International Journal of Electrical and Computer Engineering (IJECE)
Vol. 13, No. 3, June 2023, pp. 3398~3406
ISSN: 2088-8708, DOI: 10.11591/ijece.v13i3.pp3398-3406

Drivers' drowsiness detection based on an optimized random forest classification and single-channel electroencephalogram

Mouad Elmouzoun Elidrissi[1], Elmaati Essoukaki[1,2], Lhoucine Ben Taleb[2], Azeddine Mouhsen[1], Mohammed Harmouchi[1]
[1]Laboratory of Radiation-Matter and Instrumentation, Faculty of Sciences and Techniques, Hassan First University of Settat, Settat, Morocco
[2]Higher Institute of Health Sciences, Hassan First University of Settat, Settat, Morocco

Article Info

Article history:

Received Jul 20, 2022
Revised Sep 26, 2022
Accepted Oct 1, 2022

Keywords:

Drivers' drowsiness detection
Electroencephalogram signals processing
Machine learning
Python processing

ABSTRACT

The state of functioning (posture) of a driver at the wheel of a car involves a complex set of psychological, physiological, and physical parameters. This combination induces fatigue, which manifests itself in repeated yawning, stinging eyes, a frozen gaze, a stiff and painful neck, back pain, and other signs. The driver may fight fatigue for a few moments, but it inevitably leads to drowsiness, periods of micro-sleep, and then falling asleep. At the first signs of drowsiness, the risk of an accident becomes immense. In Morocco, drowsiness at the wheel is the cause of 1/3 of fatal accidents on the freeways. Thus, in this paper, a new hybrid data analysis and an efficient machine learning algorithm are designed to detect the drowsiness of drivers who spend most of their time behind the wheel over long distances (older than 35 years). This analysis is based on a single channel of electroencephalogram (EEG) recordings using time, frequency fast Fourier transform (FFT), and power spectral density (PSD) analysis. To distinguish between the two states of alertness and drowsiness, several features were extracted from each domain (time, FFT, and PSD), and subjected to different classifier architectures to conduct a general comparison and achieve the highest detection accuracy (98.5%) and best time consumption (13 milliseconds).

Corresponding Author:

Mouad Elmouzoun Elidrissi
Laboratory of Radiation-Matter and Instrumentation, Faculty of Sciences and Techniques, Hassan First University of Settat
Settat 26002, Morocco
Email: M.elmouzounelidrissi@uhp.ac.ma

1. INTRODUCTION

While driving, a complex connection of our brain signals is established, which can cause the driver to feel tired and, even more so, to feel drowsy and fall asleep (drowsiness is a transitional state between the waking and sleeping states), leading to dangerous and fatal accidents [1], [2]. In addition, the monotony of highways and especially driving long distances and for many hours are other factors that can cause drowsiness in the driver [3].

In Morocco, a 33.33% rate of fatal accidents on the highways is caused by drowsiness [4], [5]. This gave us the opportunity to think about how to solve this serious tragedy, concluding that it is to develop an intelligent and hybrid algorithm for automatic early detection of drowsiness, which will warn the driver to take precautions. The aim of this work is to improve our previous algorithms for predicting driver drowsiness, and to overcome the weaknesses and limitations of existing systems in terms of speed and accuracy of detection.

Many previous works present techniques based on sensor signals to detect drowsiness, both in literature and commercially. Some have developed a smart glasses system that detects drowsiness based on eye closure by sending infrared light between an emitter and a receiver, or by adding other information such as micro-falls of the head subtracted from accelerometers and gyroscopic sensors [6]. The use of accelerometers and an infrared transceiver have been used but implemented on a wearable cap instead of glasses. Nevertheless, these methods have multiple limitations in real driving situations, especially in the absence of physiological parameters. For example, the driver can make different actions and movements that are normal but can be attributed to signs of drowsiness based on sensor signals.

Some authors proposed a non-invasive eye-tracking method based on an optical correlator to estimate eye state, which will then be used to detect driving fatigue. An accuracy of 99.9% was achieved for the estimation of the eye state at different situations [7]. Other systems based on face detection have also been developed, based on image processing and analysis of the eye and head states in addition to physiological signals such as respiratory signals and electrocardiogram (ECG) [8]–[10]. This idea has many limitations such as eye detection and tracking error due to eye shape for some subjects (e.g., Chinese population), camera direction and camera discomfort. Another non-intrusive technique was introduced, where the authors used thermal imaging to analyze the variations in respiratory rhythms under the nose region in a normal state and in drowsiness to identify the drowsy state, they were able to achieve a detection accuracy of 90% [11]. The idea of using a thermal camera solved the problem of non-detection at night or even in the absence of light of previous facial imaging-based systems.

