

Article

A Novel Hybrid Machine Learning Classification for the Detection of Bruxism Patients Using Physiological Signals

Md Belal Bin Heyat ¹, Faijan Akhtar ², Asif Khan ², Alam Noor ^{3,4}, Bilel Benjdira ^{3,5,*}, Yumna Qamar ⁶, Syed Jafar Abbas ⁷ and Dakun Lai ^{1,*}

¹ School of Electronic Science and Engineering, University of Electronic Science and Technology of China, Chengdu 610054, China; belalheyat@gmail.com

² School of Computer Science and Engineering, University of Electronic Science and Technology of China, Chengdu 610054, China; faijanakhtar98@gmail.com (F.A.); asifkhan@uestc.edu.cn (A.K.)

³ Robotics and Internet of Thing Lab, Prince Sultan University, Riyadh 11586, Saudi Arabia; eng.alamnoor@gmail.com

⁴ Department of Information and Communication Engineering, Harbin Institute of Technology, Harbin 150001, China

⁵ SEICLab, LR18ES44, Enicarthege, University of Carthage, Tunis 2035, Tunisia

⁶ Department of Orthodontics and Dentofacial Orthopedics, ZA Dental College and Hospital, Aligarh Muslim University, Aligarh 202002, India; yumi.yumna@gmail.com

⁷ School of Automation Engineering, University of Electronic Science and Technology of China, Chengdu 611731, China; jafar1987abbas@rediffmail.com

* Correspondence: bbenjdira@psu.edu.sa (B.B.); dklai@uestc.edu.cn (D.L.)

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Featured Application: 1. The hybrid machine learning (HML) classifier can easily classify the subjects (healthy and bruxism), sleep stages (w and REM), and both with high accuracy. 2. The proposed system automatically detects the bruxism sleep disorder and sleep stages. 3. Single C4-A1 channel of the EEG signal found to be more accurate than ECG and EMG channels.

Abstract: Bruxism is a sleep disorder in which the patient clinches and gnashes their teeth. Bruxism detection using traditional methods is time-consuming, cumbersome, and expensive. Therefore, an automatic tool to detect this disorder will alleviate the doctor workload and give valuable help to patients. In this paper, we targeted this goal and designed an automatic method to detect bruxism from the physiological signals using a novel hybrid classifier. We began with data collection. Then, we performed the analysis of the physiological signals and the estimation of the power spectral density. After that, we designed the novel hybrid classifier to enable the detection of bruxism based on these data. The classification of the subjects into “healthy” or “bruxism” from the electroencephalogram channel (C4-A1) obtained a maximum specificity of 92% and an accuracy of 94%. Besides, the classification of the sleep stages such as the wake (w) stage and rapid eye movement (REM) stage from the electrocardiogram channel (ECG1-ECG2) obtained a maximum specificity of 86% and an accuracy of 95%. The combined bruxism classification and the sleep stages classification from the electroencephalogram channel (C4-P4) obtained a maximum specificity of 90% and an accuracy of 97%. The results show that more accurate bruxism detection is achieved by exploiting the electroencephalogram signal (C4-P4). The present work can be applied for home monitoring systems for bruxism detection.

Keywords: machine learning; hybrid classifier; sleep disorder; dental disorder; EEG; ECG; EMG

1. Introduction

Sleep is a vital need for human beings. It is characterized by altered consciousness, inhibited sensory movement, and reduced muscle movement [1]. It is found in all zoological species such as amphibians, animals, humans, insects, mammals, and reptiles. Some species sleep with open eyes, while most species sleep with closed eyes. Sleep stages are divided into four parts such as wake (w), light (non-rapid eye movement (NREM) 1 and 2), deep (NREM 3), and rapid eye movement (REM) [2–5].

Lack of sleep affects human life and causes many health problems: memory issues, mood changes, concentration issues, risk of diabetes, increased risk of heart diseases, weight gain, high blood pressure, and increased driver crash risk [6–9]. Lack of sleep also impacts negatively on a person's energy towards work, health, and emotional balance [10]. Good sleep is an indicator of a healthy person. It is a common phenomenon that minor sleep loss can decrease efficiency, energy levels, ability to handle stress, and mood [11]. Ignorance of sleep problems and sleep disorders is a serious issue because they may cause big damages like accidents, frustration, poor job performance, and stress [12]. The survey report of China sleep medicine and white paper on the internet (<http://en.people.cn/n3/2018/0322/c90000-9440441.html>, http://www.china.org.cn/china/2018-03/21/content_50731983.htm) in 2018 showed that 50 to 60 million Chinese people suffered from a sleep disorder [13]. Another survey shows that 3.5 million people in the UK and more than 70 million people from the US suffer from sleep disorders [14]. Another sleep survey (<https://timesofindia.indiatimes.com/city/lucknow/World-Sleep-Day-93-Indians-are-sleep-deprived/articleshow/46547288.cms>) shows that 93% of Indians suffer from poor sleep [15]. Sleep disorders are mainly classified as problems in staying awake, problems in falling asleep, and abnormal activity in sleep [16].

Bruxism is a type of sleep disorder in which people clench, chew, and grind their teeth. It is defined as a parafunctional habit consisting of involuntary rhythmic or spasmodic nonfunctional gnashing, grinding, or clenching of teeth [17]. This clenching leads to occlusal trauma, causing flattened, fractured, or chipped teeth (Figure 1). It is classified into two types such as awake bruxism and sleep bruxism. If the person grinds their teeth during awake time, it is called awake bruxism; otherwise, if the person grinds their teeth in their sleep, it is called sleep bruxism [18]. The symptoms of bruxism are grinding or clenching of teeth, flattened, fractured or tipped teeth, pain and sensitivity in teeth, abnormal jaw function, facial pain, earache, and sleep disturbances [19].

