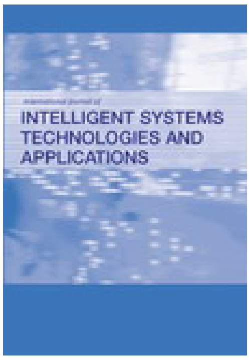

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Developing a method to detect driver drowsiness based on a single EEG channel and discriminated features

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Abstract: Driver drowsiness is one of the leading causes of road deaths and transportation industry dangers. Due to its direct evaluation of neurophysiological brain activity, electroencephalography (EEG) has been regarded as one of the most reliable physiological indicators for identifying driver drowsiness. This study proposes a straightforward, cost-effective method for detecting driver drowsiness using a single channel. The contribution of this research is the discovery of drowsiness using discriminated features [moments features (M1, M2, M3, M4), roughness features (R1, R2, R3, R4), zero crossing rate (ZCR), sample entropy (SE) and median absolute deviation (MAD)] from publicly available datasets. A novel model was introduced in this study, which involved the fusion of wavelet transform Daubechies order 4 (WTDB4) and residue decomposition (RD) techniques for feature extraction. Various classification algorithms, including the least-square support vector machine (LSSVM) and ensemble models were compared in terms of their performance metrics. The algorithm that exhibited superior accuracy with reduced computational time was chosen to classify the driver's status into two groups: awake and drowsy. Notably, the proposed model achieved an impressive accuracy of 97.95%.

Keywords: drowsy driving detection; electroencephalography; least square support vector machine; residue decomposition; wavelet transform.

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1 Introduction

Drowsiness refers to a state where an individual experiences a reduced level of awareness and diminished ability to make appropriate choices. The leading cause of the increasing number of traffic accidents globally can be attributed to drowsy driving. According to the AAA Foundation for Traffic Safety, drowsy driving crashes account for 0.32 million impacts yearly, three times more than the number of crashes reported by police departments (NHTSA) (Wright et al., 1992). Industry leaders in the automotive sector are persistently working to develop reliable subjective, in-vehicle, behavioural, and physiological methods of drowsiness detection. According to a questionnaire based on the Karolinska sleepiness scale (KSS), alertness and drowsiness levels can be determined using the questionnaires (Zhang et al., 2022). Participants in the Karolinska sleepiness scale (KSS) are instructed to assess their level of fatigue using a rating scale ranging from one to nine. A rating of one indicates a heightened state of alertness, while a rating of nine signifies a significant degree of drowsiness.

Drowsiness can be identified using physiological measures, which have been proven to be the most trustworthy and reliable method (Chowdhury et al., 2018). For detecting drowsiness, EEG signals outperform other physiological signals, even though they are low in intensity and frequency. The brain serves as the central hub for processing any stimulus. EEG signals provide a means to evaluate the interconnected states of alertness, cognition, and sleep, making them an optimal method for monitoring driver drowsiness (Balandong et al., 2018). Furthermore, the utilisation of EEG signals for measurement offers a solution that is non-invasive, free from radiation, and non-intrusive.

Many approaches have been suggested for the detection of drowsiness using EEG signals (Hussein et al., 2022). A genetic algorithm-based support vector machine is used to detect a drowsiness state by Wang et al. (2021). This study used both db10 wavelet packet transform and Haar wavelet packet transform were employed. Subsequently, the GA-SVM approach was utilised to identify the most precise rhythm for detecting drowsiness, resulting in an achieved accuracy rate of 80.94%. Nissimagoudar et al. (2021) introduced a deep neural network architecture that combines ResNets and encoder-decoder based sequence-to-sequence models with an attention-decoder. The primary objective of this model is to alleviate the computational complexity associated with feature extraction processes. It provided an overall-accuracy of 87.92%. Kulkarni et al. (2019) presented a model that utilised the db8 wavelet function to extract the frequency bands (gamma, alpha, theta, and delta) from EEG signals, and SVM was employed for classification. The dataset consisted of 1,200 samples, and a total of 13 features were considered, including mean, variance, standard deviation, kurtosis, skewness, and more. The classification results demonstrated a remarkable accuracy of 92.4% for drowsiness detection. Ghadami et al. (2022) introduced a 1D-CNN model designed to leverage the time-domain properties of EEG signals for improved prediction accuracy. To further enhance performance and robustness, the researchers incorporated averaging and stacking fusion techniques. The results of the study demonstrated an impressive accuracy of 90.73% when applied to cross-subject test data, showcasing the model's ability to effectively utilise both time-domain and frequency-domain features of EEG data.

