



Automatic identification of insomnia using optimal antisymmetric biorthogonal wavelet filter bank with ECG signals

Manish Sharma ^{a,*}, Harsh S. Dhiman ^b, U. Rajendra Acharya ^{c,e,d}

^a Department of Electrical Engineering, Institute of Infrastructure, Technology, Research and Management (IITRAM), Ahmedabad, India

^b Department of Electrical Engineering, Adani Institute of Infrastructure Engineering, Ahmedabad, India

^c School of Engineering, Ngee Ann Polytechnic, Singapore

^d Department of Bioinformatics and Medical Engineering, Asia University, Taiwan

^e School of Management and Enterprise University of Southern Queensland, Springfield, Australia



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ABSTRACT

Sleep is a fundamental human physiological activity required for adequate working of the human body. Sleep disorders such as sleep movement disorders, nocturnal front lobe epilepsy, insomnia, and narcolepsy are caused due to low sleep quality. Insomnia is one such sleep disorder where a person has difficulty in getting quality sleep. There is no definitive test to identify insomnia; hence it is essential to develop an automated system to identify it accurately. A few automated methods have been proposed to identify insomnia using either polysomnogram (PSG) or electroencephalogram (EEG) signals. To the best of our knowledge, we are the first to automatically detect insomnia using only electrocardiogram (ECG) signals without combining them with any other physiological signals.

In the proposed study, an optimal antisymmetric biorthogonal wavelet filter bank (ABWFB) has been used, which is designed to minimize the joint duration-bandwidth localization (JDBL) of the underlying filters. The \mathcal{L}_1 -norm feature is computed from the various wavelet sub-bands coefficients of ECG signals. The \mathcal{L}_1 norm features are fed to various supervised machine learning classifiers for the automated detection of insomnia. In this work, ECG recordings of seven insomnia patients and six normal subjects are used from the publicly available cyclic alternating pattern (CAP) sleep database.

We created ten different subsets of ECG signals based on annotations of sleep-stages, namely wake (W), S1, S2, S3, S4, rapid eye moment (REM), light sleep stage (LSS), slow-wave sleep (SWS), non-rapid eye movement (NREM) and W + S1+S2+S3+S4+REM for the automated identification of insomnia. Our proposed ECG-based system obtained the highest classification accuracy of 97.87%, F1-score of 97.39%, and Cohen's kappa value of 0.9559 for K-nearest neighbour (KNN) with the ten-fold cross-validation strategy using ECG signals corresponding to the REM sleep stage. The support vector machine (SVM) yielded the highest value of 0.99 for area under the curve with the ten fold cross-validation corresponding to REM sleep stage.

1. Introduction

Nowadays, at least 10% of the world population suffers from a sleep disorder [1]. Insomnia is often characterized as a sleep disturbance. This disturbance usually includes a variety of symptoms such as difficulty in initiating sleep, difficulty maintaining sleep, final awakening that occurs much earlier than desired, or sleep of low quality in terms of duration [2, 3]. Waking symptoms are associated with daytime complaints related to fatigue, sleepiness, mood disturbance, cognitive difficulties, and social

or occupational impairments [4]. It may be noted that there exists a connection between sleep disorders (which are commonly detected by EEG signals) and cardiac activities [5]. The study on insomnia identification can possibly indicate signs of heart ailments due to insufficient sleep.

A daily physiological and psychologically important routine sleep plays a vital role in shaping a healthy life. Insomnia, which is dominant in adults, leads to an erratic sleep pattern [6]. In medical diagnosis, practitioners collect data through questionnaires, polysomnography,

* Corresponding author.

E-mail addresses: manishsharma.iitb@gmail.com, manishsharma@iitram.ac.in (M. Sharma), harsh.dhiman@aii.ac.in (H.S. Dhiman), ACHARYA@np.edu.sg (U.R. Acharya).

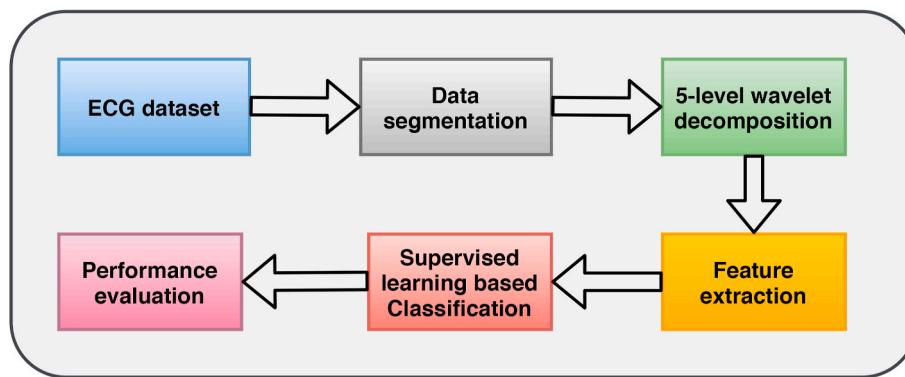


Fig. 1. Block diagram of the proposed methodology.

and measures as suggested by the American Academy of Sleep Medicine (AASM) [7]. However, due to the time-consuming nature, these procedures are not attracted to the modern-day medical diagnosis of insomnia. Several other methods like piezoelectric and pressure based sensors and electroencephalogram (EEG) are also used actively for insomnia detection [8]. Studies in Taiwan have indicated prolonged use of the internet and cellphones are among the reasons for sleep disorder [9]. A diagnostic criterion that aims to identify potential reasons for a sleep disorder is created, and 468 adolescents are analyzed. Modern-day automatic insomnia detection techniques are based on polysomnography (PSG) recordings, which includes multi-channel signals from electroencephalogram (EEG), electrocardiogram (ECG), electromyography (EMG), and electrooculography (EOG). However, the PSG-based methods are time-consuming and often uncomfortable for the patients under examination. Further, it is possible to obtain false-positive results, which may arise from the change in the detection environment due to multiple channels for signal extraction. This drawback has paved the way for insomnia detection using single-channel EEG signal [10].

