Studying Drowsiness Detection Performance while Driving through Scalable Machine Learning Models using Electroencephalography

José Manuel Hidalgo Rogel^{a,*}, Enrique Tomás Martínez Beltrán^a, Mario Quiles Pérez^a, Sergio López Bernal^a, Gregorio Martínez Pérez^a, Alberto Huertas Celdrán^b

^aDepartment of Information and Communications Engineering, University of Murcia, Murcia, 30100 Spain ^bCommunication Systems Group CSG, Department of Informatics IfI, University of Zurich UZH, CH—8050 Zürich, Switzerland

Abstract

Drowsiness is a major concern for drivers and one of the leading causes of traffic accidents. Advances in Cognitive Neuroscience and Computer Science have enabled the detection of drivers' drowsiness by using Brain-Computer Interfaces (BCIs) and Machine Learning (ML). Nevertheless, several challenges remain open and should be faced. First, a comprehensive enough evaluation of drowsiness detection performance using a heterogeneous set of ML algorithms is missing in the literature. Last, it is needed to study the detection performance of scalable ML models suitable for groups of subjects and compare it with the individual models proposed in the literature. To improve these limitations, this work presents an intelligent framework that employs BCIs and features based on electroencephalography (EEG) for detecting drowsiness in driving scenarios. The SEED-VIG dataset is used to feed different ML regressors and three-class classifiers and then evaluate, analyze, and compare the best-performing models for individual subjects and groups of them. More in detail, regarding individual models, Random Forest (RF) obtained a 78% f1-score, improving the 58% obtained by models used in the literature such as Support Vector Machine (SVM). Concerning scalable models, RF reached a 79% f1-score, demonstrating the effectiveness of these approaches. The lessons learned can be summarized as follows: i) not only SVM but also other models not sufficiently explored in the literature are relevant for drowsiness detection, and ii) scalable approaches suitable for groups of subjects are effective to detect drowsiness, even when new subjects that are not included in the models training are evaluated.

Keywords: Brain-Computer Interface, Electroencephalography, Framework, Machine Learning

1. Introduction

Drowsiness is defined as a person's tendency to fall asleep. This situation is especially critical in driving scenarios, where the dangerous combination of driving and sleepiness commonly happens. Particularly, the National

Email addresses: josemanuel.hidalgor@um.es (José Manuel Hidalgo Rogel), enriquetomas@um.es (Enrique Tomás Martínez Beltrán), mqp@um.es (Mario Quiles Pérez), slopez@um.es (Sergio López Bernal), gregorio@um.es (Gregorio Martínez Pérez), huertas@ifi.uzh.ch (Alberto Huertas Celdrán)

Highway Traffic Safety Administration (NHTSA) reported between 2013 and 2019 a total of 5 593 fatalities in motor vehicle crashes involving drowsy drivers. In 2017, exclusively in the USA, 91 000 police-reported crashes involved drowsy drivers, which led to about 50 000 people being injured [1].

In the past years, drowsiness assessment has become a topic of interest among researchers. In this sense, cognitive neuroscience, the area of knowledge responsible for studying the nervous system that supports mental functions [2], including drowsiness, has proposed different techniques for

^{*}Corresponding author.

its quantification [3]. The first ones are based on monitoring subjects' behavior such as facial expression, heart rate, and yawning in order to assess drowsiness. Although these techniques represent an advance in safety, they have significant limitations since they produce false positives and false negatives, not always being able to measure attributes related to fatigue or drowsiness.

Next, solutions based on self-assessment with scales emerged. This technique consists in asking the subject how drowsy he/she has felt in the last minutes. Examples of this technique are the Karolinska Sleepiness Scale (KSS) [4] and the NASA Task Load Index (NASA-TLX) [5]. However, the main drawback of these methods is the inclusion of subjectivity in their self-evaluation. Hence, the need to objectively quantify the sleepiness of an individual arises. For this reason, neurophysiological tests have been developed, based on monitoring the patient's brain signals to precisely identify drowsiness.

Brain signals are commonly obtained by electroencephalography (EEG), which measures the electrical activity produced in the brain through electrodes acting as sensors [6]. The different levels of brain activity are related to the different cognitive states of the subject. Due to this, there is a need to study the EEG signals in different frequency bands, being the lower frequency rhythms (delta, theta, and alpha) directly related to the states of relaxation and drowsiness, and the higher rhythms (beta, gamma) related to concentration and moderate mental load, and even stressful situations in the case of the gamma band [7, 8].

Brain-Computer Interfaces (BCIs) are normally used when studying EEG, where two categories are distinguished depending on the degree of invasiveness of the electrodes. On the one hand, invasive BCIs locate the electrodes within the skull, requiring a surgical process. On the other hand, non-invasive BCIs' electrodes are placed directly on the subject's scalp, avoiding a surgical procedure. Nevertheless, non-invasive BCIs data must be processed afterward

to remove artifacts caused by the subjects' activity [9, 10]. Due to their advantages and feasibility of experimenting with subjects, non-invasive BCIs are used for the drowsiness detection scenario. In addition to non-invasive BCIs, Machine Learning (ML) models are also used to assess drowsiness using the data collected by the BCI. For this purpose, the BCIs acquire the brain signals when the subject is driving. Then, they are processed to eliminate the noise from the signals added during the acquisition using certain techniques such as Notch and band-pass filters, sample reduction, and Independent Component Analysis (ICA). After that, features are extracted from the signals, allowing ML algorithms to classify the features according to patterns identified in the data and, therefore, to predict drowsiness.

Despite the advances and contributions of existing studies that combine BCIs and ML to detect drowsiness while driving, there is a lack of literature analyzing the performance of customized and heterogeneous ML algorithms. The current literature presents a substantial amount of studies using ML, but in most of them, Support Vector Machine (SVM) is used without analyzing and comparing other well-known and relevant algorithms. In addition, the state-of-the-art only explores the performance of customized and individual models trained with data from single subjects, presenting significant scalability issues for new subjects since a new training process per user is needed. In this sense, scalable models combining the brain activity of several subjects should be explored and analyzed to determine if they effectively detect sleepiness in various subjects, even if the models were not trained with their data.