While the previous studies achieved satisfactory outcomes, there has been a lack of investigation into the discriminant features derived from wavelet and residue decomposition. Previous literature has primarily employed linear and nonlinear features such as maximum (Max), minimum (Min), mean (Mn), standard deviation (Std), variance (Var) and skewness (Skew). With the intention of distinguishing between drowsiness and awake EEG readings, this study suggests using WTDB4 and RD for features extraction and LSSVM for classification. The contribution of this paper depends on an effective and inexpensive method for detecting driver drowsiness with a single EEG channel, using discriminated features (M1, M2, M3, M4, R1, R2, R3, R4, ZCR, SE and MAD for residue). Furthermore, a varied range of wavelet transformation strengths is evaluated.

The other sections of this study are organised as follows: Section 2 provides an overview of the feature extraction and LSSVM classification methods employed. Next, Section 3 presents the results obtained and delves into the performance of the proposed approach. Finally, Section 4 offers a summary of the suggested methodology.

2 Method

In this section, the primary datasets utilised in the study were presented, and the methodology steps were explained. Furthermore, this section thoroughly examines the technique employed for feature extraction and the classification method used.

2.1 Sleep-EDF dataset

For this research, EEG data was used, sourced from PhysioNet's Sleep-EDF datasets (expanded). The dataset encompasses 61 EEG recordings sourced from two separate studies. For this particular investigation, data from eight participants (aged 25–43) were utilised. The polysomnographic data consists of two EEG channels (Fpz-Cz and Pz-Oz), along with one EOG, one EMG, the body's temperature, and an event marker. Different data were collected from 1987–1994 from male and female Caucasian who volunteered their information. Each recording was preserved in EDF format, with the EEG signals being sampled at a frequency of 100 Hz. They rated 30 seconds of data (a total of 3,000 points) using the R&K standard (Mehmood and Lee, 2015). Six stages were labelled as awake, Stage1, Stage2, Stage3, Stage4, and Rapid eye movement. Table 1 displays the number of epochs used in this study from the Pz-Oz channel.

Table 1 the distribution of sleep stage in the EDF database

Stage	*Awake*	*Stage 1*	*Total no. of epochs*
No. of epochs	6,807	598	7,405

2.2 Methodology

Reducing EEG segment dimensionality is essential for reducing algorithm complexity and increasing performance. Therefore, WTDB4 was applied to every 30-second time interval at 100 Hz. First, the wavelet transform with five levels was used to extract ZCR, and SE. Then the residue was used to extract the M1, M2, M3, M4, R1, R2, R3, R4 and MAD for each sub-band. Then, the features were individually tested by k-mean clustering to select the effective features. Ultimately, the extracted features are fed into various classifiers including random subspace, decision tree, bagging ensemble, random force, basic ensemble, stacking ensemble, and LS-SVM classifier. These classifiers are employed to classify the data into the categories of awake and stage 1 sleep. The EEG signals classification is explained in Figure 1.

