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Automatic drowsiness detection for safety-critical operations using ensemble models and EEG signals

Plínio M.S. Ramos [a,b], Caio B.S. Maior [a,c,*], Márcio C. Moura [a,b], Isis D. Lins [a,b]

[a] CEERMA – Center for Risk Analysis, Reliability Engineering and Environmental Modeling, Universidade Federal de Pernambuco, Brazil
[b] Department of Production Engineering, Universidade Federal de Pernambuco, Brazil
[c] Technology Center, Universidade Federal de Pernambuco, Caruaru, Brazil

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ABSTRACT

Recently, industrial sectors that stage occupational and environment safety critical tasks, such as the oil and gas industry, have been interested in monitoring biological parameters to prevent human errors and enhance process safety with emergency preparedness and response. In this context, human reliability plays a fundamental role to avoid possible catastrophic accidents triggered by human factor, for example workers' fatigue. Drowsiness, as a main causes of fatigue, maybe recognized through patterns in electroencephalogram (EEG) signal. In this paper, we propose a drowsiness recognition system that combines information from different EEG signal channels and machine learning in an ensemble methodology, novel for this context. We consider two ensemble approaches: the bagging, using five and three channels, and the voting, using a single channel. To validate the proposed system, DROZY, a real and public database containing drowsiness data, was used in three cases: (1) evaluated in all available subjects; (2) evaluated in specific subjects with general model; and (3) evaluated for specific subjects and dedicated models. The results show that our proposed system has high accuracy above 90%, in most subjects for Case 3. While for Cases 1 and 2, the ensemble model is equivalent to the best results of the classifiers from the single-channels. Furthermore, collecting many channels of EEG signals is often expensive and cumbersome for humans, and the schemes using many channels of EEG signals do not necessarily lead to better performances.

1. Introduction

Industrial sectors that perform critical occupational and environmental safety operations, such as the oil and gas (O&G) industry, contain highly complex processes involving numerous equipment, complicated tasks, and a diversified workforce (Naqvi et al., 2020). Along its history, the O&G industry has experienced some devastating accidents and the analysis of maritime and offshore incidents reveals that more than 70% of them had human factors as the main responsible, while technical failures contribute with less than 30% (Cai et al., 2013). The 1988 Piper Alpha disaster is considered one of the worst offshore oil rig disasters (Shallcross, 2013) while the accident on the P-36 platform in *Bacia de Campos* (Brazil), occurred in 2001, caused more than a dozen deaths (Figueiredo et al., 2018). In addition, many other accidents such as the Ekofisk Alpha (Norway, 1975), Ocean Ranger (Canada, 1982), Anchovy (Brazil, 1984), BP Texas City refinery (2005) and Usumacinta (Mexico, 2007), had the main cause directly or indirectly attributed to human factors (de Almeida and Vinnem, 2020). In the chemical and petrochemical industries, human error has been determined to be the main cause of over 80% of accidents (Kariuki and Löwe, 2006).

A key aspect of process safety management systems is to consider human factors (Omidi et al., 2018). Especially in complex industrial processes where workers are exposed to a range of physical and psychosocial stressors including noise, vibration, high workloads, hazardous work operations, rigid safety regulations, long work shifts, isolated location, and low social status (Tong et al., 2022; Parkes, 2012; Haward et al., 2009). Hence, human reliability continues to play an important role in critical safety tasks and human factors (e.g. poor rest habits, reactions to medicines, and sleep deprivation) or factors task-related (e.g., shift night, stress, and monotony) are associated, for example, with fatigue, reducing overall employee performance in work environments and leading to drowsiness (Kariuki and Löwe, 2006; B and Chinara, 2021). Indeed, drowsiness, commonly linked to accidents with drivers, is also investigated in emotional activity during flight operations and response to threats (Drury et al., 2012) and in real-time fatigue monitoring of forestry workers (Bowen et al., 2019) as it is presented in the

* Corresponding author at: CEERMA – Center for Risk Analysis, Reliability Engineering and Environmental Modeling, Universidade Federal de Pernambuco, Brazil.
E-mail address: caio.maior@ceerma.org (C.B.S. Maior).

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daily lives of professionals. In O&G, Waage et al. (2012) analyzed drowsiness during three different shift schedules in oil rig workers during the few days and swing shifts. Golestani et al. (2020) comments that harsh operating conditions influence the physical, cognitive and emotional characteristics of human activities, particularly in offshore areas. Thus, drowsiness detection is certainly important, especially for those organizations that, in an emergency or abnormal situation, human actions play key roles in handling an emergency event.

Drowsiness recognition based on human interpretation generally requires the intervention of another person to identify fatigue events, which may be subject to errors, and alternatively, a computer-assisted drowsiness scheme may be employed. Hence, the assessment of the operator's drowsiness level is made through the use of computer vision (e.g., images/videos) or through biological information (e.g. electroencephalogram - EEG) (Maior et al., 2020). Indeed, biological information from EEG patterns is used to categorize the subject's level of sleepiness (Bajaj et al., 2020; Belakhdar et al., 2018; Lotte, 2018).

Typically, different EEG channels are used to identify states of alertness and drowsiness. For example, Li et al. (2012) and Yu et al. (2013) initially used 16 and 11 EEG channels, respectively. However, in practice, the use of multiple electrodes to collect EEG signals may become invasive in work environments, which also increases the computational cost to process the data. Alternatively, Garcés Correa et al. (2014) and Belakhdar et al. (2016) used few EEG channels and extracted 19 and 9 different features to better represent the signal. In fact, if the goal is to provide a portable drowsiness detection device, wearable in the workplace, and with real-time response, the focus may not only be the response accuracy, but also in use of a smaller number of EEG information channels. Really, emerging technologies, cost reduction and the small size of sensors have already led to the development of wearable sensor devices for use in everyday life (Qiu, 2022).

Furthermore, multiple machine learning techniques have already been used to classify drowsiness based on information from EEG data. However, to avoid data misleading a single classifier, is noteworthy the use of a scheme that combines multiple results, and therefore different information sources, also known as an ensemble model. In this paper, we analyze the performance of two ensemble approaches using distinct machine learning (ML) models to automatic drowsiness detection based on EEG signals. Despite the consideration of ensemble models for medical the depth of anesthesia (Chen et al., 2010), diagnosis and treatment of sleep-related disorders (Hassan and Bhuiyan, 2017; Abdulla et al., 2019; Zhou, 2020; Liu, 2021), detection of EEG arousals (Fernández-Varela et al., 2017), depression recognition (Li, 2019), classification of epilepsy (Li et al., 2017), the use of ensemble models considering EEG signals for drowsiness detection is novel. Here, we present a new schema in which the ML voting and bagging-based approaches are used to process the raw data as well as three well-known time-domain features for EEG signals (i.e., Higuchi Fractal Dimension (Higuchi, 1988), and the Hjorth parameters mobility and complexity (Hjorth, 1970)). We used a public database of a real drowsiness experiment considering signals from different EEG channels to differentiate between alertness and drowsiness levels. To the best of the authors' knowledge, only the work of Wang et al. (Wang et al., 2018) discusses an ensemble model to fatigue detection but the work is related to an automobilist industry and considers different features, classifiers, and EEG channels than the ones considered here. Additionally, this is the first work dealing with ensemble models using the publicly available drowsiness dataset DROZY (Massoz et al, 2016).

The remainder of this paper is organized as follows. Section 2 describes general information about EEG, as well as works related to the detection of somnolence using different channels, feature extraction, and ensemble models. Section 3 describes the database used the two proposed models to detect drowsiness considering two time-domain data representations. Section 4 explains and discusses the results considering different subjects in the dataset followed by Section 5 that concludes the paper.

2. Background and related works

The complexity of human behavior plays a key role in this process safety response mechanism (Festag, 2017). Accidents induced by drowsiness in critical systems can be avoided by detecting the subjects' changes in alertness states to drowsiness. In this context, EEG patterns provide useful biomedical information to analyze these neurological states changes (Bajaj et al., 2020; Li et al., 2015).

2.1. General EEG information

Brain waves have been used to investigate drowsiness through sleep stage analysis based on EEG patterns (Hong and Baek, 2021). The brain produces electrical impulses (i.e., brain waves) that take different forms when a change in psychosomatic states happens (e.g., from alertness to drowsiness). These brain waves may be recorded over time, and distinct bandwidths (i.e., delta (δ) theta (θ), alpha (α), beta (β) and gamma (γ)) can be determined (Okello et al., 2016; Iqbal et al., 2021). Table 1 summarizes the brainwave frequencies and functions in normal activities.

During different stages of sleep, neuronal activities from different cerebral areas interact with each other and manifest as a distinct EEG activity, leading to the differentiation of the night sleep into stages (I, II, III, and IV followed by rapid eye movement (REM) stage) (Sriraam et al., 2016). In particular, stage I may be is separated into two parts: (i) stage I immediately following wake and (ii) stage I immediately preceding stage II (Picchioni, 2008). The transition from awake to stage I (i) represents the change from alertness to drowsiness (Shepovalnikov, 2012). Transitions between the different stages can be observed in a multi-channel recording using strategically positioned electrodes that aim to achieve balanced measurements from all cerebral areas. The locations of the electrodes are based on the international system of electrode placement (Acharya et al., 2016), as illustrated in Fig. 1.

The abbreviations in Fig. 1 represent frontal (F), temporal (T), parietal (P), and occipital (O) cerebral lobes, and the central (C) area. The 'z' symbolizes 'zero' in the midline. The subscribed numbers of the remaining electrodes indicate the left (odd) or right (even) hemisphere of the brain from a relative distance from the zero line. Thus, this EEG information can be used to create models prone to identify the first signs of drowsiness.

