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IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Ensemble Computational Intelligent for Insomnia Sleep Stage Detection via the Sleep ECG Signal

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ABSTRACT Insomnia is a common sleep disorder in which patients cannot sleep properly. Accurate detection of insomnia disorder is a crucial step for disease analysis in the early stages. The disruption in getting quality sleep is one of the big sources of cardiovascular syndromes such as blood pressure and stroke. The traditional insomnia detection methods are time-consuming, cumbersome, and more expensive because they demand a long time from a trained neurophysiologist, and they are prone to human error, hence, the accuracy of diagnosis gets compromised. Therefore, the automatic insomnia diagnosis from the electrocardiogram (ECG) records is vital for timely detection and cure. In this paper, a novel hybrid approach based on the power spectral density (PSD) of the heart rate variability (HRV) is proposed to detect insomnia in three classification scenarios: (1) subject-based classification scenario (normal Vs. insomnia), (2) sleep stage-based classification (REM Vs. W. stage), and (3) the combined classification scenario using both subject-based and sleep stage-based features. The ensemble learning of random forest (RF) and decision tree (DT) classifiers are used to perform the first and second classification scenarios, while the linear discriminant analysis (LDA) classifier is used to perform the third combined scenario. The proposed framework includes data collection, investigation of the ECG signals, extraction of the signal HRV, estimation of the PSD, and AI-based classification via hybrid machine learning classifiers. The proposed framework is fine-tuned and evaluated using the free public Physio Net dataset over fivefold trails cross-validation. For the subject-based classification scenario, the detection performance in terms of sensitivity, specificity, and accuracy is recorded to be 96.0%, 94.0%, and 96.0%, respectively. For the sleep stage-based classification scenario, the detection evaluation results are recorded equally with 96.0% for ceiling level accuracy, sensitivity, and specificity. For the combined classification scenario, the LDA classifier have achieved the best insomnia detection accuracy of 99.0% of the three cases as discussed. In future, the proposed approach could be applicable for mobile observation schemes to automatically detect insomnia disorder.

INDEX TERMS Sleep Disorder; Cardiovascular Syndromes; ECG Sleep Signals; AI-based Insomnia Detection; Hybrid Classification Scenarios.

I. INTRODUCTION

Sleep is a natural phenomenon categorized due to changed awareness, reserved sensual drive, besides decreased strength drive [1]. Sleep has a vital part in the lifespan of natural creature's viz. such as toad, frogs, snakes, human beings, small creatures. Few types of creatures have their sleep with eyes open and mostly, the creatures have their sleep with eyes closed [2]. Sleeps remain classified into two stages, Fast Eye Drive (FED) and Slow Eye Drive (SED). The eye movement of a creature defines the classification of the sleep that is NREM, S1, S2, S3 and S4. According to the guideline of NREM classification in 2007, according to AASM [3], NREM are divided into three stages such as N1, N2, and N3. These two manuals (R&K and AASM) are included REM, Wake (W), and Movement Time (MT) stages[4] with NREM. Lack of sleep affects the human life such as remembrance problems, temper variations, attention problems, danger of diabetes, low sex drives, poor balance on the leg, danger of heart problems, heaviness of body, high B.P., and danger of the accident [5], [6]. Lack of sleep also do the negative impact on his calories to effort, fitness and expressive equilibrium [7], [8]. Sound sleep is an indication that a person is healthy. It is a very general procedure that decreased sleep could reduce the efficacy of a person, energy of a body, capability to withstand stress and variability in mood [9]–[12]. If this disorder will be ignored further can cause huge problems viz. pressure, reduction in efficiency, obstruction, pursuance reduction. Globally, insomnia is a highly predominant health issue. It is defined as complaint of glitches ongoing commencement sleep convoyed by concentrated day functioning ongoing aimed at small stone month [13], [14]. The human being which is suffering from sleep disorder get up in nighttime very often and feels dizziness and not feel fresh, lack of concentration and memory loss [14].Sleep disorder is a very general delinquent in common people in the current time [15], [16]. The main symptoms of insomnia are tension, headaches, sleepiness, etc. Additionally, the main causes of insomnia are depression, heartbroken in love, sleep sickness, job loss, environmental factors, etc.[17]. It also comes with discomfort and tiredness [18]. Though, sleep disorder is a very general circumstance in entire people, although doctors and the affected person are absent in the information over it. There are no common acknowledged parameters for treating. The consequences of sleep disorder are mood swings and an enhanced prospect of some miss happening while handling vehicles or doing some daily activities. Sleep disorder is not an indication of additional illnesses, nonetheless it is subordinate to additional medicinal circumstances[19]. Insomnia is classified into three basic categories including etiology, duration, and sleep pattern. According to etiology, insomnia can be categorized in two kinds viz. primary and secondary. Additionally, based on duration, insomnia can be classified into three types such as transient, chronic, and acute. Accordingly, based on sleep pattern, sleep disorder can be separated into two kinds such as sleep maintenance and sleep onset.