2.3 Features extraction

The numerical measurements of the EEG signal's sub-bands are known as features. The M1, M2, M3, M4, R1, R2, R3, R4, ZCR, SE and MAD features were extracted using WTDB4 and RD. Figure 2 shows the sub-bands of WTDB4 decomposition. Each of 30 seconds with a sampling rate of 100 was used in the EDF database. The length of a segment in the EDF database is 3,000. The signal is labelled with the help of the annotation file, the hypnogram, which is available with the dataset for each subject. Ingrid Daubechies is the mathematician who invented the Daubechies wavelet transform (Vonesch et al., 2007). This transform has four Wavelet and scaling function coefficients for the Daubechies D4 algorithm. The data input is scaled at each iteration of the wavelet transform. An $N/2$ smoothed value will be generated if an original dataset of N values is used in the wavelet transform step. The smoothed values are placed in the lower half of the N-element input vector in the ordered wavelet transform. Every time a wavelet transform is performed, the resulting data is subjected to the wavelet function. The wavelet function will calculate $N/2$ differences if the original dataset has N values (reflecting the change in the data). The wavelet values are stored in the upper half of the N-element input vector in the ordered wavelet transform. The inner product of the coefficients and the four data values are used to generate the scaling and wavelet functions. The following are the equations of the D4 scaling function (Strela et al., 1999):

$$a[i] = h_0 s[2i] + h_1 s[2i+1] + h_2 s[2i+2] + h_3 s[2i+3] \tag{1}$$

and Daubechies D4 wavelet function:

$$c[i] = g_0 s[2i] + g_1 s[2i+1] + g_2 s[2i+2] + g_3 s[2i+3] \tag{2}$$

Figure 1 The block diagram of the proposed method (see online version for colours)

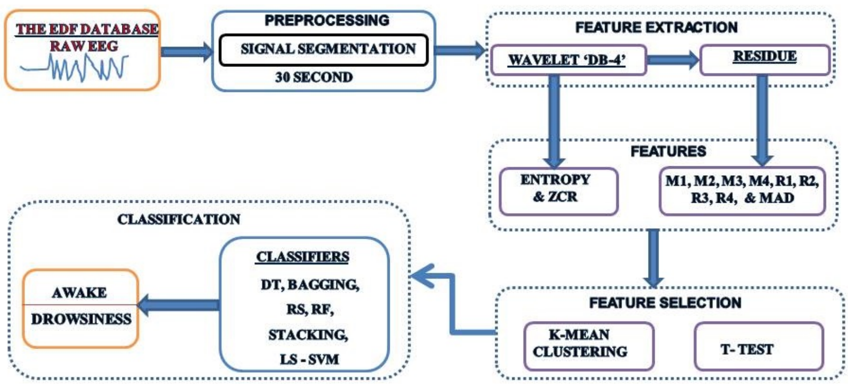
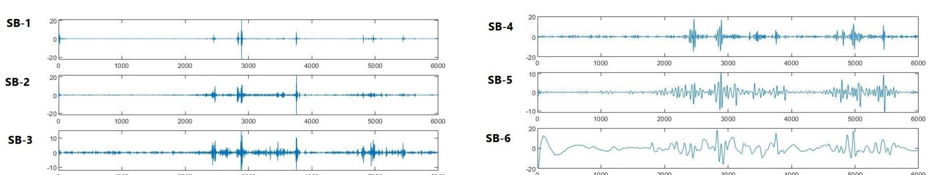


Figure 2 Sub-bands of WTDB4 decomposition (see online version for colours)



2.3.1 Sample entropy

This measure quantifies the complexity of a system by evaluating the negative logarithm of the probability that two sets of simultaneous data points, each of length $n + 1$, have a distance less than t between them, given the existence of two sets of simultaneous data points, each of length n, with a distance less than t between them (Zhao and Neng, 2021). Let us consider a dataset of length $N = \{y_1, y_2, y_3, \ldots, y_N\}$ with a constant time interval τ. The template vector of length n is defined as $y_n(i) = [y_i, y_{i+1}, \ldots, y_{i+n-1}]$. The distance function is defined as $d|y_n(i)y_n(j)|$. The number of vector pairs of length n and $n + 1$ has