2.2. EEG – drowsiness models

As previously mentioned, some studies used different EEG channels as information sources to detect drowsiness. For example, Li et al. (2012) initially analyzed 16 EEG channels and, using Gray Relational Analysis (GRA) and Kernel Principal Component Analysis (KPCA), decreased the number of electrodes analyzed for the two most significant (Fp_1 and O_1). The drowsiness assessment model was based on a straightforward regression analysis. In another example, Yu et al. (Yu) used a model based on support vector machine (SVM) for detecting drowsiness using 11 EEG channels, presenting an accuracy of approximately 95%. However, in practice, the use of multiple electrodes to collect many EEG signals may become invasive when monitoring the cognitive status of human operators in safety - critical process.

Table 1
Different EEG bandwidths and frequencies.

Bandwidth	Frequency	Normal Activities
Delta (δ)	0.1–4 Hz	artifacts, sleep, hyperventilation
Theta (θ)	4–8 Hz	drowsiness, idling
Alpha (α)	8–12 Hz	closing the eyes, inhibitory control
Beta (β)	12–30 Hz	alertness, stress, active thinking, focus
Gamma (γ)	30–70 Hz	voluntary motor movement, learning, and memory

Adapted from Birjandtalab et al. (2017).

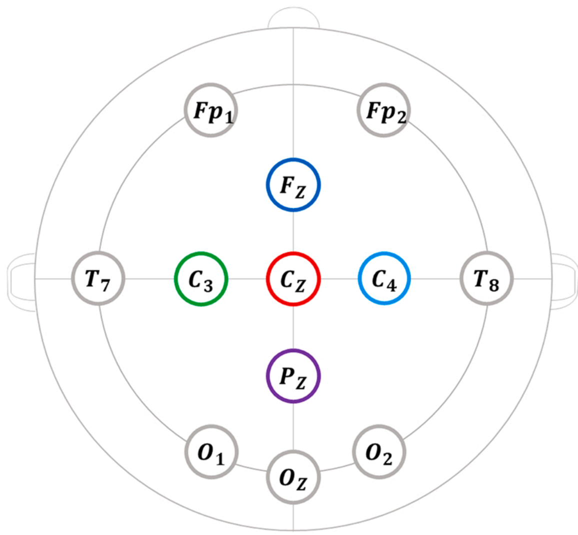

Fig. 1. 12-Electrode placement system.
Adapted from Hong and Baek (2021).

Indeed, single-channel analysis has inspired some research. For example, Garcés Correa et al. (2014) developed a method to detect the stage of drowsiness in EEG records using temporal, spectral, and wavelet analysis, from 19 features extracted from a single EEG channel. The method obtained 83.6% of correct detection rates for drowsiness. In Belakhdar et al. (2016), the authors used features based on the fast Fourier transform (FFT) to infer drowsiness based on EEG. Using a single signal from a differential EEG channel (i.e., C3-O1 electrodes), nine features are extracted from the power spectral density (PSD). Then, the performance of two well-known ML classifiers, SVM and Multilayer Perceptron (MLP), were compared in which the latter present the best result of 83.5% accuracy. In another study, Belakhdar et al. (2018) also reduced the number of EEG feature while still achieving a high accuracy level (i.e. 86%), considering the same one differential EEG channel. However, this model trains and tests specific models for each person in the database, not addressing a generalist model. Relying on the mentioned investigations, there is no strict consensus about which EEG channel is more appropriate to infer alert and drowsy states, although there seems to be a high correlation in the detection of drowsiness with the central and posterior regions of the cerebral area (Picot et al., 2008; Lin et al., 2005; Zhao et al., 2017). In addition, we mention that the performance of the drowsiness model is impacted by interindividual variability, and the selection of EEG channels also depends on electrode availability (see Fig. 1).

Nevertheless, it is known that EEG signals are large time-series sampled at a certain frequency, normally measured in hertz (Hz). Therefore, pre-processing techniques may be used to deal with complex series creating more manageable data, however, still carrying important information (Maior et al., 2019).

2.3. Features extraction

Feature extraction is a process in which the relevant characteristics of the signal are extracted for easy interpretation. The extracted characteristics aim to reflect the physiological activity going on within the brain. However, up to date, there is no such standard feature extraction technique available for EEG (Bajaj et al., 2020). In the current work, we have considered the Higuchi Fractal Dimension (HFD) (Higuchi, 1988), Complexity, and Mobility (Hjorth, 1970) which are currently used in recent EEG studies (B and Chinara, 2021; Bajaj et al., 2020; Zhou, 2020; Liu, 2021; Koley and Dey, 2012).

- HFD: given the EEG signal is represented as X of N data points $x_1, x_2, \ldots, x_N$, we first construct a new time series "X_d^m", where m and d indicate the initial time and the interval time, respectively (Higuchi, 1988). For this work, we consider the default parameters from the *eeglib* library in the Python language (Cabañero-Gomez et al., 2021). Then, the new time series is defined as in Eq. (1):

$$X_d^m = x_m, x_{m+d}, x_{m+2d}, \ldots, x_{m+\left\lfloor \frac{N-m}{d} \right\rfloor d} \tag{1}$$

For each X_d^m, the length $L_m(d)$ is computed as Eq. (2):

$$L_m(d) = \frac{\left\{ \left[\sum_{i=1}^{\left\lfloor \frac{N-m}{d} \right\rfloor} \left| X_{m+id} - x_{m+(i-1)d} \right| \right] \frac{N-1}{\left\lfloor \frac{N-m}{d} \right\rfloor d} \right\}}{d} \tag{2}$$

The mean of $L_m(d)$is computed to find the HFD as shown below in Eq. (3):

$$L(d) = \frac{1}{d} \sum_{M=1}^{d} L_m(d) \tag{3}$$

Polynomial curve fit is computed on a logarithmic value of "log $(L(d))$" and "log (d)" with a degree one. Finally, Higuchi Fractal Dimension is the coefficient (p_1) of a polynomial curve $P(x)$ show in Eq. (4):

$$P(x) = p_1(x) + c \tag{4}$$

- Hjorth parameters, i.e., Hjorth Mobility (HM) and Hjorth Complexity (HC), were introduced to describe the general characteristics of an EEG trace.
- Complexity: measures the neurophysiological changes in terms of frequency (B and Chinara, 2021). It is expressed by the square root of differences of two ratios as shown in Eq. (5)

$$Complexity = \sqrt{\left[\frac{rms\left(\frac{d(X')}{dt}\right)}{rms(X')} \right] - \left[\frac{rms(X')}{rms(X)} \right]} \tag{5}$$

where $X' = \frac{dX}{dt}$ is the rate of change of EEG signal (X) with respect to time (t) and *rms* is the root mean square.

- Mobility: is expressed as a ratio per unit of time and can also be conceived as a mean frequency (Hjorth, 1970). Mobility is measured as shown in Eq. (6).

$$Mobility = \frac{rms(X')}{rms(X)} \tag{6}$$

2.4. Classifiers

Regarding the ML classifiers that will be used in the ensemble learning process, several techniques have been used in studies to distinguish classes based on EEG signal and we briefly introduce four popular of them: k-nearest neighbors (KNN), random forest (RF), MLP and SVM (Lotte, 2018; Belakhdar et al).

- KNN assigns to an unmarked point the dominant class among its k closest neighbors within the training set. These closest neighbors are usually obtained using a metric distance. KNN can approach any function that allows it to produce non-linear decision limits, depending on the k value and the size of training samples (Lotte, 2018; Wang et al., 2018).

- RF is defined as a group of classification trees trained on samples of training data using variables or resources selected at random in the tree generation process (Wang et al., 2018). Classification is performed based on the average prediction values of multiple tree decisions. The number of trees and the depth of the tree are two parameters that can be adjusted.
- While classical approaches are designed to minimize errors in the training data set, SVM is based on the principle of structural risk minimization rooted in statistical learning theory (Widodo and Yang, 2007). SVM aims to build an optimal hyperplane that maximizes the margin between classes and handles large feature spaces (Lotte, 2018).
- MLP is one of the most popular networks that contain multiple successive layers, being the input layer, one or more hidden layers, and an output layer (Wang et al., 2020). Information is propagated from the input layer to the output layer through hidden layers and the weights of the network are updated during the training phase (Belakhdar et al, 2016).

2.5. EEG – ensemble models

Ensemble modeling is a process in which several different models are created to predict an outcome using (i) different modeling algorithms, or (ii) using different sets of training data (Kotu and Deshpande, 2015). Ensemble models considering EEG signals have already been applied in the medical field such as in the classification of epilepsy (Li et al., 2017) and recognition of depression (Li, 2019).

Ensemble models may also be used in the automation in the diagnosis of sleep disorders from EEG signals. However, unlike to the drowsiness detection studied, the sleep research distinguishes from the former in some fundamental differences as it is common to have a multi-classification problem, with different sleep stages, generally it does not require a real-time response, and usually the study is carried out in controlled environments (e.g., laboratories) (Abdulla et al., 2019).

To classify the six sleep stages, Hassan and Bhuiyan (2017) used in their study the Adaptive Boosting (AdaBoost) ensemble model. AdaBoost calls a weak classifier repeatedly and for each call the weight distribution is updated for the dataset. Thus, the weight of each misclassified example is increased so that the new weak classifier works on more examples. In this work, decision tree was used as the weak classifier. The authors use Pz-Oz channels as a source of information. Also in the context of sleep disorders, Abdulla et al. (2019) proposed a technique to classify sleep stages EEG signals using correlation graphs coupled with an ensemble extreme machine learning (EML) algorithm. The main idea of ELM is to randomly generate the input weights of a single hidden layer feedforward neural network and then deterministically obtain the output weights, presenting a good generalization and a low operational cost (Wang et al., 2015). More recently, Liu (2021) proposed an automatic staging scheme based on a single EEG channel using Empirical Ensemble Decomposition Mode (EEMD) to transform such a nonlinear and non-stationary signal into a limited number of intrinsic mode functions. Later, a ranking model with the eXtreme Gradient Boosting (XGBoost) algorithm was used. The XGBoost represents a category of algorithm based on Decision Trees with Gradient Boosting, which aims to minimize the loss function. This method, to find a local minimum of a function, uses an iterative scheme, where in each step the direction in which the function decreases the most is taken.