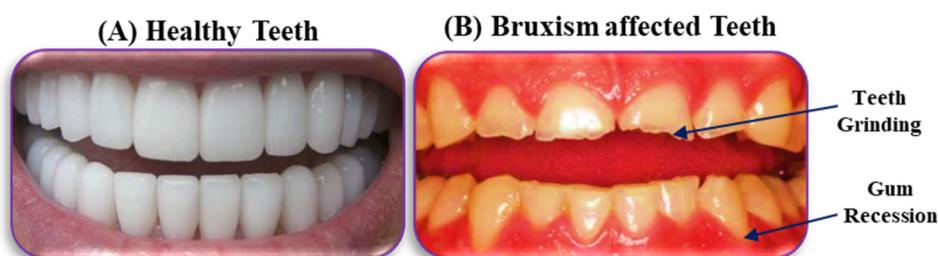


Figure 1. Comparison between (A) healthy and (B) bruxism teeth of the human. The grinding of the tooth is shown in the case of bruxism.

The diagnosis of bruxism is through various modalities, including history taking, clinical examination of teeth, intraoral appliances to observe facets, and bite force recording. A definitive diagnosis of bruxism is an expensive process that requires conducting a sleep study in an organized environment, usually at sleep clinics, to measure multiple factors and physiological indications during sleep. Some systems such as electrocardiogram (ECG) (cardiac signal) [20,21], electrooculogram (EOG) (eye signal), electroencephalogram (EEG) (brain signal) [22], and electromyogram (EMG) (muscles signal) [23] are used in automatic sleep stage detection [24]. Guillot et al. [25] evaluated the clinical practice on French dental clinicians. The authors used one thousand three hundred and eighty-eight practitioners based on five methods, such as oral rehabilitation, treatment of the patient with occlusal splints, sociodemographic characteristics, diagnosis, and management of sleep

bruxism. The work discovered 16.8% wide inequality and inadequate diagnosis, and 21.9% of applicants planned cognitive-behavioral treatment. Saczuk et al. [26] evaluated the screening and detection method of bruxism. The researchers used the total number of sixty adults, including twenty-five healthy and thirty-five with bruxism. They evaluated the masseter muscle activity of the body. Maeda et al. [27] studied the validity of the detection of bruxism using EMG and a cut-off rate with optimum sympathy and specificity. A total number of 16 subjects were used in this work. The authors suggested that one-channel EMG and a cut-off value are appropriate for the detection of bruxism disorder. Miettinen et al. [28] suggested that the ambulatory electrode is the highest-precision device for the diagnosis of bruxism sleep disorder and sleep stage scoring. Ruhland et al. [29] represented the diagnosis of sleep bruxism using analysis and acquisition of the human masseter muscle by an EMG signal. Martinez et al. [30] investigated that remote communication and piezoelectric sensors are used in the diagnosis of bruxism sleep disorder. Kostka and Tkacz [31] investigated that multi-source data with sympathovagal balance valuation are used for the early diagnosis of bruxism disorder stages. Jirakittayakom and Wongsawat [32] designed an EMG instrument for the detection of sleep bruxism patients on the masseter muscle.

We propose a new detection system for bruxism using the extraction of power spectral density on physiological sleep recordings such as ECG (ECG1-ECG2), EMG (EMG1-EMG2), and EEG (C4-P4 and C4-A1). Initially, the physiological signal is extracted from the sleep database. The 10/20 standard sleep recording system recorded these data. It is used in the research work of sleep disorders such as circadian rhythm sleep disorders, insomnia [33–37], bruxism [38–40], sleep apnea, restless leg syndrome, narcolepsy [41], and nocturnal frontal lobe epilepsy [42]. We preprocessed the signals using a low-pass finite impulse response (FIR) filter to remove the noise of the signal. After filtering the signal, we estimated the power spectral density of the signals. Finally, we classified the sleep stages (w and REM) [43,44], subjects (bruxism and healthy), and combined subjects (bruxism and healthy) and sleep stages (w and REM) from the novel hybrid machine learning (HML) classifier. The proposed hybrid classifier is the combination of ten machine learning classifiers, namely K-nearest neighbor (KNN), support vector machine (SVM), random forest (RF), naive Bayes (NB), linear regression (LR), classification and regression tree (CART), linear discriminant analysis (LDA), AdaBoost (AB), gradient boosting (GB), and extra trees (ET). There are two common issues in the previous research of bruxism. Firstly, there is a large number of features used in the studies, which results in a high computational load. Secondly, most of these methods did not represent a classification with sleep stages. We address these challenges in this study. Further, we focus on some goals, including estimation of the power spectral density, applying the novel HML classifier for the classification methods on the same feature, and comparison between the HML classifier and different previously used classifiers. The proposed study is organized as follows: the used database is presented in Section 2. The feature extraction and novel classification methods are presented in Section 3. The evaluation of the results and related discussion are presented in Section 4. Finally, the conclusions of this paper are presented in Section 5.

2. Materials

Bruxism and healthy individuals were collected from the *physionet* website, which offers free access to the collection of recorded healthy and patient data [45]. The signals of this database included EEG, ECG, EOG, EMG, and respiration [46]. The sleep monitoring system recorded bilateral EOG, six EEG channels, two channels of right- and left-leg EMG, respectively, submental EMG, nasal respiration thermistor, and ECG channel. The sampling rates of the data were 200 Hz.