II. MOTIVATION BEHIND THE STUDY

The Quality of sleep is one of the most important factors in our daily lives. It is crucial for balanced functioning of the body. There are many disorders arise due to lack of quality sleep viz. brain fog in which person cannot respond to questions as well as difficulty in focusing, depression, anxiety, deprived social skills and many other cardiovascular problems. These problems motivated us to work in this area. Early-stage detection is the most crucial step towards any disorder. Classical methods are time consuming and expensive. So, by the applied approach in our manuscript, we can automatically detect sleep disorder the stages and subjects.

III. LITERATURE SURVEY

In the previous studies, Ohayon *et al.* [20] suggested that an important quantity of the people with sleep grievances do not appropriate into the International Classification of Sleep Disorders (ICSD) and DSM-IV classifications. Additionally, efforts are desirable to classify diagnostic standards that will lead to insomnia detection. Morin *et al.*[21] proposed that the Insomnia Severity Index (ISI) is a valid instrument to diagnose insomnia in the population. Aydin *et al.*[22] Reported that Singular Spectrum Analysis (SSA) detected the oscillatory differences in sleep EEG. The EEG taste to support the medical findings for mental disorders. Israel *et al.*[23] calculated the temporary constancy of many directories of sleep in attired sleeper panels and primary sleep disorder. Presently, Polysomnography (PSG) is the gilded typical technique for the detection of insomnia. PSG includes recording & monitoring many signals viz. EEG, Electrocardiogram (ECG), Electrooculogram (EOG), Electromyogram (EMG), oxygen saturation, thoracic, and intestinal drive and additional indications. Consequently, it is expensive, as it needs immediate estimation in sleep laboratory with apparatus and experts. Insomnia detection developed a most important apprehension in current ages. Many scientists used the EEG signal for the analysis of the different diseases [24]–[26].

Siddiqui *et al.*[27] used power spectral density for the recognition of insomnia sleep disorder on 10/20 sleep EEG recording. Gemignani *et al.* [28] represented that thalamic role in the cortical expression of the Sleep Slow Oscillation (SSO) in humans through SSO features in a case of Fatal Familial Insomnia (FFI). Kaplan *et al.* [29] studied that A_1-A_2 channel are used in the automatic detection of sleep-wake. Penzel's *assembly* stated that Insomnia could be identified through Hjorth parameters and classifies the system using the deep learning classifiers [30], [31]. The ECG signal is a non-invasive and low-cost method; it can be easily applied in screening of insomnia. Therefore, automated insomnia detection based on a single-lead ECG is obtaining the consideration of sleep research community. Bahrami *et al.*[32]designed a machine learning model for the prediction

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of sleep apnea based on the ECG signals. Some other researchers used a machine learning models based on the long short-term memory neural networks (LSTM) for the recognition of the heart diseases and sleep apnea using the ECG signals [33], [34]. Demir *et al.* [35] used ECG signals for the detection of person based on the ECG signals.