To improve the previous challenges, this work presents the following main contributions:

 The design of a BCI and ML-based framework for drowsiness detection in driving scenarios employing EEG and Electrooculography (EOG) as features. The proposed framework considers ML classifiers and regressors for detecting different drowsiness levels in both individual users and groups of them.

- The creation of a personalized algorithm for PER-CLOS discretization to improve drowsiness labeling, which takes into account the subject behavior to establish the thresholds between three drowsiness levels.
- The deployment and evaluation of the framework using a publicly available dataset, SEED-VIG [11], modeling the EEG of 21 subjects while driving. The following ML algorithms have been trained and evaluated with different amounts of subjects and features for regression and three-class classification tasks: SVM, k-Nearest Neighbors (kNN), Decision Trees (DT), Random Forest (RF), and Gaussian Processes (GP).
- The obtained results indicate that algorithms such as RF or kNN offer better results than the most common in the literature, SVM. In particular, within individual models, RF performed the best with a mean f1-score of 78% and SVM with 58%. Similarly, RF is also the best alternative for scalable models, reaching an f1-score of 79% while SVM gets 52%.

The rest of this paper is organized as follows. Section 2 presents the state of the art from drowsiness detection in driving scenarios using BCIs. Subsequently, Section 3 presents the design of the proposed framework, followed by Section 4 which states the results of detecting drowsiness using the framework. Finally, Section 5 presents the conclusion and potential future work.

2. Related Work

This section analyzes how drowsiness assessment techniques using BCIs are implemented in the literature and what methodology is followed by each study. It has been analyzed what features are extracted from the subjects,

what algorithms and models are used to classify the signals, and how well they perform. In the literature, both drowsiness and fatigue are related to the same concept of a person's tendency to fall asleep. Every study analyzed shares the same starting point, an existing dataset. Some of them decide to generate their own one, whereas others opt for a public dataset [12, 13, 14].

Moreover, features are extracted from three sources, each one corresponding to a domain where EEG signals can be studied [15]. Each study analyzed chooses certain features that may differ from the rest. Firstly, timedomain features, based on mathematical models and other algebraic operations, where the most popular and widespread is the Autoregressive Model (AR) [16, 17]. It is also common to extract statistical values from the signals such as variance, standard deviation and quantiles, or Hjorth parameters [12, 17, 18]. Secondly, frequencydomain features, where Fast Fourier Transform (FFT) enables the analysis of the predominant frequencies in the original EEG signals and their amplitude. Using FFT, the Power Spectral Density (PSD) is widely used to measure the energy in each frequency band of the brain signals, providing good results when estimating drowsiness [19, 12, 20, 21, 22, 23].

Thirdly, time-frequency domain features, due to the non-stationary, non-linear and non-Gaussian behavior exhibited by the EEG signals, are useful to have a representation and decomposition of the frequency information of the signals linked to the time domain. This is why methods such as Discrete Wavelet Transform (DWT) are used [16, 24]. In addition to EEG features, it is common to combine them with other features which are extracted from the subject's behaviour. These include heart rate (HR), blink rate (BR), or the number of blinks [25, 26].

Finally, after feature extraction, the signals are classified. There are two aspects in common while classifying in the analyzed studies. First, most works use a supervised learning approach and, second, the use of a close

range of algorithms which are known to give good results [15], being the most popular and widespread SVM [24, 27, 12, 14, 26]. This algorithm is followed by linear models, such as Ridge Regression, Logistic Regression, or Lasso Regression, Naive Bayes and kNN [28, 29, 15]. To a lesser extent, and with more popularity in other branches of EEG analysis, Linear Discriminant Analysis (LDA), DT and RF are also chosen [15, 13, 20].

Regarding Deep Learning (DL), the most widely used neural networks are Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Extreme Learning Machines (ELMs) and Recurrent Self-Evolving Fuzzy Neural Networks (RSEFNNs). They are gaining relevance as they produce better results, in many cases, compared to traditional ML methods in drowsiness assessment [24, 19, 25, 16, 15].

When estimating sleepiness with supervised learning, the labels used for regression models are the values measured by KSS, NASA-TLX, Auditory Vigilance Task (AVT) or PERCLOS. If the problem is approached with a classification model, the values of the labels used in the regressive methods are discretized to different levels of drowsiness [28, 30, 31, 32, 17].

2.1. Performance of Literature Works

An in-depth examination is conducted to perceive how the algorithms perform among the literature while also taking into account the features that researchers adopt when estimating drowsiness. Therefore, to validate the stability of the developed ML models and to examine their efficiency for later comparison with our results.

Table 1 presents a summary of the examined studies. Specifically, the set of features, data labeling and the algorithms used are specified. After these fields, the results obtained are indicated. If regression is used, the results are offered based on the Root Mean Square Error (RMSE), with results between 0.15 and 0.5. In addition to RMSE, Pearson correlation coefficient (CC) or Coefficient of deter-

mination (R^2) are used. On the other hand, classification models used accuracy as metric.

In particular, it is worth highlighting the work performed by [24], where neurologists removed data artifacts and labeled the signals by visual inspection. Moreover, SVM is used for classification, reaching an accuracy of 94.7%, using DWT and eye features as well. In terms of regression, [12] achieved 0.15 RMSE and 0.83 R^2 . SVM is again the algorithm of choice. Time-domain features such as Hjorth parameters and PSD from the frequency-domain are used, and KSS is employed to self-assess drowsiness.

The work done by Li et al. (2018) [33] is relevant for our study since the dataset employed is also SEED-VIG. In this work, a Support Vector Regressor (SVR) is used as baseline together with 100 EEG and 36 EOG features, resulting in a model that achieved a RMSE of 0.17 ± 0.06 and CC of 0.76 ± 0.23 .

In studies like [34, 13, 18, 20, 15], different surveys of algorithms are presented, being some of them not so popular among the literature, such as kNN, DT or RF. In those studies, SVM is also included and, in some cases, there are other algorithms with better results. For example, in [34], Ensemble Boosted Trees (EBTs) reached 77.3% accuracy while SVM achieved 76.7%. Furthermore, in [13], RF got 81.4% while SVM only got 78.6%. The results highlight that, although SVM is the most widespread choice, there are alternatives which presented better results in their studies.

Regarding DL, its use is increasing in these studies and often produces results surpassing traditional ML algorithms. An example of this is shown by Cheng et al. (2018) [23] since with the same features and labeling, an accuracy of 69.19% is obtained with CNN compared to 64.05% using SVM.