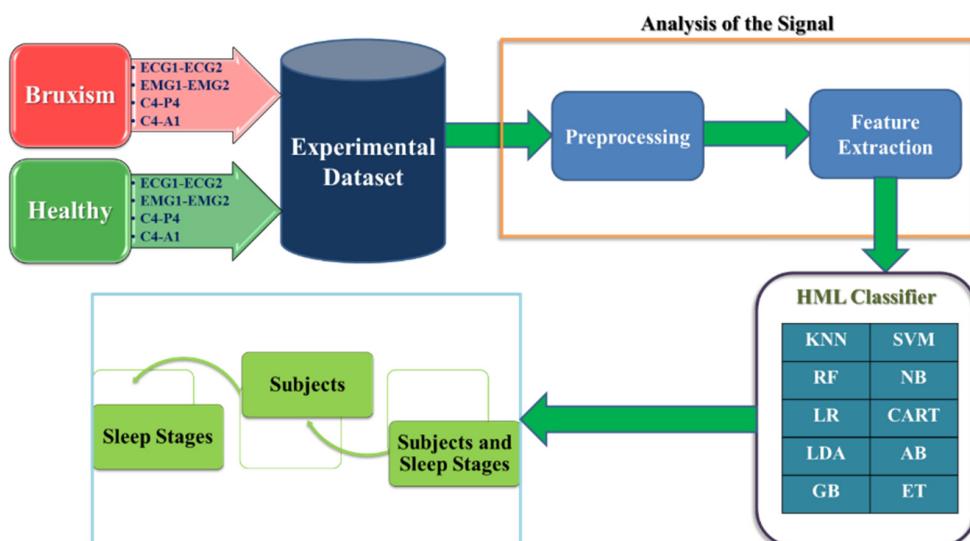
In this proposed work, we used EEG, ECG, and EMG channels such as C4-P4, C4-A1, ECG1-ECG2, and EMG1-EMG2 for the detection of bruxism. Further, we used 936 segments including 244 of ECG1-ECG2, 244 of EMG1-EMG2, 224 of C4-P4, and 224 of C4-A1 from 8.5 ± 0.577 (mean \pm SD) subjects in the proposed work shown in Table 1. The duration of one segment of the signal is 60 s. All channels have two sleep stages, such as w and REM. The total duration of the 56,160 s segments is used in the proposed work.

Table 1. Dataset of the present work.

Name of the Physiological Signal	Channel of the Physiological Signal	Number of the Subjects (n)			Number of the Segment (n)			Duration of the Signal (s)
		Male	Female	Total	Bruxism	Healthy	Total	
ECG	ECG1-ECG2	6	3	9	149	95	244	14,640
EMG	EMG1-EMG2	6	3	9	149	95	244	14,640
EEG	C4-P4	4	4	8	140	84	224	13,440
EEG	C4-A1	4	4	8	140	84	224	13,440
Mean		5	3.5	8.5	144.5	89.5	234	14,040
$\pm SD$		1.154	0.577	0.577	5.196	6.350	11.547	692.820

3. Methods

In this section, we will describe the techniques used for the detection of bruxism. For the sleep disorder, we collected, first, the dataset from the sleep database. After that, we extracted the physiological signals such as ECG (ECG1-ECG2), EMG (EMG1-EMG2), and EEG (C4-P4 and C4-A1). We preprocessed the channels and made the feature extraction of these channels. Then, the feature values were normalized before passing them to the novel HML classifier. The procedure is illustrated in Figure 2. The classification of subjects into “bruxism” and “healthy”, the classification of sleep stages into “w” and “REM”, and the combined classification (both subjects and sleep stages) were performed by the novel HML classifier.

**Figure 2.** Organizational structure of the proposed work.

3.1. Power Spectral Density

We estimated the power spectral density using the Welch method. Peter D Welch discovered this method in 1967 [47]. It converts time series into (overlapping) segment data, calculating a modified periodogram of every segment, and takes the average of the power spectral density [48]. The average altered periodogram tends to reduce the variance [49]. Further, it estimates the relation to a single periodogram of aggregate data. Power spectral density offers signal power with respect to the frequency spectrum. We require specifying the number of frequency slots to allocate the power spectral that is called the number of fast Fourier transform [50,51]. The Welch techniques are described in Equations (1)–(3) below:

$$U = \frac{1}{L} \sum_{n=0}^{L-1} \{w_{hm}(n)\}^2 \quad (1)$$

$$P_w(f) = \frac{1}{LU} \sum_{n=0}^{L-1} \{w_{hm}(n)x(n+iD)e^{-j2\pi f n}\}^2 \quad (2)$$

$$P_w(f) = \gamma \sum_{n=0}^{L-1} \left(\{X_a^n\}^2 + \{X_b^n\}^2 \right) \quad (3)$$

where U is equal to compensate for the loss of signal, L and D are the data of the segment, $w_{hm}(n)$ is the hamming window, γ is a constant, X_a^n and X_b^n are the real and imaginary part of the n th segment, and $P_w(f)$ is the Welch method.

3.2. Hybrid Machine Learning (HML) Classifier

The selection of a suitable classifier for efficient detection of bruxism is our goal in this study. However, the performance of a machine learning classifier varies from one problem to another. Hence, we opted to combine multiple machine learning classifiers to form a novel HML classifier. We combined ten classifiers including KNN, SVM, RF, NB, LR, CART, LDA, AB, GB, and ET. For implementation of the HML classifier, we used a scientific open source software, Anaconda [52,53]. We combined the machine learning output through majority voting in which we took the outputs of ten classifiers and checked the majority outputs. For example, if nine classifiers' output is bruxism patients but one classifier's output is healthy, then bruxism is the majority. Hence, our final output will be bruxism. The HML classifier improved the results and reduced the error of the system. In the literature, many classifiers based on hybridization of multiple machine learning classifiers were proposed for other problems. For example, Chen et al. [54] designed a hybrid AB classifier for the recognition of the cognitive radio network. Rawat et al. [55] designed a hybrid machine learning model using artificial neural network (ANN) and NB for the prediction of educational performance in the data mining field. Miskovic [56] suggested a hybrid model for the classification of decision support. Chen et al. [57] used the hybrid model for categorizing residential requests in natural language to provide timely replies back to citizens under the vision of digital administration services in smart cities. In these approaches, the designed HML models outperformed in all classifications.

3.3. Evaluation of the Proposed System

In this proposed work, we applied a novel 20-fold cross-validation model of the HML classifier to discriminate the bruxism and healthy subjects. It is evaluated with 234 ± 11.547 recording of the EMG1-EMG2, ECG1-ECG2, C4-P4, and C4-A1 channels, which includes 144.5 ± 5.196 bruxism and 89.5 ± 6.350 healthy recordings, with a time duration of 14.040 ± 692.820 s. The evaluations of the classification are applied in the EMG1-EMG2, ECG1-ECG2, C4-P4, and C4-A1 channels of the EMG, ECG, and EEG signals. Previously, we used these channels separately. However, in the proposed study, we used these four channels to find the best possible outcome of bruxism detection. It covered all important signals such as EMG, ECG, and EEG. We evaluated the final performance of the model by using different well-known parameters that are given in Equations (4)–(7).

$$Sensitivity = \left(\frac{TP}{(TP + FN)} \right) \quad (4)$$

$$Specificity = \left(\frac{TN}{(TN + FP)} \right) \quad (5)$$

$$Accuracy = \left(\frac{(TP + TN)}{(TP + TN + FP + FN)} \right) \quad (6)$$

$$MCC = \left(\frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \right) \quad (7)$$

where TP is the true positives, FP is the false positives, TN is the true negatives, and FN is the false negatives.

