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Automated identification of insomnia using optimal bi-orthogonal wavelet transform technique with single-channel EEG signals

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ABSTRACT

Nowadays, sleep studies have gained a lot of attention from researchers due to the immense importance of quality sleep. Human beings spend nearly one-third of their lives in sleep. Therefore, adequate quality sleep is indispensable for a healthy life. The sleep pattern may not be the same for every individual as one may either suffer from various sleep ailments such as insomnia, apnea, bruxism, epilepsy, narcolepsy, or maybe healthy with no sleep disorder.

Insomnia is a prevalent sleep disorder that can lead to many health-related issues in human beings. Usually, polysomnogram (PSG) signals are used to detect the sleep stages and sleep disorders. The PSG signals are difficult to handle, time-consuming, and not convenient for patients. Hence, in this work, we have used single-channel electroencephalogram (EEG) signals to detect insomnia automatically.

To the best of our knowledge, this is the first study on automated insomnia identification using the CAP database and EEG alone. We have used the single-channel EEG channel and created eight different subsets based on sleep-stages annotations according to American Academy of Sleep Medicine (AASM) guidelines for sleep stage scoring. The classification task is performed on each subset for the automated identification of insomnia. A new class of an optimal bi-orthogonal filter bank is used for wavelet decomposition. The wavelet-based norm features are extracted using the optimal filter bank. Then these features are fed to various machine learning algorithms. The proposed model has attained the highest classification performance with the area under receivers' operating characteristic curve (AROC) of 0.97, F1-score of 0.9645, the accuracy of 95.60%, and Cohen's Kappa value of 0.9067 using an ensemble bagged decision trees (EBDT) classifier.

Our developed model can be used to detect insomnia using sleep EEG signals accurately and provide early treatment. The method is simple and computationally fast. The proposed system can be used at home as well as at sleep labs to monitor insomnia.

1. Introduction

Sleep is a physiological activity performed by the human brain which maintains the physical and mental health of an individual. The human body repairs and rebuilds itself during sleep, healing itself and removing metabolic trash, which build up during periods of wakefulness [1]. Sleep also reorganizes memory and support the formation of long-term memory [2]. Considering the immense benefits of sleep in the daily life of human beings, it is necessary for an individual to take enough amount of sleep. Nevertheless, there are several sleep disorders such as periodic limb movement disorder (PLMD), nocturnal frontal lobe epilepsy (NFLE), rapid eye movement behavioral disorder (RBD) apnea, bruxism, and insomnia [3–5]. In recent times, studies concerning quick diagnosis and treatment of sleep disorders have attracted the attention of many researchers.

Insomnia is defined as an individual's inability to fall asleep and/or stay asleep properly. It is considered as the most prevalent sleep disorder in human beings as a study on various samples drawn from different countries showed that nearly 30% of the individuals are identified with symptoms of insomnia [6]. Insomnia can cause other ailments such as depression stroke, asthma attacks, seizures, weak immune system, obesity, diabetes mellitus, hypertension, heart disease and anxiety. It may also lead to an

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increased risk of accident, degradation in performance at work, reduced sex drive and memory-loss.

The condition of insomnia can be short-term (acute) or long-term(chronic), or may come and go. Insomnia can be categorized as primary and secondary. In the former, sleep issues are not associated with any health conditions, whereas, in the latter sleep problems are related to the health of the patient. Symptoms of insomnia may include drowsiness during the day, tiredness, grumpiness, problems with concentration or memory, and most importantly difficulty in falling asleep [7].

To analyze the brain activities, computed tomography (CT) scan, electroencephalogram (EEG), magnetic resonance imaging (MRI) or position emission tomography (PET) are used. Medical practitioners diagnose insomnia primarily through the sleep habits of patients with the help of sleep diaries and questionnaires. Doctors sometimes recommend sleep study of a subject. For the sleep-study a subject will be sent to sleep laboratory where whole night polysomnography (PSG) recordings are captured which contains multi-modal and multi-channel signals including EEG, electrocardiogram (ECG), electromyogram (EMG), and elctroocculogram (EOG). The PSG recordings are employed when the primary investigation is not satisfied due to the presence of other sleep disorders either behavioral or pharmacological [8]. However, the whole night monitoring of PSG recordings can be time-consuming, less-effective and uncomfortable to the patient [9]. Further, PSG recorded at sleep laboratories causes the first night effect. The effect is caused because of perturbations due to change in the sleep environment. This leads to an inaccurate diagnostic information. Hence, PSG-based methods are not suitable for portable home-based approaches.

There are many studies available for the classification of sleep stages [10–12] but there are very few studies published on the automated detection of insomnia using EEG signals. Even though insomnia is the most prevalent sleep ailment, the studies on the development of automated detection systems for sleep apnea [13, 14] have gained much more attention compared to insomnia. Moreover, the existing limited studies on automated detection of insomnia have used private databases using PSG. Hence, there is much scope and a high requirement to design automated insomnia identification systems using public database so that other researchers can reproduce the results. Fortunately, cyclic alternating pattern (CAP) sleep database [15] is the public database which contains 108 PSG recordings related to various sleep disorders, including insomnia. Further, to reduce the complexity of PSG based system, single-modal and single-channel based systems are highly desirable. Though recently, a couple of single-modal systems [16–18] have been proposed using their own databases.

The use of EEG is highly effective when considering sleep assessment studies [19]. EEG has been proven to be the gold standard for the identification of several other sleep disorders [20]. Therefore, it appears that machine learning-based methods [21] using EEG signals can help in immediate and accurate identification of insomnia. Single channel EEG-based insomnia monitoring system can be used at home. Home-based systems cause minimal disruption to sleep habits of patients and thus eliminate the need for overnight stays at a sleep centers. Hence, use of single-channel EEG seems more promising for the identification of insomnia in a simple, fast and convenient manner as it neither requires multiple probes attached to the patient [22,23] nor there is a need for specialized sleep labs/centers.

Morin et al. [24] suggested a psychometric test and insomnia severity index (ISI) to detect insomnia. However, the method is not automated as it is based on a questionnaire and surveying. *Israel et al.* [25] have presented a review on the analysis of sleep and heart rate variability in normal and insomnia patients. However, they do not suggest any state-of-art automated method for insomnia detection using EEG. *Aydin et al.* [18] have applied singular spectrum analysis on a private PSG recording to identify insomnia using artificial neural networks (ANN) and obtained insomnia classification error rate of 14.5%. *Abdullah et al.* [26,27] used PSG based method wherein they extracted few nonlinear features and applied them to ANN and support vector machine (SVM) classifiers. Despite using multi-modal signals they could obtain maximum classification accuracy of 83%.

Recently, a few approaches based on EEG have been developed for the automatic identification of insomnia. *Hamida et al.* [17,28] have developed the insomnia identification system using various spectral and Hjorth parameters features of EEG signals using principal component analysis (PCA) and clustering techniques. However, they used a private database and attained the maximum accuracy of 92%. *Shahin et al.* [16] proposed deep learning technique for the detection of insomnia. They trained and tested a deep neural network using a private database but they also could achieve accuracy up to 92% for the classification of normal and insomnia EEG epochs. Thus, from above-mentioned EEG based works it is clear that the existing EEG based methods cannot attain classification error lesser than 8%. Hence, these existing models are not very close to a perfect accurate model. In this work, we suggest a single-channel EEG based method for identification of insomnia , which is more accurate and simpler than existing methods, and can be used at home. Also, the model is trained and tested using a public CAP sleep database [29] unlike aforementioned methods which employed private databases.

Conventionally the sleep can be bifurcated as rapid eye movement (REM) and non-rapid eye movement (NREM) sleeps [10]. In the former, the eyes remain still, while in the latter, the eyes move rapidly, and they jointly make a single sleep cycle. NREM sleep is further subdivided into two parts: light sleep and deep sleep. Light sleep is comprised of two stages N1 and N2, and the N3 stage can be regarded as the deep sleep stage. Wakefulness (stage W) is separated from the NREM and REM sleep. Figs. 1 and 2 represent each sleep stage's EEG signal for healthy and insomnia patients, respectively. This sleep stage scoring criterion is given by R&K rules in which the whole night EEG signal is segmented into epochs of durations 30 s. Each epoch has been labeled with sleep stages as mentioned in [30]. It is to be noted that recently EEG based sleep scoring systems have been developed and obtained high-performance [10]. Having been inspired by these EEG-based automated sleep stages scoring systems, which have achieved high-performance [10], we have also explored EEG signals for the detection of insomnia. The main features of this study are mentioned below:

1. The study proposes an automated system to monitor insomnia using a single-channel EEG annotated with sleep stages. The method is simple, fast, and accurate. The proposed system can be used at home as well as at sleep labs for monitoring insomnia.
2. The model is tested and trained using a publicly available CAP sleep database, one of the largest sleep disorder-related public databases.
3. We have employed a new class of optimal wavelet filters to extract norm features (L_1-norm, L_2-norm, and $L_\infty-norm$) of EEG signals obtained from C4-A1 unipolar channel.
4. The sleep stages (W, N1, N2, N3, REM) are used individually along with further grouping into LSS (light sleep stage, i.e., N1+N2), NREM (N1+N2+N3), and ALL (all stages combined, i.e., W+REM+NREM). These eight different data subsets (DSS), viz, W, N1, N2, N3, REM, LSS, NREM, and ALL, are used to train and test the model. Hence, the model has been tested using the whole sleep recording and seven data subsets created based on sleep-stages annotations. Thus,

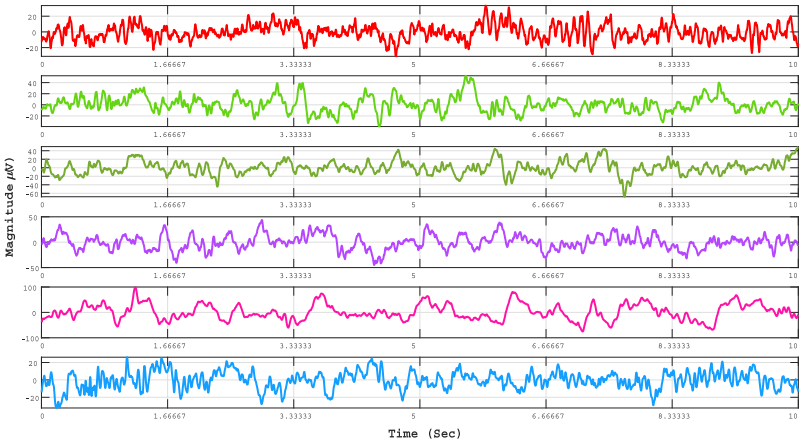

Fig. 1. Typical EEG epochs of different sleep stages according to R&K criterion (Wake, S1, S2, S3, S4, REM stages from top to bottom, respectively) of healthy subject.