We proposed a novel recognition scheme of insomnia aimed at the withdrawal of Heart Rate Variability (HRV) [36] on sleep ECG recording. Initially, the ECG channel is extracted from the sleep database of normal and insomnia. This data is record by the 10/20 normal snooze collecting scheme. This is applicable for the approach used in snooze diseases viz. bruxism [37] [38], insomnia, narcolepsy, sleep apnea, nocturnal frontal lobe epilepsy, rapid eye movement behavioral disorder. The ECG signal of the normal and insomnia with Sleep Stage was preprocessed using Low pass filter as a noise removal. After filtration of the signal, we detected the R-R interval of the ECG signal and estimation of the power spectral density.

The Choice of an appropriate classifier to have the best possible result is compulsory. There is no rule and proof to select the best classifiers for the research work. We had to goals by the evaluation of the classifiers such as indicating the best classifier for the same feature and clarifying the condition in which they provide high performance. For this work, we achieved the subject-based and the sleep stage-based using decision tree (DT) and Random Forest (RF)classifiers. Whereas, the combined scenario (i.e., subjects-based and sleep stage-based) is classified using Linear Discriminant Analysis (LDA). In the proposed work, the following techniques have been designed for the detection of insomnia sleep disorder such as extraction of the data set from sleep database, analysis of the work. We had to aim by the evaluation of the classifiers such as indicating the best classifier for the same features and clarifying the condition in which they provide high performance.

Bahrami *et al.* [32] designed a machine learning model for the prediction of sleep apnea based on the ECG signals. Some other researchers used a machine learning models based on the long short-term memory neural networks (LSTM) for the recognition of the heart diseases and sleep apnea using the ECG signals [33], [34]. Demir *et al.* [35] used ECG signals for the detection of person based on the ECG signals.

Salari et.al [56] illustrate about the sleep apnea disorder in which different machine and deep learning approaches have been used to detect the disorder. The RNN approach found to be more efficient as compared to SA and CNN. Different types of machine learning algorithms and their constituent accuracies for automatic detection for patients with sleep apnea. The different types of databases have been discussed viz. IEEE database, Pub med database. The highest accuracy among machine learning algorithms was obtained to be 100%. Among all the deep learning algorithm the highest accuracy was experienced in case of RNN.

Widasri et. al [58] has illustrated an efficient approach for quality sleep classification and sleep stage classification for 30 seconds frequency. The epochs which are to be taken are 30 seconds. The algorithm used here is decision tree classifier.

Stephansen et. al [59] here also the sleep stages have been determined by applying the suitable algorithm T1N marker based on unusual sleep stage overlaps achieved a specificity of 96% and a sensitivity of 91%, validated in independent datasets.

IV. METHODS

Insomnia is a common sleep disorder in which patients cannot sleep properly. Accurate detection of insomnia disorder is a crucial step for disease analysis in the early stages. The disruption in getting quality sleep is one of the big sources of cardiovascular syndromes such as blood pressure and stroke. The traditional insomnia detection methods are time-consuming, cumbersome, and more expensive because they demand a long time from a trained neurophysiologist, and they are prone to human error hence the accuracy of diagnosis gets compromised. Therefore, the automatic insomnia diagnosis from the electrocardiogram (ECG) records is vital for timely detection and cure. The insomnia problem has been solved by applying novel approach that is LDA and gives the precision of 99% for combined sleep stages and subjects. The proposed method consists of five-stages, as shown in the first stage is the pre-processing of the ECG signal. Afterward, we extract the spectral features from the ECG signal in the second stage. The assessment of sleep quality performs in the fourth stage. In the final stages, sleep disorder classifies using an ensemble of Linear Discriminant Analysis. We use MATLAB software for all computations in the proposed method. The proposed method consists of five-stages shown in Figure 1. The first stage is to collect the sleep stage ECG signals from the Physio Net database. Second, the signal pre-processing step of the ECG signals is performed to segment the signals and noise removal. Third, we extract and normalize the spectral HRV features from the ECG signals. Fourth, the sleep quality assessment is performed. In the final stages, sleep disorder is classified in three different scenarios:(1) subject-based classification scenario (normal Vs. insomnia), (2) sleep stage-based classification (REM Vs. W. stage), and (3) the combined classification scenario using both subject-based and sleep stage-based features. The ensemble learning of random forest (RF) and decision tree (DT) classifiers are used to perform the first and second classification scenarios, while the linear discriminant analysis (LDA) classifier is used for the third scenario. Previously, the most of the sleep disorder investigation had concentrated on sleep stage regardless the subject-based status. The MATLAB software is used to execute the experimental study in this work.