4. Results and Discussion

4.1. Analysis of the Physiological Signals

The physiological sleep channels, including ECG1-ECG2, EMG1-EMG2, C4-P4, and C4-A1 of the bruxism and healthy subjects, are shown in Figures 3 and 4 [19,40,48]. The 10/20 standard sleep recording system records these channels. Firstly, we extracted each channel and filtered each channel with a 200th order low-pass finite impulse response filter with a cut-off frequency of 25 Hz as noise removal. After filtration, we extracted the power spectral density of each physiological channel shown in Figures 5 and 6. After normalizing the value of the power spectral density, we classified the signals in terms of subjects, sleep stages, and combined using the novel HML classifier.

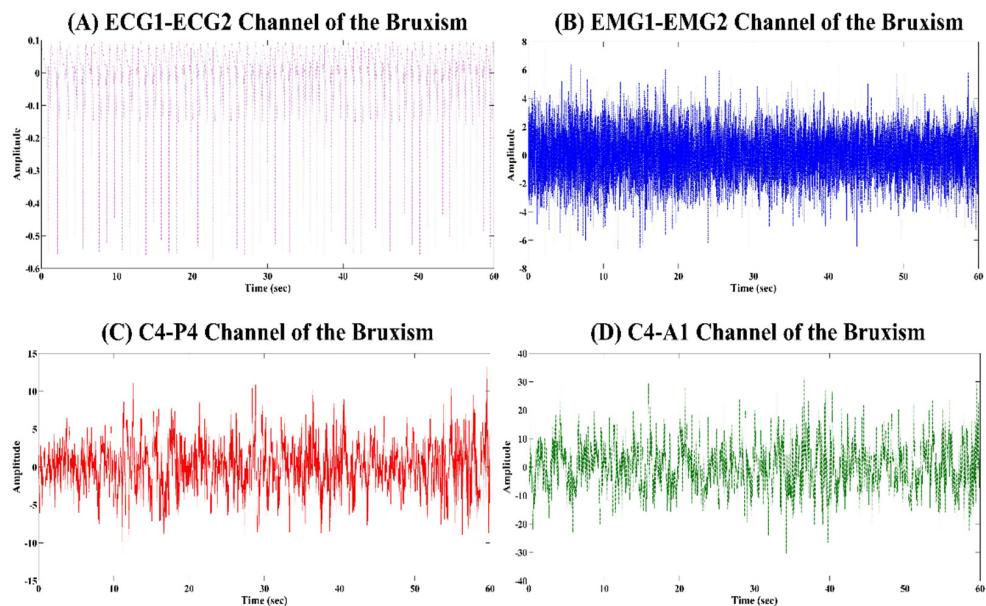


Figure 3. Signal representation of the sixty-second sleep physiological channels such as (A) ECG1-ECG2, (B) EMG1-EMG2, (C) C4-P4, and (D) C4-A1 of the bruxism subjects. A 10/20 standard sleep recording system recorded them.

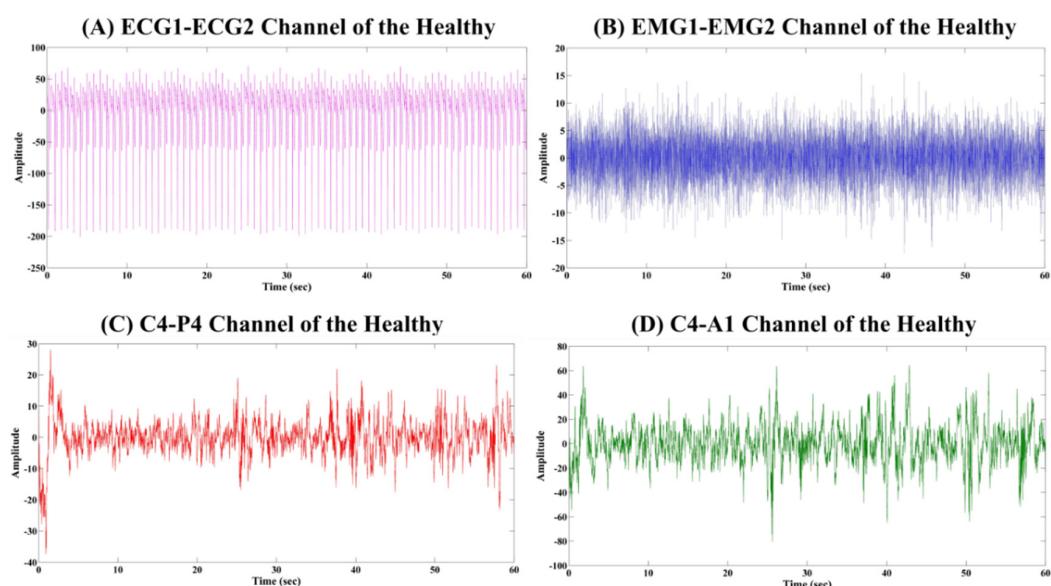


Figure 4. Signal representation of the sixty-second sleeps physiological channels such as (A) ECG1-ECG2, (B) EMG1-EMG2, (C) C4-P4, and (D) C4-A1 of the healthy subjects. A 10/20 standard sleep recording system recorded them.