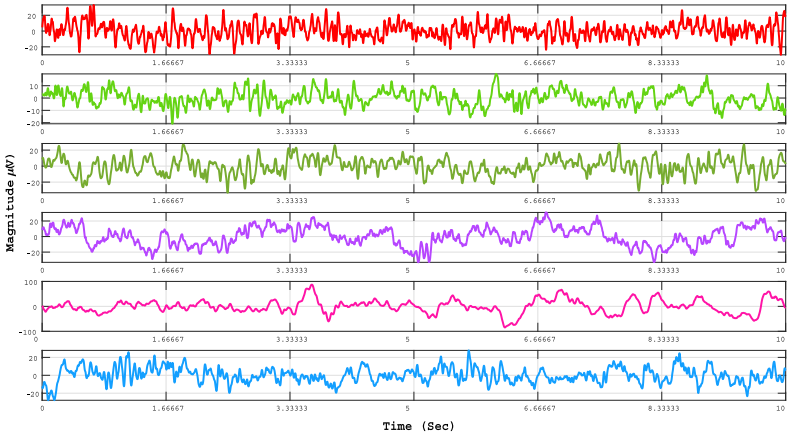

Fig. 2. EEG epochs corresponding to different sleep stages of insomnia patient (Wake, S1, S2, S3, S4, REM from top to bottom respectively).

we performed both sleep stage-independent and stage-dependent classification schemes. The EBDT classifier is used for classification on each subset.

5. The proposed study is simple in terms of data processing, feature extraction, and classification compared to other studies and achieved significant performance with machine learning techniques.
6. The model is very close to an accurate model as it attained 0.97 for the area under receivers' characteristic (AROC) and an F1 score of 0.9645. Cohens' Kappa coefficient is also computed to take care of the data balancing problem and obtained a high Kappa value of 0.9067. Our method outperformed all other EEG as well as PSG-based methods.

The subsequent portion of the paper is structured as follows. Section 2 delineate the material or data set used for the study. Section 3 explains methodology and Section 4 describes the results achieved using our method. Section 5 presents discussion and concludes in Section 6.

Table 1
Details of data used in this study.

Patient	Sleep duration			fs	Gender	Age
Name	Start time	End time	Minutes	(Hz)		
Normal-1	22:09:33	7:42:33	573	512	F	37
Normal-2	22:19:06	6:38:36	499	512	M	34
Normal-3	23:06:12	07:26:12	500	512	F	35
Normal-5	22:49:48	07:13:18	503	512	F	35
Normal-10	23:24:52	06:34:22	429	512	M	23
Normal-11	22:37:16	07:23:16	526	512	F	28
Insomnia-2	18:25:38	08:22:38	837	512	F	58
Insomnia-4	21:34:04	03:40:04	366	512	F	58
Insomnia-5	17:58:48	08:18:18	859	512	F	59
Insomnia-6	22:37:17	07:25:17	528	512	F	54
Insomnia-7	19:58:14	08:19:14	741	512	F	47
Insomnia-8	22:43:04	05:42:34	419	512	M	64
Insomnia-9	22:28:44	07:13:14	524	512	M	72
Mean ± Std			561.84 ± 154.84			46.46 ± 15.38

2. Material used

The data used by us in the proposed work was downloaded from CAP-sleep dataset which can be accessed from Physionet website(https://physionet.org/content/capslpdb/1.0.0/). The Physionet website provides a number of physiological data sets to be used for the research purpose which has free access to everyone [29]. The CAP database was created at the sleep disorder center of Ospedale Maggiore of Parma, Italy, and it consists of 108 PSG recordings (which includes 16 normal and 9 insomnia subjects along with other sleep disordered patients). The waveforms of the database are contained in the '.edf' file which can be read using 'edfread' function in MATLAB software. These PSG recording comprise muti-modal signals which include electroencephalogram (EEG) with minimum of 3 channels, electrooculogram (EOG) with 2 channels, electrocardiogram (EKG or ECG), electro-myogram (EMG) and other respiratory signals (airflow, abdominal and thoracic effort and SpO2). In addition, the manual

Table 2
Number of epochs used in each sleep stage for various subjects.

Patient	No. of epochs (for C4-A1 channel)					
Name	Wake	N1	N2	N3	REM	Total
Normal-1	39	33	513	322	239	1146
Normal-2	142	141	368	197	151	999
Normal-3	135	49	348	280	188	1000
Normal-5	9	49	414	303	232	1007
Normal-10	65	2	262	312	218	859
Normal-11	55	6	267	343	381	1052
All Normal	445	280	2172	1757	1409	6063
Insomnia-2	836	5	455	145	233	1674
Insomnia-4	62	6	352	158	154	732
Insomnia-5	917	5	430	194	173	1719
Insomnia-6	493	62	227	166	88	1056
Insomnia-7	609	19	509	125	220	1482
Insomnia-8	231	73	268	189	78	839
Insomnia-9	653	53	215	88	40	1049
All Insomnia	3801	223	2456	1085	986	8551

labeling of each 30 s epoch of recordings into individual sleep stages (W,S1,S2,S3,S4,REM) is done according to R&K rules by trained neurologists [30] in the whole database.

Tables 1 and 2 show the subject information along with their gender & age and number of epochs used for each subject, respectively. To maintain the uniformity of data only subjects with sampling frequency of 512 Hz were used with 6 normal(n1–n3,n5,n10,n11) and 7 insomnia(ins2,ins4-ins9) subjects. In this work, "n" and "ins" indicate normal and insomniac subjects. Among total patients four were male and nine were female with 46 years average age. In this study, EEG signals from unipolar C4-A1 channel were used. As majority of the subjects (16 healthy and 9 insomniac) include recording of EEG with C4-A1 channel, while other two EEG channels can be found in few subjects only as depicted in Tables 3 and 4.

3. Methodology

The presented approach for the detection of insomnia include, data collection, data pre-processing, wavelet decomposition, feature extraction and classification. Fig. 3 shows the flow diagram for the suggested method. The EEG signals are segmented into epochs of 30 s and preprocessed. The sleep scores (stages) for all epoch have been obtained. A Matlab code is written to segregate the sleep stages. Then, we used an optimal filter bank for wavelet decomposition of each epoch into six subbands (SBs). We extracted norm-based features $L_1 - norm$, $L_2 - norm$ and $L_\infty - norm$ from each SB. Subsequently, ensemble bagging technique with decision trees is used to classify normal and insomniac EEG epochs.

3.1. Segregation of EEG into sleep stages

In our study, we divided EEG signal from each subject according to sleep stages. The CAP Sleep Database contains text file along with '.edf'(signal file) for each subject. This text file comprises of annotation for each sleep stage for an EEG epoch of 30 s according to R&K rules [30]. To utilize this annotations for the segmentation of EEG into sleep stages we took the help of 'ScoreReader', a MATLAB program available in the Physionet website to read such text files containing sleep stage annotations. The 'ScoreReader' program generated hypnogram ('.hyp') file for each subject. We developed the MATLAB code which can identify EEG samples corresponding to a particular sleep stage according to annotations mentioned in the hypnogram file. Following this, we arranged the samples into epochs and matrices containing

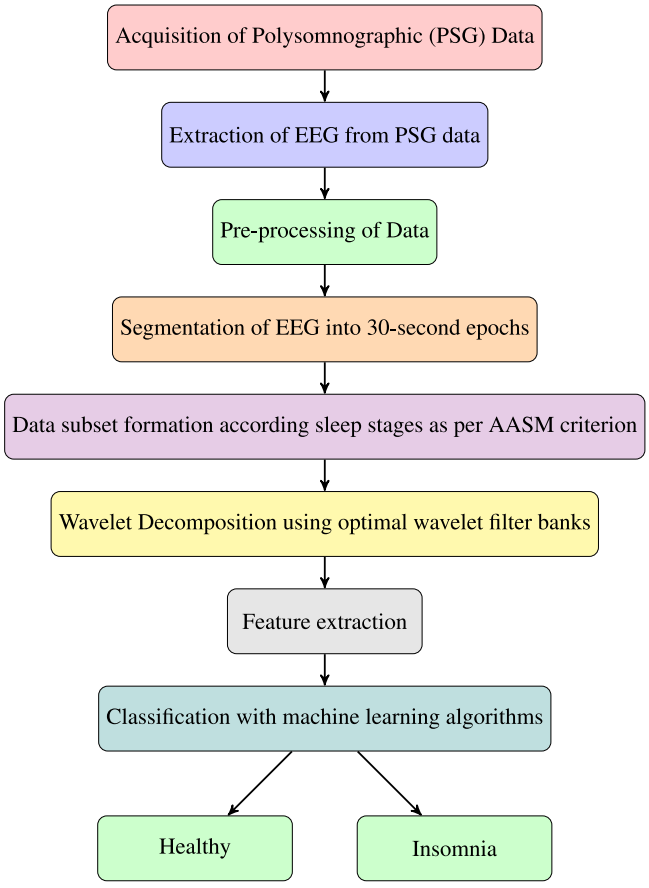

Fig. 3. Flowchart of the proposed study.

these epochs for each sleep stage were created. These epochs contain number of samples equal to sampling frequency times 30 s (duration of epoch). Considering the matrix for a particular stage, each row corresponds to an epoch. Such a segmentation was performed for normal as well as insomnia subjects. Table 2 shows number of epochs pertaining to each sleep stage for all the subjects used in study.