In the context of accidents, especially for the detection of drowsiness, only the study by Hu and Min (2018) dealt with the inference of driver fatigue from an ensemble model. In this study, the authors used Gradient Boosting Decision Tree (GBDT) as an ensemble method, based on characteristics of the EEG signals using four features, that is, sample entropy, fuzzy entropy, approximate entropy, and spectral entropy. The GBDT output determined whether a driver was fatigued or not based on the EEG signals from the TP7 channel. The highest average recognition rate was 94.0%. In this paper, two different ensemble models named bagging and voting models are used, with a different proposal in the former, to detect drowsiness. An approach in a new context is intended, with the use of simpler and more viable methods for applications in an environment without the need for more powerful hardware that brings good performance.

2.5.1. Bagging model

In order to achieve accurate results, a common ensemble approach used to generate diversity aggregation is bagging. The proposed method was initially developed by Breiman (1996) and has been one of the most effective ML algorithms to solve classification problems. Bootstrap Aggregating, as it is also known, is one of the earliest procedures for generating sub-datasets and combining based learners. Using the training dataset, this technique generates bootstrap samples in which some are replicated, and some are omitted. These bootstrap samples (i.e., bootstrapped sub-datasets) are used to construct based learners using the same classification algorithm. These based learners are then combined using some strategy (e.g., the majority voting (Truong, 2018)). Fig. 2 shows the scheme of the originally proposed bagging model.

2.5.2. Voting model

The concept behind a voting classifier is to combine different ML classifiers and use a voting criterion to predict classification (Saqlain et al., 2019). Brewster et al. (2018) mention that the decision rule can be based on the majority vote, averaging probabilities, or product of probabilities.

An ensemble voting model can balance out the individual weakness of the classifiers involved. While the bagging model uses several samples and a single classifier, this model is based on the idea of using a single sample with several learners. Hassan and El-Hag (2020) mention two types of voting classifiers: (i) hard (majority) voting and (ii) soft voting. While the former uses the predictions of the individual classifiers and presents the output rank by the majority, the latter returns the class label as the weighted sum of each classifier and therefore the output is assigned from that result. Fig. 3 shows the scheme of the originally proposed hard voting model.

3. Proposed work

Here, we analyze different EEG channels from two ensemble model architectures considering both the raw data and the three features described in Section 2.3. The first ensemble model is a bagging-based using different EEG signal channels, which were measured synchronously and considering the same classifier. The second ensemble model is a voting-based, in which the four known classifiers are used considering a single EEG channel. The models are trained and tested in DROZY, a real and public database for drowsiness studies, detailed in the following subsection.

3.1. DROZY dataset

The "ULg multimodality sleepiness database", also called DROZY (Massoz et al., 2016), is a database that contains various types of data related to sleepiness, including EEG. In this case, the system recorded the Fz, Pz, Cz, C3, and C4 channels sampled at a rate of 512 Hz. In total, fourteen subjects/participants (3 males, 11 females) with a mean age of 22.7 years old and a standard deviation of 2.3 years old were considered (Massoz et al., 2016).

The experimental protocol considered that each subject performed three psychomotor vigilance tests (PVTs) during two consecutive days, in conditions of increased induced and prolonged sleep deprivation. After the subjects performed the first PVT, they were not allowed to sleep before the third PVT, resulting in a total sleep deprivation of 28–30 h. Each PVT was around 10 min long, in which the various data of

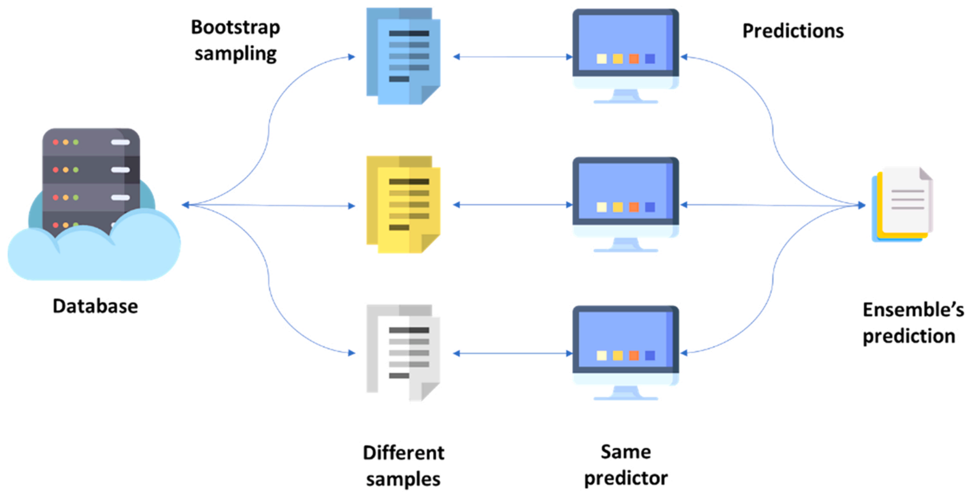

Fig. 2. Scheme for bagging model.

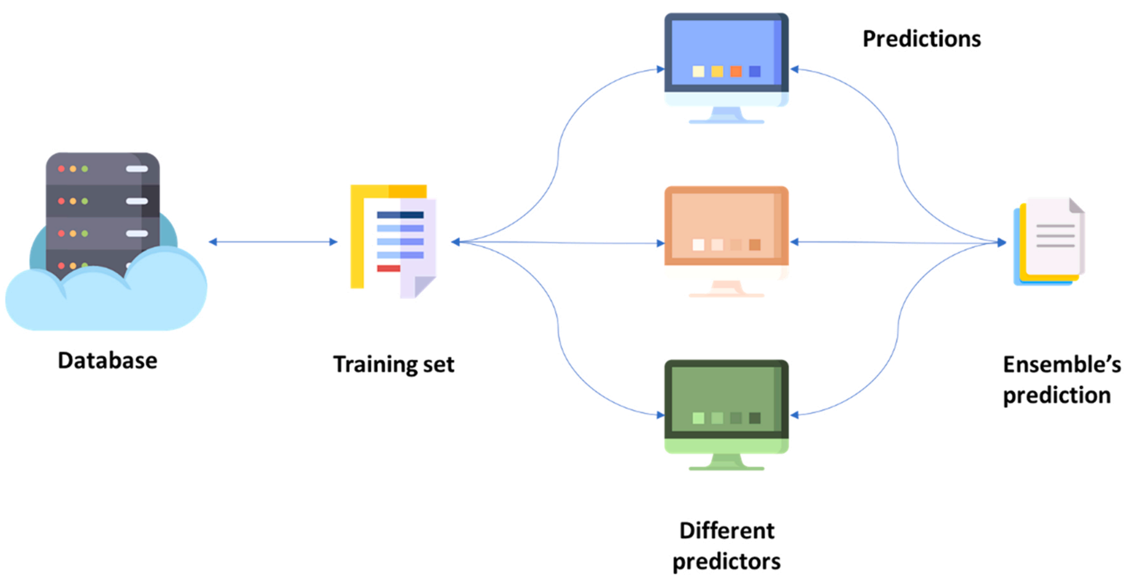

Fig. 3. Scheme for voting model.

the database were recorded, including the EEG channels. Fig. 4 shows a measurement scheme for the three PVTs.

In DROZY, subjects were also asked to fulfill a Karolinska Sleepiness Scale (KSS) form, an established method to measure the subjective level of sleepiness at a particular period of the day (Kaida, 2006). The KSS consists of a nine-point scale with drowsiness rated 1 = very alert, 3 = alert, 5 = not alert or drowsy, 7 = drowsy, and 9 = very drowsy, effort to stay awake (Waage et al., 2012). Lower KSS levels correspond to situations where the subjects do not have reduced performance due to drowsiness, while higher KSS levels represent states of sleepiness registered by the subjects. Here, for the binary classification, we consider two possible categorizations, which have been previously used in the literature and are also suitable for EEG: alert (KSS $\leq$ 3) and drowsy (KSS $\geq$ 7), which (Maior et al., 2020; Ogino and Mitsukura, 2018; Sandberg et al., 2011).

According to these categories, among the 14 participants in the database, only those who classified themselves as a KKS $\leq$ 3 for the first PVT and KKS $\geq$ 7 for the third PVT were selected for analysis. Thus, as shown in Table 2, 8 subjects classified themselves in the first PVTs as alert and 10 subjects classified themselves as drowsy in the third PVT.

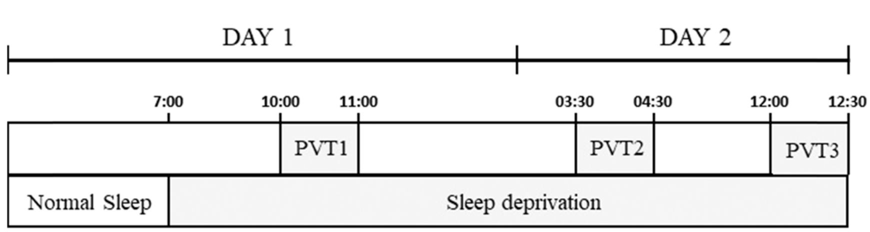

Fig. 4. Scheme for three PVTs in two consecutive days.

Table 2
KSS classification for the selected subjects.

