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A new hybrid and optimized algorithm for drivers' drowsiness detection

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ABSTRACT

The human brain generates millions of signals as they translate all our movements and thoughts, our physical and psychological state. While driving, all these signals are generated simultaneously. Vigilance at the wheel is necessary. However, when the roads are monotonous, especially on the highways, this state of vigilance decreases and the state of drowsiness appears. In Morocco, 1/3 of fatal accidents on the highway are caused by drowsiness and sleepiness at the wheel. Therefore, we proposed the idea of developing an automatic system based on electroencephalogram (EEG) signals that can predict the state of drowsiness in real time using several features extracted from EEG recordings when this state occurs in drivers while driving. The proposed work is based on time-frequency analysis of EEG signals from a single channel (FP1-Ref), and drowsiness is predicted using a modified 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.

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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 by (Des et al., 2016) and (Statistiques, 2017) [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 algorithms to perform a better hybrid and automatic method of detecting drowsiness based on single-channel of EEG signals [3]. As a result, our model based on an optimized Decision Tree classifier shows a higher performance compared to our previous one and to all the previous works, improving the accuracy and the time consuming.

2. RELATED WORKS

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 electroencephalogram, electrocardiogram, electro-oculogram (EEG, ECG, EOG) [4] - [8] , or even a mix of these two techniques [9]. Chang et al, proposed at the year of 2018 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 [10] . Other works used algorithms that can detect drowsiness using a facial recognition or eyes regions detection like (Ouabida et al., 2020) & (Dhanalakshmi et al., 2016) or also using a thermal imaging tehniques (Kiashari et al., 2020) [11] - [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., 2018) proposed a technique that analyses the spectral domain of the EEG signals using MATLAB, applying the Fourier transform and an artificial neural network classification. Their work reached an accuracy of 88.8% [19]. (Bajaj et al., 2020) reached an accuracy of 91% using tunable Q-factor wavelet transform (TQWT) algorithm applied on the EEG signals, and the extreme machine learning classifier (ELM) [20]. The highest accuracy of 94.45% is reached in the work of (B et al., 2021) using the wavelet packet transform (WPT) method and fed to the extra-trees classifier[21]. 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 Decision Tree classifier that we will explain next.

3. PROPOSED APPROACH

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 in (Strijkstra et al., 2003) work [22] . Our proposed method is shown in the figure 1 .

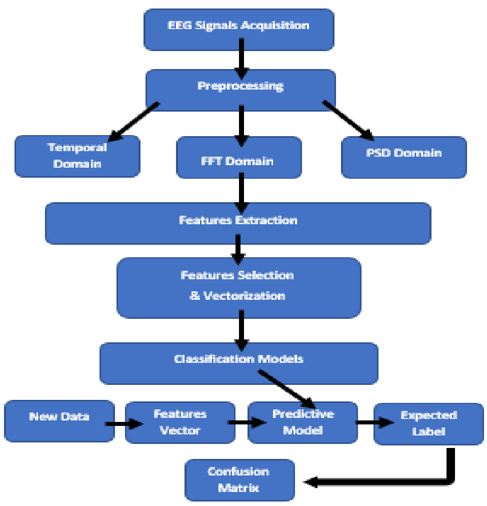

Figure 1. Flow chart of our proposed method

3.1. 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] .

3.2. Time Segmentation Phase :

We applied a segmentation of 3 seconds of EEG signals to ensure stationarity of spectral analysis (FFT and PSD analysis).

3.3. 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.

3.3.1. Temporal domain analysis:

Eight parameters are calculated in the time domain in a way to distinguish the awake from the drowsy state. After that, we calculate 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:

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

The variance:

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

The standard deviation:

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

The root-mean-square:

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

3.3.2. Fourier 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 :

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

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

3.3.3. Power Spectral Domain Analysis :

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.

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

3.4. Features Selection & Classification :

A total of eight machine learning 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 (with its four kernels), our previous Decision Tree classifier (DT), and finally the proposed optimized DT.

4. RESULTS AND DISCUSSION

After extracting the features, all the calculated parameters were scaled and processed using machine learning 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.
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:

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

$$Sensitivity(Recall) = \frac{TP}{TP + FN} \tag{9}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

$$F1 - score = 2 * \frac{precision * recall}{precision + recall} \tag{11}$$

Classifier	**F**irst method	**S**econd method	**T**hird method	**H**ybrid 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)	**4**9.7%	**4**9.9%	**4**9.4%	**4**9.5%
SVM(Plynomial kernel)	**5**4.6%	**8**5.5%	**9**3.2%	**8**3.6%
SVM(Sigmoid kernel)	**3**5.3%	**6**6.8%	**8**8.7%	**6**6.0%
SVM(RBF kernel)	**7**1.9%	**8**6.5%	**9**3.3%	**8**7.8%
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%

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

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 Decision Tree 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 (Table.1).

We used a personalized SearchGrid algorithm to select the best hyperparameters values of the DT classifier to achieve the best of accuracies (Figure 2).

```
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

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 the 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 machine learning model (Figure 3).

```
--- 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
```

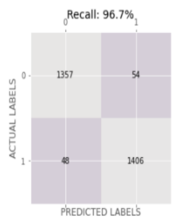

Figure 3. Output of our optimized model (Confusion matrix)

Comparing the results in the 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 Decision Tree classifier is the most efficient and effective (Accuracy of 96.4% and execution time within 53 milliseconds).
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.

5. CONCLUSION

The present work proposed an optimized hybrid method of detecting drivers' drowsiness based on time-frequency analysis of a single channel (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 machine learning models, Multi-layer Perceptron (MLP), Gaussian process (GP), K-Nearest-Neighbors (KNN), support vector machine (with its four

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

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

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

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

kernels), Decision Tree (DT) and finally our optimized Decision Tree. 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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