McCloskey et al. implemented a data-driven cluster analysis for identifying people with different phenotypes of insomnia [11]. Physiology-based spectral quantitative electroencephalography (qEEG) signals representing brain activity are considered for cluster analysis, where a Bayes Gaussian mixture model is used with principal component analysis. The variational Bayes Gaussian mixture (VB-GMM) model is compared with standard clustering algorithms like K-means and Agglomerative clustering. Comparison is evaluated in terms of average silhouette score and results VB-GMM-PCA outperformed K-means and agglomerative clustering with a score of 0.624. Hamida et al. [12] studied the performance of sleep stages for insomnia detection using EEG signals, and results revealed that slow-wave sleep (SWS) yielded the highest accuracy of 91% followed by rapid eye movement (\sREM) with 90.1% of the tested stages. Shahin et al. [13] presented a two-stage automated insomnia detection model using EEG signals. A deep neural network (DNN) classified the input samples based on the different sleep stages in the first stage. In the second stage, the DNN classifier discriminates insomniac subjects from normal ones regardless of the sleep stage. Finally, the corresponding outputs from the first stage are used to train five algorithms, namely, classification and regression trees (CART), linear discriminant analysis (LDA), support vector machines (SVM) with linear, radial basis function (RBF), and sigmoid kernel function. Results reveal that SVM with radial basis function kernel yielded an accuracy of 83%, followed by SVM (with linear) with 81%. Angelova et al. [14] used an actigraphy time-series to detect insomnia in patients. Features pertaining to the statistical properties, sample entropy, and Poincare plot are used to train SVM and Random forest models. Results reveal that the random forest model yielded an accuracy of 84% while SVM obtained around 73%. Mulaffer et al. [15] presented SVM based insomnia detection in which the EEG signals from C3 and C4 channels are used. In

the second model, features extracted from hypnogram with SVM classifier resulted in an accuracy of 71.3%.

Morin et al. [16] proposed an insomnia severity index (ISI) as a useful tool to identify and detect insomnia among patients. ISI aims to analyze potential inconsistency present in insomnia patients. Abudullah et al. [17] discussed SVM based classification to identify primary insomnia patients. The PSG data is collected from ten healthy subjects and ten patients diagnosed with primary insomnia, where sleep stages are scored for every 30-s epochs. Non-linear features such as the largest Lyapunov exponent (LLE) and detrended fluctuation analysis (DFA) are used to achieve an accuracy of 83% with SVM and 75% with linear discriminant analysis (LDA). Yang et al. [18] presented sleep identification based on single-channel EEG signals using deep learning techniques. EEG signals for nine healthy subjects, and nine insomnia patients are analyzed, and four different subsets are constructed from the EEG signals. Based on these four subsets, REM and SWS stages achieved the highest accuracy using a one-dimensional convolutional neural network (CNN) model. Heart rate variability (HRV) is another factor used to discriminate insomnia patients from normal ones. Variation in a heart-beat can be characterized by RR (R wave to R wave) or NN (normal beat to normal beat) interval. Farina et al. [19] presented HRV analysis for insomnia detection where 85 patients affected by chronic insomnia are analyzed. Results revealed an increased heart rate activity in wake before sleep, early-stage S2, and late-stage S2. Shahin et al. [20] presented a deep learning technique using 57 EEG signals extracted from two EEG channels. The analysis is carried out in two stages, wherein stage I used the entire EEG signal irrespective of the sleep stage. In stage II, only specific sleep stages are used to differentiate between insomnia and normal classes. Results reveal that the non-rapid eye movement (NREM)+REM stage yielded an accuracy of 92% when compared to other sleep stages. In Ref. [21], the authors study classification of sleep stages for the subjects suffering from Insomnia, Sleep-Disordered Breathing (SDB), REM Behavior Disorder (RBD) using ECG data and results indicate that decision tree based SVM yields an accuracy of 86.27% for scoring the sleep stages. However, it is to be noted that they have not made an attempt to identify the insomnia using ECG signals unlike the proposed study by us. In this study, we classify normal sleepers and insomniacs using optimal wavelet based norm features.

This work's motivation arose from the limitations posed by the usage of PSG signals, as mentioned above. Further, the current literature on insomnia detection is carried out using a private database [20,22]. In this work, ECG signals are used for automated detection of insomnia among patients with a public database. The methodology used in this work involves the segmentation of complete ECG signals (normal and insomniac) into sleep stages like S1, S2, S3, S4, wake, and REM. Further, an optimal class of antisymmetric biorthogonal wavelet filter bank (ABWFB) is applied to each of the epoch to fragment the signal into six different sub-bands. The optimal wavelet filter bank is designed by minimizing the joint duration-bandwidth localization of the filters.

Table 1

Details of ECG channel and it's sampling frequencies of normal subjects.

Subject	Channel (ECG)	Frequency
n1	ECG1-ECG2	512
n2	ECG1-ECG2	512
n3	ECG1-ECG2	512
n4	EKG	200
n5	ECG1-ECG2	512
n6	ECG	128
n7	ECG	128
n8	EKG	200
n9	ECG	128
n10	ECG1-ECG2	512
n11	ECG1-ECG2	512
n12	EKG	100
n15	EKG	200
n16	NO ECG CHANNEL	-

Supervised learning-based classification is used for automated detection of insomnia using ECG signals.

The major contributions of this manuscript are as follows:

1. Developed an automated system to detect insomnia using ECG signals captured during various sleep stages.
2. Proposed model is developed using publicly available CAP sleep database.
3. Model performance is developed for individual sleep stages (wake, S1, S2, S3, S4, REM) and their combinations light-sleep stage (LSS) (S1+S2), slow-wave sleep (SWS) (S3+S4), non-rapid eye movement (NREM) (S1+S2+S3+S4), and ALL (all stages combined) (W + REM + NREM).
4. Proposed model attained an accuracy of 97.87%, F1 score of 0.9737, and Kappa value of 0.9559 in detecting insomnia class automatically using ECG signals with REM stage. Our method outperformed all other EEG and PSG based methods.

This manuscript is organized as follows: Section 2 discusses the method(s) used for the classification of ECG signals. The results obtained using the proposed method are presented in Section 3 followed by discussion in Section 4. Conclusions of this work are presented in Section 5.

2. Methods and materials

Fig. 1 shows the proposed system used for the automated detection of insomnia using ECG signals. First, the sleep disorder cyclic alternating pattern (CAP) database [23] is downloaded. Then it is segmented into normal and insomnia classes with 30-sec durations (epochs). The epochs are normalized using Z-score. Then, these epochs are subjected to wavelet decomposition (up to 5 levels). Then norm features are extracted from the decomposed subband (SB) coefficients. Then the significant features are fed to the KNN classifier for automated classification.