After analyzing in detail the most related works, it can be seen that SVM is generally present among the literature but, at the same time, there is evidence of other approaches, such as neural networks or other ML algorithms, that offer similar or even better results. In addition, there is also a lack of studies that consider scalable models since all of the identified studies focus on individual models which can only detect drowsiness in a specific subject.

3. Proposed Solution

This section describes the design and implementation of the proposed framework to detect drowsiness while driving. An overview of the framework is shown in Figure 1, presenting its different components. Starting from the upper side, the first two components refer to the data acquisition process and its processing. Next, a feature extraction stage, where the most relevant aspects of the acquired data are selected. Finally, it consists of a data classification block, where individual models for each subject and scalable models with data from several users are implemented based on different ML algorithms.

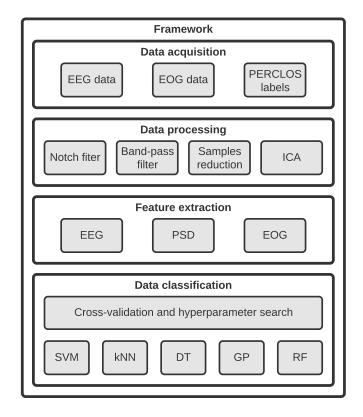


Figure 1: Framework overview.

3.1. Data Acquisition

The design and implementation of the proposed framework is generic enough to be compatible with different datasets, as well as data acquired in real-time using a BCI. Nevertheless, this work has used the SEED-VIG dataset [11] due to its realistic conditions, the suitability with the study purpose, and the amount and quality of the data provided.

More in detail, the SEED-VIG dataset consists of 23 experiments among 21 different subjects (two subjects repeated the experiment). Each experiment has about two hours of EEG signals recorded while the subjects were using a driving simulator. The data were acquired from 17 electrode channels according to the 10-20 system (see Figure 2), using a sample rate of 200 Hz. Particularly, a Neuroscan device was used to measure EEG and EOG [35]. The raw data from the different experiments are provided, together with a variety of already processed data. Particularly, the following data subsets are used during this study: 1) raw EEG data from the 17 channels, 2) moving average PSD relative to the five frequency bands of the brain signals and, 3) raw data from the EOG vertical channel.

The dataset was labeled every eight seconds with subjects' PERCLOS values obtained by an eye-tracking device from *SensoMotoric Instruments* [36]. PERCLOS is a psycho-physiological measure of the subject that quantifies the percentage of time that a subject has been with the eyes at least 80% closed during the time interval of measurement [37].

3.2. Data Processing

As a result of using a non-invasive BCI, the EEG signals obtained contain artifacts, so they must be filtered following the process presented in Figure 3. Initially, the signals are processed with two filtering techniques. First, a Notch filter is applied at 60 Hz in order to eliminate the artifact introduced by the power grid. Secondly, a band-

Table 1: Summary of the literature works reviewed and their results.

Reference	Features	Labeling	Classification Methods	Results
Chen et al.			SVM	96.90%
(2015) [24]	Four from DWT	Visual inspection	ELM	97.30%
Igasaki et al. (2015) [28]	HR and breathing	KSS	Logistic regression	84%
Liu et al. (2016) [19]	PSD	Reaction time	RSEFNN	96.18%
Cheng et al.	DCD	Desetion times	SVM	64.05%
(2018) $[23]$	PSD	Reaction time	CNN	69.19%
C .1 .4 .1		E	SVM	78.60%
Gwak et al.	PSD, HR, EOG and simulator data	Expressions and	kNN	75.30%
(2018) [13]		performance	Random Forest	81.40%
T 1				CC: 0.76 ± 0.23
Li et al.	$100~{\rm from~EEG}$ and $36~{\rm from~EOG}$	PERCLOS	SVR	RMSE:
(2018) [33]				$0.17 {\pm} 0.06$
Wei et al. (2018) [20]	PSD	Reaction time	SVM	80.0±8.6%
			kNN	$77.3 \pm 10.7\%$
			LDA	$79.4 {\pm} 8.7\%$
A11 1		KSS	SVM	R^2 : 0.64
Akbar and	Three from EEG and PSD			RMSE: 0.56
Igasaki			Recurrent SVM	R^2 : 0.83
(2019) [12]			Recurrent SVM	RMSE: 0.15
C			kNN	CC: 0.439
Cuui et al.	PSD	Reaction time		RMSE: 0.268
(2019) [29]			Ridge regression	CC: 0.504
			Kidge regression	RMSE: 0.362
Chakladar et	PSD, mean, SD, Skewness, Kurtosis,	NASA-TLX from 1	SVM	83.33%
al. (2020) [17]	AR and Approximate Entropy	to 9	Random Forest	83.00%
Zhu et al. (2020) [22]	PSD	Reaction time	SVM	93.6%
			Decision trees	60.70%
Contract 1			Random Forest	62.60%
Cui et al. (2021) [18]	Oz EEG channel	Reaction time	kNN	63.42%
			Gaussian Naive Bayes	67.44%
			SVM	69.72%
Shen et al. (2021) [21]	PSD	Reaction time	SVM	62.51%

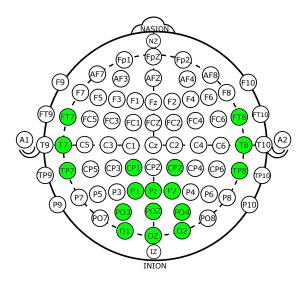


Figure 2: Placement of the EEG electrodes used in the SEED-VIG dataset, highlighted in color.

pass filter between one and 30 Hz is applied since this is the frequency range of interest for the study of drowsiness [7]. The signals are then downsampled to 60 Hz following the Nyquist-Shannon sampling theorem to reduce the size of the data and speeding up its subsequent classification without losing information and, finally, ICA is applied to remove the remaining artifacts such as subjects' blinks while the essential information for detecting drowsiness is preserved. Once the artifacts are removed from the initial raw data, it is also necessary to split the signals in portions (Epochs) of eight seconds. This allows to perform a correct feature extraction since there is a PERCLOS value every eight seconds.

