A new hybrid and optimized algorithm for drivers' drowsiness detection

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

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ABSTRACT

When the roads are monotonous, especially on the highways, the state of vigilance decreases and the state of drowsiness appears. Drowsiness is defined as the transitional phase from the awake to the sleepy state. However, In Morocco, the majority of fatal accidents on the highway are caused by drowsiness at the wheel, reaching 33.33% rate. Therefore, we proposed the conception and realization of an automatic method based on electroencephalogram (EEG) signals that can predict drowsiness in real time. The proposed work is based on time-frequency analysis of EEG signals from a single channel (FP1-Ref), and drowsiness is predicted using a personalized and optimized machine learning model (optimized decision tree classification method) under Python. The results are much significant and optimized, improving the accuracy from 95.7% to 96.4% and a time consuming from 0.065 to 0.053 seconds.

Corresponding Author:

Mouad Elmouzoun Elidrissi
Laboratory of Radiation-Matter and Instrumentation, Faculty of Science and Technology, University Hassan 1st
Settat, Morocco
Email: M.elmouzounelidrissi@uhp.ac.ma

1. INTRODUCTION

The rate of deadly accidents on highway caused by drowsiness and falling asleep while driving based on the latest statistics of the ministry of equipment, transport, logistics and water, directorate of roads in Morocco is 33.3% as provided in [1], [2]. These statistics gave us the idea of developing an automatic model that can predict drowsiness when occurring and before the situation becomes worst leading to dangerous accidents. Therefore, the idea of our system is not new, but it came to improve the performance and solve the limitations of the existing ones by using the latest processing software 'Python', also by providing the best processing techniques 'time and frequency' and machine learning (ML) algorithms to perform a better hybrid and automatic method of detecting drowsiness based on single-channel of electroencephalogram (EEG) signals [3]. As a result, our model based on an optimized decision tree (DT) classifier shows a higher performance compared to our previous one and to all the previous works, improving the accuracy and the time consuming. Our previous study (conference paper publishing in progress) was to conceive an efficient model based on a heavy analysis, during that period a detailed study was carried on the existing systems and their limitations.

Therefore, the existing works like cited in our previous work were based on sensors only, based on physiological signals like EEG, electrocardiogram (ECG), and electro-oculogram (EOG) [4]–[8], or even a mix of these two techniques [9]. Chang *et al.* [10] proposed a smart glasses system that detects drowsiness using signals generated by accelerometers and gyroscopes, capturing the head 's micro-falls in addition to an infra-red transceiver for capturing the blinking frequency and the eyes-closure degree. Other works used algorithms that can detect drowsiness using a facial recognition or eyes regions detection by [11], [12], or also using a thermal imaging tehniques proposed by [13]. However, We did mention on our last work that using signals issued only from sensors and not physiological signals is not accurate nor evident to confirm the detection's efficiency, because a driver's blinking or eyes closure or even his head's movement are a standard and spontaneous actions. So, the solution was to use a method and technique based on signals recorded from EEG, ECG, EOG and others, EEG signals in our work [14]–[18]. To situate our work, the following works used a single channel study in addition to using the same dataset of EEG signals available at the Physionet database to compare our results and show the improvement added by our hybrid method. Belakhdar *et al.* [19] proposed a technique that analyses the spectral domain of the EEG signals using MATLAB, applying the Fourier transform and an artificial neural network (ANN) classification. Their work reached an accuracy of 88.8%. Bajaj *et al.* [20] reached an accuracy of 91% using tunable Q-factor wavelet transform (TQWT) algorithm appliyed on the EEG signals, and the extreme machine learning classifier (ELM). The highest accuracy of 94.45% is reached by [21] using the wavelet packet transform (WPT) method and fed to the extra-trees classifier.

The proposed work aims to improve our previous algorithm's efficiency of detecting drowsiness of drivers in the terms of rapidity and accuracy, using a personalized and optimized DT classifier that we will explain next. Our method proposed in this paper aims to provide an optimized and new hybrid algorithm drivers' drowsiness detection based on the mixed temporal and frequential domains by processing a single channel of EEG records (FP1). Many researchers have confirmed that the most accurate position for detecting drowsiness is the FP1 position like published by [22]. Our proposed method is shown in Figure 1.