3.2. Data subsets preparation

The PSG recordings contain various physiological signals like EEG, EOG, ECG, and respiratory signals. Out of these all, we have selected EEG signals to perform our study. The scoring of sleep stages for these signals is done according to R&K criterion [30] in which whole-night sleep is divided into six different sleep stages named wakefulness (W), S1, S2, S3, S4, and REM. Although the scoring of sleep stages for CAP data is based on R&K rules, we have considered using the American Academy of Sleep Medicine (AASM) guidelines [31] for sleep scoring to group different sleep stages. According to new AASM guidelines, the sleep is divided into five stages: wakefulness (W), N1, N2, N3, and REM. According to the AASM guidelines, we have re-labeled epochs, and sleep stages S3 and S4 (as per R& K rules) are combined to form a new deep sleep stage named N3 (deep sleep stage). Then, we created eight different subsets based on the sleep stages.

A total of 8 data subsets (DSS) have been created for our study. In that, five DSS contain epochs of five sleep stages (W, N1, N2, N3, REM) according to AASM guidelines, another three DSS are created by combining different sleep stages together as given below.

Table 3
Healthy subjects with recorded signals (EEG, ECG/EKG, EMG and EOG).

Subject	Signals and their sampling frequency, fs (Hz)								
Normal-1	ROC-LOC 512 P3-O1 512	LOC-ROC 512 C4-A1 512	F2-F4 512 EMG1-EMG2 256	F4-C4 512 ECG1-ECG2 512	C4-P4 512	P4-O2 512	F1-F3 512	F3-C3 512	C3-P3 512
Normal-2	Fp2-F4 512	F4-C4 512	C4-P4 512	P4-O2 512	C4-A1 512	ROC-LOC 128	EMG1-EMG2 512	ECG1-ECG2 512	
Normal-3	Fp2-F4 512 P3-O1 512	F4-C4 512 F7-T3 512	C4-P4 512 T3-T5 512	P4-O2 512 C4-A1 512	F8-T4 512 ROC-LOC 128	T4-T6 512 EMG1-EMG2 512	FP1-F3 512 ECG1-ECG2 512	F3-C3 512	C3-P3 512
Normal-4	EOG dx 100	Fp2-F4 100	F4-C4 100	C4-P4 100	P4-O2 100	C4-A1 100	EOG sin 100	EKG 200	
Normal-5	Fp2-F4 512 P3-O1 512	F4-C4 512 F7-T3 512	C4-P4 512 T3-T5 512	P4-O2 512 C4-A1 512	F8-T4 512 ROC-LOC 128	T4-T6 512 EMG1-EMG2 512	FP1-F3 512 ECG1-ECG2 512	F3-C3 512	C3-P3 512
Normal-6	LOC-A1 128	ROC-A2 128	EMG-EMG 128	C3-A2 128	O2-A1 128	ECG 128			
Normal-7	LOC-A1 128	ROC-A2 128	EMG-EMG 128	C3-A2 128	O2-A1 128	ECG 128			
Normal-8	C3-A2 100	C4-P4 100	EKG 200	EOG-L 100	EOG-R 100	F4-C4 100	Fp2-F4 100	P4-O2 100	
Normal-9	LOC-A1 128	ROC-A2 128	EMG 128	C3-A2 128	O2-A1 128	ECG 128			
Normal-10	Fp2-F4 512 P3-O1 512	F4-C4 512 F7-T3 512	C4-P4 512 T3-T5 512	P4-O2 512 C4-A1 128	F8-T4 512 ROC-LOC 512	T4-T6 512 EMG1-EMG2 512	FP1-F3 512 ECG1-ECG2 512	F3-C3 512	C3-P3 512
Normal-11	Fp2-F4 512 P3-O1 512	F4-C4 512 F7-T3 512	C4-P4 512 T3-T5 512	P4-O2 512 C4-A1 128	F8-T4 512 ROC-LOC 512	T4-T6 512 EMG1-EMG2 512	FP1-F3 512 ECG1-ECG2 512	F3-C3 512	C3-P3 512
Normal-12	LOC-A2 100	ROC-A1 100	C3-A2 100	C4-A1 100	O1-A2 100	O2-A1 100	EKG 100		
Normal-13	LOC 200	ROC 200	F3-A2 200	F4-A1 200	C3-A2 200	C4-A1 200	O1-A2 200	O2-A1 200	ECG 100
Normal-14	LOC 200	ROC 200	F3-A2 200	F4-A1 200	C3-A2 200	C4-A1 200	O1-A2 200	O2-A1 200	ECG 200
Normal-15	EOG-L 200	EOG-R 200	F3-A2 200	F4-A1 200	C3-A2 200	C4-A1 200	O1-A2 200	O2-A1 200	EKG 200
Normal-16	Fp2-F4 100	F4-C4 100	C4-P4 100	P4-O2 100	C4-A1 100				

- **LSS (light sleep stage)**: DSS created by combining sleep stages N1 and N2.
- **NREM**: DSS formed by combining sleep stages (N1 + N2 + N3), which belongs to Non-REM sleep.
- **ALL**: It is formed by combining all sleep stages (W + N1 + N2 + N3 + REM). The classification using this DSS leads to the stage-independent classification.

3.3. Optimal Bi-orthogonal wavelet filter bank

There are various applications associated with wavelet filter banks (FB) like image processing and compression, speech processing, analysis of pathological signals, communications, beamforming, and medical investigations [32]. A FB can be designed by setting or defining an optimization problem. However, the filter design problem could be a highly constrained non-convex optimization problem as the FBs must satisfy certain non-linear conditions. Because of the non-convex nature of the problem, optimal global solutions are not assured. Hence, designing a FB convex optimization formulation, which yields optimal global solutions is highly desirable. Therefore, in this study, we formulated a convex optimization that yielded optimal filters with the desired attributes.

The standard Daubechies [33] biorthogonal FBs have maximum number of zero-moments and, therefore, do not provide any flexibility to optimize the desired attributes of filters or wavelets. Hence, by relaxing some zero-moments, one can design a wavelet filter with desired characteristics such as minimal duration-bandwidth localization, double half-band property, and frequency selectivity [34]. Phoong et al. [34] designed biorthogonal FB with double half-band property and desired regularity by relaxing some of the zero-moments. We have proposed a new optimal FB that also satisfies the half-band property. However, the proposed FB can be considered better than the proposed by Phoong et al. [34] as our method is a direct method without the need for the design of standard kernel filters. Also, the method is a purely time-domain technique without any parametrization. It is more flexible in shaping filter attributes and does not present any restrictions like the half-band pair filter bank (HPFB) design technique. Most importantly, we can optimize duration-bandwidth localization, double half-band property, and frequency selectivity and regularity simultaneously, unlike the method by Phoong et al. [34].

In the proposed technique, we designed an optimal linear-phase biorthogonal FB that satisfies the desired constraints with

Table 4
Insomnia subjects with recorded signals (EEG, ECG/EKG, EMG and EOG).

Subject	Signals and their sampling frequency, fs (Hz)							
Insomnia-1	Fp2-F4 256	F4-C4 256	C4-P4 256	P4-O2 256	C4-A1 256	ROC-LOC 128	EMG1-EMG2 128	ECG1-ECG2 128
Insomnia-2	Fp2-F4 512	F4-C4 512	C4-P4 512	P4-O2 512	C4-A1 512	ROC-LOC 128	EMG1-EMG2 512	ECG1-ECG2 512
Insomnia-3	ROC-LOC 128 F8-T4 256	Fp2-F4 256 F7-T3 256	F4-C4 256	C4-P4 256	P4-O2 256	C4-A1 256	EMG1-EMG2 256	ECG1-ECG2 256
Insomnia-4	ROC-LOC 128	Fp2-F4 512	F4-C4 512	C4-P4 512	P4-O2 512	C4-A1 512	EMG1-EMG2 512	ECG1-ECG2 512
Insomnia-5	Fp2-F4 512	F4-C4 512	C4-P4 512	P4-O2 512	C4-A1 512	ROC-LOC 128	EMG1-EMG2 512	ECG1-ECG2 512
Insomnia-6	ROC-LOC 128	Fp2-F4 512	F4-C4 512	C4-P4 512	P4-O2 512	C4-A1 512	EMG1-EMG2 512	ECG1-ECG2 512
Insomnia-7	Fp2-F4 512	F4-C4 512	C4-P4 512	P4-O2 512	C4-A1 512	ROC-LOC 128	EMG1-EMG2 512	ECG1-ECG2 512
Insomnia-8	ROC-LOC 128 P3-O1 512	Fp2-F4 512 C4-A1 512	F4-C4 512 EMG1-EMG2 512	C4-P4 512 ECG1-ECG2 512	P4-O2 512 F8-T4 512	FP1-F3 512 F7-T3 512	F3-C3 512	C3-P3 512
Insomnia-9	ROC-LOC 128 P3-O1 512	Fp2-F4 512 C4-A1 512	F4-C4 512 EMG1-EMG2 512	C4-P4 512 ECG1-ECG2 512	P4-O2 512 F8-T4 512	FP1-F3 512 F7-T3 512	F3-C3 512	C3-P3 512

minimal complexity. Our method simultaneously regulates duration-bandwidth concentration, selectivity, and smoothness of filters efficiently. First, the optimal half-band analysis low-pass filter (HALF) is designed for the chosen length and zero moments [35].