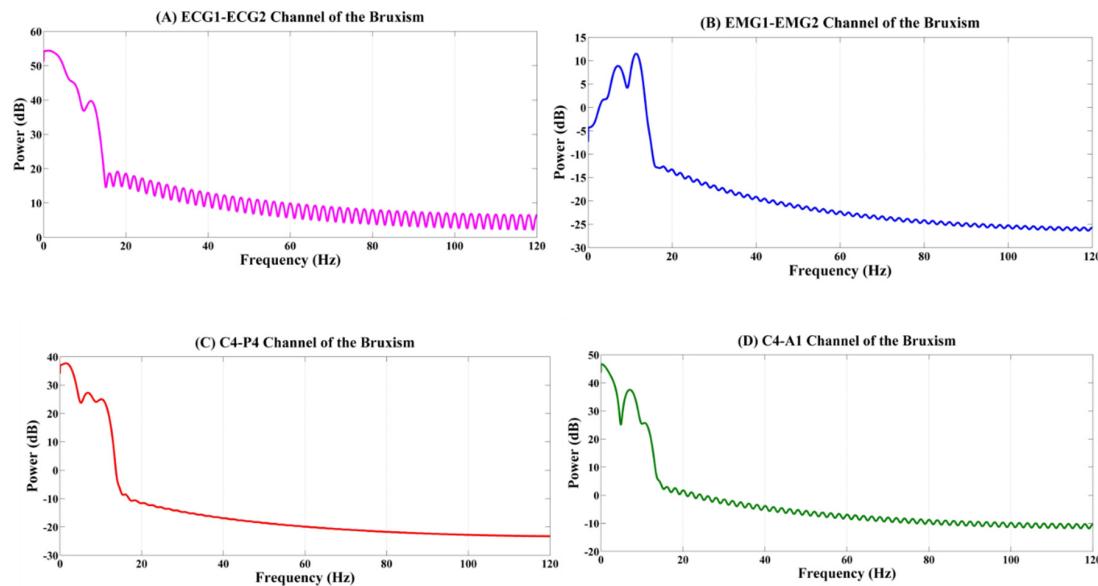


Figure 5. Power spectral analysis of the channels such as (A) the ECG1-ECG2 channel, (B) EMG1-EMG2 channel, (C) C4-P4 channel, and (D) C4-A1 channel of the bruxism subjects.

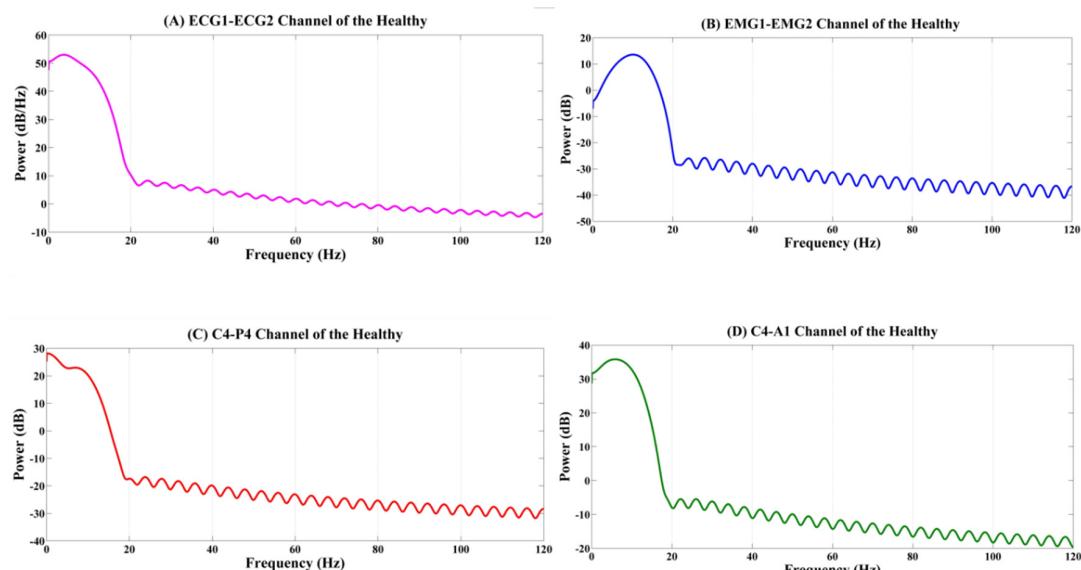


Figure 6. Power spectral analysis of the channels such as (A) the ECG1-ECG2 channel, (B) EMG1-EMG2 channel, (C) C4-P4 channel, and (D) C4-A1 channel of the healthy subjects.

4.2. Classification Results Using Proposed Novel HML Classifier

The performance for the classification of the subjects is shown in Table 2. Previously, we designed the diagnostic of bruxism sleep syndrome and sleep stages using a decision tree classifier with 81.25% accuracy [19]. Lai et al. [40] showed that the ECG channel and EMG channel are used for the detection of bruxism syndrome using power spectral density (PSD) techniques. They used the 488-min data for the two channels and classification of the subjects and stages using the machine learning method. Our proposed system, the C4-A1 channel, has the best performance in the subjects (bruxism and healthy) classification based on sensitivity, specificity, and accuracy, which are 95%, 92%, and 94%, respectively (Figure 7).

Table 2. Performance of the subjects (bruxism and healthy) classification using the novel 20-fold cross-validation model of the HML classifier.

Name of the Channel	PT	NT	TP	TN	FP	FN	F1	MCC	Sen	Spe	Acc
EMG1-EMG2	64	17	46	17	18	0	0.83	0.59	1	0.48	0.77
ECG1-ECG2	78	3	46	3	32	0	0.74	0.22	1	0.08	0.60
C4-P4	48	26	45	24	3	2	0.94	0.85	0.95	0.88	0.93
C4-A1	47	27	45	25	2	2	0.95	0.88	0.95	0.92	0.94
Mean	59.2	18.2	45.5	17.2	13.7	1	0.86	0.63	0.97	0.59	0.81
±SD	14.7	11.1	0.57	10.1	14.1	1.15	0.09	0.30	0.02	0.39	0.16

PT: positive test; NT: negative test; TP: true positive; TN: true negative; FP: false positive; FN: false negative; MCC: Matthews correlation coefficient; Sen: sensitivity; Spe: specificity; Acc: accuracy. Bold is the best model.