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A. DATASET

For this work, the sleep electrocardiogram (ECG) signals are extracted from the freely public Physio Net dataset [39] and they are used to build the proposed insomnia-based framework. The Physio Net dataset has different waveform signals such as electroencephalogram (EEG), Electrocardiogram (ECG), Electrooculogram (EOG), Electromyogram (EMG), and the respiration signals [40]. As it is proven that the insomnia detection system based on the features of REM and W stages of sleep is more accurate than others [41], [42] we choose to build our framework based on those insomnia features as well. In this work, the total number of 2,752 ECG data recordings including 14 normal and insomnia subjects (i.e., six males and eight females) are collected and used as described in *Table 1* where a single ECG recording is collected in a one minute. Additionally, two sleep stages of REM and W stage are used. The sleep dataset from the PhysioNet has 1,600 ECG recordings of the REM stage, and 1,600 ECG recordings of W stage.

TABLE I. DATASET DESCRIPTION

Subjects	Gender	Age (Years)	No of Recordings/ Time of the Recording (Minutes)
Normal cases (6 patients: 2 Males and 4 Females)	Female	37	124
	Male	34	125
	Female	35	140
	Female	35	109
	Male	23	131
	Female	28	213
Insomnia cases (8 patients: 4 Males and 4 Females)	Male	54	130
	Male	82	177
	Female	58	90
	Female	59	507
	Female	54	278
	Female	47	454
	Male	64	144
	Male	72	130
Mean		48.714	196.571
±SD		±16.807	±124.917

B. HRV Extraction from the ECG Signal

ECG signal have six types of waves such as P, Q, R, S. T, and U for the measurement of the cardiac signal. The P wave represents the atrial depolarization, QRS represented the ventricular depolarization, T wave represented the ventricular re-polarization, and U wave represented the muscle re-polarization [43]. The HRV measurements are captured non-invasively from the ECG signal. The results from HRV data are capable of portraying physiological condition of the patient and indicator of the heart diseases [44]–[46]. We estimated the HRV signal per subject using the Pan-Tompking method [36]. The HRV is the beat-to-beat variant of the ECG recording. It is also called the variation of peak-to-peak samples. We used the R peak for finding the HRV

signals. We detected the R peak and then R-R distance from

the sleep ECG signal of normal and insomnia cases. The R-R intervals are described in equation (1),

$$RR(n) = R(n+1) - R(n), \tag{1}$$

where, *RR(n)* is the R-R interval and *R(n)* is the position of n^{th} order of the R wave.

C. Estimation of the Power Spectral Density (PSD)

The power spectral density (PSD) has been estimated and evaluated via the P.D. Welch approach that was found in 1967[47]. This approach could change the period sequence into the section information, and evaluate the changeable periodic signal representation of the entire information. Some sections could be overlaid in the section's samples[48], [49]. The approaches are described in equations (2) to (4),

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

$$P_w(f) = \frac{1}{LU}\sum_{n=0}^{L-1}\left\{w_{hm}(n)\,x(n+iD)\,e^{-j2\pi fn}\right\}^2 \tag{3}$$

$$P_w(f) = \gamma\sum_{n=0}^{L-1}\left(\{X_a^n\}^2 + \{X_b^n\}^2\right) \tag{4}$$

where, U is equivalent to the reimburse for the harm of signal and D information of section in which $w_{hm}(n)$ is the segment range, γ is the parametric value which is non-changeable, and X_b^n be the actual and invented stage of n^{th} section, and $P_w(f)$ is the Welch approach.