The objective function employed to design the optimal filter is a combination of duration and bandwidth concentration of the filter, as well as stop-band and pass-band errors [36,37]. The filter design problem has been formulated as a convex optimization problem. The optimal filter is derived from the eigenvector of a positive semi-definite matrix [38,39]. After designing the HALF, the synthesis lowpass filter (SLPF) is designed using complementary design technique [40]. The synthesis filter design is similar to the HALF except for the following changes: SLPF is not a half-band filter, and perfect reconstruction (PR) conditions need to be satisfied along with the regularity conditions.

3.3.1. Overview

A typical bi-orthogonal two-channel wavelet filter bank (BTWFB) comprises of analysis filter bank as well as a synthesis filter bank. The analysis and synthesis filter banks both consists of low-pass as well as high-pass filters. The analysis low-pass filter is designed first, and the high-pass analysis filter can be derived from it. After that, synthesis filters are produced [35].

Consider $H_0(z)$ and $H_1(z)$ as the analysis low-pass and high-pass filters, respectively and $G_0(z)$ and $G_1(z)$ as the synthesis low-pass and high-pass filters, respectively of the BTWFB.

The FB satisfies PR conditions given below [21]:

$$G_0(z)H_0(-z) + G_1(z)H_1(-z) = 0 \tag{1}$$

$$G_0(z)H_0(z) + G_1(z)H_1(z) = 2z^{-k}, \quad k \in Z \tag{2}$$

The product filter is defined as [21]:

$$Q(z) = z^k H_0(z)F_0(z) \tag{3}$$

From (1) , (2) and (3)

$$Q(z) + Q(-z) = k \tag{4}$$

The product filter $Q(z)$ which satisfies (4) is recognized as half-band filter, and it satisfies the following condition in time domain [41]:

$$Q(2n) = \delta(n) \tag{5}$$

Consider $h_0(n)$ and $g_0(n)$ as the impulse responses of HALF and SLPF, respectively. Let the impulse response of the low-pass FIR filter be $g(n)$ having length $2N + 1$. The $h(n)$ denotes the impulse response of either the analysis filter $h_0(n)$ or the synthesis filter $g_0(n)$. The frequency response of the filter $g(n)$ is denoted by $G(\omega)$ is defined as given below [42]:

$$G(\omega) = g(0) + 2\sum_{n=1}^{+N} g(n)\cos(\omega n) \tag{6}$$

3.3.2. Objective function

The following cost (objective) function will be minimized to design the low-pass filter $g(n)$ [38]:

$$\phi = \beta_1\sigma_n^2 + \beta_2\sigma_\omega^2 + \beta_3 E_p + \beta_4 E_s \tag{7}$$

where σ_n^2 and σ_ω^2 denote duration and bandwidth of the unit the filter, respectively, which are defined below [38]. Without the loss of generality, the filter can be assumed to possess unit energy filter.

$$\sigma_n^2 = \sum_{n=-\infty}^{\infty} n^2\left|g(n)\right|^2 = \frac{1}{\pi}\int_0^{\pi}\left|\frac{d}{d\omega}G(\omega)\right|^2 d\omega \tag{8}$$

$$\sigma_\omega^2 = \frac{1}{\pi}\int_0^{\pi}\omega^2\left|G(\omega)\right|^2 \tag{9}$$

The pass-band and stop-band errors are denoted by E_p and E_s, respectively. The E_p and E_s can be given by [38]

$$E_p = \frac{1}{\pi}\int_0^{\omega_p}\left|G(0) - G(\omega)\right|^2 d\omega \tag{10}$$

$$E_s = \frac{1}{\pi}\int_0^{\omega_s}\left|G(\omega)\right|^2 d\omega \tag{11}$$

In (10) and (11), ω_p and ω_s denotes the pass-band edge and stop-band edge frequencies respectively. Let **a**, **b** and **c** be the following

vectors of the length $(N+1)$ [38]:

$$\mathbf{a} = \begin{bmatrix} g(0) & \sqrt{2}g(1) & \cdots & \sqrt{2}g(N) \end{bmatrix}^T \tag{12}$$

$$\mathbf{b} = \begin{bmatrix} 1 & \sqrt{2}\cos(\omega) & \cdots & \sqrt{2}N\cos(N\omega) \end{bmatrix}^T \tag{13}$$

$$\mathbf{c} = \begin{bmatrix} 0 & -\sqrt{2}\sin(\omega) & \cdots & -\sqrt{2}N\sin(N\omega) \end{bmatrix}^T \tag{14}$$

Duration, bandwidth, pass-band and stop-band errors can be now represented in terms of above vectors as [38]:

$$\sigma_n^2 = \mathbf{a}^{\mathbf{T}} \left\{ \int_0^{\pi} \frac{\mathbf{c}(\omega)\mathbf{c}^{\mathbf{T}}(\omega)}{\pi} \mathbf{d}\omega \right\} \mathbf{a} = \mathbf{a}^{\mathbf{T}}\mathbf{P}\mathbf{a} \tag{15}$$

$$\sigma_\omega^2 = \mathbf{a}^{\mathbf{T}} \left\{ \int_0^{\pi} \frac{\omega^2\mathbf{b}(\omega)\mathbf{b}^{\mathbf{T}}(\omega)}{\pi} \mathbf{d}\omega \right\} \mathbf{a} = \mathbf{a}^{\mathbf{T}}\mathbf{Q}\mathbf{a} \tag{16}$$

$$E_p = \mathbf{a}^{\mathbf{T}} \left\{ \int_0^{\omega_p} \frac{\left[\mathbf{b}(\mathbf{0}) - \mathbf{b}(\omega)\right]\left[\mathbf{b}(\mathbf{0}) - \mathbf{b}(\omega)\right]^{\mathbf{T}}}{\pi} \mathbf{d}\omega \right\} \mathbf{a} = \mathbf{a}^{\mathbf{T}}\mathbf{R}\mathbf{a} \tag{17}$$

$$E_s = \mathbf{a}^{\mathbf{T}} \left\{ \int_0^{\omega_s} \frac{\mathbf{b}(\omega)\mathbf{b}^{\mathbf{T}}(\omega)}{\pi} \mathbf{d}\omega \right\} \mathbf{a} = \mathbf{a}^{\mathbf{T}}\mathbf{S}\mathbf{a} \tag{18}$$

Hence, the minimizing function depicted in (7) can be rewritten as:

$$\boldsymbol{\phi} = \mathbf{a}^{\mathbf{T}}\{\boldsymbol{\beta_1}\mathbf{P} + \boldsymbol{\beta_2}\mathbf{Q} + \boldsymbol{\beta_3}\mathbf{R} + \boldsymbol{\beta_4}\mathbf{S}\}\mathbf{a} = \mathbf{a}^{\mathbf{T}}\mathbf{W}\mathbf{a} \tag{19}$$

The trade-off between duration, bandwidth, pass-band and stop-band errors is provided by β_i, which are called as trade-off or weighting factors [32]. These trade-off factors satisfy the following conditions: $0 \leq \beta_i \leq 1$ and $\sum \beta_i = 1$. The matrices $\mathbf{P}$, $\mathbf{Q}$, $\mathbf{R}$, $\mathbf{S}$ and $\mathbf{W}$ are positive definite matrices having dimension of $(N+1)\times(N+1)$. Thus, it can be observed from Eq. (19) that the optimization problem is now a convex one with the optimization variable $\mathbf{a}$, and so the global solution which is feasible can be obtained.

3.3.3. Constraints

Regularity and PR are various constraints to be imposed on the filter deign problem [43]. The regularity of filters is crucial requirement to design a wavelet filter bank. For two-channel FB, it can be achieved by forcing zeros at $z = -1$. The F-regular filter (i.e F zeros at $z = -1$) should satisfy the below condition for $G(\omega)$ [44]

$$\left.\frac{d^n G(\omega)}{d\omega^n}\right|_{\omega=\pi} = 0, \quad n = 0, 1, 2, \ldots, F-1 \tag{20}$$

The regularity order F must be even for the case of type-1 filter, which is F = 2M. The above mentioned regularity condition can be represented as a set of linear equations, $\mathbf{Ka} = 0$. The $(i,j)^{th}$ element of $(N+1)\times V$ matrix $\mathbf{K}$ is given by [45]:

$$\left[\mathbf{K}\right]_{i,j} = \begin{cases} 1 & i,j = 0 \\ \sqrt{2}(j)^{2i}(-1)^j & \text{otherwise} \end{cases} \tag{21}$$

For $g(n)$ to be a half-band filter, it must satisfy below condition [46]:

$$g(2n) = 0 \quad \text{excluding } n = 0 \quad \text{i.e} \quad g(2n) = \delta(n) \tag{22}$$

The above half-band condition is formulated as a set of linear equations, $\mathbf{La} = 0$. The (i,j)th element of $(N+1)\times(N-1)/2$ matrix $\mathbf{L}$ is given by [46]:

$$\left[\mathbf{L}\right]_{i,j} = \begin{cases} 1/\sqrt{2} & i = 0, 1, 2, \ldots, N \quad ; \quad j = 2, 4, \ldots (N-1) \\ 0 & \text{otherwise} \end{cases} \tag{23}$$

For half band filter N is an odd integer [47].