Subject	PVT 1 (KSS)	PVT 3 (KSS)
1	3	7
2	3	–
3	2	–
4	–	9
5	3	8
6	2	7
7	–	9
8	2	8
9	–	8
10	3	7
11	–	7
12	2	–
13	–	–
14	–	8

Moreover, there are specific subjects (i.e., subjects 1, 5, 6, 8, and 10) that alternate the classification of alert to drowsy from the first PVT to the third PVT, which enables a direct analysis for those in the two tests.

In addition, the EEG signals of all participants were grouped as a 'single-subject', as a generalist representation. In this case, the EEG channel signals belonging to each participant eligible for PVT1 (8 subjects), were grouped as single-subject channels and assigned as an alert. Likewise, the signals from 10 subjects in PVT3 were designated as drowsiness signals for that 'single-subject'. From now on, we call this "single-subject" as 'multiple subject', since it gathers available signals from several subjects participating in the experiment. For further descriptions of these subjects (and PVTs) as well as the previously mentioned selection, see (Maior et al., 2020).

3.2. Proposed bagging based model

Here, we adapted the classical bagging model to take the different sub-samples monitored synchronously from the same subject in different EEG channels. Thus, it is possible to create a new hybrid model, coupling a single classifier with different sub-samples (i.e., EEG channels) to detect drowsiness. Initially, our model considers five EEG channels (Fz, Cz, C3, C4, and Pz) available in the database. Note that the signal has different behaviors and frequencies as illustrated in Fig. 5.

The signals from each channel are separated into training and test sets for the five subjects for which the first and third PVTs are available (i.e., 1, 5, 6, 8, and 10). The remaining subjects who have only the first or third PVT available (recall Table 2) are grouped in the test data for their respective states of alertness or drowsiness. As the proposal is a real-time drowsiness detection, different sizes of signal segments were tested from raw data and also by feature extraction, aiming at the smallest possible but bringing important characteristics.

As the ensemble model requires different sub-samples but only a single classifier, the four ML classifiers discussed in the previous section were tested in order to verify which one presents the best accuracy. Furthermore, in order to make the ensemble model less intrusive, different schemes were developed, with different numbers of channels in this ensemble model. The following Fig. 6 shows the scheme of the bagging-based ensemble model with five channels and Fig. 7 shows the pseudo-code for this scheme.

Fig. 8 explains depicts how the proposed bagging ensemble model works. First, the segments of each EEG channel containing a specific size of values, from a sampling frequency, are trained in the ML model. Through a simple vote, the ensemble model combines the responses of the models of each previously executed channel. The result combines the

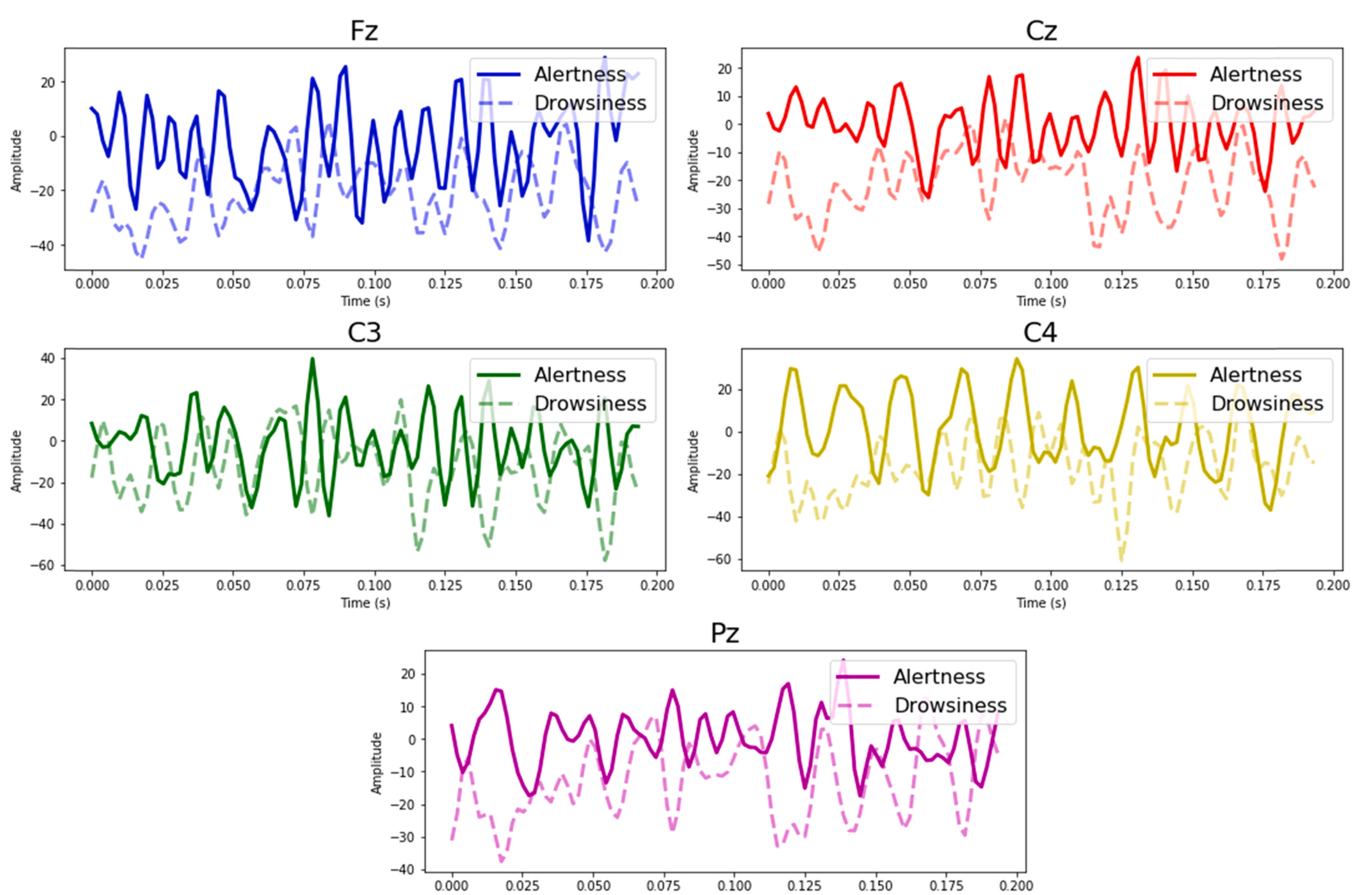

Fig. 5. Difference in signals for the five EEG channels available.

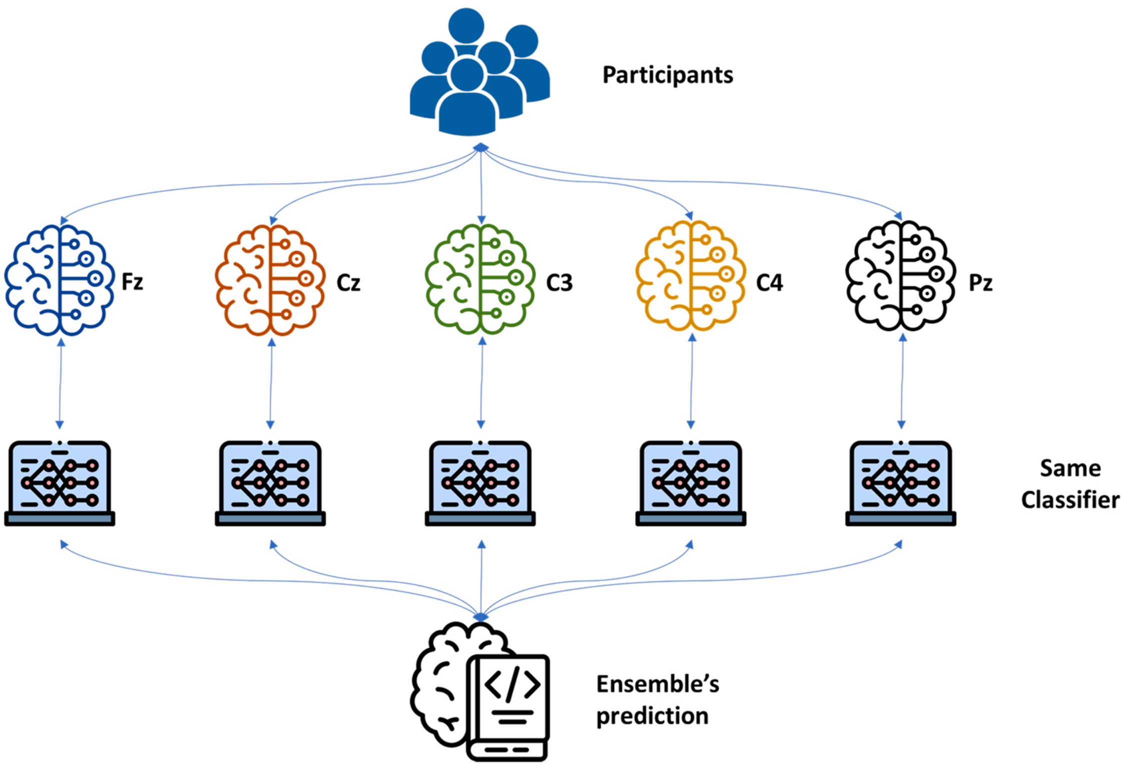

Fig. 6. Scheme of the proposed bagging model.

Input:
- Five or three EEG channel signals of 512Hz each.
- Function to separate vectors with EEG data into smaller vectors for analysis.
- Functions with classifiers algorithms.

for channel in channels
    if (features):
        feature extraction: 'HDF', 'Complexity', 'Mobility'.
    end
    Separates training and testing data;
    Train the ML model;
    Test the ML model;
    Predictions: Keep the prediction of each EEG channel.
end
Bagging-based model (Predictions):
    Hard voting.
Output:
- Accuracy of the ensemble model.