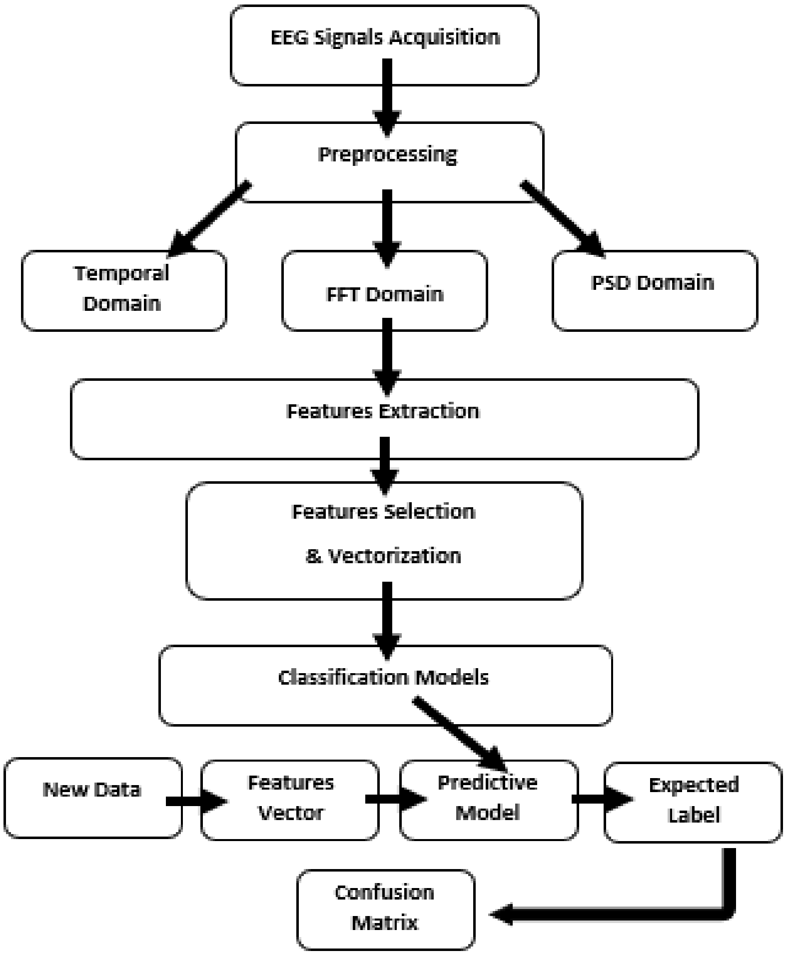

Figure 1. Flowchart of our proposed method

2. METHOD

2.1. Pre-processing Phase

The open Physionet database is the one we used in our works because it's the best to use for similar works. All the EEG records were artefact-free and noise filtered right after the acquisition step using a 30 Hz low-pass filter and a 50 Hz notch. The signals were extracted from the subjects under the 10-20 international system, they were males and females with different ages [23], [24].

2.2. Time segmentation phase

We applied a segmentation of 3 seconds of EEG signals instead of using the whole 30 seconds recording. The benefice of this time segmentation is to ensure stationarity of spectral analysis (fast Fourier transform (FFT) and power spectral density (PSD) analysis). In other terms also, to ensure the real time condition so that the process of detecting the drowsiness state do not take a higher time consumption.

2.3. Features Extraction Phase

This step aims to extract the most significant features using a single-channel of EEG from three mixed domains (temporal, Fourier and spectral). We designed a function that can extract all the features one by one, and scales all of them in the right shape for the classification step. The use of the mixing features was not chosen randomly but after an analyze where we found that this mixture shows the highest accuracies and results.

2.3.1. Temporal domain analysis

Eight parameters are calculated in the time domain in a way to distinguish the awake from the drowsy state. Using conditions to process intervals of 3 seconds, we calculated all the features manually according to the best ones resulting the best accuracies of the models. These features were the minima, the maxima, the amplitude peaks and our proper mean of amplitude peaks parameter, in addition to the following ones:
The median:

$$P(y \leqslant x) = P(x \leqslant z) \tag{1}$$

The mean:

$$\bar{X} = \sum \frac{x_i}{n} \tag{2}$$

The variance:

$$Var = \frac{\sum (x_i - \bar{x})^2}{n} \tag{3}$$

The standard deviation:

$$Std = \sqrt{Var} \tag{4}$$

The root-mean-square:

$$\text{RMS} = \sqrt{\frac{\sum {x_i}^2}{n}} \tag{5}$$

2.3.2. Fourier and power spectral domain analysis

In this phase, we proposed a frequency analysis of the recorded EEG signals using the fast Fourier transform. After extracting the same previous feature, the modulus of these features is calculated to eliminate the imaginary part and have only the real significant part.