2.1. Dataset used in this work

The recording of insomnia patients and healthy subjects were obtained from the publicly available CAP sleep database [23]. The CAP sleep database comprises of 108 polysomnographic recordings, composed of 16 healthy subjects who did not have any sleep disorder and 92 recordings of patients diagnosed with sleep disorder like bruxism, insomnia, and narcolepsy. The waveforms (contained in the edf files of the database) include at least 3 EEG channels (F3 or F4, C3 or C4 and O1 or O2, referred to A1 or A2), electrooculogram (EOG) (2 channels), electromyogram (EMG) of the submental muscle, bilateral anterior tibial EMG, respiration signals (airflow, abdominal and thoracic effort and SaO2) and EKG. Additional traces include EEG bipolar traces, according to the 10–20 international system (Fp1-F3, F3-C3, C3-P3,

Table 2

Details of ECG channel and it's sampling frequencies of insomniac patients.

Subject	Channel (ECG)	Sampling frequency
ins1	ECG1-ECG2	128
ins2	ECG1-ECG2	512
ins3	ECG1-ECG2	256
ins4	ECG1-ECG2	512
ins5	ECG1-ECG2	512
ins6	ECG1-ECG2	512
ins7	ECG1-ECG2	512
ins8	ECG1-ECG2	512
ins9	ECG1-ECG2	512

Table 3

Details of CAP dataset used.

S. No.	Subject	Gender	Age	No. of Epoch	Duration (in S)
1	ins2	Female	58	1674	50220
2	ins4	Female	58	732	21960
3	ins5	Female	59	1719	51570
4	ins6	Female	54	1056	31680
5	ins7	Female	47	1482	44460
6	ins8	Male	64	839	25170
7	ins9	Male	72	1049	31470
8	n1	Female	37	1146	34380
9	n2	Male	34	999	29970
10	n3	Female	35	1000	30000
11	n5	Female	35	1007	30210
12	n10	Male	23	859	25770
13	n11	Female	28	1052	31560
Range	-	-	23 to 72	732 to 1719	21960 to 51570
Mean	-	-	46.4615	1124.2	33725
±SD	-	-	±15.3819	±309.6247	±9288.7
Total	-	-	-	14614	438420

Table 4

Number of epochs in each sleep stage.

S. No.	Subject	W	S1	S2	S3	S4	REM	Total No. of Epoch
1	ins2	836	5	455	145	0	233	1674
2	ins4	62	6	352	61	97	154	732
3	ins5	917	5	430	96	98	173	1719
4	ins6	493	62	227	64	122	88	1056
5	ins7	609	19	509	64	61	220	1482
6	ins8	231	73	268	189	0	78	839
7	ins9	653	53	215	51	37	40	1049
Total no. of epoch for Insomnia subject								8551
8	n1	39	33	513	136	186	239	1146
9	n2	142	141	368	83	114	151	999
10	n3	135	49	348	112	168	188	1000
11	n5	9	49	414	134	169	232	1007
12	n10	66	2	262	46	265	218	859
13	n11	56	6	267	61	282	380	1052
Total no. of epoch for healthy subject								6063
Total no. of epoch for both subject								8551 + 6063 = 14614

P3-O1 and/or Fp2-F4, F4-C4, C4-P4, P4-O2) [24].

The details of ECG channels for normal and insomnia subjects and its frequencies are given in Tables 1 and 2, respectively. In this work, we have used the ECG1-ECG2 channel with sampling frequency = 512 sample/second. We have used a total of 14614 epochs of duration 30 s obtained from thirteen subjects. In this, we have used 8551 epochs of insomnia subjects and 6063 epochs of healthy subjects. The one epoch is equal to 30 s. Nine female and four male aged between 23 and 72 were considered for this study, and details are provided in Table 3.

The total number of 14614 epochs including epochs which includes various sleep stages are considered in this study. The number of epochs in each stage is given in Table 4. The proposed work involves the automated classification of insomnia and healthy subjects using all

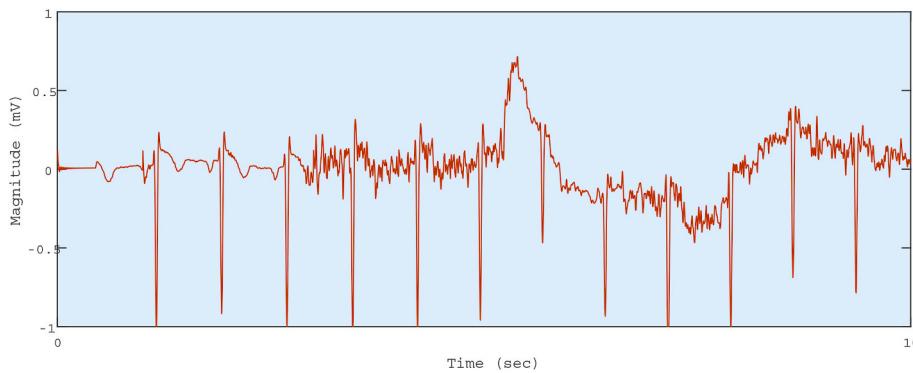


Fig. 2. Sample insomnia ECG signal.



Fig. 3. Sample normal ECG signal.

individual and combination of sleep stages.

2.2. Proposed approach

The flow chart of the proposed work is depicted in Fig. 1. The sample waveform of ECG1-ECG2 signal for insomnia and healthy subjects is given in Figs. 2 and 3 respectively. The ECG1-ECG2 signals are segmented to obtain epochs of duration 30s, which are used for wavelet decomposition, features extraction and classification. It is to be noted that in the CAP database, ECG recordings are digitized at various sampling frequencies such as 100, 128, 200 and 512 Hz. In this study, we have considered only those ECG recordings which are sampled at 512 Hz sampling frequency for both insomniac patients and normal sleepers. Therefore, the total number of 13 ECG recordings (7 insomniacs + 6 normal) are considered in this study as shown in Table 3.

In order to analyze the ECG signal properly, it is segmented into epochs of 30 s. The ECG signals are non stationary and non-linear in nature. Hence, the analysis of ECG needs special tools. An efficient method need to be employed to achieve the localization both in time and frequency domains for accurate analysis. Wavelet transform methods perform well in both time and frequency domains. Therefore, in this work, a biorthogonal wavelet filter [25,26] is used to segment the ECG signal into low and high frequency components.