Fig. 7. Algorithm for scheme of bagging model.

most votes for a given class, thus producing its final prediction. This model is further tested with the test sets and finally, the accuracy is measured.

The set of these classifiers considering different EEG channels makes the bagging-based model a strong classifier with low bias and low variance. Furthermore, bagging has been reported to consistently deliver good performance despite its simplicity (Hassan and Haque, 2016).

3.3. *Proposed voting model proposed*

Here, the ensemble model considers the hard voting using a single set of signals but distinct classification methods trained and tested in all five EEG channels available. As in the previous model, the training data of each subject are also grouped with the other data of subjects who had only one type of state. For voting, the method takes a conservative approach, that is, if at least two of the four models have a classification as drowsiness, the ensemble model will classify the signal segment as drowsiness. Fig. 9 below shows the scheme of the model described.

Figs. 10 and 11 show the algorithm and a fictitious example of the voting model, respectively.

4. Results and discussions

In this study, both ensemble models, Bagging and Voting, were

	Predicted Values							
	S_1	S_2	S_3	...	S_{n-2}	S_{n-1}	S_n	ACC(%)
True Value	0	1	0	...	1	0	1	
Model-FZ	1	0	1	...	0	0	1	85.25
Model-CZ	1	1	1	...	0	0	1	90.67
Model-C3	0	1	1	...	1	0	0	92.20
Model-C4	0	1	0	...	1	0	1	97.08
Model-PZ	0	0	0	...	0	1	1	91.54
Final Pred	0	1	1	...	0	0	1	93.78

Fig. 8. General example of how the proposed bagging-based works.

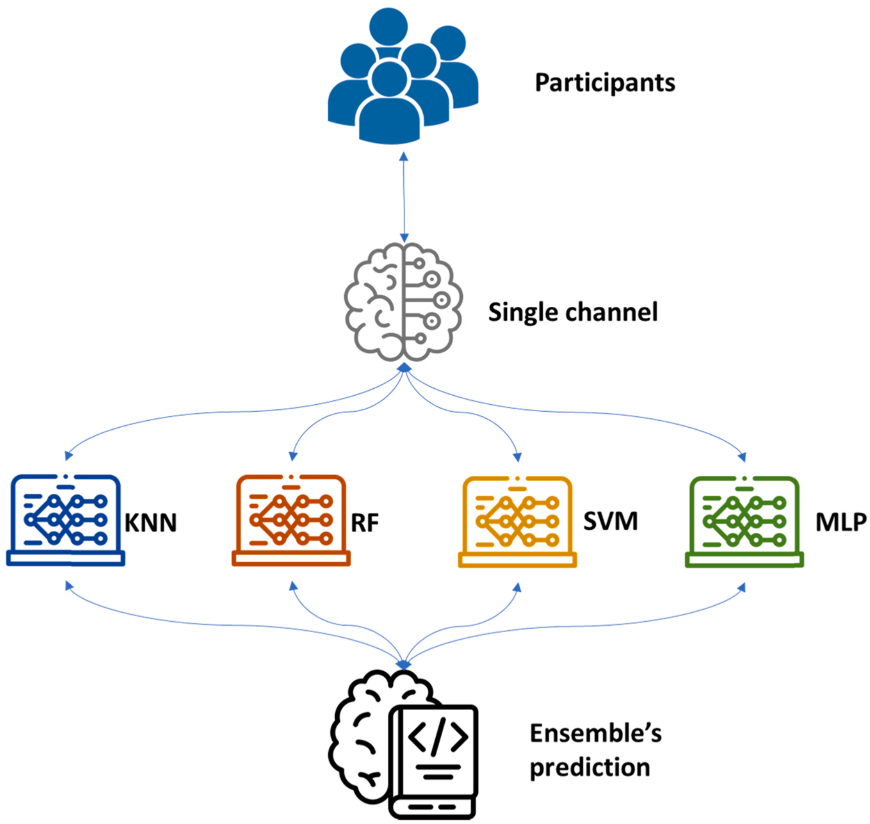

Fig. 9. Scheme of the proposed voting model.

Input:

- Single-channel of EEG signals of 512Hz each.
- Function to separate vectors with EEG data into smaller vectors for analysis.
- Functions with classifiers algorithms.

for model in models:

    if (features):
        feature extraction: 'HDF', 'Complexity', 'Mobility'.
    end
    Separates training and testing data;
    Train the EEG channel;
    Test the EEG channel;
    Predictions: Keep the prediction of each ML model.

end

Voting model (Predictions):

    Hard voting.

Output:

- Accuracy of the ensemble model.

Fig. 10. Algorithm for scheme of voting model.

executed considering two representations of the EEG signals: (i) raw data and (ii) the three time-domain EEG features presented in Section 2.3. Numerous tests were performed to identify the most suitable ML for the bagging mode and the most suitable channel for the voting model. For the sake of brevity, the results presented are for the best performed one, achieved for the MLP classifier for the bagging case and for the C4 channel for the voting case. To consider real-time drowsiness detection, an EEG time-window containing 100 points was selected, which at a sampling frequency of 512 Hz, represents < 0.2 s. This means that each video contains 307,200 data points considering the 10 min for each alert state per subject, that is, more than 5,000,000 data points are treated by our models for subjects with available data (see Table 2). The time-windows were split into an 80/20 ratio for training and testing respectively. All the experiments were run on a PC running Python Version 3.7 with a 2.3 GHz Intel CORE i3 processor (7th generation), 4 GB of RAM.

The results are presented in three parts as presented in Fig. 12. Case 1 contains information from all subjects, in which, after grouping the data from the alertness and drowsiness categories, they are separated into

	Predicted Values							
	S_1	S_2	S_3	...	S_{n-2}	S_{n-1}	S_n	ACC(%)
True Value	0	1	0	...	1	0	1	
Channel-KNN	1	0	1	...	0	0	1	85.25
Channel-RF	1	1	1	...	0	0	1	90.67
Channel-SVM	0	1	1	...	1	0	0	92.20
Channel-MLP	0	1	0	...	1	0	1	97.08
Final Pred	1	1	1	...	1	0	1	93.78

Fig. 11. General example of how the voting model works.

training and test data to verify if the representations in the time-domain and the ML techniques are appropriate for this detection. Case 2 makes use of this generic training model, containing information from all subjects but tested on data from the five specific subjects discussed in the previous section. Finally, in Case 3, the data from the five specific subjects are separated and tested individually, in which a dedicated model for each subject is created.

4.1. Case 1: All subjects

4.1.1. Raw data

For the raw data, results from bagging with five channels present good accuracy (80%), as seen in Fig. 13. The ensemble models were able to take advantage of the good predictions, surpassing all other models for the bagging approach.

Then, we also investigate the performance in the bagging-based model reducing the number of channels to three (i.e., C3, C4, Pz), which is less intrusive. Once again, majority voting is used for the prediction and the result is shown in Fig. 14 indicates the best performance from the ensemble model.

Compared to the result for the five-channels bagging models, the three-channels ensemble model obtained the same performance of accuracy, once again surpassing all single-channel models, however using less of them. Thus, it is noted that although it is important to have a significant number of channels to provide greater robustness to the model's prediction, it is equally important that these channels are able to provide good predictions so as not to harm the output of the ensemble model.

For the voting model for all subjects, the results can be seen in Fig. 15. Here, the result of the ensemble model was at least equal to or greater than the results of the individual classifiers. Comparing with the results obtained previously, despite having considered only one channel (C4), the result was slightly inferior to those of the bagging-based model.

4.1.2. EEG features

For the three features, the performance of the bagging-based approach considering the five-channels brought poor results and with all models presenting similar performances (Fig. 16).

Considering the reduction of the bagging-based model to three-channels, the performance of the ensemble model is competitive to the best result of the classifier (C3) for this approach. For the sake of brevity, this result can be seen in supplementary material.

A similar pattern is seen in the voting approach, with all models presenting a close, but poor result, around 55% (Fig. 17). This suggests that feature extractions considering coupled information from all subjects for training and testing, makes performances not only similar in all approaches, but also poor in detecting drowsiness in random subjects.

Thus, considering Case 1, the performance of ensemble models, whether bagging-based or voting, was better for raw data. The advantages of these models can be seen when tested on different subjects in the next subsection.

4.2. Case 2: Specifics subjects with a general model

4.2.1. Raw data

In this case, the model is trained with data from all participants but tested in data from the five specific subjects individually. Analogously to the previous case, we analyzed raw data, applying the bagging-based model with five-channels and, then, for three-channels considering a specific ML model (i.e., MLP). Fig. 18 shows the results for bagging-based model and five-channels.

Once again, the ensemble model is useful. Comparing the best results, for a few subjects, channel C3 present brought a more significant performance (i.e., subjects 1 and 6), for other subjects (i.e., 5 and 10) the results are equivalent to the proposed ensemble model. But in subject 8 the performance of the C3 channel is better compared to the ensemble model. Moreover, the mean performance of the model based on C3 and on bagging are 73.2% and 70.4%, respectively, but the standard deviation using C3 is 15.75% compared to 11.88% for the bagging approach. These variabilities may be explained by the interpersonal characteristics of each participant, endorsing the use of the ensemble model as a positive and generalist contribution.

When considering only three-channels for the bagging-based model (supplementary material), the ensemble model remains with the second-highest accuracy, but no specific channel has a dominant characteristic over the proposed ensemble model, leaving it in a competitive position.

For the voting model, results are similar to those of the previous models, and can be seen in Fig. 19. The performances of the ensemble model are slightly lower than the best accuracy of the different ML techniques tested, except for subject 8. Furthermore, no specific ML technique presents dominant results over the ensemble.