3.3.4. Filter design optimization problems

The optimization approach in order to design the optimal half-band analysis low-pass filter and synthesis low-pass filter can be formulated as follows [35]. Consider the lengths of $h_0(n)$ and $g_0(n)$ be $L_A = 2X+1$ and $L_S = 2Y+1$ respectively and their regularity orders be $2V_A$ and $2V_S$ respectively. From the cost function in (19), the optimization problem for HALF is formulated as [35]:

$$\begin{aligned} \min_{h} \quad & \mathbf{h}^{\mathbf{T}}\mathbf{W}\mathbf{h}, && \text{(Cost function)} \\ \text{subject to} \quad & \mathbf{K}\mathbf{h} = 0, && \text{(Regularity constraint)} \\ & \mathbf{L}\mathbf{h} = 0, && \text{(Half-band constraint)} \\ & \mathbf{h}^{\mathbf{T}}\mathbf{h} = 1, && \text{(Unit-norm constraint)} \end{aligned} \tag{24}$$

Here, $\mathbf{h}$ is the optimization vector of length $X+1$ obtained using Eq. (12). And the matrices $\mathbf{K}$ and $\mathbf{L}$ are defined earlier in (21) and (23) respectively. Now, after having designed the HALF, the optimization problem for SLPF can be defined as below [35]:

$$\begin{aligned} \min_{g} \quad & \mathbf{g}^{\mathbf{T}}\mathbf{W}\mathbf{g}, && \text{(Cost function)} \\ \text{subject to} \quad & \mathbf{K}\mathbf{g} = 0, && \text{(Regularity constraint)} \\ & \mathbf{D}\mathbf{g} = 0, && \text{(PR constraint)} \\ & \mathbf{g}^{\mathbf{T}}\mathbf{g} = 1, && \text{(Unit-norm constraint)} \end{aligned} \tag{25}$$

In this work, $\mathbf{g}$ is the optimization vector of length $Y+1$ obtained using Eq. (12). $\mathbf{D}$ is a matrix of size $(Y+1)\times(X+Y-1)/2$ and its (i,j)th element is given by [40]:

$$\left[\mathbf{D}\right]_{i,j} = \begin{cases} h_0\left[2i+2\right] & j = 0 \\ h_0\left[2(i+1)-j\right] + h_0\left[2(i+1)+j\right] & 1 \leq j \leq Y \end{cases} \tag{26}$$

It can be observed from (24) and (25) that the filter design problems for HALF and SLPF are convex problems.

3.3.5. Filter design process

On solving (24) and (25), the optimal HALF and SLPF filters are derived as eigenvectors with the smallest eigenvalues of the suitable positive definite matrix. The design procedure can be outlined as [35]:

1. By selecting the suitable filter length $\mathbf{L_A}$, regularity order $\mathbf{2V_A}$ and trade-off factors $\boldsymbol{\beta_i}$ for half-band analysis low-pass filter ($H_0(z)$), the optimization problem (24) is formulated.
2. Matrices $\mathbf{K}$ and $\mathbf{L}$ are augmented into matrix $\mathbf{A} = \left[\mathbf{K}; \mathbf{L}\right]$ to merge the linear constraints into a single constraint.
3. Consider a rectangular unitary matrix $\mathbf{J}$, with its columns forming the orthonormal basis for the null space of $\mathbf{A}$ and let $\mathbf{q}$ be any vector. Then $\mathbf{h}$ being inside the null space of $\mathbf{D}$ can be represented as $\mathbf{h} = \mathbf{Jq}$.
4. Now, the cost function in (24) is represented as, $\mathbf{h}^{\mathbf{T}}\mathbf{W}\mathbf{h} = \mathbf{q}^{\mathbf{T}}\mathbf{J}^{\mathbf{T}}\mathbf{W}\mathbf{J}\mathbf{q} = \mathbf{q}^{\mathbf{T}}\mathbf{S}\mathbf{q}$, where $\mathbf{S} = \mathbf{J}^{\mathbf{T}}\mathbf{W}\mathbf{J}$.
5. By employing the Rayleigh theorem, an optimal eigenvector $\mathbf{q}$ for the smallest eigenvalue of matrix $\mathbf{S}$ is obtained. And from $\mathbf{h} = \mathbf{Jq}$, an optimal vector $\mathbf{h}$ is acquired.
6. In a similar way by selecting suitable $\mathbf{L_S}$, $\mathbf{2M_S}$, $\boldsymbol{\beta_i}$ and defining the optimization problem (25), the optimal synthesis low-pass filter (SLPF) can be obtained, following steps 3, 4 and 5.

3.4. Wavelet decomposition and sub-bands

Five-level 1-D wavelet decomposition is implemented on each epoch of EEG signal using the aforementioned optimal bi-orthogonal wavelet filter bank. It yielded six SBs containing approximate and detailed information of EEG epochs.

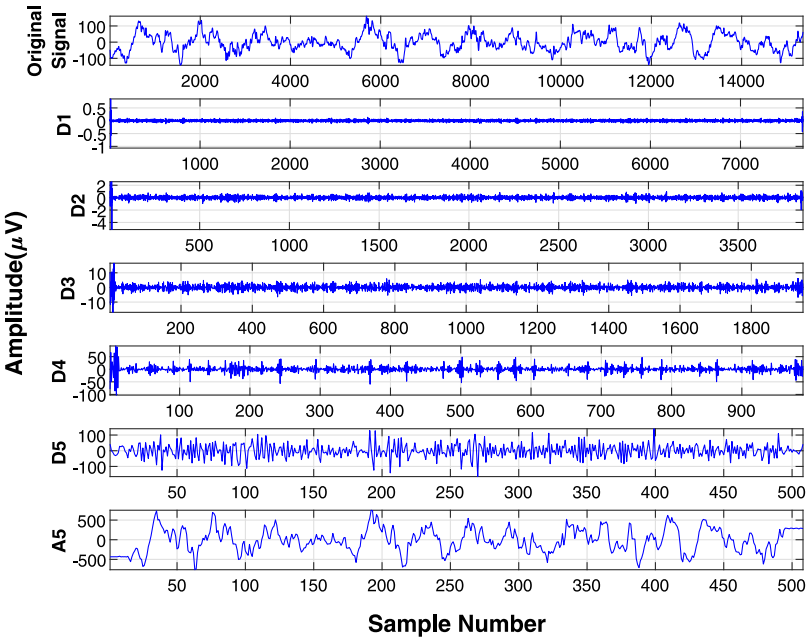

Fig. 4. Sub-bands after wavelet decomposition for an epoch in S4 sleep stage.

Thus, a total of six sub-bands namely A, D1, D2, D3, D4 and D5 are obtained after the 1-D wavelet decomposition. The approximate wavelet coefficients are denoted by A. Similarly, the detailed coefficients corresponding to level one to five are denoted by D1, D2, D3, D4 and D5 respectively. Fig. 4 represents six sub-bands for an epoch of S4 sleep stage after wavelet decomposition.

3.5. Feature extraction

In the proposed work, we have extracted norm–based features from six sub-bands (A, D1, D2, D3, D4, D5). The l_1-norm, l_2-norm and $l_\infty - norm$ are extracted from each sub-band yielding a total of 18 features.

In general, the $p-norm$ (also called as l_p-norm) of a sequence $x(n)$ is defined as [32]:

$$\|x\|_p = \left(\sum_{n=1}^{\infty} |x(n)|^p\right)^{\frac{1}{p}}, p \in Z^+ \tag{27}$$

3.5.1. $\mathbf{l_1 - norm}$

Let $x(n)$ be a sequence, its $l_1 - norm$ is given by [32]:

$$\|x\|_1 = \sum_{n=1}^{\infty} |x(n)| \tag{28}$$

3.5.2. $\mathbf{l_2 - norm}$

The $l_2 - norm$ of the sequence $x(n)$ can be defined as [32]:

$$\|x\|_2 = \left(\sum_{n=1}^{\infty} |x(n)|^2\right)^{\frac{1}{2}} \tag{29}$$

It can be observed that $l_2 - norm$ of $x(n)$ gives the RMS (root mean squared) value of the sequence.

3.5.3. $\mathbf{l_\infty - norm}$

The $l_\infty - norm$ of a sequence $x(n)$ gives its maximum absolute value, it is also called peak absolute value of the sequence [32]. It can be expressed as:

$$\|x\|_\infty = |x(n)|_{max} \tag{30}$$

3.6. Feature selection and ranking

We have performed Kruskal–Wallis test [48] on the extracted features to obtain the p-value corresponding to each feature. The p-value indicates the statistical significance of a quantity and if the p-value of extracted feature is more than the threshold (0.05), then the feature cannot be considered a significantly distinctive, and therefore may be left out from the classification task. Table 5 shows the p-value and rank of each feature along with their mean and standard deviation (Std). It can be observed that for our study the p-value of most of the features are nearly equal to zero, which indicates its statistical significance and relevance. Hence, we considered all features during the classification process.