$d|y_n(i)y_n(j)| < t$ are denoted by V_n and V_{n+1}, respectively. SE is defined as (Acharya et al., 2015):

$$SE = -\log\frac{V_{n+1}}{V_n} \tag{3}$$

2.3.2 Zero-crossing rate

The count of how many times an EEG signal crosses the relevance line, which is determined based on the mean, is provided (Satapathy et al., 2021). This characteristic proves effective in the characterisation of sleep spindles and aids in the analysis of sleep stage activities using EEG data (Chen et al., 2022).

$$ZCR = \frac{1}{2}\sum_{i=2}^{n}\left|sign(a_i) - sign(a_{i-1})\right| \tag{4}$$

2.4 Residue decomposition

The residue, as defined in Iravanian and Tung (2002), represents the difference between the input signal and the average signal value at each data point. Equation (5) allows for the calculation of the local signal average, which serves as an estimate of the stationary component of the signal. To calculate the residue (*Res*), the local signal average is subtracted from the corresponding points of *X*, as shown in equation (6). Consequently, the local signal average of *X*, computed as a signal of size *N*, is obtained.

$$S(i) = \frac{1}{2M+1}\sum_{j=1}^{2M+1} X(j), \qquad \text{for } i = 1, \dots, N;\ M = 9 \tag{5}$$

$$Res = abs\left|X(i) - S(i)\right| \tag{6}$$

2.5 Moments and roughness features

The first, second, third, and fourth moments have been accounted for residue signal with local mean. The moment features were computed using (7) while The roughness features were calculated using (8).

$$Mom_{Res}(n, j) = \left(\frac{1}{N-j}\sum_{i=j/2}^{N-1-j/2}\left|S(i) - \overline{S_j(i)}\right|^n\right)^{1/n} \tag{7}$$

$$Rough_{Res}(n, 2j) = \left(\frac{1}{N-2j}\sum_{i=j}^{N-1-j}\left|S(i) - \overline{S_{2j}(i)}\right|^n\right)^{1/n} \tag{8}$$

where

$$\overline{S_j(i)} = \frac{1}{j}\sum_{k=-j}^{j} S_{i-k} \tag{9}$$

2.6 K-mean clustering

Feature selection is a commonly employed strategy in classification applications (Bansal et al., 2017). The selection of features greatly influences the quality of the classification outcome (Bradley et al., 2000). Clustering is regarded as the most effective tool for tasks such as data mining, compression, and estimating probability density functions. Among various clustering algorithms, the K-means algorithm stands out. The K-means algorithm is widely used as the primary method for aggregation. By utilising the K-means algorithm, the dataset can be divided into two clusters. The accuracy of the classification was evaluated using the K-means cluster with replicates 10 and $k = 2$, which yielded the highest accuracy, as presented in Table 2.

Table 2 Parameters of K-means cluster

K-means cluster	*Parameters*
No. of clusters	2
Distances	City block
Replicates	10

2.7 Least-square support vector machine

Suykens et al. (1999) created the least-square support vector machine (LS-SVM), which developed the original support vector machine). The LS-SVM has two key parameters that must be carefully set to achieve the required classification results. The proposed method's performance can be improved or harmed by these two variables (Wang and Hu, 2005). This method for classifying the awake and drowsiness (S1) pair performed best when the values were set to their highest (3, 9.1). Figure 3 compares all classifier's performances. The outcomes of the classification demonstrate that the LS-SVM classifier achieves the best level of accuracy.

3 Experimental results and discussion

Many tests were conducted to assess the effectiveness of the suggested method. In the experiments, the database mentioned in Section 2 was utilised. To classify awake and S1 using WTDB4 and RD for extract features and the LSSVM classifier. In this experiment, five features were selected and fed into classifiers. Once features were extracted to improve the classification rate of the suggested model, redundant features were eliminated, and only the most influential ones were chosen for the classification of EEG signals. The extracted features were individually tested by k-means clustering and t-test, and all results were recorded. According k-means clustering, Table 3 shows the detection rate based on features. The roughness features scored the highest detection compared to other features. However, MAD for residue was recorded with the lowest detection rate. This paper also subjected the extracted features to a t-test evaluation. The outcomes of the feature analysis are presented in Table 4. It was observed that certain statistical and nonlinear features were rejected by the t-test, indicating their lack of significance at a significance level of $\alpha = 0.05$. However, based on the t-test results, features such as

Roughness (R1, R2, R3, R4), Moments (M1, M2, M3, M4), Ent, ZCR, and MAD for residue were deemed significant and accepted.