2.2.1. Overview of bi-orthogonal wavelet filter bank

Wavelet filter banks find numerous applications in communication and signal processing. Nowadays, design approach involves the use of an optimization problem that aims to achieve convergence in any one of compaction energy, stop-band energy, frequency selectivity, roll off factor, ripples and joint duration-bandwidth localization (JDBL) of filters [25]. In particular, the role of JDBL of filters is dominant in image processing, edge detection and feature extraction. Further, JDBL filter banks are found be an excellent tool for the analysis of non-stationary

physiological signals including ECG [27,28]. Few researchers have used them for the classification of bio signals and obtained optimum results, which has motivated us to use this filter bank [29,30].

Consider a Type-II, linear phase, real-valued, finite impulse response (FIR) filter with length $L = 2N$, and impulse response, $h(n), 0 \leq n \leq L - 1$. Given the frequency response with a real valued amplitude

$$H(e^{j\omega}) = e^{(j\omega(L-1)/2)} \overline{H}(e^{j\omega}) \quad (1)$$

The mean-squared duration σ_n^2 , mean-squared bandwidth σ_w^2 of a low-pass filter can be written as

$$\sigma_n^2 = \frac{1}{E} \sum_{n=-\infty}^{\infty} n^2 |h(n)|^2 = \frac{1}{\pi E} \int_0^\pi |\mathbf{H}'(\omega)|^2 d\omega$$

$$\sigma_w^2 = \frac{1}{\pi E} \int_0^\pi \omega^2 |H(\omega)|^2 d\omega$$

where E is the energy content of the filter $h(n)$ and $\mathbf{H}'(\omega)$ is the derivative of $\mathbf{H}(\omega)$. In order to describe the design process of antisymmetric bi-orthogonal wavelet filter banks (ABWFB), the optimization function can be given as [31].

$$J = v\sigma_n^2 + (1-v)\sigma_w^2 \quad (2)$$

where the term $v \in (0, 1)$ represents duration-bandwidth trade-off factor. Further the product of duration-bandwidth product is lower bounded by the inequality $\sigma_n^2 \sigma_w^2 \geq 0.25$. The convex objective function then can be written as [32].

$$J = \gamma \mathbf{D}^T \mathbf{D} + (1-\gamma) \mathbf{B}^T \mathbf{B} = \mathbf{b}^T \mathbf{Q} \mathbf{b} \quad (3)$$

where \mathbf{D} and \mathbf{B} are known as mean-duration and mean-bandwidth matrices [33]. The above objective function (JDBL) has been minimized for both the analysis and synthesis lowpass filters, subject to the

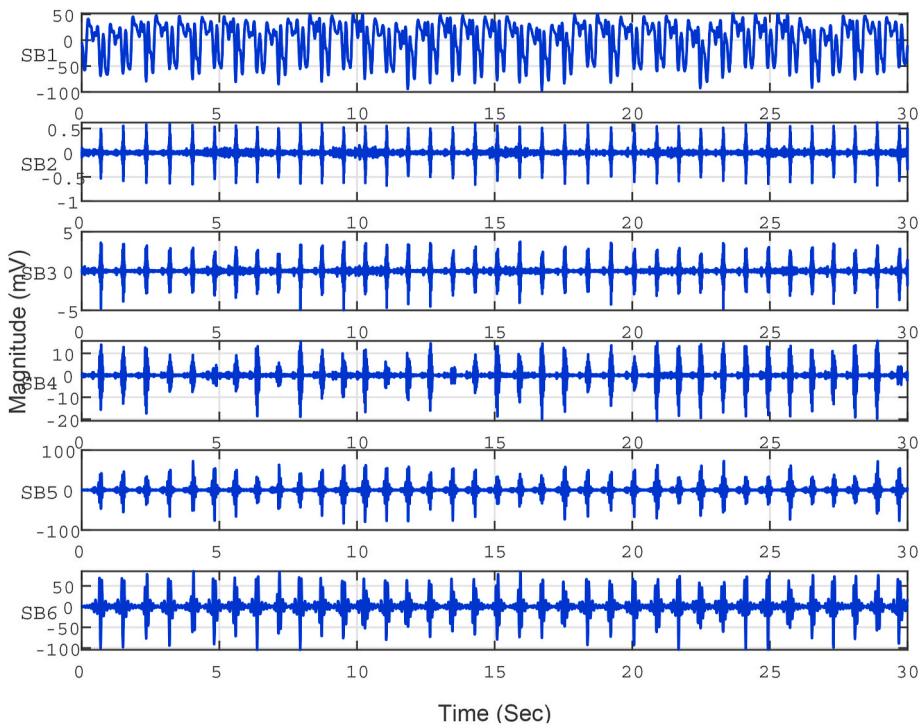


Fig. 4. Sub-bands for the sample Normal REM-ECG epoch.

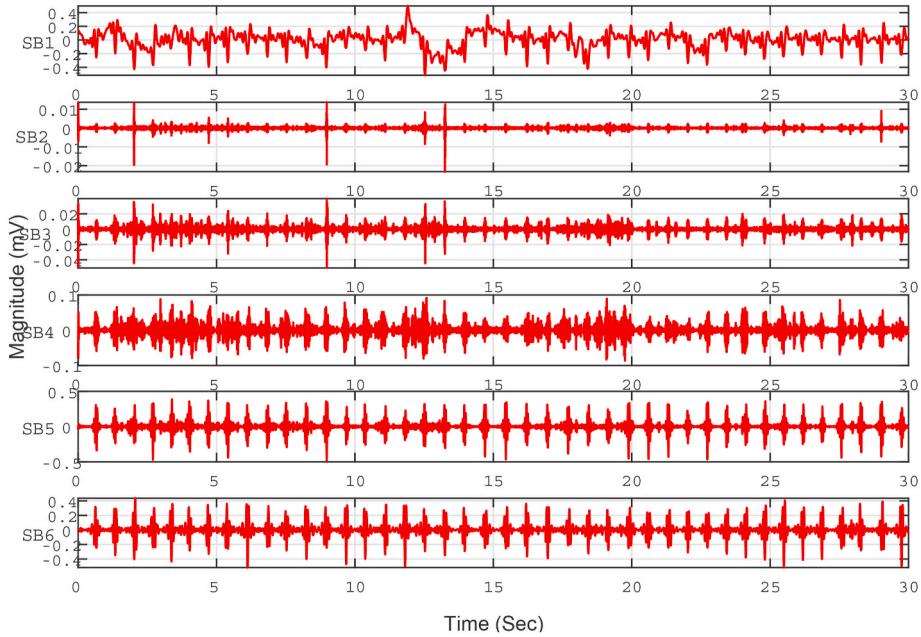


Fig. 5. Sub-bands for the sample Insomniac REM-ECG epoch.

conditions of perfect reconstruction and regularity (vanishing moments) by formulating semidefinite programs (SDPs) [27,34].

