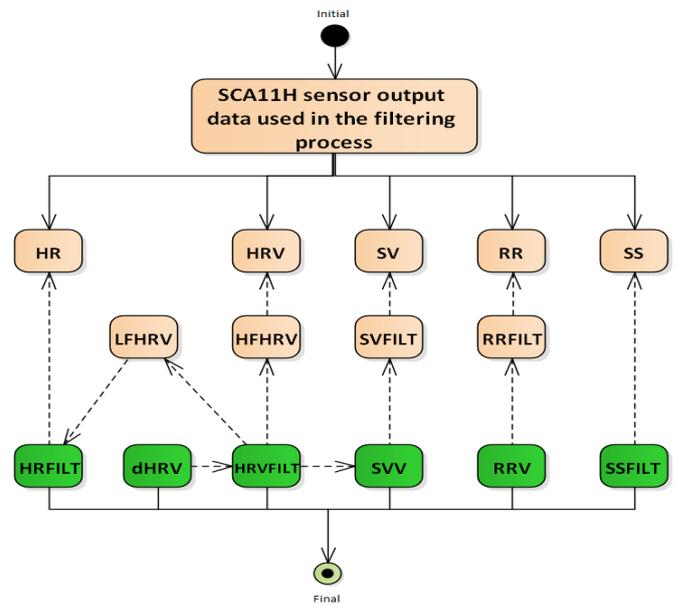


Fig. 4. Dependencies between the expressions present in the data filtering.

IV. TESTS AND RESULTS

The first tests regard the filtering process. The need for filtering arises from the fact that we need to eliminate noise from signals. This is required in order to remove unwanted information from signals and to extract relevant information, that is, a signal with the minimum of noise and the maximum of relevant information.

For this, the choice of the constant (k), that should be used for the filtering process, is a very important step. This constant may have a value between 0 and 1. All expressions involved in the filtering process have gone through this decision phase. That is, they were all subjected to similar tests in order to obtain the best k values. The tests have been restricted to k values that are the reciprocal of powers of 2. These divisions have the advantage of being processed faster and require less energy, due to the fact that division operations are not used,

but rather binary shifts made in just one clock cycle on the processor. This is particularly important, because data filtering is made in real time. With this strategy no significant device resources are necessary for this process.

After this initial testing phase, for each signal subject to the filtering process, the best value for the filtering constant was obtained. In the expressions for LFHRV, HFHRV, SVV, dHRV, RRFILT, RRV, and SSFILT, the adopted value was $\frac{1}{1024}$ and for the filtering expressions for HRFILT and SVFILT the value was $\frac{1}{256}$.

During evaluation, we have also performed several tests that compare some classification algorithm, in order select the ones with more potential for sleep classification. Performance tests carried out for each classification algorithm under study, have used a set of test data. For this analyses, Murata Electronics (Finland) has provided sleep data, obtained with twelve people, women and men, aged between 24 and 46 years old, over twelve nights. These data consist of the SCA11H sensor output signals (BCG) and the sleep state reference value (PSG), taken every 30 seconds, for all those 12 nights. This data was used to performance data analysis and explore the performance of numerous predictive models, that can use several learning technics. For this, the Weka Experiment Environment tool [4] [3] has been used. The aim here was to obtain the best four classification algorithms, that should be implemented in our application.

The classification algorithms under study were: rules.ZeroR, bayes.NaiveBayes, functions.Logistic, functions.SMO, lazy.IBk, rules.PART, trees.REPTree, trees.J48, trees.RandomForest.

When analyzing Table III, it possible to conclude that the best classification algorithms, at the performance level, are as follows: trees.RandomForest [16] [14], lazy.IBk [15] [13], trees.J48 [9] [12] and rules.PART [11] [18].

TABLE III
PERFORMANCE FOR DIFFERENT CLASSIFICATION ALGORITHMS.