D. Decision Tree (DT) Classifier

Decision tree (DT) is a supervised machine-learning classifier where information is constantly separately applicable on the different constant values. It is separated into two stages: classification sapling and reversion sapling. Here in manuscript the classifier is dual few parameters of the random moment in saplings are dividing into small subparts which must be in range of five. The main benefits of this classifier are that computation time is lower, de-noising is embedded in it. Pseudo code of the DT classifier is shown in *Table II*. The DT classifier described in equation (5) and (6),

$$E(H_t) = \sum_j P_j H_j \tag{5}$$

$$R_t = H - E(H_t) \tag{6}$$

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where, H_t is the regular indecision after execution test t, P_j is the chance that the examination has j outcome, and R_t is the regular lessening in doubt attained by examination t.

TABLE II. THE DECISION TREE **(**DT) Pseudo Code (ALGORITHM)

Input: Information	
1.	Loop: 1 to N // To get forecast period **1.1**Compute the detachment Di (Euclidian/ Cosine/ Chebyshev) amid information example in exercise information and examination information
2.	Progressively position the calculated detachments (Di)
3.	Inhabit the higher k consequences from the decided slope
4.	Pick up the most frequent class from the list
5.	Repeat steps: 1 to 4 and build the forest by generating 'n' number of decision trees
6.	Pick up the most frequent class from the list
7.	Create separate two stages by the classification sapling
8.	Then divide the saplings into sub parts.
9.	The range of the sub parts is in the range of 5
Output: Subsequent lesson	

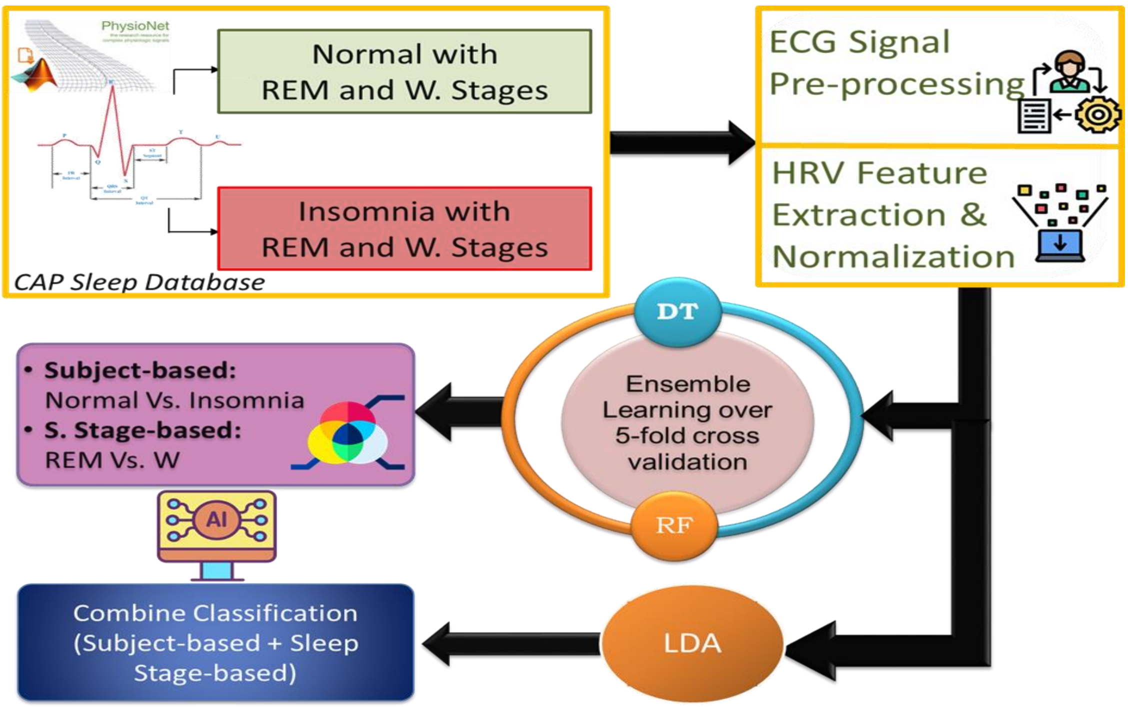

Figure 1. Organizational diagram of the proposed study based on DT and RF machine learning classifier.