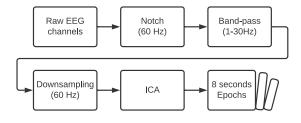


Figure 3: EEG signals processing phase.

3.3. Feature Extraction

Table 2 shows the sources where features are extracted, their description, and the total number of features ex-

Table 2: Feature sources and description for each Epoch.

Feature sources	Description		
	Eight features representing the behavior of		
EEG	the signal for each particular electrode in a		
	summarized version via statistical measures.		
	Therefore, 136 features are obtained.		
	Five features, each one corresponding to the		
PSD	averaged power of a particular frequency		
	band among the 17 EEG channels.		
EOG	One feature corresponding to the number of		
EOG	blinks from the subject.		

tracted. Focusing on EEG features, the eight extracted features for each channel are: mean, standard deviation, variance, 5th percentile, 1st quartile, median, 3rd quartile and 95th percentile. Thus, a total of $8\times17=136$ features are obtained. Subsequently, three feature vectors are assembled to train the models. The first one, referring to the 136 EEG features; the second, making use of the five PSD features alone; and the third, combining PSD with the EOG, containing a total of six features.

3.4. PERCLOS Discretization Algorithm and Drowsiness Classification

There are two main categories of supervised learning techniques: regression, which predicts numerical values, PERCLOS values in this study; and classification, which produces class assignments. Both categories are used in the framework since either approaches are used in the literature, thus facilitating subsequent comparison of the results.

Since PERCLOS values range from zero to one, it is necessary to map them into three levels of sleepiness as recommended by Trejo et al. (2007) [38] and Chang et al. (2007) [39]. Regarding the literature, fixed thresholds are commonly chosen to divide the PERCLOS range of values into the levels of sleepiness. Nevertheless, Gu et al.

(2018) [40] stated that it is not possible to directly borrow other studies' thresholds since they are related to the different detection methods used by different researchers, concluding that the PERCLOS thresholds should be obtained from experiments themselves.

Based on the above, the proposed framework proposes a dynamic PERCLOS discretization algorithm to calculate the thresholds between classes for each subject. With this algorithm, the physiological particularities of each subject are taken into account and, therefore, a personalized division of drowsiness levels that improves data labeling is obtained. The threshold between the *minor* and *moderate* drowsiness levels (th_minor) is calculated with equation (1) while the threshold between moderate and severe drowsiness levels (th_moder) is obtained by equation (2). In each equation, there is a fixed value that is obtained after testing different possibilities to find the best option that divides the data for the subjects in the experiments. th minor = min(PERCLOS) +

$$(max(PERCLOS) + (max(PERCLOS) - min(PERCLOS)) * 0.125$$
(1)

$$\label{eq:th_moder} \begin{split} & \texttt{th_moder} = min(PERCLOS) + \\ & \left(max(PERCLOS) - min(PERCLOS) \right) * 0.30 \end{split}$$

A visual output of the PERCLOS discretization with the proposed algorithm in this study is shown in Figure 4. The green zone, marked as (1), contains the values where the subject's drowsiness is considered *minor* or fully awake. Subsequently, the yellow zone, marked as (2), indicates *moderate* drowsiness while the red zone, highlighted by (3), represents severe drowsiness.

During the classification stage, the framework uses two different model approaches. The first one focuses on training individual and customized models for each user. The second category is based on training scalable models suitable for groups of subjects. Particularly, the two best-performing combinations in the individual models, together with the best one from SVM, are used for the scalable

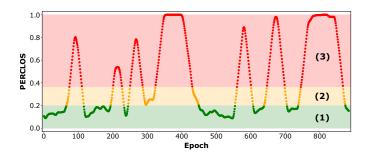


Figure 4: Output of the PERCLOS discretization algorithm with tree levels of drowsiness.

analysis, aiming to reduce the complexity of the experimentation. A combination is defined as a ML algorithm together with a vector of features.

To train each model, the PSD and EOG features are normalized using a MinMax scaler. Then, the split strategy is to shuffle the data before splitting 25% of the data as the test set and the remaining 75% as the training set, except for some scalable models which have their own evaluation sample proportion. Ten-fold cross validation together with hyperparameter search allows finding the best configuration parameters of a model and achieving the best performance while avoiding overfitting. The algorithms of choice are: SVM, kNN, DT, GP, and RF. DT, kNN, and RF, which are selected via the conducted literature review, where it is observed that in some cases, these models perform better than SVM. Finally, GP is selected because it is based on Gaussianity while the EEG signals behavior is non-Gaussian but measures such as PSD are not, so it is interesting to evaluate its performance.

4. Experiments and Results

This section presents a set of experiments aiming to evaluate the drowsiness detection performance of individual and scalable ML models using regression and threeclass classification techniques.

Concerning trained models, there is one type of individual models while three types are explored for scalable models:

- Individual models: Individual classifier and regressor trained and evaluated for each subject.
- 100 models: General classifier and regressor trained and evaluated with the 100% of subjects.
- 90-10 models: General classifier and regressor trained with the 90% of subjects and evaluated with the remaining 10%.
- 70-30 models: General classifier and regressor trained with the 70% of subjects and evaluated with the remaining 30%.

Regarding regressive models, two metrics are used to measure the quality of the results: RMSE and R^2 . On the contrary, for classification models, four metrics are used to measure how well the models performs: accuracy, precision, recall, and f1-score. Particularly, f1-score is prioritized because it involves both precision and recall, making it the most robust and meaningful metric for the analysis.

Since the results of individual, 90-10, and 70-30 models present multiple combinations of different algorithms and subjects tested, the results are presented averaged, subsequently indicated with the following format: Mean \pm SD. On the other hand, there is no need to do this for 100 model, since there is only one test set with the data reserved from every experiment.

4.1. Individual Models

The performance of the trained regressive individual models is shown in Table 3, where the three assembled feature vectors (EEG, PSD, and EOG+PSD) are used to train each model to observe the performance of each one together with the different ML algorithms evaluated. Generally, it is observed that the lowest RMSE occurs in most cases when only the PSD features are used, followed closely by those using PSD together with EOG and, finally, those using only EEG data. It should also be noted that, although the EEG gives the worst results in all cases, these

results are acceptable to obtain a good prediction of sleepiness.