Algorithms	Performance (%)
rules.ZeroR	44.35
bayes.NaiveBayes	51.02
functions.Logistic	55.57
functions.SMO	52.17
lazy.IBk	90.29
rules.PART	85.47
trees.REPTree	81.54
trees.J48	86.42
trees.RandomForest	91.81

We have obtained figures, like the one shown in Figure 5, to the analyse the best nights resulting from the study for the selected four algorithms/models. These confusion matrices are composed by the fundamental truth, that is, the sleep phases obtained with the PSG (columns) and the machine learning predicted values of the sleep phases obtained with the BCG (rows). Thus, in practice, BCG and PSG values are compared using a confusion matrix. The perfect confusion matrix will have values greater than zero only in cells that form a diagonal (figure 5). Analysing Figure 5, the highest values between

columns and rows are in the desired positions for a great performance. It is concluded that the result of the confusion matrix regarding the tree algorithm RandomForest (Figure 5) presents the best performance. That is, the highest values for each column are in the proper cells (0: 0 = 27; 1: 1 = 85; 2: 2 = 206; 3: 3 = 192), forming an expected diagonal, shown in orange in the figure.

	0	1	2	3
0	27	22	37	19
1	0	85	69	0
2	2	63	206	102
3	0	0	40	192

Fig. 5. Confusion matrix between the night sleep data PSG14 and the BCG prediction for the Weka trees.RandomForest algorithm.

We have also obtained figures, like the one shown in Figure 6, to compare predictions with reference data, in particular to compare the sleep phase indicated by PSG with the one obtained with the prediction models using the BCG filtered signals. Figure 6 presents the sleep data from the PSG night 'PSG14' and the BCG prediction from the final model created with the support of the Weka trees.RandomForest classifier algorithm. Again, when analysing this figure, it is noticeable, as expected, that there is a great similarity in the transitions between the PSG signal and the BCG prediction signal.

Thus, the algorithm chosen to be implemented in the application is Random Forest. Finally, it is concluded that this prediction is effective for non-medical applications, in order to implement actions on the environment, to improve sleep quality.

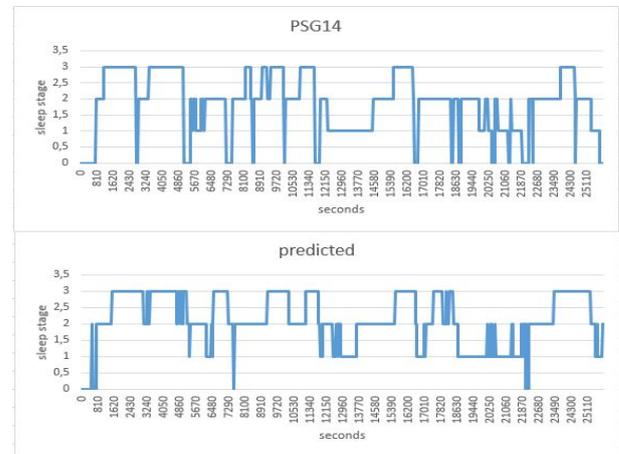


Fig. 6. Graphs between PSG14 night sleep state data and BCG prediction for the Random Forest algorithm.

V. CONCLUSIONS

This work has as its main goal the monitoring of sleep, in order to improve its quality. This monitoring includes a strategy that tries to wake up users in the light sleep phase. The developed application for Android mobile phone has been a mean to achieve this goal.

It has been concluded that PSG monitoring is an intrusive, expensive and complex method in the analysis of sleep. While BCG is a method that does not have any type of invasive mechanism and is the best solution for home use.

Regarding signal filtering process, a sliding exponential average has been used with an accessed specific constant value for each metric.

Subsequently, several classification algorithms were tested and analysed with a given reference data set. This evaluation resulted in the best classification algorithms, in terms of performance: Random Forest, J48, IBk (KNN), and PART. From these mentioned learning classification algorithms, Random Forest was the one to present the best values. The final model has created based on this algorithm. In the presence of this model, it is possible to make the predictions of the various sleep phases using BCG data and compare them with those indicated by PSG, using confusion matrices. With this, it can also be concluded that the Random Forest is, in fact, the classification algorithm that presents the best results for sleep monitoring.

With the prediction of the various phases of sleep, using the best classification algorithm in the implementation in the "GoToBed" application, it was possible to manipulate sleep states, so that the user wakes up in the lightest sleep phase, by using a relaxing sound. The functional analysis and the actions present in the application came to prove, that the application works and fulfils the proposed objective.

We can say that this application is useful to wake a person in the light phase of sleep and it makes possible, as a result, a calmer and more relaxing waking up experience by the user.

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