2.2.2. Wavelet decomposition

The biorthogonal wavelet filter bank [30] is used for detection of insomnia. In this work, five-level wavelet decomposition on the ECG1-ECG2 signal is performed. The five level decomposition produces total six sub bands, out of six, five are detailed wavelet sub-bands (WSB) and the remaining one is the approximate WSBs. The WSBs corresponding to sample normal and insomniac epochs are shown in Figs. 4 and 5.

2.2.3. Feature extraction

The next step is to compute features from the obtained WSBs. The norm feature is computed for each six WSBs for automated identification of insomnia. The generalized equation of a p -norm for a signal (x) can be given as

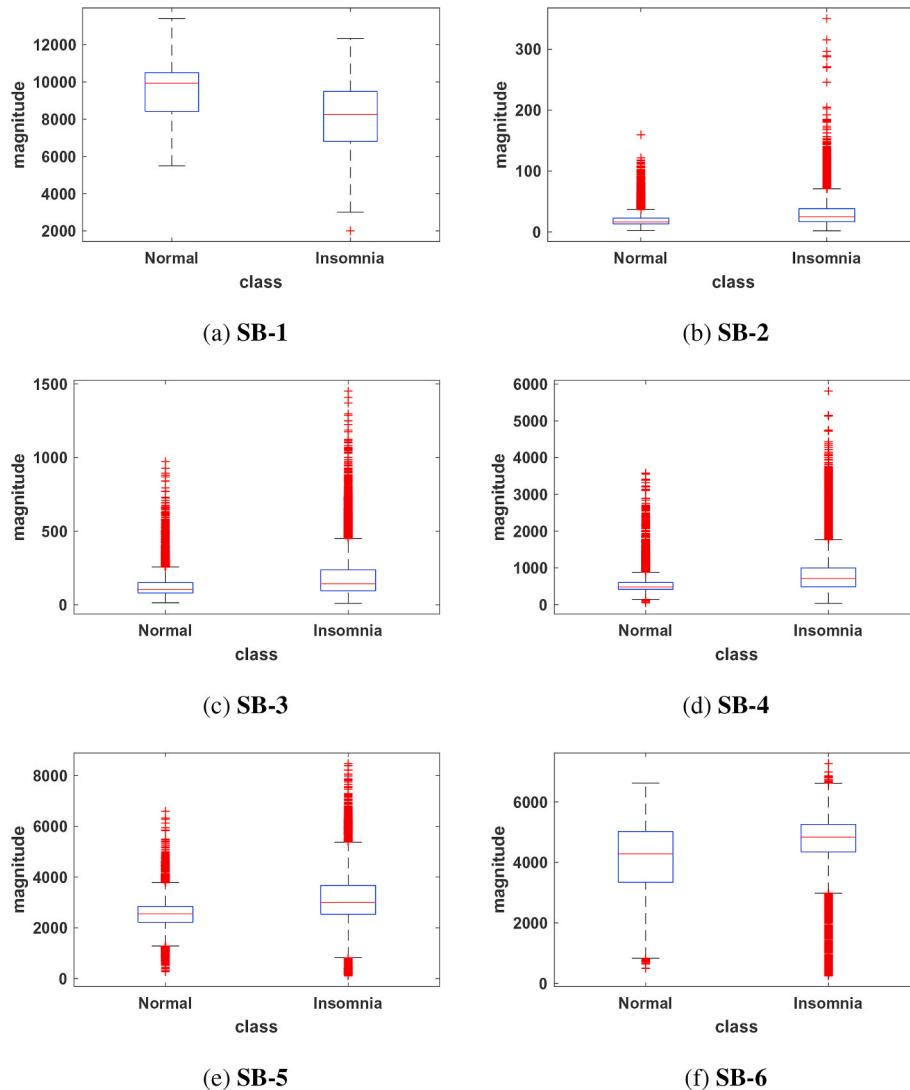
$$\left\| x \right\|_p = \left(\sum_{i=1}^n |x_i|^p \right)^{1/p} \quad (4)$$

where p is positive integer. For $p = 1$, the \mathcal{L}_1 -norm can be given as

Table 5

Mean and standard deviation of features for the combined stage.

SBs	Insomnia	Normal	P-values	Rank	relative difference
	Mean ± Standard deviation	Mean ± Standard deviation			of mean values of two classes in %
1 (a1)	8181.87 ± 1404.08	9540.46 ± 1195.9	0	6	14.24
2 (d5)	32.22 ± 24.55	20.44 ± 12.77	2.7407e-270	5	-57.63
3 (d4)	200.39 ± 162.53	132.06 ± 86.67	1.6356e-287	1	-51.74
4 (d3)	880.64 ± 614.03	588.34 ± 325.32	0	4	-49.68
5 (d2)	3144.01 ± 1002.42	2537.48 ± 615.01	0	3	-23.91
6 (d1)	4683.36 ± 907.55	4167.75 ± 1070.65	0	2	-12.37

Fig. 6. Box plots of the \mathcal{L}_1 feature corresponding to six sub-bands for all-combined stage.

$$\|x\|_1 = \sum_{i=1}^n |x_i| \quad (5)$$

The extracted features from SBs are combined column wise and labelled to generate a feature matrix. The generated feature matrix is applied for classification.

2.2.4. Classification and performance evaluation

The extracted features are fed for classification with 10-fold cross-validation [35] strategy. It is observed that maximum accuracy is obtained using weighted KNN and KNN classifiers. The \mathcal{L}_1 -norm feature is computed from the wavelet decomposed ECG1-ECG2 signal. In order to

evaluate the classification performance parameters such as, accuracy, sensitivity, specificity, precision, and F1 score, and Cohen's kappa are calculated.