As expected, GP performs the worst for all three feature sets since this algorithm is based on the probabilistic theory of the Gaussian distribution, as discussed above. On the other hand, SVM and DT offer similar results in terms of their error, improving the results of GP. Finally, KNN and RF are the algorithms with the lowest RMSE. The combination offering the best performance is RF with PSD and EOG features both in RMSE (0.08 ± 0.02) and R^2 (0.83 ± 0.09) .

Table 3: Regression performance for the individual models.

Algorithm	Features	RMSE	R^2
	EEG	0.16 ± 0.05	0.42 ± 0.22
SVM	PSD	0.12 ± 0.04	0.67 ± 0.20
	PSD+EOG	0.12 ± 0.04	0.65 ± 0.21
	EEG	0.15 ± 0.05	0.49 ± 0.20
kNN	PSD	0.09 ± 0.03	0.82 ± 0.09
	PSD+EOG	0.10 ± 0.04	0.75 ± 0.18
	EEG	0.21 ± 0.06	0.06 ± 0.39
DT	PSD	0.12 ± 0.04	0.68 ± 0.19
	PSD+EOG	0.12 ± 0.03	0.68 ± 0.17
	EEG	0.21 ± 0.06	-0.07 ± 0.69
GP	PSD	0.13 ± 0.04	0.55 ± 0.26
	PSD+EOG	0.17 ± 0.05	0.26 ± 0.54
	EEG	0.14 ± 0.05	0.56 ± 0.17
RF	PSD	0.09 ± 0.03	0.83 ± 0.09
	PSD+EOG	0.08 ± 0.02	0.83 ± 0.09

In the same way, the best combinations for classification are quite similar to those previously shown for regression since the algorithms are the same but focused on classification. Particularly, they are presented in Table 4. Nevertheless, it is worth commenting on the best combinations of the classification approach since the metrics used are different and yield a series of considerations that cannot be studied from the regressive point of view. The three best combinations, regarding now f1-score, are again the same but in a different order. In this case, the best one is RF with PSD as features with an f1-score of 0.78 ± 0.07 .

Table 4: Classification performance for the individual models.

Algorithm	Features	Accuracy	Precision	Recall	f1-score
	EEG	0.72 ± 0.10	0.71 ± 0.16	0.51 ± 0.12	0.50 ± 0.13
SVM	PSD	0.76 ± 0.10	0.78 ± 0.12	0.58 ± 0.13	0.58 ± 0.14
	$_{\rm PSD+EOG}$	0.76 ± 0.09	0.074 ± 0.12	0.58 ± 0.12	0.58 ± 0.13
	EEG	0.71 ± 0.09	0.61 ± 0.13	0.52 ± 0.10	0.51 ± 0.11
kNN	PSD	0.85 ± 0.05	0.81 ± 0.50	0.77 ± 0.08	0.78 ± 0.07
	PSD+EOG	0.79 ± 0.08	0.73 ± 0.12	0.63 ± 0.12	0.64 ± 0.12
	EEG	0.67 ± 0.11	0.63 ± 0.14	0.47 ± 0.09	0.46 ± 0.10
DT	PSD	0.80 ± 0.08	0.73 ± 0.09	0.71 ± 0.08	0.71 ± 0.09
	$_{\rm PSD+EOG}$	0.80 ± 0.09	0.74 ± 0.09	0.72 ± 0.07	0.72 ± 0.08
	EEG	0.71 ± 0.10	0.70 ± 0.13	0.48 ± 0.09	0.46 ± 0.09
GP	PSD	0.70 ± 0.11	0.79 ± 0.17	0.46 ± 0.12	0.42 ± 0.13
	$_{\rm PSD+EOG}$	0.71 ± 0.10	0.77 ± 0.12	0.48 ± 0.11	0.45 ± 0.12
·	EEG	0.74 ± 0.09	0.74 ± 0.12	0.54 ± 0.10	0.54 ± 0.10
RF	PSD	$\boldsymbol{0.86 \pm 0.06}$	$\boldsymbol{0.83 \pm 0.06}$	$\textbf{0.76} \pm \textbf{0.08}$	$\boldsymbol{0.78 \pm 0.07}$
	PSD+EOG	0.85 ± 0.06	0.83 ± 0.05	0.74 ± 0.08	0.76 ± 0.07

4.2. Scalable Models

Once the results of the individual models are available, the two best-performing algorithms in the individual approach (kNN and RF) and the most promising features for each one are selected for further study. In addition, the best combination for SVM is also included due to its large presence in the literature. These three combinations are used to evaluate a single model. Subsequently, each scalable model created is presented along with its performance.

4.2.1. 100 Models

Regression performance is shown in Table 5 where it can be seen that both kNN with PSD and RF with PSD plus EOG have a fairly good RMSE and \mathbb{R}^2 . SVM with PSD, however, provides inferior performance compared to the other options. These results follow the same trend as the individual models presented in Table 3.

As for the scalable classification models (Table 6), and in the same way as the regression models, the best options are again kNN and RF, in this case, both using PSD as features. Similarly to the results evaluating individual models, SVM has been the worst in performance.

Table 5: Regression performance for the 100 models.

Algorithm	Features	RMSE	R^2
SVM	PSD	0.21	0.43
kNN	PSD	0.14	0.75
\mathbf{RF}	PSD+EOG	0.12	0.80

Table 6: Classification performance for the 100 models.

Algorithm	Features	Accuracy	Precision	Recall	f1-score
SVM	PSD	0.63	0.59	0.51	0.52
kNN	PSD	0.79	0.76	0.76	0.76
\mathbf{RF}	PSD	0.83	0.80	0.78	0.79

4.2.2. 90-10 Models

Since there are a total of 23 experiments among 21 different subjects in the dataset, two subjects (avoiding those who had more than one experiment) corresponding to $\sim 10\%$ of the total are reserved for the evaluation of the model. Subsequently, 21 experiments from a total of 19 subjects are used for training the model.

As presented in Table 7, SVM offers the worst performance of the three combinations studied. After that, kNN presents better results using PSD, followed by RF using PSD and EOG data as the most promising combination.

Table 7: Regression performance for the 90-10 models.