Table 3 Ranking of the top 5 features using k-mean arranged in descending order

Features	*Weights*
Roughness features (R1, R2, R3, R4)	89.55
Moments features (M1, M2, M3, M4)	87.10
Ent	84.35
ZCR	82.95
MAD for residue	73.43

Table 4 feature assessment using t-test

t-test	*Roughness*	*Moments*	*ZCR*	*Entropy*	*MAD*	*SD*	*Max*	*Min*
α value	0.0252	0.0272	0.0324	0.0233	0.0211	0.5996	0.6219	0.6190
t-test	*Variant*	*Skew*	*Mean*	*Energy*	*1st gradient*	*2nd gradient*	*3rd gradient*	
α value	0.6442	0.5221	0.0743	0.0621	0.6291	0.7001	0.7212	

The sub-bands of EEG signals are used to obtain discriminated features (M1, M2, M3, M4, R1, R2, R3, R4, ZCR, SE, and MAD for residue) that can be used in signal analysis. The classifiers in this study utilise a 10-fold cross-validation technique, where a feature matrix is provided as input. To facilitate the classification process, the data is divided into ten subsets, with nine subsets allocated for training purposes and the remaining subset utilised for testing in an iterative fashion. Subsequently, the sub-bands are classified using the LS-SVM classifier. The evaluation of the suggested model's performance is presented in Table 5, encompassing four performance metrics: accuracy, sensitivity, specificity, and F1-score. A classification system's accuracy is measured by the number of instances in which it correctly classifies objects. We obtain 98.5% in sub-band 1, the highest possible classification ACC, and the lowest is 90.8% in sub-band 6. The proportion of correctly identified positive and negative instances is measured by sensitivity (SEN) and specificity (SPE). SB1 has the greatest SEN at 97.39%, while SB5 has the lowest SEN at 96.39%. Using the F1-score, the harmonic mean of precision and recall, the highest and lowest values for SB1 with a score of 96.6, respectively. Table 6 displays the confusion matrix for an awake and drowsy class. The awake state has 97.3% correct prediction and 2.7% misclassification, according to Table 6.

Table 5 Performance for various sub-bands using LS-SVM

Sub band	*Accuracy*	*Sensitivity*	*F1-score*	*Pre*
SB1	98.51	97.39	96.62	96.22
SB2	95	96.23	93	94.67
SB3	92.32	93.24	93.71	95
SB4	92.61	95.74	95.45	94.32
SB5	94.8	93.31	96	93.52
SB6	90.83	92	94.33	94.31

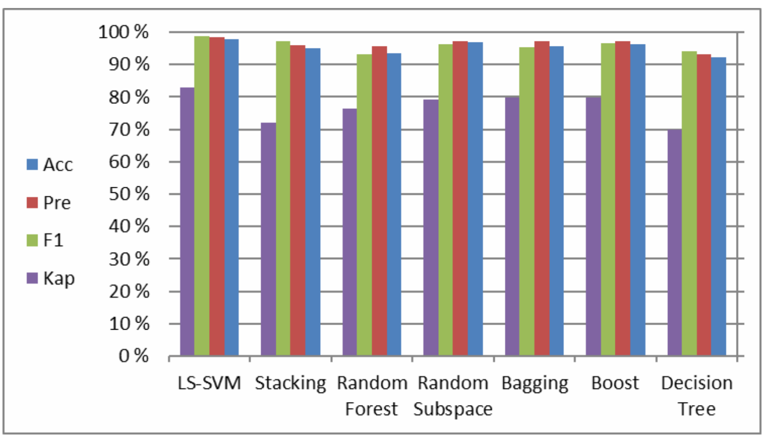
Table 6 Confusion matrix of awake and drowsiness