In 2010, a study focused on the analysis of physiological signals such as electrocardiogram (ECG) [12] or using electrooculogram (EOG) signals in 2013 [13]. The analysis of EEG signals becomes the main field in the study of human body phenomena such as epilepsy, sleep apnea, and especially the study of awake and drowsiness states based on the difference between brain waves.

The difference between works is basically in the method of signals analysis (algorithms), the classification method, or the number of electrodes and even their position. A study cited the use of 32 electrodes for the acquisition before extracting the spectrum entropy, approximate entropy, sample entropy, and fuzzy entropy. So as to feed a support vector machine (SVM) with a radial basis function (RBF) kernel to achieve an accuracy of 98.75% [14]. Decreasing the number of electrodes down to 24 was also performed besides using the logarithm of energy, and chaotic feature extraction such as Petrosian and Higuchi fractal dimension or also empirical mode decomposition (EMD) [15], [16]. The accuracies obtained were 83.3% and 84.8%, respectively, or even 12 electrodes [17], where they proposed a method to explore the spectrogram of each EEG channel using the short-time Fourier transform (STFT), and the discrete Fourier transform (DFT). The accuracy reached an average of 91.72% after using the linear kernel of the SVM classifier. Another study developed a method based on fast Fourier transform (FFT) to calculate the spectrum and signal power spectral density (PSD) instead of STFT and showed an accuracy of 88.8% [18].

A method based on a single EEG channel parietal-zero-occipital-zero (Pz-Oz) and the zero means that the electrodes are placed in the midline sagittal plane of the skull), was proposed to detect drowsiness using the decomposition of the signal into frequency sub-bands according to a time-domain distribution called Haar wavelet packet transform (WPT) [19]. These techniques are the most widely used in these studies, whether brain waves are decomposed into Delta [<4 Hz], Theta [4 to 8 Hz], Alpha [8 to 16 Hz], Beta [16 to 32 Hz], and Gamma [>32 Hz] bands. In general, the increase in Theta waves and the decrease in Alpha waves correspond to a high level of transition from the awake to the drowsy state. The discrete wavelet transform (DWT), Tunable Q-factor wavelet transform (TQWT), and continuous wavelet transform (CWT) have also been discussed in previous works [20]–[22], respectively. These works have shown high detection accuracy of up to 91.842%. The positions of the electrodes used are important to extract the most significant signals to detect drowsiness when the number of these electrodes is reduced, according to the international 10 to 20 system, especially if a single channel of EEG recordings is used, as in our proposal.

The complexity is reduced due to the absence of a large number of electrodes, but it is more difficult to extract all the information from a single channel. Therefore, in this paper, we present a novel EEG signal analysis method based on hybrid features extracted from the time and spectral domains and our optimized random forest (RF) classification architecture to predict driver drowsiness, which achieved 98.5% of detection accuracy in 13 milliseconds, overcoming all the limitations of existing methods that we will explain in the next section.

2. METHOD

The objective of this paper is to develop a hybrid algorithm for drowsiness detection that encompasses three signal processing domains (temporal, and spectral using FFT, and PSD) and achieves a higher performance of speed and accuracy than the cited works. Each of the domains has been performed and tested separately, the distribution of features is analyzed to eliminate those that decrease the accuracy, and finally using the total of the most significant ones, then building different machine learning models to test their accuracies and maintain the best. The target population, as mentioned previously, is drivers working in transportation, who spend the majority of their time driving long distances and are over 35 years old. However, in terms of algorithm approval, we used an open database with an average of subjects aged 18 years (between 17 and 26 years).

2.1. Acquisition phase

The data used in this article were obtained from the Physionet database [23]. EEG signals were recorded monopolar using the 23-channel Neurocom EEG system (Ukraine, XAI-MEDICA). The 36 subjects were of both genders, aged 16-24 years (an average of 18 years).

Electrodes were placed according to the international 10 to 20 system. All electrodes were referenced to the interconnected ear reference electrodes (Ref). To remove artifacts from the EEG segments, a low-pass filter with a cutoff frequency of 30 Hz and a power-line notch filter (50 Hz) were used. This database is published for use in research work due to the high quality of its signals.

The data is available in European data format (.edf), so we took 6 male and female subjects of different ages (an average of 18 years) and converted the data file into a comma-separated values (.csv) extension with 3s EEG signal segments using Python and started our processing algorithm. In this work, we focused on a single channel of EEG recordings FP1-Ref. FP1 is known to be an optimal location for detecting sleepiness, studies based on the FP1 spot also showed a high correlation for detecting the sleepiness state [24].