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

$$\text{Xk} = \sum_{n=0}^{n-1} xn e^{-2\pi i \frac{kn}{N}} \tag{6}$$

A comparison of the brain band's power is calculated using the burg algorithm (spectrum analysis) to allow a good discrimination between the awake and drowsy states.

$$\text{PSD} = \frac{1}{N}\sum_{k=0}^{N-1} Y(n)e^{-2k\frac{n}{N}} = \frac{1}{N}\, Xk \tag{7}$$

2.4. Features selection & classification

A total of eight ML classification methods is tested in our study to compare the efficiency and keep the best model, and secondly, to select the most appropriate features. As a result, our optimized model showed the best of accuracies and time performance. The classifiers we used to compare our model's efficiency are gaussian process (GP), K-nearest-neighbors (KNN), multilayer perceptron (MLP), support vector machine (SVM) (with its four kernels), our previous DT classifier, and finally the proposed optimized DT.

3. RESULTS AND DISCUSSION

After extracting the features, all the calculated parameters were scaled and processed using ML classifiers. These classifiers depend on four parameters: i) True positive (TP): Prediction is positive (Drowsy state is predicted) and X is Drowsy; ii) True negative (TN): Prediction is negative (Awake state is predicted) and X is Awake; iii) False positive (FP): Prediction is positive (Drowsy state is predicted) and X is Awake; and iv) 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:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{8}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

$$\text{Sensitivity (Recall)} = \frac{TP}{TP+FP} \tag{10}$$

$$\text{F1\_score} = 2 * \frac{Precison * R\ ecall}{Precision + Recall} \tag{11}$$

Achieving a higher accuracy of a model depends on two studies, either we use a large segment of data to give the classifier a higher margin for the training and testing, or you try to build the analysis on solid features, therefore the first method is based on only PSD features, the second on only FFT features, the third method used only time features and the last one is our method based on the mixed features. As we can conclude, our hybrid model based on the mixed domains of features and our optimized DT classifier achieved the best accuracy compared to our previous work presented during an international conference (BML21: publishing on progress) and all the other selection of features and classifiers shown in Table 1. We used a personalized SearchGrid algorithm to select the best hyperparameters values of the DT classifier to achieve the best of accuracies as shown in Figure 2. A two-axes study was conducted to compare our method to the previous ones using the same dataset and the aspect of single-channel-based processing in order to situate our method. The results are shown in Table 2. Right after we generated a comparison in terms of the executing time and accuracies. In addition to the confusion matrix result of our optimized ML model shown in Figure 3.

Comparing the results in Table 3, we conclude that the execution time is different from one classifier to another. But in terms of both time and accuracy, our optimized DT classifier is the most efficient and effective. The accuracy reached 96.4% and the execution time was within 53 milliseconds.

Table 1. Performance comparison between different classifiers applied on our selected features

Classifier	First method	Second method	Third method	Hybrid method
Optimized DT	51.2%	94.7%	95.0%	96.4%
DT (previous work)	49.3%	93.6%	94.3%	95.7%
SVM (Linear kernel)	49.7%	49.9%	49.4%	49.5%
SVM (Plynomial kernel)	54.6%	85.5%	93.2%	83.6%
SVM (Sigmoid kernel)	35.3%	66.8%	88.7%	66.0%
SVM (RBF kernel)	71.9%	86.5%	93.3%	87.8%
MLP	49.8%	74.1%	48.9%	75.6%
KNN	90.6%	92.9%	94.1%	93.1%
GP	49.1%	86.9%	49.0%	56%

```
DTclassifier.get_params()

{'ccp_alpha': 0.0,
 'class_weight': None,
 'criterion': 'entropy',
 'max_depth': 32,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'presort': 'deprecated',
 'random_state': None,
 'splitter': 'best'}
```

Figure 2. Search Grid output

Table 2. Performance comparison between our proposed model and existing models using same Physionet EEG dataset