Classes	*Awake*	*Drowsiness*
Awake	97.3	2.7
Drowsiness	1.5	98.5

Table 7 Performance comparison with previous studies using the same dataset

Authors	*Year*	*Methods*	*Features type*	*Acc*
Ghadami et al.	2022	1D-CNN	PSD	90.73%
Gangadharan and Vinod	2022	SVM	Sample entropy, envelope mean, Hjorth parameters, SD, spectral entropy	78.3%
Wang et al.	2021	GA-SVM	PSD	80%
Nissimagoudar et al.	2021		Deep neural network	87.92%
Phanikrishna and Chinara	2020	SVM	Hjorth parameters, PSD	87%
Kulkarni et al.	2019	SVM	Hjorth parameters, PSD, mean, ZCR, SD and entropy	92.4%
Proposed method		LS-SVM	M1, M2, M3, M4, R1, R2, R3, R4, ZCR, SE and MAD for residue	97.95%

Figure 3 Performance comparison with different classifiers (see online version for colours)



In contrast, drowsiness is correctly identified in 98.5% of cases, whereas just 1.5% of cases are misclassified. Table 7 compares the existing methods' accuracy with the proposed method. The comparison included classification techniques, features type, and accuracy. Ghadami et al. (2022) used power spectral density (PSD) methods to extract features with CNN achieved an accuracy of 90%. Wang et al. (2021), Gangadharan and Vinod (2022), Nissimagoudar et al. (2021), Phanikrishna and Chinara (2020) and Kulkarni et al. (2019) used the multimodal analysis to extract features, with SVM claim classification accuracy of 87.3%, 80%, 87.92%, 87% and 92.4%, respectively. Fixed tuning settings are used in the WTDB4 approach to claim 97.95% accuracy. Table 7 shows that the suggested WTDB4 and RD method for detecting drowsiness has the highest accuracy of classification for all the preceding state-of-the-art. When combined

WTDB4 and residue with LS-SVM classifiers, the presented system achieved 97.95%. It is more accurate than any other method for detecting drowsiness. Comparing the proposed work to existing methods also demonstrates its advantages. Based on the findings depicted in Figure 3, LS-SVM outperforms multiple classifiers in terms of performance. The LS-SVM achieves an accuracy of 97.95%, outperforming all other classifiers. In contrast, the accuracy of DT was the lowest at 92.12%.

4 Conclusions

The inherent non-stationarity of EEG signals poses challenges in extracting meaningful information from these signals. Therefore, the decomposition of the signal into sub-bands is necessary to obtain the unseen information. In the proposed method, we evaluated the features and selected the more discriminated features to be interred into the proposed classifiers. In addition, the classifiers were evaluated, and the robust and more effective classifier was chosen with more accuracy. In comparison to previous studies, the proposed method demonstrates superior classification performance for distinguishing between awake and drowsy states. In this framework, WTDB4 and RD are utilised to decompose EEG signals into sub-bands. From these sub-bands, discriminative features such as M1, M2, M3, M4, R1, R2, R3, R4, ZCR, SE, and MAD for residue are extracted. To achieve accurate classification, the LS-SVM classifier is employed to classify the sub-bands into two distinct classes. Moreover, the Ens, Bag, RS, RF, DT, and St classifiers were also implemented to enable comparisons, and their results were contrasted against those obtained with the LSSVM.

Future research endeavours may focus on validating the findings of this paper by applying them to various datasets. Additionally, the exploration and development of hybrid methods could be pursued to enhance the classification accuracy of machine learning algorithms. Although this study focused on an offline detection method, it is crucial to apply this research to a live online database in order to assess its real-world impact. Accomplishing this would necessitate additional effort, thereby requiring the implementation of all the proposed methods for online detection. Such an achievement would be highly significant in the field of biomedical signal processing, particularly for work conducted under challenging conditions.

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