Algorithm	Features	RMSE	R^2
SVM	PSD	0.26 ± 0.06	-1.91 ± 0.10
kNN	PSD	0.20 ± 0.08	-0.66 ± 0.04
RF	PSD+EOG	0.16 ± 0.07	0.03 ± 0.18

Relative to the 90-10 classification models (see Table 8), it is important to note that, in this case, kNN with PSD as features performs slightly better than RF with PSD. On the other hand, SVM together with PSD offers results almost similar to the last two combinations mentioned, but always a step below.

4.2.3. 70-30 Models

Analogous to the reasoning in the previous models, in this case, 16 experiments (from 14 different subjects) are

Table 8: Classification performance for the 90-10 models.

Algorithm	Features	Accuracy	Precision	Recall	f1-score
SVM	PSD	0.57 ± 0.23	0.37 ± 0.14	0.41 ± 0.18	0.38 ± 0.15
kNN	PSD	$\boldsymbol{0.60 \pm 0.17}$	0.46 ± 0.12	$\boldsymbol{0.48 \pm 0.12}$	$\textbf{0.46} \pm \textbf{0.12}$
RF	PSD	0.61 ± 0.19	0.44 ± 0.18	0.45 ± 0.19	0.43 ± 0.17

assigned to model training while the remaining seven experiments, from seven different subjects, are reserved for evaluation.

Table 9 presents the regression results while the corresponding to classification are shown in Table 10. In both approaches, SVM is always the worst of the three combinations. In regression, RF with PSD and EOG remains the best alternative, followed by kNN with PSD. Moving to classification, both kNN and RF with PSD are alternatives to consider, as RF offers a better accuracy compared to kNN but the second one slightly outperforms it in the rest of the metrics. It is interesting to mention that the average f1-score has fallen in all three cases below 40%, which makes this set of models not as interesting as others presented above.

Table 9: Regression performance for the 70-30 models.

Algorithm	Features	RMSE	R^2
SVM	PSD	0.26 ± 0.07	-1.90 ± 3.02
kNN	PSD	0.22 ± 0.05	-0.70 ± 0.65
\mathbf{RF}	PSD+EOG	0.18 ± 0.05	-0.17 ± 0.45

Table 10: Classification performance for the 70-30 models.

Algorithm	Features	Accuracy	Precision	Recall	f1-score
SVM	PSD	0.40 ± 0.20	0.38 ± 0.07	0.41 ± 0.09	0.29 ± 0.14
kNN	PSD	$\textbf{0.45} \pm \textbf{0.16}$	$\textbf{0.44} \pm \textbf{0.07}$	$\textbf{0.44} \pm \textbf{0.11}$	$\boldsymbol{0.37 \pm 0.11}$
\mathbf{RF}	PSD	$\textbf{0.46} \pm \textbf{0.15}$	$\textbf{0.41} \pm \textbf{0.06}$	$\boldsymbol{0.41 \pm 0.07}$	$\textbf{0.35} \pm \textbf{0.08}$

4.3. Discussion

The results for both individual and scalable models suggest that there are better algorithms than SVM when estimating subjects' drowsiness, which is surprising given the tendency in the literature of using SVM. In addition, it is observed that the feature vectors containing PSD features, both used individually or along with EOG, tend to produce the best results for every trained algorithm. In the case of classification algorithms, to make a fair comparison with the literature, this section relies on accuracy and not on f1-score.

Regarding individual models, and comparing the metrics with [33], who used the same dataset but different features, the RMSE obtained in almost every combination of algorithm and features in the framework improves the RMSE of 0.17 ± 0.06 provided in their research with SVR. Moreover, the accuracy of 93.6% obtained in [22] is close to the $86\pm6\%$ obtained by the best combination in the framework.

As can be seen in Table 11, the best results for the trained individual models are in line with the claims of Gwak et al. (2018) [13] where RF performed better than SVM. On the contrary, the results contradict Cui et al. (2021) [18] and Chakladar et al. (2020) [17] since in both studies, SVM performed better or similarly than the other tested algorithms.

This, which may look controversial, can be explained by the features employed by Gwak et al. (2018) [13] and the present study, where PSD and EOG features are used. On the contrary, Cui et al. (2021) [18] used an entire EEG channel as feature and Chakladar et al. (2020) [17] combined PSD with time-domain features. Therefore, a common pattern is observed. If PSD is used, the model performance obtained is increased compared to not using it and, thus, algorithms such as RF tend to perform better or, at least, similar to SVM. This pattern is also found in studies like [13] with an accuracy of 81.40% using RF and [17] with 83.33% in SVM and 83.00% in RF. This may contribute to a clearer understanding of which features and algorithms should be taken into account when considering training a model for the prediction of drowsiness while driving.

Concerning scalable models, the 100 model performance

is similar to the individual models, implying that having just one model for all users could be enough, compared to having one model per subject. Moreover, the 90-10 and 70-30 models reach an accuracy of 0.60 ± 0.17 and 0.46 ± 0.15 respectively. In both cases, the performance is greater than 33%, which represents the accuracy of predicting the level of sleepiness randomly. Because of that, these results suggest that it could be possible to develop a scalable model which can predict drowsiness in subjects that are not involved in the experimentation and training phase of the model, although this may depend on the similarity of the subject's features distribution to those used during training.

Nevertheless, the generalization of the results is limited by the data provided by the dataset as the models are trained for a specific group of 21 subjects who participated in its creation. Further research is needed to establish the generalization of our findings, making use of a larger number of subjects during the training phase.

5. Conclusions

Drowsiness while driving is a major source of accidents and fatalities. To try to improve this situation, this research presents a framework for drowsiness detection in driving scenarios employing BCIs based on EEG, where different algorithms and feature vectors are used for regression and three-class classification. This is done for both individual and scalable models, where the first ones offer predictions for just one subject, whereas the latter are capable of estimating sleepiness in various subjects despite not having been trained with data from them. In particular, three configurations of scalable models are evaluated, based on the percentage of users used to evaluate the models that are not included in the training phase. To evaluate the framework, the SEED-VIG dataset is used, which contains a total of 23 experiments performed in a driving simulator involving 21 different subjects. The labels to be predicted are PERCLOS values whose discretization

is obtained via a dynamic PERCLOS discretization algorithm, taking into account the physiological particularities of each subject.