2.2. Processing method

The EEG recordings were free from artifacts, as all noises were filtered out during recording, as described in the European Commission Study (section 2.1). After the EEG recordings were collected/acquired, a first arrangement was applied to the data in order to prepare them for the extraction of the selected features. The second step consists of grouping all features into a vector following the form of the classifier, dividing them into training and test inputs, adding the corresponding label, and finally obtaining the confusion matrix containing all the results about the applied training method. Here is the flowchart of our method presented in Figure 1.

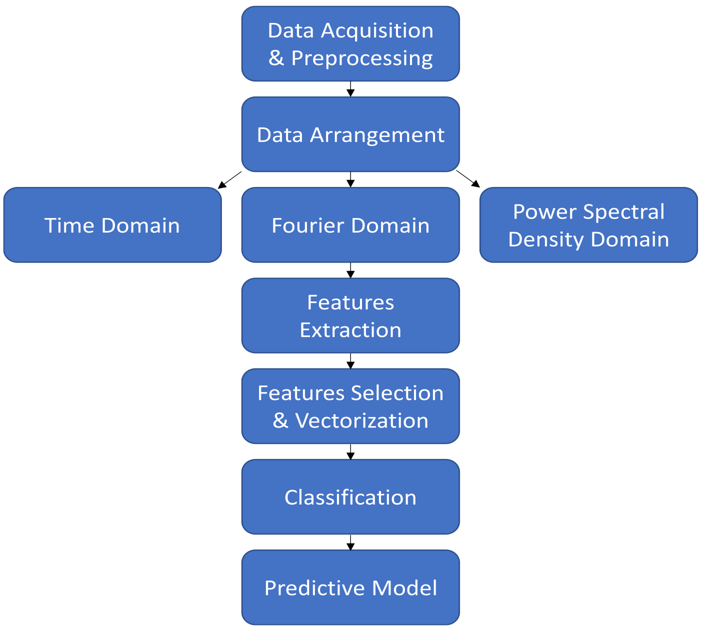

Figure 1. Flowchart of the treatment method

2.2.1. Time domain analysis

The objective of this step is the extraction of features in the time domain, i.e., the processing of the potential difference generated by the electrodes but considering first the single channel (Fp1-Ref) instead of the total of 23 electrodes, in order to reduce the hardware consumption and to keep the analysis in real-time, as shown in Figure 2. The detection of the drowsy state must be based on several parameters that make the difference between the two states, awake and drowsy, these characteristic parameters are called "features". The more these features are well dispersed between the two states, the more efficient and accurate the detection is.

In this work, the features chosen and extracted are the median, the mean, the standard deviation (Std), the variance (Var), the root mean square (RMS), the minima (Min), the maxima (Max), and a new parameter that we called mean of peaks (MOP) which represents the average of all the peaks of the signal.

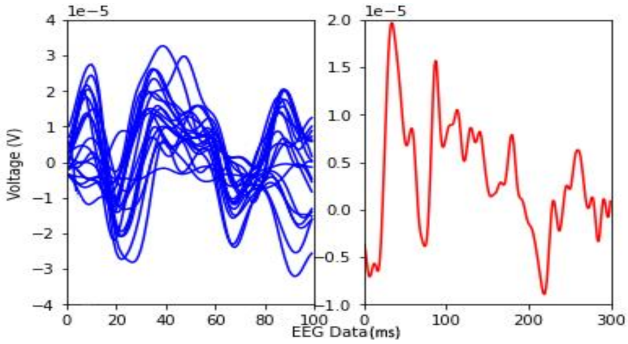

Figure 2. EEG signals recorded from 23 electrodes (left) and Fp1-Ref (right)

2.2.2. Frequency domain analysis

a. Fast Fourier transform approach

This second analysis starts by switching from the time domain to the frequency domain and extracting the most significant features. It aims at computing the one-dimensional DFT by a function that computes the one-dimensional n-point DFT with the efficient FFT algorithm.

For $0 \leqslant k \leqslant N-1$

$$\mathrm{Xk} = \sum_{n=0}^{n-1} xne^{-2\pi i \frac{kn}{N}} \tag{1}$$

After calculating the Fourier transform of all the data, in the same way as in the time domain, the features were extracted but were in the complex domain (real and imaginary values), so we adopted a method to convert these real and imaginary value into a pure real value in order to start our classification step. This method consists in calculating the modulus of the features.

$$Fi = Re(Fi) + i * Im(Fi)$$

$$|\mathrm{Fi}| = \sqrt{R_e^2 + I_m^2} \tag{2}$$

Fi is the extracted feature number i.

b. Power spectral density approach

In this section, the spectrum was estimated based on Burg's algorithm, which estimates the power spectral density of the data of each segment. PSD represents the spectral power per unit frequency. Using this technique, we might be able to distinguish the two states, especially after extracting the eight features mentioned earlier but this time from the spectrum of each sample/segment.

$$\mathrm{PSD} = \frac{1}{N}\sum_{k=0}^{N-1} Y(n)e^{-2k\frac{n}{N}} = \frac{1}{N}\, Xk \tag{3}$$

2.3. Classification

In this step, different analyses were adopted to obtain the best accuracy in drowsiness detection. Each approach (time, FFT, PSD) was tested separately and went through different classifier architectures, and then a method combining all the approaches was used (hybrid algorithm) to get the best efficiency of our proposed method based on the best classifier. The classifiers used in our study are SVM with its RBF kernel, RF, multilayer perceptron (MLP), nearest centroid (NC), K-nearest neighbors (KNN), Gaussian process, decision tree (DT), optimized decision tree (ODT), and finally stochastic gradient descent (SGD).