3. Results

In the proposed work, we have used 8551 epochs of insomnia and 6063 epochs of healthy subjects (Total = 14,614 epochs). The classification is carried out by considering individual sleep stages, LSS, SWS and combined sleep stages. We have computed performance parameters such as F1 score, precision, sensitivity, specificity, and accuracy for the classification of insomnia and healthy subjects. The mean and standard

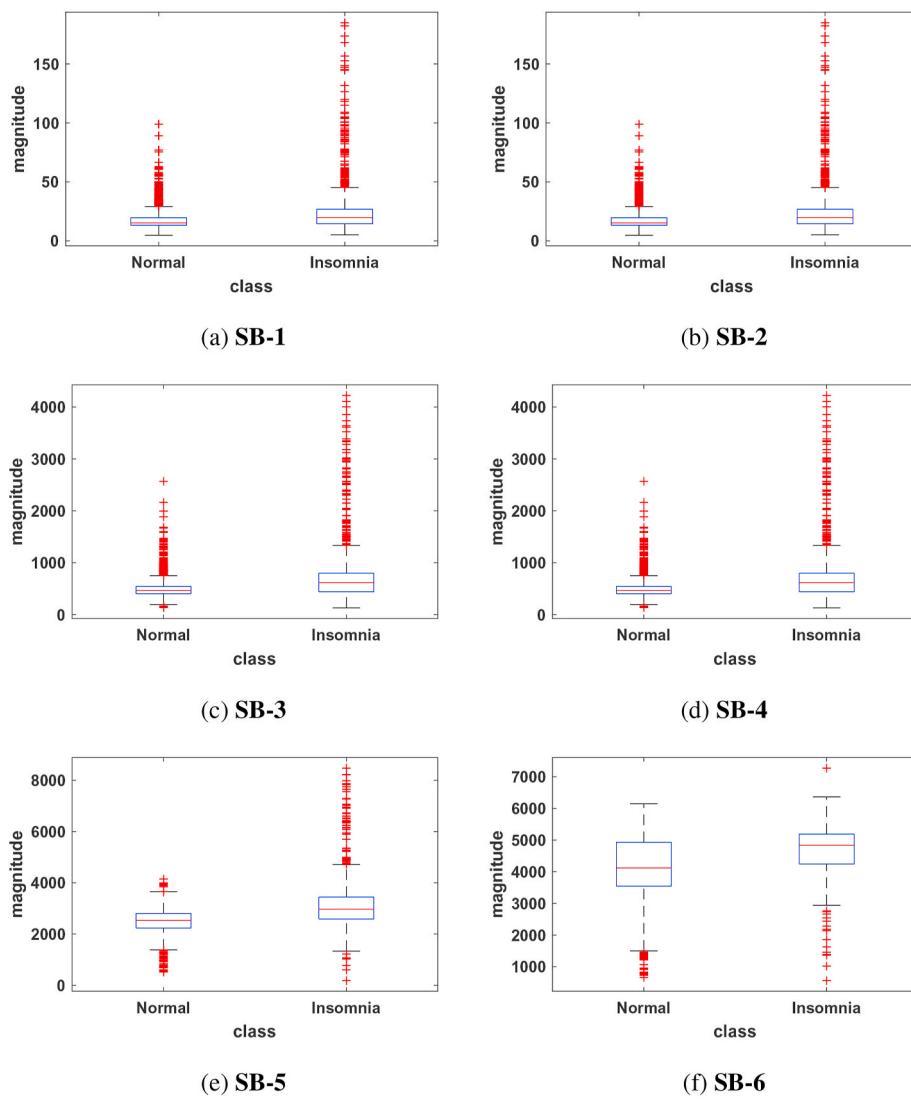


Fig. 7. Box plots of the \mathcal{L}_1 feature corresponding to six sub-bands for REM stage.

Table 6
Classification result for identification of insomnia for different stages using KNN classifier.

Sleep Stage	No. of epoch	Accuracy	Precision	Sensitivity	Specificity	F1 score	Cohen's kappa	AUC
W	4248	0.9670	0.9704	0.9934	0.7427	0.9818	0.8079	0.96
S1	503	0.9145	0.9245	0.8789	0.9429	0.9011	0.8259	0.91
S2	4628	0.9542	0.9543	0.9597	0.9480	0.9570	0.9080	0.99
S3	1242	0.9436	0.9518	0.9433	0.9441	0.9475	0.8867	0.94
S4	1599	0.9644	0.9106	0.9566	0.9671	0.9330	0.9088	0.99
REM	2394	0.9787	0.9815	0.9665	0.9872	0.9739	0.9559	0.98
LSS (S1+S2)	5131	0.9507	0.9595	0.9455	0.9564	0.9524	0.9013	0.99
SWS (S3+S4)	2841	0.9571	0.9357	0.9530	0.9596	0.9443	0.9094	0.99
NREM (S1+S2+S3+S4)	7972	0.9528	0.9515	0.9485	0.9567	0.9500	0.9054	0.95
All combined	14614	0.9440	0.9466	0.9583	0.9238	0.9524	0.8843	0.99

deviation values of features with p-values and ranking for different SBs are shown in Table 5. It can be observed that for each SB, the p-value is close to zero which implies that all features are statistically significant and good discrimination between normal and insomnia classes is possible. From Table 5, it can be observed that the feature obtained from SB3 has the highest rank followed by SB6, SB5, SB4, SB2 and SB1. The mean value of \mathcal{L}_1 -norm for SB1 is found to be higher for healthy subjects compared with insomnia patients, whereas for SB2 to SB6 the mean values of \mathcal{L}_1 -norm are higher for insomniacs than healthy subjects. Figs. 6 and 7 illustrate the box plots of sub-bands for combined and REM

stage respectively.

A summary of results obtained for automated detection of insomnia corresponding to different sleep stages based on KNN classifier is depicted in Table 6. Results indicate a highest accuracy of 97.87% is achieved in the REM stage followed by an accuracy of 96.7% in the W stage. Further, as insomnia identification is carried out using several machine learning classifiers such as Quadratic SVM, Gaussian SVM and Cubic SVM, Ensemble bagged tree and KNN because apriori it cannot be predicted which classifier will perform the best due to the non-stationarity and non-linearity nature of ECG signals. Table 7 depicts

Table 7

Classification results obtained for identification of insomnia in REM stage using different classifiers.

Classifier	Accuracy	Precision	Sensitivity	Specificity	F1 score
KNN	0.9779	0.9655	0.9804	0.9761	0.9729
Gaussian SVM	0.9779	0.9706	0.9755	0.9795	0.9731
Weighted KNN	0.9728	0.9584	0.9752	0.9712	0.9668
Cubic SVM	0.9724	0.9655	0.9675	0.9759	0.9665
Cubic KNN	0.9678	0.9493	0.9720	0.9651	0.9605
Ensemble Bagged Tree	0.9591	0.9381	0.9615	0.9574	0.9497
Cosine KNN	0.9574	0.9584	0.9394	0.9705	0.9488
Quadratic SVM	0.9541	0.9381	0.9497	0.9570	0.9439

the classification results using these classifiers for the REM sleep stage. The KNN and SVM yielded superior results compared to others with an accuracy of 97.79%. Fig. 8 illustrates the confusion matrices of classification results obtained for automated insomnia detection in W, S1, S2, S3, S4 and REM stage, and all combined stages using the KNN classifier with the ECG signal. In terms of area under receivers operating

characteristic (AUC), Fig. 9a and b depict the performance of the Gaussian SVM and KNN for REM sleep stage. It can be noted from the plots that, the SVM classifier performed better than the KNN classifier in terms of the AUC curve.