The results obtained suggest that PSD features are highly relevant when estimating drowsiness since the best performance for almost every tested algorithm involved PSD, regardless of the learning technique or type of model used. Also, this research illustrates that algorithms such as kNN, RF, or DT may perform better than SVM, the most used algorithm in the literature. Furthermore, GP algorithms are the worst in performance, due to the intrinsic properties of the EEG signals.

Lastly, looking at the drowsiness detection performance of the different trained models, the individual models offer the best results, with the limitation of being restricted to a single subject, not being scalable and valid for new subjects. Next, 100 models, which use the 100% of the subjects for training and testing, provide remarkably similar results to the previous ones while reducing the complexity of the experimentation into a single model. Finally, the performance of 90-10 and 70-30 models, which reserve the 10% and 30% of subjects for evaluating the models, respectively, show the possibility of predicting drowsiness in subjects not involved during the training phase of the model.

As future work, this study first proposes the generation of a dataset using a BCI of our own, aiming to compare the current results with those obtained with this equipment. Next, it is intended to apply deep learning algorithms for drowsiness estimation, as they are becoming increasingly popular in the literature and could provide better results. It is worth mentioning that preliminary tests have been performed with this approach, offering promising results. Lastly, it is planned to continue working with the scalable 90-10 and 70-30 models to obtain more realistic and robust models capable of predicting drowsiness on a larger set of new subjects.

Table 11: Summary of the literature analyzed focusing on individual models and comparison with our results.

Reference	Features	Labeling	Classification	Results
	Touvares	Lasoning	Methods	Testares
Gwak et al.		Expressions and	SVM	78.60%
(2018) [13]	PSD, HR, EOG and simulator data	performance	kNN	75.30%
(2018) [13]		performance	Random Forest	81.40%
T 1				CC: 0.76 ± 0.23
Li et al.	$100~{\rm from~EEG}$ and $36~{\rm from~EOG}$	PERCLOS	SVR	RMSE:
(2018) [33]				$0.17 {\pm} 0.06$
Chakladar et	PSD, mean, SD, Skewness, Kurtosis,	NASA-TLX from 1	SVM	83.33%
al. (2020) [17]	AR and Approximate Entropy	to 9	Random Forest	83.00%
	Oz EEG channel	Reaction time	Decision trees	60.70%
Cui et al.			Random Forest	62.60%
			kNN	63.42%
(2021) [18]			Gaussian Naive Bayes	67.44%
			SVM	69.72%
			SVM	76±10%
Our			kNN	$85\pm5\%$
framework	PSD and EOG	PERCLOS	Decision Trees	$80 \pm 9\%$
iramework			Gaussian Process	$71{\pm}10\%$
			Random Forest	$86\pm6\%$

Funding

This work has been partially supported by (a) Bit & Brain Technologies S.L. under the project CyberBrain: Cybersecurity in BCI for Advanced Driver Assistance, associated with the University of Murcia (Spain), (b) the Swiss Federal Office for Defense Procurement (armasuisse) with the CyberSpec (CYD-C-2020003) project, and (c) the University of Zürich UZH.

References

- [1] Facts + statistics: Drowsy driving.

 URL https://www.iii.org/fact-statistic/
 facts-statistics-drowsy-driving
- [2] G. M. Shepherd, Neurobiology, Oxford University Press, 1988.
- [3] V. Ibáñez, J. Silva, O. Cauli, A survey on sleep assessment methods, PeerJ 6. doi:10.7717/peerj.4849.

- [4] A. Shahid, K. Wilkinson, S. Marcu, C. M. Shapiro, Karolinska sleepiness scale (kss) (2011). doi:10.1007/ 978-1-4419-9893-4_47.
- [5] S. G. Hart, L. E. Staveland, Development of nasa-tlx (task load index): Results of empirical and theoretical research (1988). doi:10.1016/s0166-4115(08)62386-9.
- [6] J. Malmivuo, R. Plonsey, Bioelectromagnetism. 13. Electroencephalography, 1995, pp. 247–264.
- [7] J. Ward, The student's guide to cognitive neuroscience, Routledge, 2019.
- [8] R. A. Ramadan, A. V. Vasilakos, Brain computer interface: control signals review (2017). doi:10.1016/j.neucom.2016.10.
- [9] L. F. Nicolas-Alonso, J. Gomez-Gil, Brain computer interfaces, a review, Sensors 12 (2). doi:10.3390/s120201211.
- [10] S. López Bernal, A. Huertas Celdrán, G. Martínez Pérez, M. T. Barros, S. Balasubramaniam, Security in brain-computer interfaces, ACM Computing Surveys 54 (1) (2021) 2–3. doi: 10.1145/3427376.
- [11] W.-L. Zheng, B.-L. Lu, A multimodal approach to estimat-

- ing vigilance using eeg and forehead eog (2017). doi:10.1088/1741-2552/aa5a98.
- [12] I. A. Akbar, T. Igasaki, Drowsiness estimation using electroencephalogram and recurrent support vector regression, Information 10 (6). doi:10.3390/info10060217.
- [13] J. Gwak, M. Shino, A. Hirao, Early detection of driver drowsiness utilizing machine learning based on physiological signals, behavioral measures, and driving performance, in: 2018 21st International Conference on Intelligent Transportation Systems (ITSC), IEEE, 2018. doi:10.1109/itsc.2018.8569493.
- [14] C.-T. Lin, C.-H. Chuang, C.-S. Huang, S.-F. Tsai, S.-W. Lu, Y.-H. Chen, L.-W. Ko, Wireless and wearable eeg system for evaluating driver vigilance, IEEE Transactions on Biomedical Circuits and Systems 8 (2) (2014) 165–176. doi:10.1109/TBCAS. 2014.2316224.
- [15] N. Padfield, J. Zabalza, H. Zhao, V. Masero, J. Ren, Eegbased brain-computer interfaces using motor-imagery: Techniques and challenges, Sensors 19 (6). doi:10.3390/s19061423.
- [16] A. Garcés Correa, L. Orosco, E. Laciar, Automatic detection of drowsiness in eeg records based on multimodal analysis, Medical Engineering & Dhysics 36 (2) (2014) 244–249. doi:10. 1016/j.medengphy.2013.07.011.
- [17] D. D. Chakladar, S. Dey, P. P. Roy, D. P. Dogra, EEG-based mental workload estimation using deep BLSTM-LSTM network and evolutionary algorithm 60 (2020) 101989. doi:10.1016/j. bspc.2020.101989.
- [18] J. Cui, Z. Lan, Y. Liu, R. Li, F. Li, O. Sourina, W. Müller-Wittig, A compact and interpretable convolutional neural network for cross-subject driver drowsiness detection from single-channel EEG.doi:10.1016/j.ymeth.2021.04.017.
- [19] Y.-T. Liu, S.-L. Wu, K.-P. Chou, Y.-Y. Lin, J. Lu, G. Zhang, W.-C. Lin, C.-T. Lin, Driving fatigue prediction with pre-event electroencephalography (eeg) via a recurrent fuzzy neural network, in: 2016 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), 2016, pp. 2488–2494. doi:10.1109/FUZZ-IEEE. 2016.7738006.
- [20] C.-S. Wei, Y.-T. Wang, C.-T. Lin, T.-P. Jung, Toward drowsiness detection using non-hair-bearing EEG-based braincomputer interfaces 26 (2) (2018) 400–406. doi:10.1109/tnsre. 2018.2790359.
- [21] M. Shen, B. Zou, X. Li, Y. Zheng, L. Li, L. Zhang, Multi-source signal alignment and efficient multi-dimensional feature classification in the application of EEG-based subject-independent drowsiness detection 70 (2021) 103023. doi:10.1016/j.bspc. 2021.103023.
- [22] M. Zhu, F. Liang, D. Yao, J. Chen, H. Li, L. Han, Y. Liu, Z. Zhang, Heavy truck driver's drowsiness detection method using wearable EEG based on convolution neural network, IEEE,