3.7. Classification, validation and testing

For training the model, we have used various classifiers such as k-nearest neighbor(KNN), support vector machine (SVM), and decision trees. However, we obtained the optimal performance with an ensemble bagged decision tree. In an ensemble classification method, various machine learning classifiers are combined, which further improve the classification performance and reduce over-fitting chances. An ensemble method employs several decision trees to generate high performance instead of utilizing a single tree. One of the most widely used ensemble techniques of classification is the bagging algorithm. Decision trees are sensitive towards specific data on which they are trained. Suppose a tree is trained on a subset of training data. In that case, the resulting decision tree can be quite different, leading to different predictions and high variance in the decision tree algorithm. Bagging helps minimizing the variance [49]. In the EBDT classifier, the number of trees is increased run after run until the accuracy ceases to improve further. Many learners can take a longer duration, but the chances of over-fitting can be reduced.

We have plotted a graph (Fig. 5) between the mis-classification rate versus the number of trees. The converging performance is obtained for $(n - 1)$ splits (where n is the total number of epochs). The parameters corresponding to minimum error are chosen as the optimal parameters. Fig. 5 shows a sample plot of hyperparameters tuning of EBDT classifier using N3-DSS.

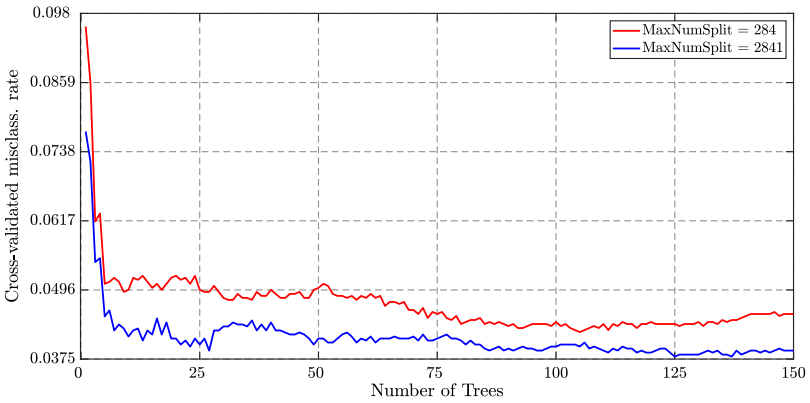

Fig. 5. Hyper parameters tuning for EBDT classifier using N3-DSS. Plot of mis-classification error Vs number of trees.

Table 5
Details of ranking and p-values of 18 extracted features.

Sr. No.	Feature	Sub-band	*p*-value	Rank	Mean ± Std	
					Healthy	Insomnia
1	L_1- norm	SB-1	4.62×10^{-33}	7	$(8.07 \pm 3.16) \times 10^{+04}$	$(5.99 \pm 1.67) \times 10^{+04}$
2		SB-2	0.0255	1	$(2.65 \pm 2.18) \times 10^{+02}$	$(2.39 \pm 0.94) \times 10^{+02}$
3		SB-3	1.92×10^{-10}	13	$(1.15 \pm 0.97) \times 10^{+03}$	$(8.79 \pm 7.13) \times 10^{+02}$
4		SB-4	5.77×10^{-29}	5	$(3.13 \pm 1.74) \times 10^{+03}$	$(2.51 \pm 0.84) \times 10^{+03}$
5		SB-5	9.67×10^{-28}	11	$(7.46 \pm 1.91) \times 10^{+03}$	$(6.32 \pm 2.01) \times 10^{+03}$
6		SB-6	0.0023	4	$(1.27 \pm 0.24) \times 10^{+04}$	$(1.32 \pm 0.53) \times 10^{+04}$
7	L_2- norm	SB-1	8.78×10^{-35}	3	$(4.59 \pm 1.76) \times 10^{+03}$	$(3.41 \pm 0.94) \times 10^{+03}$
8		SB-2	0.1489	10	4.06 ± 4.18	3.93 ± 4.37
9		SB-3	4.31×10^{-12}	17	$(2.48 \pm 2.79) \times 10^{+01}$	$(2.42 \pm 6.05) \times 10^{+01}$
10		SB-4	1.25×10^{-28}	2	$(9.31 \pm 7.61) \times 10^{+01}$	$(7.52 \pm 3.88) \times 10^{+01}$
11		SB-5	1.79×10^{-26}	18	$(3.23 \pm 1.02) \times 10^{+02}$	$(2.71 \pm 0.92) \times 10^{+02}$
12		SB-6	7.28×10^{-04}	6	$(7.42 \pm 1.41) \times 10^{+02}$	$(7.62 \pm 3.04) \times 10^{+02}$
13	$L_\infty-$ norm	SB-1	5.82×10^{-35}	16	$(7.38 \pm 2.88) \times 10^{+02}$	$(5.47 \pm 1.75) \times 10^{+02}$
14		SB-2	1.88×10^{-11}	12	$(4.34 \pm 6.37) \times 10^{-01}$	$(4.41 \pm 11.95) \times 10^{-01}$
15		SB-3	2.58×10^{-19}	15	2.82 ± 6.08	$(0.32 \pm 1.04) \times 10^{+01}$
16		SB-4	1.20×10^{-19}	8	$(1.08 \pm 2.34) \times 10^{+01}$	$(0.92 \pm 1.57) \times 10^{+01}$
17		SB-5	1.33×10^{-17}	9	$(5.08 \pm 3.17) \times 10^{+01}$	$(4.23 \pm 2.44) \times 10^{+01}$
18		SB-6	1.36×10^{-07}	14	$(1.28 \pm 0.33) \times 10^{+02}$	$(1.23 \pm 0.52) \times 10^{+02}$

Validation and Model Evaluation: For each of ten DSS, models are trained separately using ten-fold cross-validations (CV). The classification performance are computed in terms of average classification accuracy (ACC), sensitivity, specificity and area under the receiver operating characteristics (AROC). In order to take care of data imbalance issue, Kappa value is also computed for all the ten models corresponding to the ten different DSS employed by us. Since κ includes the agreement occurring by chance, it is generally considered as more robust measure than simple percent agreement. ACC can be considered a good performance metric when the number of observations are almost equal in all classes (data is balanced). However, as the number of observations is different for each class in our study, ACC is not sufficient to evaluate such systems. Therefore, Cohens' kappa coefficient (κ) is used to evaluate these models.

We have trained ten models corresponding to each DSS. Having validated each model using ten-fold CV, we selected the model that gave the best classification performance for further testing (model evaluation). We observed that the model obtained through N3-DSS outperformed all state-of-art systems. Therefore, the model corresponding to N3 is further tested using leave one subject out cross validation (LOSOCV) in order to avoid the bias caused due to inclusion of samples from the same subject, and to mitigate the over-fitting issue.

Table 6
Details of number of epochs for healthy and insomniac subjects used in the original unbalanced data.

Sleep stage	Number of epochs		
or Data subset	Total	Healthy	Insomnia
W	4246	445	3801
N1	503	280	223
N2	4628	2172	2456
N3 (SWS)	2842	1757	1085
R	2395	1409	986
N1+N2 (LSS)	5131	2452	2679
N1+N2+N3 (NREM)	7973	4209	3764
W+N1+N2+N3+R (ALL)	14614	6063	8551

4. Results

We have conducted the entire study presented in this paper on a Windows Server 2019 equipped with Intel Xeon Platinum 8168 CPU @2.7 GHz (4 cores) and 8 GB of RAM. We have performed our study on both *'unbalanced'* as well as *'balanced'* data-sets. The results obtained using both datasets are given in the subsequent two subsections.

4.1. Classification results considering 'unbalanced' data

A total of 14614 epochs (6063 epochs for healthy + 8551 epochs for insomnia) were used for the classification task using

Table 7
Results of classification obtained using EBDT classifier with ten-fold CV strategy using unbalanced data.

Sleep stage or Data set	Number of epochs.	Performance Evaluation parameters						
		Accuracy (%)	Precision	Specificity	Sensitivity	F1-Score	κ	AROC
W	4246	93.43	0.7677	**0.9811**	0.5348	0.6305	0.5957	0.89
N1	503	87.08	0.8772	0.8430	0.8929	0.8850	0.7376	0.93
N2	4628	91.79	0.8951	0.9031	0.9346	0.9144	0.8356	0.94
N3 (SWS)	2842	**95.60**	**0.9621**	0.9382	**0.9670**	**0.9645**	**0.9067**	**0.97**
R	2395	93.57	0.9391	0.9118	0.9524	0.9457	0.8669	0.98
N1+N2 (LSS)	5131	90.96	0.8926	0.8985	0.9217	0.9069	0.8190	0.93
N1+N2+N3 (NREM)	7973	91.33	0.9328	0.9275	0.9007	0.9165	0.8265	0.97
W+N1+N2+N3+R (ALL)	14 614	92.06	0.9087	0.9359	0.8991	0.9038	0.8363	0.97

Table 8
Confusion matrix obtained for each unbalanced DSS using EBDT with ten-fold CV strategy.