A general study on these classifiers is done to compare their efficiency and accuracy depending on the type of data used which are random signals (EEG signals). This means that the most meaningful method is to analyze our data and train a classifier that has a random architecture instead of a linear architecture. In the following section, we will show the results obtained for several aspects of our study.

3. RESULTS AND DISCUSSION

In this section, we will provide all the results of our proposed method, these results are the major sign of the performance of our model. The training and test scores (accuracies) indicate the ability of the model to predict drowsiness against all predictions made, the recall (sensitivity or also called success rate) is the ability to detect drowsiness when the subject is actually drowsy, the F1-score gives an idea of the prediction rate of sleepiness and wakefulness and the total accuracy of the classifier. The results are based on four parameters, their total is called the confusion matrix of a classifier.

- True positive (TP): Prediction is positive (Drowsy state is predicted) and X is Drowsy.
- True negative (TN): Prediction is negative (Awake state is predicted) and X is Awake.
- False positive (FP): Prediction is positive (Drowsy state is predicted) and X is Awake.
- False negative (FN): Prediction is negative (Awake state is predicted) and X is Drowsy.

Based on these parameters, we could calculate our different scoring outputs.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{4}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{5}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \tag{6}$$

$$\text{F1}-\text{score} = 2 * \frac{precision*recall}{precision+recall} \tag{7}$$

Tables 1 to 4 show all the results obtained when we trained different models using only the PSD domain features extracted from EEG data samples in Table 1, FFT-only features in Table 2, time-only features in Table 3, and our hybrid approach of features selection in Table 4.

Table 1. Performance comparison between different classifiers applied on only PSD features

Classifier	Precision	Accuracy	Recall	F1-score D/A
SVM (RBF kernel)	70.4%	71.9%	75.9%	0.71 / 0.71
Gaussian process	49.1%	49.1%	100%	0.00 / 0.66
Stochastic gradient descent	50.2%	50.2%	100%	0.00 / 0.67
Multi-layer perceptron	49.8%	49.8%	100%	0.00 / 0.66
Nearest centroid	54.6%	57%	86.3%	0.39 / 0.67
Random forest	49.7%	49.7%	100%	0.00 / 0.66
K-nearest neighbors	90.6%	90.6%	90.8%	0.90 / 0.91

Table 2. Performance comparison between different classifiers applied on only FFT features

Classifier	Precision	Accuracy	Recall	F1-score D/A
SVM (RBF kernel)	84.6%	86.5%	89.7%	0.86 / 0.87
Gaussian process	63.7%	68.9%	87.6%	0.62 / 0.74
Stochastic gradient descent	49.7%	49.7%	100%	0.00 / 0.66
Multi-layer perceptron	69.4%	74.1%	84.1%	0.72 / 0.76
Nearest centroid	69.6%	72.9%	82.6%	0.70 / 0.76
Random forest	96.7%	96.5%	96.1%	0.97 / 0.96
K-nearest neighbors	93.3%	92.9%	92.4%	0.93 / 0.93

Table 3. Performance comparison between different classifiers applied on only time features

Classifier	Precision	Accuracy	Recall	F1-score D/A
SVM (RBF kernel)	92.0%	93.3%	94.5%	0.93 / 0.93
Gaussian process	49.0%	49.0%	100%	0.00 / 0.66
Stochastic gradient descent	50.5%	50.5%	100%	0.00 / 0.66
Multi-layer perceptron	48.9%	48.9%	100%	0.00 / 0.66
Nearest centroid	84.4%	88.4%	95.0%	0.87 / 0.89
Random forest	93.5%	94.6%	95.5%	0.95 / 0.95
K-nearest neighbors	95.8%	94.1%	92.3%	0.94 / 0.94

Table 4. Performance comparison between different classifiers applied on our hybrid method