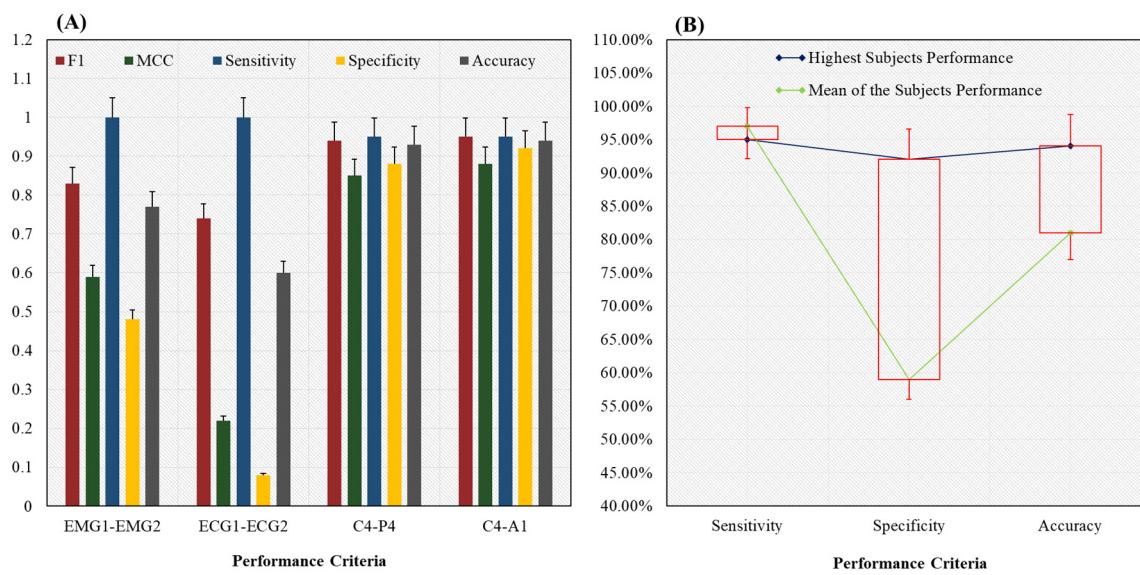


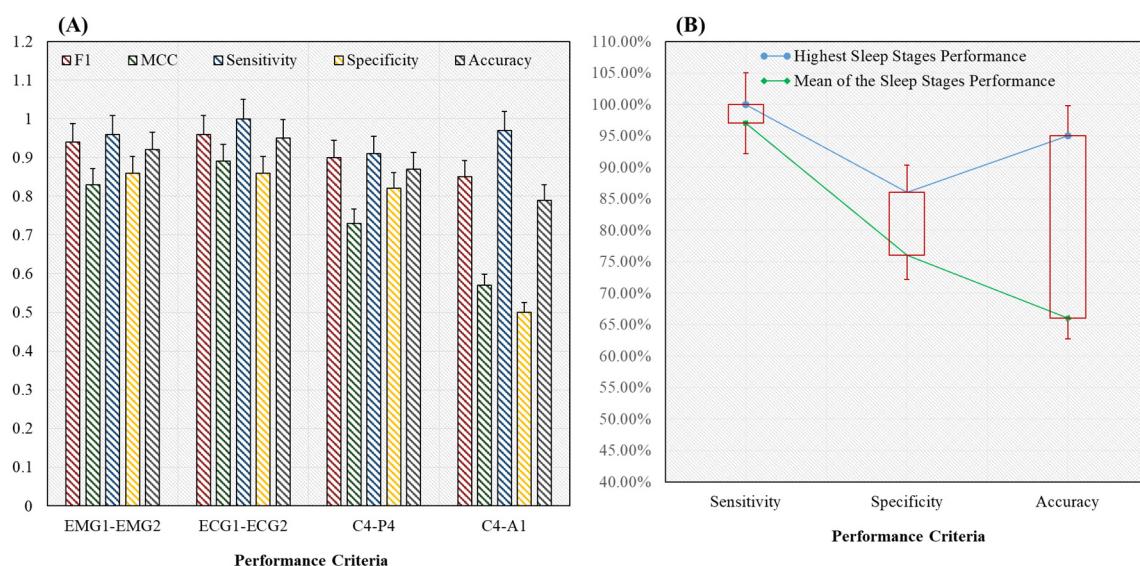
Figure 7. Performance analysis of the subjects (bruxism and healthy) classification using the novel 20-fold HML classifier. (A) Comparison between all channels such as EMG1-EMG2, ECG1, ECG2, C4-P4, and C4-A1 channels of the subjects classification. In addition, (B) highest and mean performance of the subjects classification. The C4-A1 channel of the EEG signal has the highest accuracy (94%) in the subjects classification.

The performance of the sleep stages classification is shown in Table 3. Previously, the unsupervised learning architecture and hidden Markov model were used for the detection of sleep stages [58]. Boe et al. [59] used a multimodal sensor system evaluating hand acceleration, ECG, and ActiWatch for diagnosing sleep stages such as w, REM, and NREM. Bajaj et al. [60] designed an automatic system for diagnosing sleep stages using time–frequency images of the EEG signals. Matsuura et al. [61] studied that heart rate measurement is helpful and easy to use in sleep stage monitoring. They successfully calculated four stages and overall five stages with 66% accuracy of the system. Our proposed system, the ECG1-ECG2 channel, has the best performance in the sleep stages (w and REM) classification based on sensitivity, specificity, and accuracy, which are 100, 86, and 95%, respectively (Figure 8).

Table 3. Performance of the sleep stages (w and REM) classification using the novel 20-fold cross-validation model of the HML classifier.