4. Discussion

Features for sleep stages are obtained by computing \mathcal{L}_1 -norm from the coefficients of wavelet sub-bands. The \mathcal{L}_1 -norm is used for feature extraction as it helps in faster computation of features which enables sparsity in the solution. We tested many norm based features such as $\mathcal{L}_1, \mathcal{L}_2, \mathcal{L}_3, \mathcal{L}_4$ and \mathcal{L}_{∞} -norms as well as a few non-linear features such as fractal dimension, hurt exponent and lyapunov exponent. Among these features, we obtained the best performance with the \mathcal{L}_1 -norm. Further, the \mathcal{L}_1 -norm captured the size of sub-bands and can be computed easily with computational complexity of $O(3n)$, but the complexity of other non-linear features is higher than the norm-based features.

Further, in 10-fold cross-validation, epochs may arise from the same subject during the training and testing phase. In order to avoid this bias,



Fig. 8. Confusion matrices for different sleep stages based on KNN classifier.

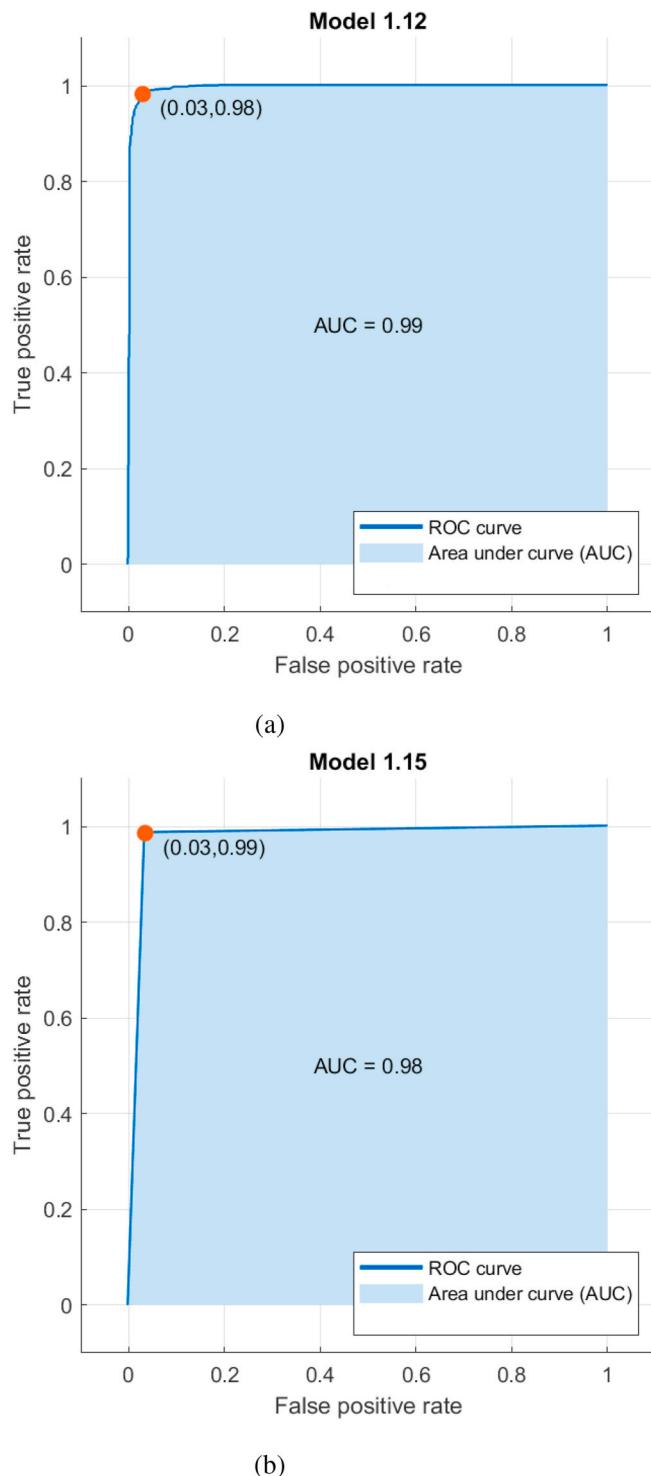


Fig. 9. Area under ROC corresponding to REM: (a) Gaussian SVM and (b) KNN.

we have used hold-out cross-validation where 70% and 30% of epochs are used for training and testing respectively. The epochs considered for training and testing do not belong to the same subjects. Thus, hold-out validation is considered, and, training and testing epochs are mutually exclusive and disjoint. The results of hold-out validation are found to be comparable with 10-fold cross-validation and are depicted in Table 8. It can be observed that highest classification accuracy of 97.35% is achieved in the REM stage.

A few physiological and cortical activation are found between insomniac and normal subjects [36]. Authors did not observe any fixed

power spectra in normal and insomnia classes using HRV and ECG signals [37,38]. Studies have shown diverse and contradictory results for normal control and insomniac classes using power spectra based features [39,40]. Moreover, characteristics of ECG and HRV signals have varied in sleep stages. A few studies have been conducted to analyze the variation in ECG patterns of various sleep stages in normal and insomnia classes [41], however consistent results are not obtained. It has been observed that insomnia patients have a faster cardiac rhythm than healthy subjects [39]. Several studies have shown an increased heart rate and blood pressure [19,37,42]. It can be noted from our study that for the low-frequency ECGs, insomnia classes will have lower \mathcal{L}_1 -norm values than the healthy subjects. However, as frequency increases, the \mathcal{L}_1 -norm for insomnia patients become greater than normal subjects. In particular, at SB-1, which is an approximate lowest frequency sub-band (a1), the mean value of \mathcal{L}_1 -norm is found to be lesser for insomnia class compared to normal. However, at SB2-SB6 (detailed wavelet coefficients), the mean value of the ECG-norm corresponding to insomnia class is more than healthy subjects. It is also interesting to note that the relative difference of means values between insomniac and normal classes is highest for the detailed wavelet coefficient (d5), which is the highest sub-band frequency, and the difference is least for the minimum frequency detailed wavelet coefficient (d1) (Table 5). Due to substantial hereditary and individual variability, it is difficult to generalize the statistical rules for features extracted by us using a small database developed using limited subjects. Therefore, a more extensive database is required to establish specific statistical rules or trends using wavelet-based features in this study. We also propose that the identification of insomnia using HRV would be an interesting study. Also, it is worth exploring changes occurring in various sleep stages of normal and insomnia patients. Further, for automated detection of insomnia, few studies [43,44] have used EEG, however, the relationship and interplay between various EEG rhythms during various sleep stages and ECG can be explored in the future.