Classifier	Precision	Accuracy	Recall	F1-score D/A
SVM (RBF kernel)	85.3%	87.8%	91.3%	0.87 / 0.88
Gaussian process	53.2%	56.0%	96.1%	0.27 / 0.68
Stochastic gradient descent	59.9%	65.5%	90.4%	0.55/ 0.72
Multi-layer perceptron	70.7%	75.6%	85.5%	0.73 / 0.78
Nearest centroid	68.7%	73.4%	85.3%	0.70 / 0.76
Random forest	98.2%	98.5%	98.0%	0.98 / 0.98
K-nearest neighbors	93.2%	93.1%	92.6%	0.93 / 0.93

As a result, our proposed method (hybrid approach) presented in Table 4 showed a remarkable performance improvement in terms of accuracy. The accuracy reached 98.5% for drowsiness detection based on our chosen features. To justify these good results here is for example the distribution of some randomly chosen features along the extracted data lines. We can also observe that the classifiers that obtain the best accuracy are RF and KNN, due to the adherence between the nature of our EEG signals (which has a random distribution) and the architecture of these classifiers presented in Figure 2.

To show that our results are far from so-called overfitting and to justify these good results, in Figure 3 we present a distribution of randomly selected features (standard deviation and variance) extracted from awake and drowsy subjects over all EEG data row samples, and we notice that the features extracted from each state of the subjects are very distinct and could summarize that we are dealing with two different states called classes.

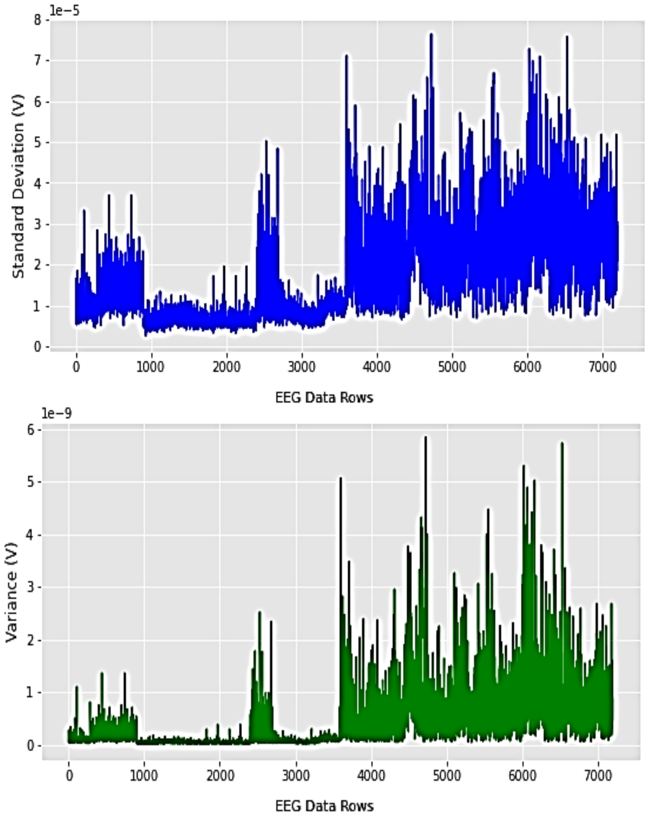

Figure 3. Features distribution along the total rows of EEG data extracted

It can be clearly seen that the two classes awake (from 0 to 3,599) and drowsy (from 3,600 to 7,199) are well separated, except for the distribution of the characteristics of some subjects, but in general, the classification reached a high percentage of detection (98.5%). In order to situate our method, a two-axis study was conducted to compare all previous work that used the same dataset and the single-channel-based processing shown in Table 5. Achieving higher accuracy of a system depends on two studies: either we use a large data segment to give the classifier a higher margin for training and testing, or we try to build the analysis on robust features. As shown in Table 5, our proposed method performed best using only 3-second data segments instead of 5 s, 10 s, or 30 s segments.

In terms of time consumption, this Table 6 compares the classifiers used and the time taken during the entire training process from data entry to classifier output (prediction). By comparing these results in Table 6, we conclude that the runtime is different from one classifier to another. But in terms of time and accuracy, the RF classifier is the most efficient and effective for our work. The final phase was to save our (trained) model and use it to predict the state of new subjects to validate our work and calculate the prediction time. The state of these subjects used for approval was already known and tested by our new hybrid model.

The average prediction time was 13 milliseconds as shown in Table 6 and Figure 4. The reason why the RF and KNN classifiers show the highest accuracies in each approach is that our data type is compatible with the nature of the classifier. Using a nonlinear classifier for random, nonlinear data like ours (EEG signals) is the best method for building a predictive model. Linear classifiers will not be as effective as nonlinear ones due to the non-possibility of finding a linear separator between the distribution of the data called a hyperplane.