(a) Wake stage

True class	Predicted class	
	Healthy	Insomnia
Healthy	53.5%	46.5%
Insomnia	1.9%	98.1%

(b) N1 stage

True class	Predicted class	
	Healthy	Insomnia
Healthy	89.3%	10.7%
Insomnia	15.7%	84.3%

(c) N2 stage

True class	Predicted class	
	Healthy	Insomnia
Healthy	93.5%	6.5%
Insomnia	9.7%	90.3%

(d) N3 stage (SWS)

True class	Predicted class	
	Healthy	Insomnia
Healthy	96.7%	3.3%
Insomnia	6.2%	93.8%

(e) REM stage

True class	Predicted class	
	Healthy	Insomnia
Healthy	95.2%	4.8%
Insomnia	8.8%	91.2%

(f) LSS stages (N1+N2)

True class	Predicted class	
	Healthy	Insomnia
Healthy	92.2%	7.8%
Insomnia	10.2%	89.8%

(g) NREM stages (N1+N2+N3)

True class	Predicted class	
	Healthy	Insomnia
Healthy	90.1%	9.9%
Insomnia	7.3%	92.7%

(h) ALL stages combined

True class	Predicted class	
	Healthy	Insomnia
Healthy	89.9%	10.1%
Insomnia	6.4%	93.6%

the original unbalanced CAP database. The number of epochs used to develop the model using each of the eight DSS is given in Table 6.

Table 7 depicts the summary of various performance evaluation parameters for each of eight DSS using unbalanced data. The highlighted values in the table indicates peak value in that column. We attained the highest classification performance for N3-DSS with ACC of 95.60%, AROC of 0.97 and $\kappa = 0.9067$. We have achieved above 87% ACC for all eight DSS. Table 7 shows that the models achieved average accuracies of 93.43%, 87.08%, 91.79%, **95.60%**, 93.57%, 90.96%, 91.33% and 92.06% for W, N1, N2, **N3**, R, LSS, NREM and ALL DSS, respectively. Table 8 represents the confusion matrices corresponding to each DSS. To ensure the robustness of the proposed method, we have further tested our best model using the leave one subject out (LOSO) cross-validation (CV) strategy. Our observations indicate that the best performance of insomnia identification was obtained using the N3 sleep stage in our study. Therefore, we used only N3 epochs of subjects to test the trained model. In LOSO-CV, we arbitrarily excluded a pair of healthy and insomnia subjects during the training phase, and the remaining patients were utilized for training purposes. Then, we tested this leaved out pair using a trained model. The classification performance was measured by averaging the results of overall experiments of LOSO-CV. Thus, we avoided the bias caused by the inclusion of recordings from the same subject in the model's development and testing. Table 9 shows the performance evaluation parameters obtained for the N3 sleep stage using LOSOCV. In this work, the testing accuracy of 89.56% and F1 score of 93.07% is attained. This indicates that our model is robust and accurate, hence can be utilized in real-time applications.

Table 9
classification results obtained for N3-DSS with LOSO-CV.

Evaluation parameters	Value (%)
Accuracy	89.56
Precision	98.69
Specificity	95.45
Sensitivity	88.05
F1-Score	93.07

Table 10
Details of training time and prediction speed obtained for each unbalanced DSS.

Sleep stage or DSS	Prediction speed (obs/s)	Training time (s)
W	7400	18.89
N1	3100	3.25
N2	16 000	12.26
N3 (SWS)	13 000	7.81
R	10 000	6.76
N1+N2 (LSS)	10 000	24.09
N1+N2+N3 (NREM)	22 000	21.04
W+N1+N2+N3+R (ALL)	25 000	42.46

The training time and prediction speed obtained for each DSS using EBDT classifier is shown in Table 10.

4.2. Classification results considering 'balanced' data

To avoid the inaccuracy and bias involved in the classification using unbalanced data, we have balanced each dataset's epochs and tested our method's performance using balanced DSS. We have used the under-sampling technique to balance the number of EEG epochs for healthy and insomniac corresponding to each DSS. For example, considering the N3 stage for insomnia identification, initially, the number of healthy and insomniac EEG epochs is 1757 and 1085, respectively, in the case of unbalanced data. As the number of healthy epochs is higher than insomnia, the healthy epochs are reduced to the number of insomnia EEG epochs by randomly selecting 1085 healthy epochs from the unbalanced healthy epochs. So, there are 1085 healthy and insomnia EEG epochs in the balanced data of N3-DSS. The healthy and insomniac EEG epochs of other DSS are also balanced similarly.

A total of 12 126 epochs were used for classification (6063 epochs for both healthy and insomnia) using balanced data. The epoch distribution considering balanced data for each DSS is shown in Table 11.

The summary of performance evaluation parameters obtained for each of eight balanced DSS is shown in Table 12. Using the balanced data also, we have obtained the highest performance for N3-DSS with ACC of 95.53%, AROC of 0.98, and $\kappa = 0.9106$. Table 12 shows that models achieved ACC of 85.06%, 83.41%,

Table 11
Details of number of epochs for healthy and insomnia classes in the balanced data.

Sleep stage or DSS	Number of epochs		
	Total	Healthy	Insomnia
W	890	445	445
N1	446	223	223
N2	4344	2172	2172
N3 (SWS)	2170	1085	1085
R	1972	986	986
N1+N2 (LSS)	4904	2452	2452
N1+N2+N3 (NREM)	7528	3764	3764
W+N1+N2+N3+R (ALL)	12 126	6063	6063

92.45%, **95.53%**, 92.75%, 90.65%, 91.50% and 91.51% for W, N1, N2, **N3**, R, LSS, NREM and ALL DSS, respectively using EDBT classifier with 10-fold CV strategy. The confusion matrices obtained using EBDT classifier corresponding to each DSS with balanced DSS are shown in Table 13. From the results obtained using balanced data, it can be seen that each DSS's performance is comparable and nearly the same as that of unbalanced DSS.

The details of prediction speed and training time obtained for each balanced DSS is shown in Table 14

Table 13
Confusion matrix obtained for each DSS using EBDT classifier considering balanced data.

(a) Wake stage

True class	Predicted class	
	Healthy	Insomnia
Healthy	85.8%	14.2%
Insomnia	15.7%	84.3%

(b) N1 stage

True class	Predicted class	
	Healthy	Insomnia
Healthy	90.1%	9.9%
Insomnia	23.3%	76.7%

(c) N2 stage

True class	Predicted class	
	Healthy	Insomnia
Healthy	94.6%	5.4%
Insomnia	9.7%	90.3%

(d) N3 stage (SWS)

True class	Predicted class	
	Healthy	Insomnia
Healthy	95.6%	4.4%
Insomnia	4.5%	95.5%

(e) REM stage

True class	Predicted class	
	Healthy	Insomnia
Healthy	93.3%	6.7%
Insomnia	7.8%	92.2%

(f) LSS stages (N1+N2)

True class	Predicted class	
	Healthy	Insomnia
Healthy	93.1%	6.9%
Insomnia	12.3%	87.7%

(g) NREM stages (N1+N2+N3)

True class	Predicted class	
	Healthy	Insomnia
Healthy	89.3%	10.7%
Insomnia	6.3%	93.7%

(h) ALL stages combined

True class	Predicted class	
	Healthy	Insomnia
Healthy	92.0%	8.0%
Insomnia	9.0%	91.0%

5. Discussion

The study presents an automated identification of insomnia using EEG signals alone. Novelties of this study are as follows: (i) Proposes an automated system to monitor insomnia using only a single-channel EEG signal. (ii) Presented a novel design of new filter bank with certain desirable features for automated insomnia detection. (iii) Used norm-based features and hence method is computationally less complex. Time required to train the model is 43 s, and testing speed is observed to be 25 000 obs/s. The average computation time to extract a feature is 2.12 ms. (iv) Developed model does not require any pre-processing of EEG signals. (v) Attained an accurate model with AROC of 0.98, F1 score of 0.98 and Cohen's Kappa coefficient of 0.93.

We found that the p-values of extracted features are close to zero. Therefore, each feature is statistically significant for the classification. Simple norm-based features are used, which require less computation time for classification. Other studies used Hjorth parameters features(Hamida et al. [17]) and singular spectrum features(S. Aydin et al. [18]), which are computationally more intensive.

Table 15 shows our method's comparison with other methods reported for the automated insomnia identification using sleep EEG signals. Hamida et al. [17] also used the EEG-based method. It is to be noted that we have used a public CAP database, while they have used a private database. We have developed eight different models using eight DSS, whereas they used only five (W, N1, N2, N3, and REM) classes. We obtained our best model with an accuracy of 95.60% for N3-DSS, while they have obtained the highest accuracy of 91.0% for the same DSS, N3 stage. Thus, our method achieved significantly better performance compared to Hamida et al. [17]. Our method achieved an AROC of close to 1 for each of eight DSS. The Kappa value attained by the proposed model is very high (0.91), whereas the kappa value is significantly less (nearly 9% less) for the model presented by Hamida et al. [17].

The highest accuracy is achieved using EEG epochs of N3 deep sleep stage EEG signals. Hence, it appears that recordings corresponding to only deep sleep EEG signals are needed instead of entire overnight sleep recordings in case one has EEG epochs that are already sleep scored. However, if one does not intend to classify sleep stages, one can identify insomnia reliably with an accuracy of 92.06% (as per Table 7) by combining all epochs together. The classification performance using all epochs together (without considering sleep stage scoring) is comparable with the accuracy attained by using N3 scored epochs. Hence, it is not essential to score the sleep stages for the classification of insomnia. We can classify insomnia using the proposed model using either the sleep-stage-independent approach or the sleep-stage-dependent approach.