4.2.2. EEG features

Here, the relatively good performance of using the ensemble model is presented again. For the bagging-based model, Fig. 20 bring the results with five-channels. From it, compared to the ensemble model, the single-

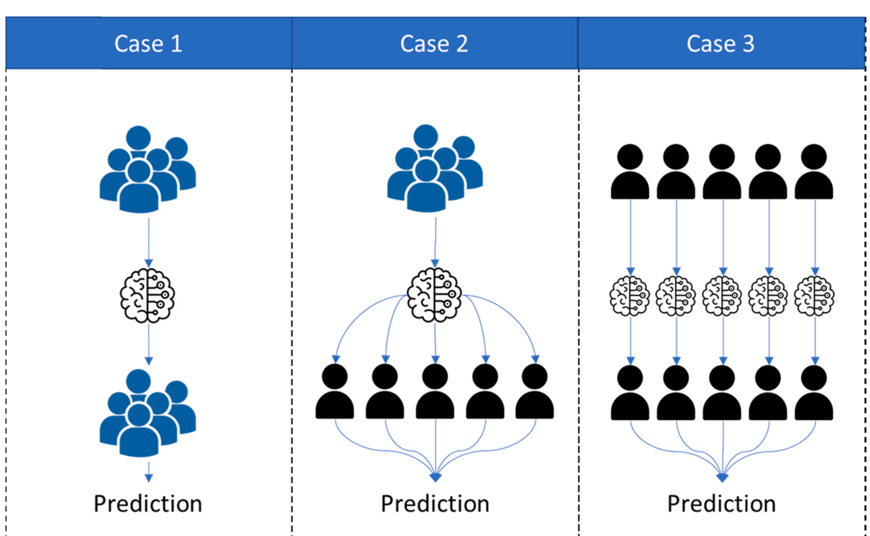

Fig. 12. Scheme of the three cases.

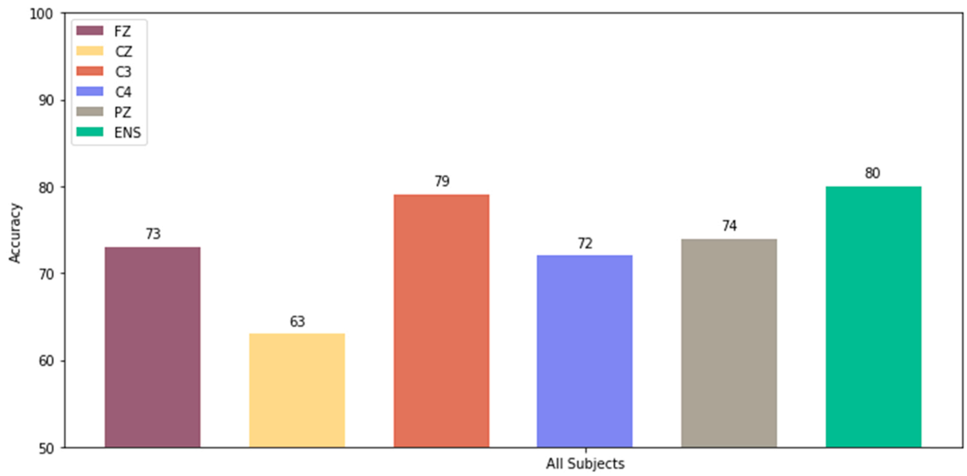

Fig. 13. Bagging-based model for all subjects from the MLP technique with raw data and five-channels.

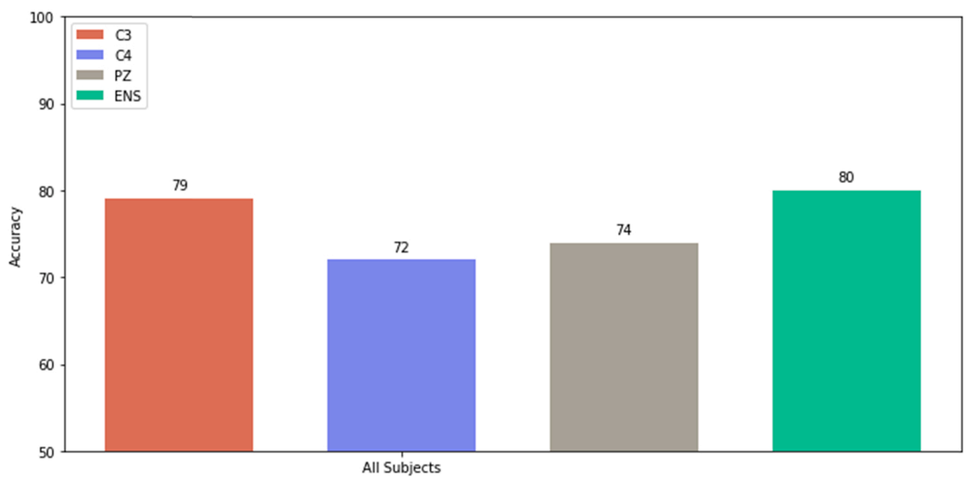

Fig. 14. Bagging-based model for all subjects from the MLP technique with raw data and three-channels.

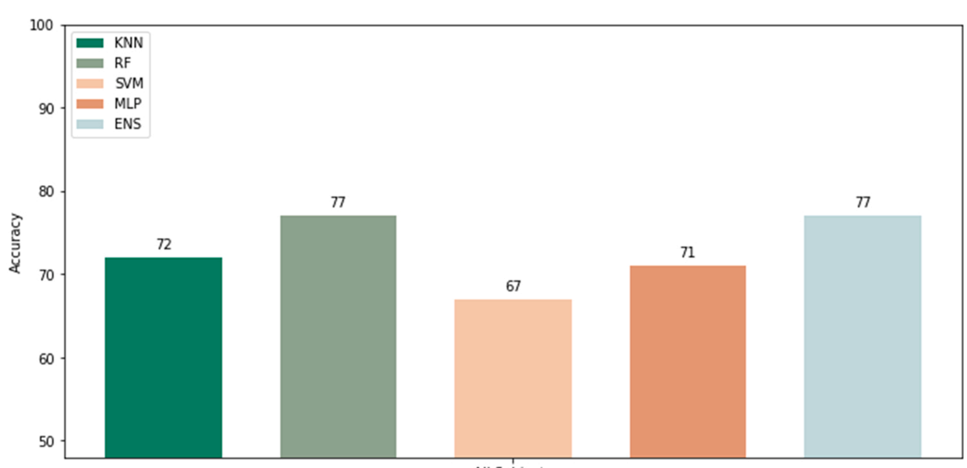

Fig. 15. Voting models for all subjects from the C4 channel with raw data.

channel C3 presents superior results in subjects 1, 5, and 10 and inferior in subjects 6 and 8. Particularly in this model, considering the EEG feature, the single-channel Fz seems to leverage the results of the ensemble, while the single-channel Pz does not seem to contribute significantly to the results in any subject.

For the three-channel configuration, the ensemble model presents good results when comparing the accuracies of the best classifiers and, once again, no single-channels presented a result strictly dominant to the ensemble model. The performance can be seen in supplementary material.

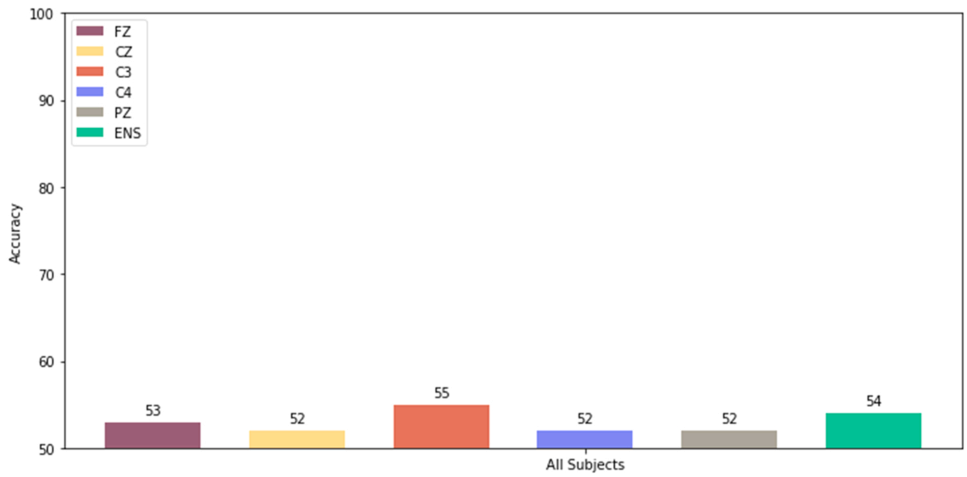

Fig. 16. Bagging-based model for all subjects from the MLP technique with features extraction and five channels.

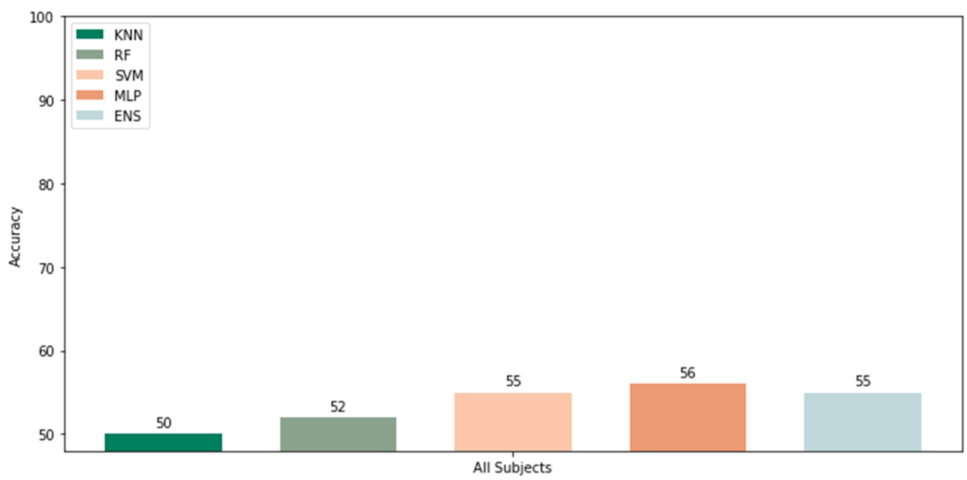

Fig. 17. Voting model for all subjects from the C4 channel with features extraction.