It is to be noted that in the proposed method, the model identified each 30s epoch from the whole night EGG recording of insomniac or normal. The automated identification system developed using one epoch can not be considered to screen 7–8 h of night sleep. Hence, to deploy the proposed model in the clinical environment, one should use the entire night data to classify normal and insomnia classes. Further, our study indicates that there is a connection between sleep disorders (which are commonly detected by EEG signals) and cardiac activities. During the sleep, some heart-related issues such as chest pain or some other malfunction of ECG may be due to the presence of sleep disorder of the patients, rather than being due to cardiac ailments [45]. The study on insomnia identification can possibly indicate signs of heart ailments due to insufficient sleep.

Our model is developed with a 10-fold cross-validation technique, which ensures no data leakage during the training and testing phase. Dimensionality reduction can also improve the classification performance; however, we did not perform it as we have used only six features. Using KNN classifier, the detection accuracy of 96.7%, 91.45%, 95.42%, 94.36%, 96.44%, 97.87%, 95.28% is obtained for W, S1, S2, S3, S4, REM and NREM stages respectively. Based on this observation, it can be inferred that using \mathcal{L}_1 features obtained from ECG epochs corresponding to the REM stage yielded maximum classification accuracy followed by the S4 stage. Further, with all stages combined, KNN achieved the accuracy and precision of 94.4% and 94.66%, respectively.

The proposed identification of insomnia is developed using CAP sleep ECG recording. First, we have extracted the ECG1-ECG2 channel from PSG data. The sleep stages are separated according to the extracted channel's annotations and segmented into epochs of 30 s. Each ECG epoch is subjected to wavelet decomposition, and \mathcal{L}_1 -norm features are computed. Kruskal-Wallis test is performed to find the p-value of each feature. The clinically significant features ($p < 0.05$) are fed to the classifiers for automated classification. To achieve better performance, we have used individual sleep stages (Wake, S1, S2, S3, S4, REM) and

Table 8

Classification results obtained using normalized data with hold-out cross-validation (30%).

Classifier	Accuracy	Precision	Sensitivity	Specificity	F1 score	AUC
W	0.9662	0.9930	0.9700	0.9252	0.9814	0.97
S1	0.9667	0.9545	0.9692	0.9647	0.9618	0.96
S2	0.9546	0.9430	0.9707	0.9375	0.9566	0.99
S3	0.9489	0.9353	0.9691	0.9270	0.9519	0.96
S4	0.9729	0.9274	0.9664	0.9750	0.9465	0.96
REM	0.9735	0.9661	0.9694	0.9764	0.9677	0.97
LSS (S1+S2)	0.9539	0.9589	0.9530	0.9549	0.9559	0.99
SWS (S3+S4)	0.9519	0.9479	0.9279	0.9672	0.9378	0.99
NREM (S1+S2+S3+S4)	0.9573	0.9495	0.9597	0.9553	0.9546	0.99
All combined	0.9389	0.9548	0.9416	0.9349	0.9481	0.98

also subsets of sleep stages (LSS, SWS, NREM, all combined). We evaluated various performance parameters from the confusion matrix of different sleep stages and achieved the highest accuracy of 97.87% for the REM sleep stage. The proposed method based on ECG recordings yielded more accurate results for the identification of insomnia than using EEG based methods [43]. The ECG based method is easy to use, non-invasive, fast, and accurate. The ECG signals obtained can be visualized easily, but EEG signals are challenging to decipher as they are chaotic in nature.

In this study, we have used a small number of subjects to develop the model. This is one of the limitations of this work. We intend to use more data with more number of subjects to validate our developed system in the future. We are also planning to explore the possibility of developing a deep learning model using huge database. Further, we also plan to extend this work using CAP database with other physiological signals such as multi-modal EEG and EOG. Some other disorders such as bruxism and narcolepsy, nocturnal frontal lobe epilepsy (NFLE), periodic leg movement (PLM), rapid-eye movement (REM) behavioral disorder and sleep-disordered breathing can also be detected using such automated models.

5. Conclusion

In this work, we proposed an optimal wavelet-based model for the automated detection of insomnia. The proposed model achieved better performance than the existing EEG and PSG based system using sleep stage annotated ECG1-ECG2 channel. The ECG signals are separated into sleep stages and segmented into 30 s of epochs according to the annotations. Each epoch is subjected to the optimal antisymmetric biorthogonal wavelet filter bank. The wavelet decomposition produced six sub-bands for each epoch. Subsequently, \mathcal{L}_1 -norm of each sub-band has been computed for the classification of normal and insomnia epochs. Individual and subsets of ECG epochs corresponding to various sleep stages and their combinations are used for the classification employing various supervised machine learning algorithms to achieve the optimum performance. The best results are exhibited by ECG epochs corresponding to REM sleep stages using the KNN classifier. We obtained average accuracies of 96.7%, 91.45%, 95.42%, 94.36%, 96.44%, 97.87%, 95.07%, 95.71%, 95.28%, 94.40% for sleep stages W, S1, S2, S3, S4, REM, LSS, SWS, NREM and all combined stages, respectively. The highest accuracy of 97.71% is obtained using ECG signals corresponding to the REM sleep stage, followed by the S4 stage. Insomnia detection is carried out using several machine learning classifiers in the REM stage. Results indicate that the performance of SVM is comparable with KNN. In the future, we intend to validate our developed model using more data from a large number of subjects and plan to employ it for clinical application to confirm the insomnia diagnosis by the sleep specialists. We propose developing a model using heart rate variability signals extracted from ECG signals using the proposed optimal wavelet-based features in combination with machine learning or deep learning techniques to identify insomnia and other sleep disorders like narcolepsy and nocturnal front-lobe epilepsy, periodic leg movement (PLM), rapid-eye

movement (REM) behavioral disorder and sleep-disordered breathing.

Declaration of competing interest

Authors do not have any conflict of interests.

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