Table 5. Comparison of performance between our and existing models obtained using Physionet EEG database and single-EEG-channel approach

Work	Platform used	Sampling frequency	Size of segments	Processing method	Classification method	Accuracy
Proposed	Python	100 Hz	3s	Hybrid	RF	98.50%
[25]	Python	100 Hz	3s	Hybrid	ODT	96.40%
[26]	Python	100 Hz	3s	Hybrid	DT	95.70%
[27]	MATLAB	100 Hz	5s	WPT	ET	94.45%
[28]	--	--	--	TQWT	ELM	91.80%
[29]	MATLAB	250 Hz	30s	STFT, TQWT	LSTM	94.31%
[18]	MATLAB	250 Hz	30s	FFT	ANN	88.80%
[30]	iPad app	512 Hz	10s	PSD	SVM	72.70%

Table 6. Time comparison between the different classifiers used

Classifier	Accuracy	Time (s)
Random forest	98.5%	0.013
Optimized decision tree	96.4%	0.053
Decision tree	95.7%	0.065
SVM (RBF kernel)	87.8%	0.985
Gaussian process	56.0%	12.57
Stochastic gradient descent	65.5%	0.366
Multi-layer perceptron	75.6%	5.144
Nearest centroid	73.4%	0.006
K-nearest neighbors	93.1%	0.142

```
- - -  Execution time is : 0.011465549468994l4 seconds - - -
'Attention !!! Subject is drowsy '
```

```
- - -  Execution time is : 0.014030694961547852 seconds - - -
'Subject is Awake '
```

Figure 4. Output of our model showing the total time consumed

4. CONCLUSION

The proposed method represents a new hybrid method based on time processing (FFT, and PSD techniques) to predict sleepiness from physiological signals (EEG signals), this work shows an interesting performance improvement under three axes: the software used (Python), the prediction accuracy (98.5%) and the prediction time (0.013 s). Using the features extracted from the three domains (time, FFT, and PSD), we were able to train different classifiers to predict sleepiness and compared each of them to get an overview and concluded that our method offered the best performance among all existing works.

The only limitation of this work is that the average age used is related to the database used (18 years) which is different from the target population (over 35 years). This limitation will be overcome once we have realized our own prototype (hardware acquisition system).

ACKNOWLEDGEMENTS

The author is extremely grateful for receiving an excellence scholarship from the National Center of Scientific and Technical Research (CNRST Morocco).