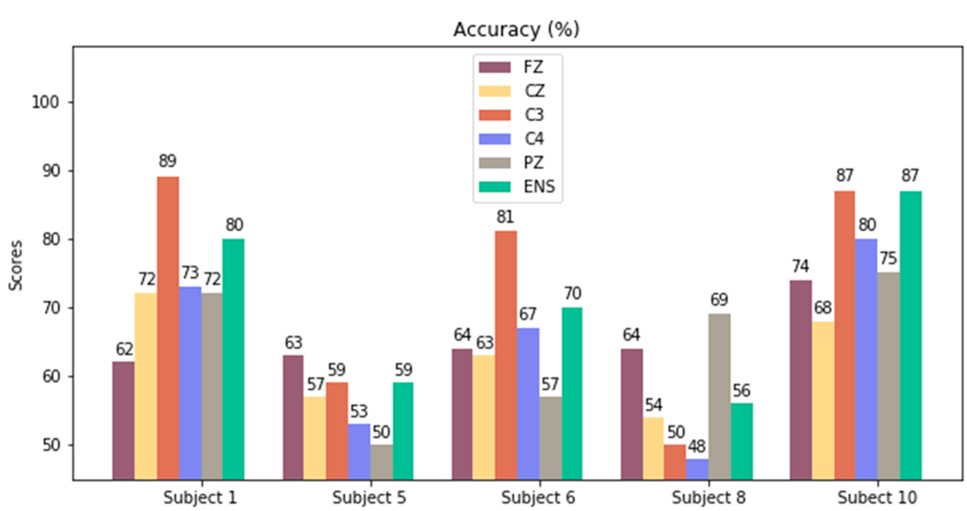

Fig. 18. Bagging-based model for five specific subjects from the MLP technique with raw data and five-channels.

For the voting model (Fig. 21), learners behave very similarly, except for subject 6, which shows a greater difference between the performance of the ensemble and the KNN technique. Furthermore, for that specific model, the ensemble model remains in a competitive position (except for subject 8) with the performance of the RF technique.

Likewise, raw data results continue to show better achievement when contrasted with features extraction. The next subsection aims to present the behavior of these same subjects tested, from now on, with

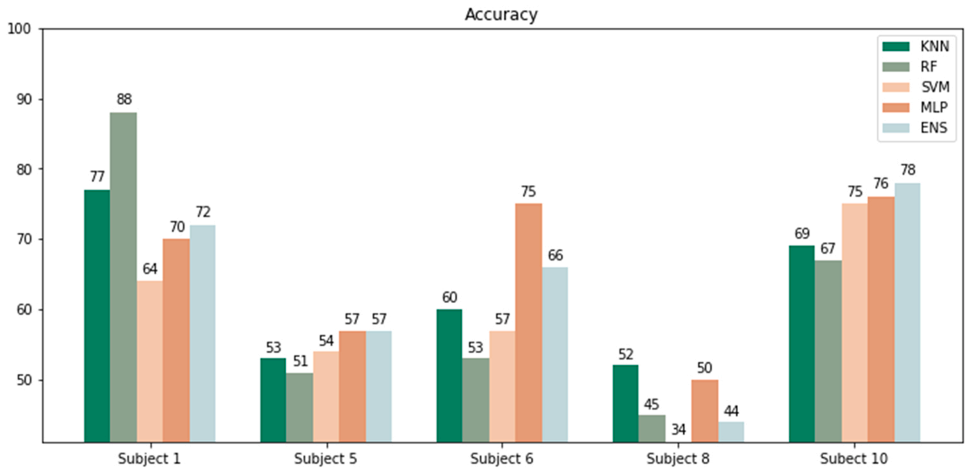

Fig. 19. Voting model for five specific subjects from the C4 channel with raw data.

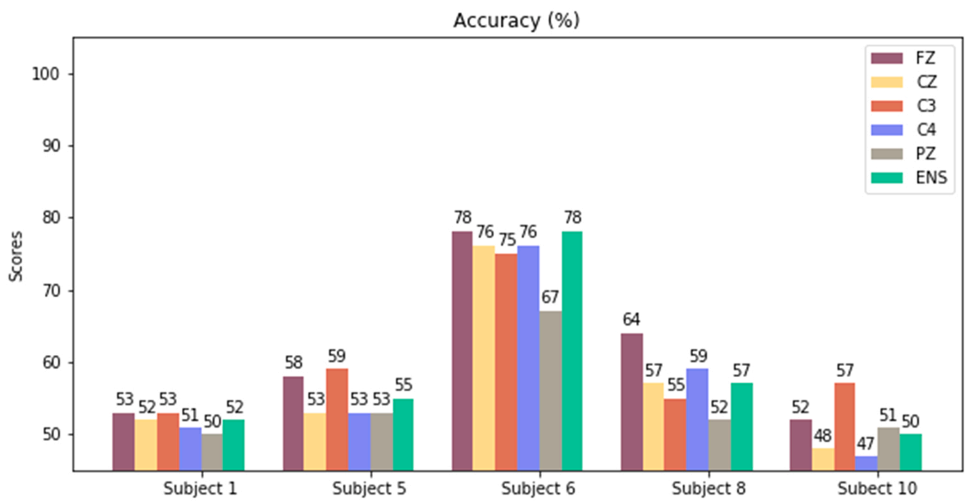

Fig. 20. Bagging-based model for five specifics subjects from the MLP technique with features extraction and five-channels.

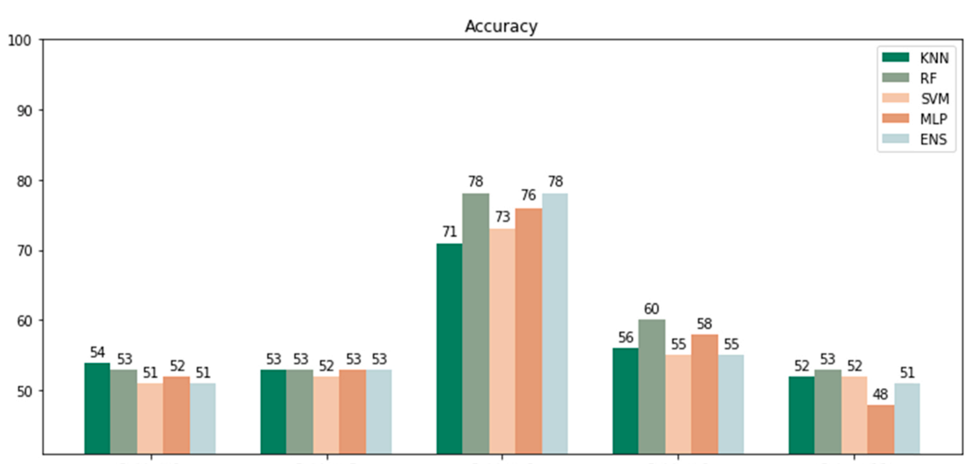

Fig. 21. Voting model for five specific subjects from the C4 channel with features extraction.

classifiers trained with data from the subjects themselves.

4.3. Case 3: Specifics subjects with dedicated model

4.3.1. Raw data

Finally, the third case considers data from the five specific subjects trained and tested individually, creating a dedicated model for each of them. For the bagging-based (Fig. 22) subject 5 presents the lowest accuracy of the tested subjects. This may be explained by the low accuracy from some channels (Fz and Cz) which brings noise to the final prediction, as can also be seen in subject 1. For subject 8, even though few channels are accurate around 80%, for the final prediction of the ensemble model it was above 90%.

Once again, the 3-channels training is performed, and the results are shown in supplementary material. In this case, almost all ensemble predictions presented an accuracy above 90%, achieving a better performance for the singles-channels in almost all subjects, except for subject 5 that achieved a slightly lower accuracy compared to the single-channel C4, and subject 8 who had the accuracy of the model MLP of the single-channel Pz superior to the bagging-based model. In comparison with the previous five-channel bagging-based model, the result of the accuracy of almost all data samples was surpassed by the three-channel model, except for subjects 5 and 8, which presented a similar result.

For the voting model with raw data (Fig. 23), when compared to the results of the bagging-based model, the accuracy was slightly lower, being below 80% for subjects 5 and 8. However, the result is somehow expected as the models are fed by data from only a single-channel (C4) and less information is provided, which is, therefore, a satisfactory result.

4.3.2. EEG features

The same processing was applied for the three features. In Fig. 24, subjects 1 and 5 presents poorest results in all channels, while subject 8 provided accuracy of 99% in the five available channels. This demonstrates the interpersonal variability, considering that even the appropriate EEG features cannot always accurately classify between awake and drowsy. Indeed, this interpersonal variability is in close agreement with the results of (Maior et al., 2020) who mentioned that even though the subject 1 is drowsy, it remained quite attentive, with only one lapse (i.e., reaction time greater than 0.5 s) during the whole PVT.

Then, the same reduction was performed, performing the three-channel model and similar results were obtained when compared to the five-channel model. In fact, the improvement was only made in reducing the number of channels required, and the results can be seen in supplementary material.

While the voting model, similar results were obtained when compared to the bagging-based model for the three features. Furthermore, we realized that for the three features extraction, regardless of the ML technique or EEG channel, the accuracy achieves similar results. The performances are shown in Fig. 25.