- 2020. doi:10.1109/iv47402.2020.9304817.
- [23] E. J. Cheng, K.-Y. Young, C.-T. Lin, Image-based EEG signal processing for driving fatigue prediction, IEEE, 2018. doi:10. 1109/cacs.2018.8606734.
- [24] L.-l. Chen, Y. Zhao, J. Zhang, J.-z. Zou, Automatic detection of alertness/drowsiness from physiological signals using waveletbased nonlinear features and machine learning, Expert Syst. Appl. 42 (21) (2015) 7344-7355. doi:10.1016/j.eswa.2015. 05.028.
- [25] C. Jacobé de Naurois, C. Bourdin, C. Bougard, J.-L. Vercher, Adapting artificial neural networks to a specific driver enhances detection and prediction of drowsiness, Accident Analysis & Prevention 121 (2018) 118–128. doi:10.1016/j.aap. 2018.08.017.
- [26] S. Hu, G. Zheng, Driver drowsiness detection with eyelid related parameters by support vector machine, Expert Systems with Applications 36 (4) (2009) 7651–7658. doi:10.1016/j.eswa. 2008.09.030.
- [27] M. V. Yeo, X. Li, K. Shen, E. P. Wilder-Smith, Can svm be used for automatic eeg detection of drowsiness during car driving?, Safety Science 47 (1) (2009) 115-124. doi:10.1016/j.ssci. 2008.01.007.
- [28] T. Igasaki, K. Nagasawa, N. Murayama, Z. Hu, Drowsiness estimation under driving environment by heart rate variability and/or breathing rate variability with logistic regression analysis, in: 2015 8th International Conference on Biomedical Engineering and Informatics (BMEI), 2015, pp. 189–193. doi:10.1109/BMEI.2015.7401498.
- [29] Y. Cuui, Y. Xu, D. Wu, Eeg-based driver drowsiness estimation using feature weighted episodic training (2019). arXiv:1909. 11456.
- [30] K.-Q. Shen, X.-P. Li, C.-J. Ong, S.-Y. Shao, E. P. Wilder-Smith, Eeg-based mental fatigue measurement using multi-class support vector machines with confidence estimate, Clinical Neurophysiology 119 (7) (2008) 1524–1533. doi:10.1016/j.clinph. 2008.03.012.
- [31] Q. Zhuang, Z. Kehua, J. Wang, Q. Chen, Driver fatigue detection method based on eye states with pupil and iris segmentation, IEEE Access 8 (2020) 173440-173449. doi:10.1109/access.2020.3025818.
- [32] B. K. Savas, Y. Becerikli, Real time driver fatigue detection system based on multi-task ConNN, IEEE Access 8 (2020) 12491–12498. doi:10.1109/access.2020.2963960.
- [33] H. Li, W.-L. Zheng, B.-L. Lu, Multimodal vigilance estimation with adversarial domain adaptation networks (2018). doi:10. 1109/ijcnn.2018.8489212.
- [34] V. Bajaj, S. Taran, S. K. Khare, A. Sengur, Feature extraction method for classification of alertness and drowsiness states EEG

- signals, Applied Acoustics 163 (2020) 107224. doi:10.1016/j.apacoust.2020.107224.
- [35] 64-channel quik-cap.

 URL https://compumedicsneuroscan.com/product/
 64-channels-quik-cap-synamps-2-rt/
- [36] Smi eye tracking glasses imotions.

 URL https://imotions.com/hardware/
 smi-eye-tracking-glasses/
- [37] T. A. Dingus, H. L. Hardee, W. W. Wierwille, Development of models for on-board detection of driver impairment, Accident Analysis & Drevention 19 (4) (1987) 271–283. doi:10. 1016/0001-4575(87)90062-5.
- [38] L. J. Trejo, K. Knuth, R. Prado, R. Rosipal, K. Kubitz, R. Kochavi, B. Matthews, Y. Zhang, Eeg-based estimation of mental fatigue: Convergent evidence for a three-state model, in: D. D. Schmorrow, L. M. Reeves (Eds.), Foundations of Augmented Cognition, Springer Berlin Heidelberg, Berlin, Heidelberg, 2007, pp. 201–211.
- [39] B.-C. Chang, J.-E. Lim, H.-J. Kim, B.-H. Seo, A study of classification of the level of sleepiness for the drowsy driving prevention, in: SICE Annual Conference 2007, IEEE, 2007. doi:10.1109/sice.2007.4421521.
- [40] W. H. Gu, Y. Zhu, X. D. Chen, L. F. He, B. B. Zheng, Hierarchical CNN-based real-time fatigue detection system by visual-based technologies using MSP model, IET Image Processing 12 (12) (2018) 2319–2329. doi:10.1049/iet-ipr.2018.5245.