Name of the Channel	PT	NT	TP	TN	FP	FN	F1	MCC	Sen	Spe	Acc
EMG1-EMG2	54	27	50	25	4	2	0.94	0.83	0.96	0.86	0.92
ECG1-ECG2	56	25	52	25	4	0	0.96	0.89	1	0.86	0.95
C4-P4	47	27	42	23	5	4	0.9	0.73	0.91	0.82	0.87
C4-A1	59	15	45	14	14	1	0.85	0.57	0.97	0.5	0.79
Mean	54	23.5	47.25	21.75	6.75	1.75	0.91	0.75	0.97	0.76	0.88
±SD	5.09	5.74	4.57	5.25	4.85	1.70	0.04	0.13	0.03	0.17	0.06

Bold is the best model.

**Figure 8.** Performance analysis of the sleep stages (w and REM) classification using the novel 20-fold HML classifier. (A) Comparison between all channels such as EMG1-EMG2, ECG1, ECG2, C4-P4, and C4-A1 channels of the sleep stages classification. In addition, (B) highest and mean performance of the sleep stages classification. The ECG1-ECG2 channel of the ECG signal has the highest accuracy (95%) in the sleep stages classification.

The performances for the combination of subjects and sleep stages classification are shown in Table 4. Our proposed system, the C4-P4 channel, has the best performance in the combined (subjects and sleep stages) classification based on sensitivity, specificity, and accuracy, which are 98, 90, and 97%, respectively (Figure 9).

Table 4. Performance for the combination of subjects (bruxism and healthy) and sleep stages (w and REM) classification using the novel 20-fold cross-validation model of the HML classifier.

Name of the Channel	PT	NT	TP	TN	FP	FN	F1	MCC	Sen	Spe	Acc
EMG1-EMG2	63	18	63	17	0	1	0.99	0.96	0.98	1.00	0.98
ECG1-ECG2	65	16	63	15	2	1	0.97	0.88	0.98	0.88	0.96
C4-P4	63	11	62	10	1	1	0.98	0.89	0.98	0.90	0.97
C4-A1	65	9	62	8	3	1	0.96	0.77	0.98	0.72	0.94
Mean	64	13.5	62.5	12.5	1.5	1	0.97	0.87	0.98	0.65	0.96
±SD	1.15	4.20	0.57	4.20	1.29	0	0.01	0.07	0	0.37	0.01

Bold is the best model.

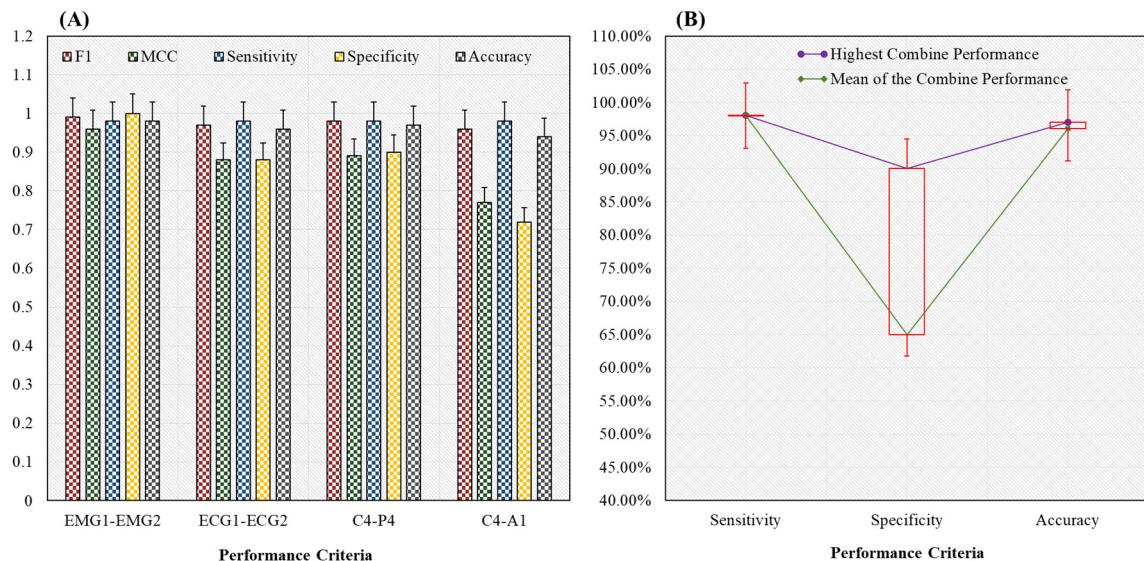


Figure 9. Performance analysis for the combination of subjects (bruxism and healthy) and sleep stages (w and REM) classification using the novel 20-fold HML classifier. (A) Comparison between all channels such as EMG1-EMG2, ECG1, ECG2, C4-P4, and C4-A1 channels of the sleep stages classification. In addition, (B) highest and mean performance of the combined classification. The C4-P4 channel of the EEG signal has the highest accuracy (97%) in the combined classification.

4.3. Comparison with the Previous and Proposed Sleep Disorders and Sleep Stage Detection Methods

Performances of the subjects (healthy and bruxism) classification on the EEG (C4-A1 channel) signal in terms of sensitivity, specificity, and accuracy were found to be 0.95, 0.92, and 0.94, respectively. The performance of the sleep stages (w and REM) classification on the ECG (ECG1-ECG2 channel) signal in terms of sensitivity, specificity, and accuracy were found to be 1, 0.86, and 0.95, respectively. Additionally, the performance of the combined (subjects and sleep stages) classification on the EEG (C4-P4 channel) signal in terms of sensitivity, specificity, and accuracy were found to be 0.98, 0.90, and 0.97, respectively. The C4-P4 channel of the combined classification has better performance than the others. Previously, bruxism detection methods were limited, so we compared with sleep disorder and sleep stage detection methods. Patients of bruxism are recognized through various diagnosis methods involving questionnaires, clinical examinations, and various appliances. The questionnaires involve the patient history of tooth mobility and tooth wear, muscle pain, hypersensitivity of teeth and masticatory muscle discomfort, fatigue, or pain [62]. Clinically, Ekfeldt et al. [63] detected a bruxism patient through intraoral and extraoral examination. Takeuchi et al. [64] suggested that bruxism is more accurately measured extraorally through masticatory muscle EMG recordings and polysomnography. We compare our proposed method with previously selected sleep disorders and sleep stage methods in terms of author, publication year, subject detection, signal, classifier, sensitivity, specificity, and accuracy, as mentioned in Table 5. The data from sleep disorders and sleep stage detection methods include EEG, EMG, and ECG signals. The classifiers involve decision tree (DT), KNN, SVM RBF kernel, threshold, and the novel HML classifier. Compared with them, our method shows a better performance in detecting bruxism (Figure 10A). Additionally, the proposed HML classifier is also compared with some existing hybrid classifiers, which are reported in Table 6. Our proposed HML classifier achieves satisfactory performance in detecting bruxism (Figure 10B).