REFERENCES

[1] Narsa, "Collection of statistics on road traffic injuries 2016," (in French), *Narsa*, 2016. Accessed: Mar. 11, 2022. [Online], Available: http://narsa.ma/sites/default/files/2021-08/recueil 2020.pdf
[2] "Collection of statistics on road traffic injuries 2017," (in French) *Ministère de l'Equipement, du Transport, de la Logistique et de l'Eau Royaume du Maroc*, 2017. Accessed: Mar, 11, 2022. [Online], Available: http://www.equipement.gov.ma/AR/Infrastructures-routieres/Reseau-Routier-du-Maroc/Documents/RECUEIL%20ACCIDENTS%202017.pdf
[3] T. Wijayanto, S. R. Marcillia, G. Lufityanto, B. B. Wisnugraha, T. G. Alma, and R. U. Abdianto, "The effect of situation awareness on driving performance in young sleep-deprived drivers," *IATSS Research*, vol. 45, no. 2, pp. 218–225, Jul. 2021, doi: 10.1016/j.iatssr.2020.10.002.
[4] Narsa, "Physical accidents," (in French), *Narsa*, 2020. Accessed: Mar. 11, 2022. [Online], Available: https://narsa.ma/sites/default/files/2021-08/recueil%202020.pdf (accessed Mar. 11, 2022).
[5] Narsa, "On the final statistical data on road traffic accidents with injuries for the year 2019," (in French), *Narsa*, 2019. Accessed: Mar. 11, 2022. [Online], Available: https://narsa.ma/sites/default/files/2020-11/Comm%20accid%202019%20%281%29.pdf (accessed Mar. 11, 2022).
[6] W. Chang, L. Chen, and Y. Chiou, "Design and implementation of a drowsiness-fatigue-detection system based on wearable smart glasses to increase road safety," *IEEE Transactions on Consumer Electronics*, vol. 64, no. 4, pp. 461–469, Nov. 2018, doi: 10.1109/TCE.2018.2872162.
[7] E. Ouabida, A. Essadike, and A. Bouzid, "Optical correlator based algorithm for driver drowsiness detection," *Optik*, vol. 204, Feb. 2020, doi: 10.1016/j.ijleo.2019.164102.
[8] C. Jacobé de Naurois, C. Bourdin, C. Bougard, and J.-L. Vercher, "Adapting artificial neural networks to a specific driver enhances detection and prediction of drowsiness," *Accident Analysis & Prevention*, vol. 121, pp. 118–128, Dec. 2018, doi: 10.1016/j.aap.2018.08.017.
[9] S. Dhanalakshmi, J. J. Rosepet, G. L. Rosy, and M. Philominal, "Drowsy driver identification using MATLAB," *International Journal for Research in Applied Science and Engineering Technology*, vol. 4, no. 4, pp. 198–205, 2016.
[10] A. Dash and B. N. Tripathy, "Prototype drowsiness detection system," National Institute of Technology Rourkela, 2012.
[11] S. E. H. Kiashari, A. Nahvi, H. Bakhoda, A. Homayounfard, and M. Tashakori, "Evaluation of driver drowsiness using respiration analysis by thermal imaging on a driving simulator," *Multimedia Tools and Applications*, vol. 79, no. 25–26, pp. 17793–17815, Jul. 2020, doi: 10.1007/s11042-020-08696-x.
[12] M. Tasaki, M. Sakai, M. Watanabe, H. Wang, and D. Wei, "Evaluation of drowsiness during driving using electrocardiogram - a driving simulation study," in *2010 10th IEEE International Conference on Computer and Information Technology*, Jun. 2010, pp. 1480–1485. doi: 10.1109/CIT.2010.264.
[13] M. L. Jackson *et al.*, "The utility of automated measures of ocular metrics for detecting driver drowsiness during extended wakefulness," *Accident Analysis & Prevention*, vol. 87, pp. 127–133, Feb. 2016, doi: 10.1016/j.aap.2015.11.033.
[14] Z. Mu, J. Hu, and J. Min, "Driver fatigue detection system using electroencephalography signals based on combined entropy features," *Applied Sciences*, vol. 7, no. 2, Feb. 2017, doi: 10.3390/app7020150.
[15] Z. Mardi, S. N. Ashtiani, and M. Mikaili, "EEG-based drowsiness detection for safe driving using chaotic features and statistical tests," *Journal of Medical Signals & Sensors*, vol. 1, no. 2, 2011, doi: 10.4103/2228-7477.95297.
[16] R. Kaur and K. Singh, "Drowsiness detection based on EEG signal analysis using EMD and trained neural network," *International Journal of Science and Research (IJSR)*, vol. 2, no. 10, pp. 157–161, 2013.
[17] Ç. İ. Acı, M. Kaya, and Y. Mishchenko, "Distinguishing mental attention states of humans via an EEG-based passive BCI using machine learning methods," *Expert Systems with Applications*, vol. 134, pp. 153–166, Nov. 2019, doi: 10.1016/j.eswa.2019.05.057.
[18] I. Belakhdar, W. Kaaniche, R. Djemal, and B. Ouni, "Single-channel-based automatic drowsiness detection architecture with a reduced number of EEG features," *Microprocessors and Microsystems*, vol. 58, pp. 13–23, Apr. 2018, doi: 10.1016/j.micpro.2018.02.004.
[19] T. L. T. da Silveira, A. J. Kozakevicius, and C. R. Rodrigues, "Automated drowsiness detection through wavelet packet analysis of a single EEG channel," *Expert Systems with Applications*, vol. 55, pp. 559–565, Aug. 2016, doi: 10.1016/j.eswa.2016.02.041.
[20] N. Gurudath and H. B. Riley, "Drowsy driving detection by EEG analysis using wavelet transform and K-means clustering," *Procedia Computer Science*, vol. 34, pp. 400–409, 2014, doi: 10.1016/j.procs.2014.07.045.
[21] S. K. Khare and V. Bajaj, "Optimized tunable Q wavelet transform based drowsiness detection from electroencephalogram signals," *IRBM*, vol. 43, no. 1, pp. 13–21, Feb. 2022, doi: 10.1016/j.irbm.2020.07.005.
[22] Y. Jiao, Y. Deng, Y. Luo, and B.-L. Lu, "Driver sleepiness detection from EEG and EOG signals using GAN and LSTM networks," *Neurocomputing*, vol. 408, pp. 100–111, Sep. 2020, doi: 10.1016/j.neucom.2019.05.108.
[23] A. L. Goldberger *et al.*, "PhysioBank, PhysioToolkit, and PhysioNet," *Circulation*, vol. 101, no. 23, Jun. 2000, doi: 10.1161/01.CIR.101.23.e215.
[24] A. M. Strijkstra, D. G. M. Beersma, B. Drayer, N. Halbesma, and S. Daan, "Subjective sleepiness correlates negatively with global alpha (8–12 Hz) and positively with central frontal theta (4–8 Hz) frequencies in the human resting awake electroencephalogram," *Neuroscience Letters*, vol. 340, no. 1, pp. 17–20, Apr. 2003, doi: 10.1016/S0304-3940(03)00033-8.
[25] M. E. Elidrissi, E. Essoukaki, L. Ben Taleb, A. Mouhsen, and M. Harmouchi, "A new hybrid and optimized algorithm for drivers' drowsiness detection," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 11, no. 3, pp. 1101–1107, Sep. 2022, doi: 10.11591/ijai.v11.i3.pp1101-1107.
[26] M. E. Elidrissi *et al.*, "Automatic drowsiness detection based on a single channel of EEG signals using a hybrid analysis and decision tree classification method under python," in *Proceedings of the 2nd International Conference on Big Data, Modelling and Machine Learning*, 2021, pp. 301–305. doi: 10.5220/0010732900003101.
[27] B. V. Phanikrishna and S. Chinara, "Automatic classification methods for detecting drowsiness using wavelet packet transform extracted time-domain features from single-channel EEG signal," *Journal of Neuroscience Methods*, vol. 347, p. 108927, Jan. 2021, doi: 10.1016/j.jneumeth.2020.108927.
[28] V. Bajaj, S. Taran, S. K. Khare, and A. Sengur, "Feature extraction method for classification of alertness and drowsiness states EEG signals," *Applied Acoustics*, vol. 163, Jun. 2020, doi: 10.1016/j.apacoust.2020.107224.