Works	Platform used	Sampling frequency	Size of segments	Processing method	Classification method	Accuracy
Proposed	Python	100 Hz	3s	Hybrid	Optimized Decision Tree	96.4%
Previous work	Python	100 Hz	3s	Hybrid	Decision Tree	95.7%
(B and Chinara, 2021) [21]	MATLAB	100 Hz	5s	WPT	ET	94.45%
(Bajaj *et al.*, 2020) [20]	–	–	–	TQWT	ELM	91.8%
(Budak *et al.*, 2019) [25]	MATLAB	250 Hz	30s	STFT, TQWT	LSTM	94.31%
(Belakhdar *et al.*, 2018) [19]	MATLAB	250 Hz	30s	FFT	ANN	88.8%
(Ogino and Mitsukura, 2018) [26]	Ipad app	512 Hz	10s	PSD	SVM, SWLDA	72.7%

```
--- Execution time is : 0.0536646842956543 seconds ---
Train Accuracy : 100.0%
Test Accuracy : 96.4%
Test precision : 96.3%
Classifier's Accuracy : 96.4%
Recall : 96.7%
              precision    recall  f1-score   support

           0       0.96      0.97      0.96      1405
           1       0.97      0.96      0.96      1460

    accuracy                           0.96      2865
   macro avg       0.96      0.96      0.96      2865
weighted avg       0.96      0.96      0.96      2865
```

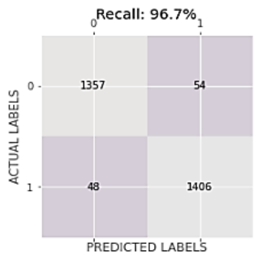

Figure 3. Output of our optimized model (confusion matrix)

Table 3. Time comparison between the different classifiers used in our method

Classifier	Accuracy	Time(s)
Proposed (Optimized DT)	96.4%	0.053
Previous Work (DT)	95.7%	0.062
SVM (Linear kernel)	87.8%	0.985
Gaussian Process	56%	12.57
Stochastic Gradient Descent	65.5%	0.366
Multi-Layer Perceptron	75.6%	5.144
Nearest Centroid	73.4%	0.006

The final phase was to save our model (trained) and using it to predict the state of new subjects in order to approve our work and calculate the prediction time. The state of these subjects used for the approval was known already and tested by our new hybrid model. Effectively, the model could predict all the given data and gave perfect predictions.

4. CONCLUSION

The present work proposed an optimized hybrid method of detecting drivers' drowsiness based on time-frequency analysis of a FP1 of EEG signals. We extracted a total of eight features from the three domains, the time, Fourier and PSD. After that, we trained eight ML models, MLP, GP, KNN, SVM (with its four kernels), DT and finally our optimized DT. We compared our proposed work to our previous one and to the ones based on the same dataset and the use of a single channel of EEG records. The added value of our model is the improvement of the detection's performance in the term of accuracy, which achieved 96.4% and the processing time 0.053 seconds.

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BIOGRAPHIES OF AUTHORS

Mouad Elmouzoun Elidrissi Born in 10 September 1996 in Casablanca, Morocco. He is a PhD student, received his master degree in Biomedical Engineering: Instrumentation and Maintenance from Faculty of Science and Technology Settat, in 2019. His research areas include EEG signals analysis for the use in drivers' drowsiness detection, machine learning models conception, Application of artificial intelligence for drivers and road safety. Laboratory of Radiation-Matter and Instrumenta- tion (RMI), Faculty of Sciences and Technology, Hassan 1st University, Morocco. BP: 577, route de Casablanca. Settat, Morocco. His researches are in fields of machine learning and artificial intelligence, EEG signal processing, and biomedical instrumentation. He can be contacted at email: m.elmouzounelidrissi@uhp.ac.ma.

Elmaati Essoukaki Born in 1 January 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 email: e.essoukaki@uhp.ac.ma.

Lhoucine Ben Taleb Born in February 20, 1991. He is a professor of Electrical and Biomedical Engineering at Hassan First University (UHP), Morocco, since 2021. After a Master degree from UHP (2014), he obtained in 2020 a PhD from the same university speciality electrical and biomedical engineering (in the Laboratory of Radiation-Matter and Instrumentation). He has taught courses in instrumentation for the functional exploration and therapeutic applications, medical imaging technologies as well as microcontrollers and programmable logic controllers. He has published 6 scientific papers, and he is an inventor of one patent and a co-inventor of another one. He can be contacted at email: l.bentaleb@uhp.ac.ma.

Azeddine Mouhsen Born in 10 July 1967, He is Professor of Physics at Hassan First University, Morocco, since 1996. He holds a PhD from Bordeaux I University (France) in 1995 and a thesis from Moulay Isma¨ıl University, Morocco, in 2001. He specializes in instrumentation and measurements, sensors, applied optics, energy transfer, radiation-matter interactions. He has taught courses in physical sensors, chemical sensors, instrumentation, systems tech- nology, 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 Laboratory of radiation-matter and Instrumentation. He can be contacted at email: az.mouhsen@gmail.com.

Mohammed Harmouchi 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 9 October 2020). He can be contacted at email: mharmouchi14@gmail.com.