However, when comparing the models considering the raw data, the results are evidently better in the latter, especially when considering the raw data through the three-channel model. Nevertheless, even if the ensemble models are not benefited because the single model presented similar performances, the use of features can be useful if you consider the use for some specific subjects (e.g., 6, 8 and 10). In addition, the presented results suggest that it is possible to extract significant information even with a short period of time (~ 0.2 s).

Finally, it is noteworthy that the superior performance of bagging for our presented scheme benefits from the extraction features dedicated to EEG signals and the consideration of different signals as different samples when compared to traditional bagging.

5. Conclusion

The recognition of drowsiness initiated by workers' fatigue, whether by task-related or human factors, is desirable in order to avoid possible catastrophic accidents caused by human errors where emergency response is of paramount importance. The recognition of human drowsiness through EEG signal patterns has already been studied by several researchers, mainly in the context of drivers. However, for process safety in industries with critical occupational and environmental tasks this is new approach. For example, the O&G industry has been interested, in recent years, in monitoring workers' biological parameters based on wearable devices that can be used in indoor or outdoor scenarios.

Thus, although the use of biomedical data (e.g., EEG signals) has already been used in the detection of drowsiness before, the application in ensemble models is new in this field. To consider the order of magnitude and process these datasets, in addition to the raw data, there are a variety of methods based on a physical-mathematical understanding of the behavior of signals, which are developed for feature extraction. The combination of models considering different data sources, as well as the combination of different ML techniques from the same sample are useful as multiple sources may complement each other and improve recognition performance. Our proposed recognition system combines information from different EEG signal channels for three different architectures and, moreover, the results were divided into three cases.

The experimental results show that our proposed system has high accuracy above 90% in most subjects for Case 3. This result even surpasses most of the performances of single-channels, learners of the ensemble model, for this specific case. This is probably due to the use of the model dedicated to each subject, which makes sense considering that

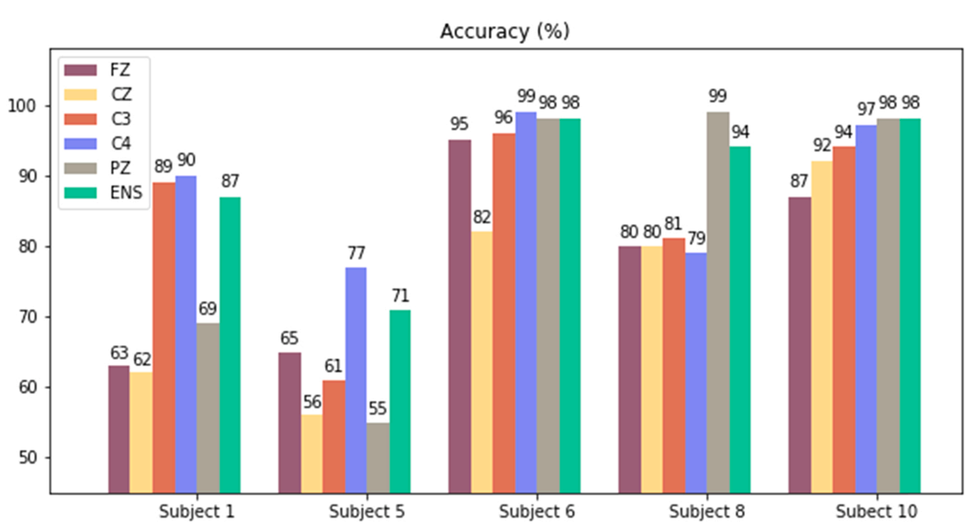

Fig. 22. Bagging-based model for five specifics subjects in a dedicated model from the MLP technique with raw data and five channels.

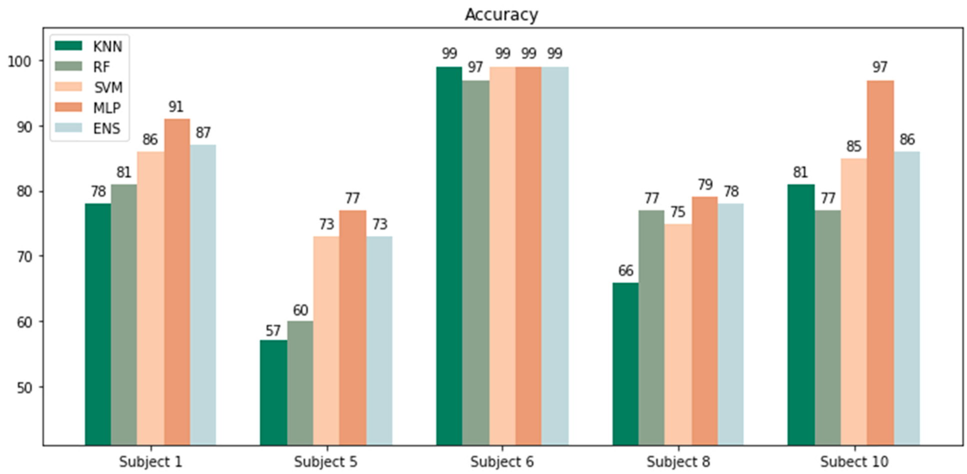

Fig. 23. Voting model for five specifics subjects in a dedicated model from the C4 channel with raw data.

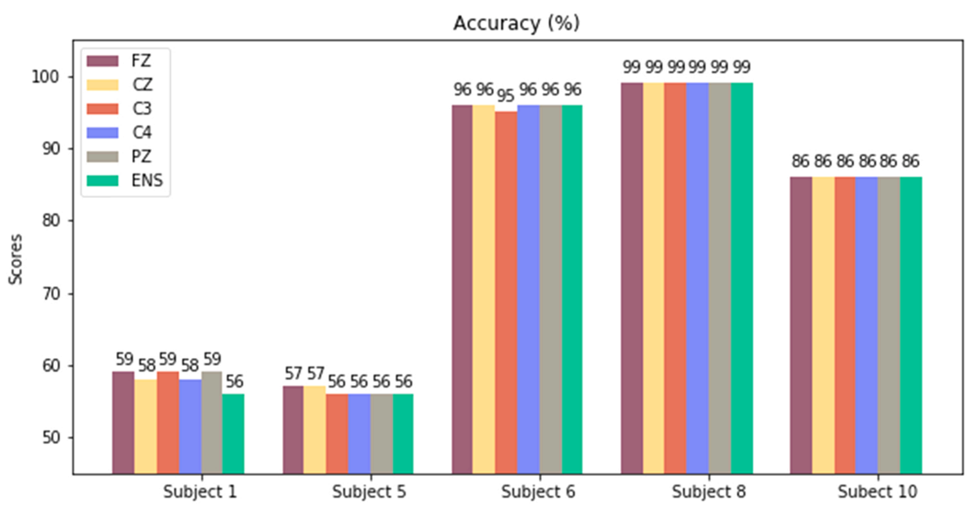

Fig. 24. Bagging-based model for five specific subjects in a dedicated model from the MLP technique with features extraction and five-channels.

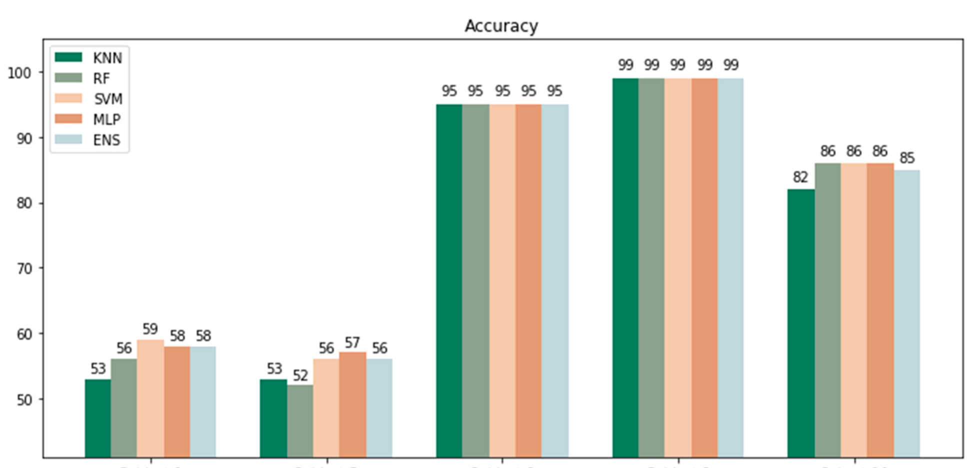

Fig. 25. Voting model for five specific subjects in a dedicated model from the C4 channel with features extraction.

ML learns more easily with that subject's interindividuality. Considering Case 2, the findings are still promising, as the ensemble model is equivalent to the best results of the classifiers from the single-channels. And even in results where the performance of the ensemble model is in second place, no single-channel is dominant in the proposed model. It is noteworthy that although the extraction of three known features for EEG data have been used, the application of the ensemble model considering these features was not significantly relevant, making the performance of the ensemble model analogous with the single-models.

Finally, the results also demonstrated that schemes that use many channels of EEG signals do not necessarily lead to better results, and may even introduce new stresses to workers in these critical processes. Collecting many channels of EEG signals is often expensive and annoying for humans, in addition to the need for more data processing. Our results are in close agreement with the studies mentioning the strong correlation of drowsiness estimation with central and posterior areas EEG channels. For future research directions, we intend to consider models based on deep learning to be used as classifiers, as well as considering other biological signals with data fusion.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Plinio Marcio da Silva Ramos reports financial support was provided by National Agency of Oil Natural Gas and Biofuels. Marcio das Chagas Moura reports financial support was provided by National Council for Scientific and Technological Development. Isis Didier Lins reports financial support was provided by National Council for Scientific and Technological Development. Caio Souto Maior reports financial support was provided by Fundação de amparo a Ciencia e Tecnologia de Pernambuco.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.psep.2022.06.039.

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