[29] U. Budak, V. Bajaj, Y. Akbulut, O. Atila, and A. Sengur, "An effective hybrid model for EEG-based drowsiness detection," *IEEE Sensors Journal*, vol. 19, no. 17, pp. 7624–7631, Sep. 2019, doi: 10.1109/JSEN.2019.2917850.
[30] M. Ogino and Y. Mitsukura, "Portable drowsiness detection through use of a prefrontal single-channel electroencephalogram," *Sensors*, vol. 18, no. 12, Dec. 2018, doi: 10.3390/s18124477.

BIOGRAPHIES OF AUTHORS

Mouad Elmouzoun Elidrissi was born on September 10, 1996 in Casablanca, Morocco. He is a Ph.D. student and received his master's degree in biomedical engineering: instrumentation and maintenance from the Faculty of Science and Technology Settat, in 2019. His research areas include EEG signals analysis for drivers' drowsiness detection, machine learning model conception, and application of artificial intelligence for drivers and road safety. He works at the Laboratory of Radiation-Matter and Instrumentation (RMI), Faculty of Sciences and Technology, Hassan 1st University, Morocco. BP: 577, route de Casablanca. Settat, Morocco. His research areas are in machine learning and artificial intelligence, EEG signal processing, and biomedical instrumentation. He can be contacted at m.elmouzounelidrissi@uhp.ac.ma.

Elmaati Essoukaki was born on January 1, 1990. He is currently a professor of Instrumentation and Biomedical Engineering at Higher Institute of Health Sciences (ISSS), Hassan First University. His research interests include Instrumentation and Biomedical Engineering, biomedical imaging, and signal processing. He holds several publications and innovation patents in the fields of biophysics and biomedical engineering. He can be contacted at e.essoukaki@uhp.ac.ma.

Lhoucine Ben Taleb was born on February 20, 1991. He is a professor of Electrical and Biomedical Engineering at Hassan First University (UHP), Morocco, since 2021. After having a master's degree from UHP (2014), he obtained a Ph.D. in 2020 from the same university specialty in electrical and biomedical engineering (in the Laboratory of Radiation-Matter and Instrumentation). Ben Taleb has taught courses in instrumentation for functional exploration and therapeutic applications, medical imaging technologies as well as microcontrollers and programmable logic controllers. He has published several scientific papers, and he is an inventor of one patent and a co-inventor of another one. He can be contacted at l.bentaleb@uhp.ac.ma.

Azeddine Mouhsen was born on July 10, 1967 and is now a professor of Physics at Hassan First University, Morocco, since 1996. He holds a Ph.D. from Bordeaux I University (France) in 1995 and a thesis from Moulay Ismail University, Morocco, in 2001. He specializes in instrumentation and measurements, sensors, applied optics, energy transfer, and radiation-matter interactions. Azeddine Mouhsen has taught courses in physical sensors, chemical sensors, instrumentation, systems technology, digital electronics, and industrial data processing. He has published over 30 papers and he is the co-inventor of one patent. Actually, he is the Director of the Laboratory of Radiation-Matter and Instrumentation. He can be contacted at az.mouhsen@gmail.com.

Mohammed Harmouchi was born in Sefrou, Morocco, in 1959. He is in charge of the master's degree in biomedical engineering: instrumentation and maintenance. He is the Ex-Director of the Laboratory of Radiation-Matter and Instrumentation, Hassan First University, Settat, Morocco, where he is currently a professor of Higher Education and the Ex-Head of the Department of Applied Physics, Faculty of Science and Technology. He holds several publications and innovation patents in the fields of biophysics and biomedical engineering. (Based on document published on October 9, 2020). He can be contacted at mharmouchi14@gmail.com.