Table 5. Comparison of the proposed method with the existing methods.

Reference	Year	Disease	Signal	Classifier	Sen (%)	Spe (%)	Acc (%)
Heyat et al. [40]	2019	Bruxism	EEG	DT	89	78	81
Lai et al. [19]	2019	Bruxism	EMG	DT	94	92	93
Bhattacharjee et al. [65]	2019	SA	EEG	KNN	98	83	91
Zarei et al. [66]	2019	OSA	ECG	SVM RBF Kernel	94	94	94
Dong et al. [67]	2018	OSA	ECG	Threshold	88	90	90
Kassiri et al. [68]	2017	Sleep Stage	EEG, EMG	Threshold	81	93	81
Kohtoh et al. [69]	2008	Sleep Stage	EEG, EMG	Threshold	71	96	84
Louis et al. [70]	2004	Sleep Stage	EEG, EMG	Threshold	66	84	82
Proposed				Subjects (Bruxism and Healthy)			
				EEG (C4-A1)			
				Sleep Stages (w and REM)			
				ECG (ECG1-ECG2)			
				Combine			
				EEG (C4-P4)			

SA: sleep apnea; OSA: obstructive sleep apnea; DT: decision tree. Bold is the best model.

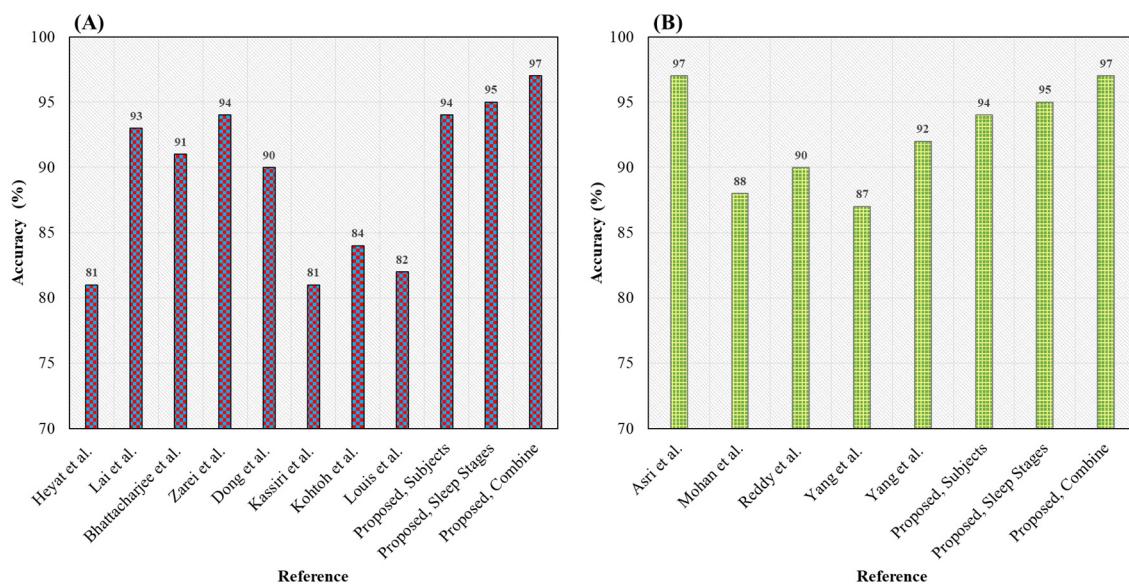


Figure 10. A comparison of the (A) proposed method with the existing methods and (B) proposed HML classifier with the existing hybrid classifiers.

Table 6. Comparison of the proposed HML classifier with the existing hybrid classifiers.

Reference	Year	Disease	Acc (%)
Asri et al. [71]	2020	Cancer	97
Mohan et al. [72]	2019	Heart	88
Reddy et al. [73]	2019	Heart	90
Yang et al. [74]	2010	Schizophrenia	87
Yang et al. [75]	2007	Cushing	92
Proposed		Bruxism	94
			95
			97

Bold is the best model.

4.4. Application and Limitation of the Proposed System

The proposed work showed an application for the detection of bruxism disorder and sleep stages using ECG1-ECG2, EMG1-EMG2, C4-P4, and C4-A1 channels. This work would provide a more

effective and accurate detection system of bruxism and sleep stages for medical application. The most important application of the present research is to diagnose people with a mental health condition in a fast and accurate manner. This system also helps to find the problem during the sleep stage.

The present work has some limitations in that the proposed data from the *physionet* website were old and small for the evaluation. Further work could be required for a large number of real-time data to analyze the present work for higher accuracy. Secondly, the proposed physiological signals, including ECG, EEG, and EMG, did not cover all sleep recordings. Moreover, we used two sleep stages, including w and REM. In the future, we will use different signals and different sleep stages for the detection of bruxism sleep disorders.

5. Conclusions

Bruxism is a sleep disorder in which people clinch, grind, and gnash their teeth during sleep. In this proposed study, we have developed a novel HML classifier to detect bruxism. The results show that the HML classifier can effectively discriminate subjects, sleep stages, and these two combined (subjects and sleep stages) with 94, 95, and 97% accuracy, respectively. In our knowledge, this method (HML classifier) is used for the first time to detect bruxism. We summarized that the EEG (C4-P4 channel) signal of the HML classifier could be utilized in bruxism detection. This method can achieve an effective result with PSD with potential application for sleep disorder and sleep stage detection. The upcoming study will quickly detect sleep disorders with higher accuracy.

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