Further, we found that EEG epochs corresponding to N1, N2, N3 and their combinations exhibited better classification performance than epochs corresponding to REM and W subsets. Few studies in the past have shown that insomniac patients and healthy controls have different EEG power for NREM and REM sleep stages during sleep [50–52]. This might be the reason that N3-DSS exhibited better performance than other DSS. The advantages of our proposed method are as follows:

Table 12
Results of classification obtained using EBDT classifier with ten-fold CV using balanced DSS.

Sleep stage or DSS	Number of epochs.	Performance evaluation parameters						
		Accuracy (%)	Precision	Specificity	Sensitivity	F1-Score	κ	AROC
W	890	85.06	0.8451	0.8427	0.8584	0.8517	0.7011	0.93
N1	446	83.41	0.7945	0.7668	0.9013	0.8445	0.6682	0.90
N2	4344	92.45	0.9072	0.9033	0.9457	0.9261	0.8490	0.95
N3 (SWS)	2170	**95.53**	**0.9549**	**0.9548**	**0.9558**	**0.9553**	**0.9106**	**0.98**
R	1972	92.75	0.9228	0.9219	0.9331	0.9279	0.8550	0.98
N1+N2 (LSS)	4904	90.65	0.8835	0.8772	0.9307	0.9065	0.8079	0.93
N1+N2+N3 (NREM)	7528	91.50	0.9336	0.9365	0.8935	0.9131	0.8300	0.97
W+N1+N2+N3+R	12 126	91.51	0.9113	0.9104	0.9197	0.9154	0.8301	0.97

Table 14
Details of model training time and prediction speed corresponding to each DSS using balanced data.

Sleep stage or DSS	Prediction speed (obs/s)	Training time (s)
W	3600	9.15
N1	2200	3.76
N2	15 000	11.28
N3 (SWS)	9900	5.71
R	9100	6.23
N1+N2 (LSS)	16 000	12.35
N1+N2+N3 (NREM)	22 000	17.76
W+N1+N2+N3+R (ALL)	27 000	30.75

- The multi-channel PSG procedure involves acquiring ECG and EOG signals requiring many electrodes to be placed on the patient's head, making the patient uncomfortable to move and disturb the entire night's sleep. Hence, in this work, we have used single-channel EEG to develop the automated insomnia detection system.
- In the existing studies [17,18,26] for analyzing sleep disorders including insomnia, first brain waves ($\delta, \alpha, \theta, \sigma, \beta, \omega$) are extracted from EEG signals using fast Fourier transform or bandpass filtering. Then their relative power features are computed by dividing the power of each frequency band by the total power of all frequency bands. However, the extraction of brain waves increases the pre-processing cost. Moreover, these studies [17,18,26] have used non-linear features such as largest Lyapunov exponent (LLE), sample entropy, correlation dimension, and Hjorth parameters along with relative powers extracted from brain waves. Thus, for the existing methods, not only pre-processing complexity is high, but the computational cost of non-linear feature extraction is also high compared to our norm-based features.
- Further, our method is simple compared to others as we have used only norm-based features for the classification. As few features are used to obtain a high classification performance which reduces the computational time. The method yielded high performance with less complexity. Hence, it can be integrated into the sleep monitoring device.
- The number of computations performed during convolution between the input signal and the filter is directly proportional to the number of non-zero coefficients of the filter for the given input. In this study, we have proposed half band analysis pair filter (HALF) whose half the filter coefficients are zero, and at the same time, the filter is symmetrical (linear-phase). The half-band property reduces the computational cost by half, and the linear phase (symmetrical) structure further reduces the cost by the factor of half. Hence, the computational complexity for sub-band coding using the proposed HALF is one-fourth of standard wavelet filters.
- Our results suggest that the proposed model can reliably identify insomnia using 30-second epoch with single-channel EEG instead of multi-channel, multi-modal, and cumbersome PSG signals.
- Due to the deployment of computationally less expensive HALF wavelet filter for subband computation, extraction of computationally less expensive norm features, usage of only single EEG channel, short-duration EEG epochs, and without requiring any pre-processing to obtain brain waves reduces the overall computational cost. Hence, it can be installed in an embedded hardware device for clinical usage.
- The original data is unbalanced, the balanced dataset is also created, and both DSS are considered for classification tasks. The model obtained from both DSS has shown comparable classification performance, indicating that the model is not biased towards the class. We have also used ten-fold cross-validation and leave one subject out cross-validation to avoid the over-fitting of model.
- The nonstationary nature of EEG signals requires analysis other than traditional Fourier transform (FT). Purely time domain, frequency domain techniques (based on FT) cannot analyze nonstationary signals [53]. In contrast, wavelet transform is considered an excellent tool for analyzing nonstationary signals [44]. This motivated us to employ a wavelet-based method for the analysis of EEG signals. Further, during the analysis of nonstationary signals, wavelet bases with minimum joint time–frequency product (TFP) are highly desirable [38]. The smaller the TFP of the wavelet better would be the analyzing ability of the wavelet [45]. However, Gabor's uncertainty principle [54] poses lower bound on the TFP, which states that TFP cannot be less than 0.25 [55]. One cannot arbitrarily minimize the localization of wavelets in time and frequency at the same time. Thus, the wavelets that have joint time–frequency localization close to 0.25 are highly desirable in the analysis of signals [56]. Standard wavelets such as Daubechies orthogonal and biorthogonal [57] do not possess good joint localization though they have a maximum number of zero moments [58]. Further, orthogonal wavelet filters designed by Daubechies [58] and Sharma et al. [36,40,59] cannot have symmetry (linear-phase) property, which is desirable in the analysis of signals [55]. Hence, we used an optimal biorthogonal symmetrical wavelet filter that possesses minimal joint localization, good frequency selectivity, and double half-band property [60] simultaneously. The proposed optimal wavelet filter's employment leads to better performance than the standard wavelet filter in analyzing the EEG signals.

Table 15
Comparison of classification performance with other methods.

Study	DSS	Number of epochs.	Performance evaluation parameters (%)			
			Accuracy	Specificity	Sensitivity	k
Proposed method	W	4246	93.4	98.0	53.5	0.59
	N1	503	87.1	84.3	89.3	0.74
	N2	4628	91.8	90.3	93.5	0.83
	N3 (SWS)	2842	95.6	93.8	96.7	0.90
	R	2395	93.5	91.2	95.2	0.86
	N1+N2 (LSS)	5131	90.9	89.8	92.2	0.82
	N1+N2+N3 (NREM)	7973	91.3	92.7	90.0	0.83
	W+N1+N2+N3+R (ALL)	14 614	92.1	93.6	89.9	0.84
Hamida et al. [17]	W	3402	67.9	73.6	65.3	0.34
	N1	1600	79.0	77.0	68.1	0.43
	N2	5535	86.9	84.5	89.7	0.73
	N3 (SWS)	2491	91.0	90.2	91.6	0.81
	R	2487	90.1	94.3	87.5	0.79

A comparison has been presented between the optimal HALF proposed by us and standard Daubechies popularly used biorthogonal wavelet filter to identify insomnia. Our wavelet-based features surpassed the performance of existing state-of-the-art techniques in identifying insomnia automatically. We obtained the kappa value of 0.72 and accuracy of 84.62% with Daubechies biorthogonal wavelet filters, whereas, with our optimal HALF, we obtained kappa value of 0.84 and an accuracy of 92.06%, when all epochs are combined to classify normal and insomniac EEG signals. Hence, the optimal wavelet-based features used in the study are better than the standard wavelet-based features.

The limitations of developed model are described as follows:

- Though we are using single channel EEG signals, it may still causes little discomfort to the patients. Also, the portable EEG sensors/ recoding machines those can be used at homes are relatively expensive.
- Used limited number of subjects in this study. Model need to be tested further with more database before the clinical use.

It may be noted that the CAP database employed in this study consists of only seven insomnia and six healthy subjects. Given the small number of subjects, we have used supervised machine learning-based technique on optimal wavelet-based features to identify insomnia automatically. Nowadays, deep learning (DL) have become popular in the classification of physiological signals [61]. However, the training and testing of DL-based methods require a huge database. Since the CAP data size is limited in size, we have not employed DL-based techniques in our present study. However, we intend to explore the possibility of using DL methods such as convolutional neural networks (CNN), long short-term memory (LSTM) networks, and autoencoders using large databases in our future work.

6. Conclusion

We have proposed a novel method to identify insomnia automatically using single-channel EEG signals of sleep stages of 30 s epochs. We have used novel optimal bi-orthogonal wavelet-based features for the identification of insomnia. In our study, we performed the classification of healthy and insomnia using the CAP sleep database. The highest classification accuracy of 95.6% and Kappa value of 0.97 is achieved using the N3 deep sleep stage. Hence, we propose that only deep sleep can be used instead of entire overnight sleep recordings if sleep scoring is performed; otherwise, all EEG epochs irrespective of their sleep scores need to be combined and used for the identification of insomnia. Our method has achieved better performance than the existing methods. The proposed single-channel EEG automated insomnia identification method is accurate, useful, fast, and simple. The suggested model can be used in home-based systems and hospitals for quick and precise identification of insomnia. In the future, we intend to explore the performance of the proposed model in identifying other sleep disorders such as bruxism, narcolepsy, and nocturnal frontal lobe epilepsy using EEG, electrocardiogram (ECG), electromyogram (EMG), and elecrtooculogram (EOG) signals. We also plan to use deep learning techniques to identify various sleep disorders, including insomnia.

CRediT authorship contribution statement

Manish Sharma: Conceptualization, Methodology, Software, Writing - original draft, Visualization, Investigation. **Virendra Patel:** Software, Validation, Writing - review & editing. **U. Rajendra Acharya:** Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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