E. Random Forest Classifier

Random forest (RF) is an arrangement of the tree predictors such that every tree depends on the values of a random vector sampled individually and with the same circulation for all trees in the forest [50]. RF is an ensemble learning technique for regression, classification, and other works. It is constructed by a multitude of trees in training and output is based on singletree[51], [52]. It was designed by Tin Kam Ho using random subspace method [53], [54]. We used ten numbers of trees in this proposed work. Pseudo code of the RF classifier is mention in *Table III*.

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TABLE III. THE RANDOM FOREST (RF) PSEUDO CODE (ALGORITHM)

Input: Training set S with F features
1. Randomly pick 'p' features 'F' features, ∀ p< F
2. Using 'p' features, determine the node 'd' by the finest fragmented
3. Break the node into child bulges by smearing the best fragmented method
4. Iterate steps: 1 to 3 until '1' number of nodes has been touched
5. Till 3 number of nodes are obtained.
6. The circulation of the trees.
7. Create separate two stages by the classification sapling
8. Then divide the saplings into sub parts.
9. The range of the sub parts is in the range of 5
Output: Random Forest Trees (RFTs)

F. Linear Discriminant Analysis (LDA) Classifier

The renowned scientist RA Fisher discovered the LDA in 1936. It is based on the idea of incisive for a linear arrangement of predictors that discriminate two targets [55], [77]. The LDA are described in equations (7) to (12),

$$Z = L_{mc1}x_1 + L_{mc2}x_2 + L_{mc3}x_3 + ...+ L_{mcn}x_n \tag{7}$$

$$S(f) = \frac{L^t_{mc}\mu_1 - L^t_{mc}\mu_2}{L^t_{mc}CL_{mc}} \tag{8}$$

$$L_{mc} = \frac{1}{C}(\mu_1 - \mu_2) \tag{9}$$

$$C = \frac{1}{n_1 + n_2}(n_1C_1 + n_2C_2) \tag{10}$$

$$M_g^2 = L^t_{mc}(\mu_1 - \mu_2) \tag{11}$$

$$L^t_{mc}\left[x - \left(\frac{\mu_1 - \mu_2}{2}\right)\right] > -\log\frac{P_{c1}}{P_{c2}} \tag{12}$$

where, *S(f)* is a score function, L_{mc} is a linear model coefficient, *C* is the pooled covariance matrix, C_1 and C_2 are the covariance matrices, μ_1 and μ_2 are the mean vector, M_g is the Mahalanob is distance between two groups, and *x* is the coefficient vector.

G. Evaluation of the Proposed Framework

After selection the suitable collection of the features, robust machine learning classifiers such as DT and RF are used as an ensemble learning for better evaluation of the subject-based and sleep stage-based classification scenarios. For the third classification scenario (i.e., combined features from both subject-based and sleep stage-based scenarios), the LDA classifier is used. The proposed framework is evaluated using 3,200 ECG signal recordings including 1,600 REM stage and 1,600 W-stage of both normal and insomnia subjects. We designed the classification of subject and Sleep Stage based on models such as cross-validation (2 and 5-fold) with random sampling. The evaluation process is achieved using the F1-score, precision, sensitivity, specificity, and accuracy for the classification for all classification scenarios[56]–[60]. The definition of such metrics is described in equations (13)-(16) below:

$$precision = \left(\frac{TP}{(TP+FP)}\right) \tag{13}$$

$$Sensitivity = \left(\frac{TP}{(FN+TP)}\right) \tag{14}$$

$$Specificity = \left(\frac{TN}{(FP+TN)}\right) \tag{15}$$

$$Accuracy = \left(\frac{(TP+TN)}{(TP+TN+FP+FN)}\right) \tag{16}$$

$$F_1 = 2*Precision * Recall/ Precision +Recall \tag{17}$$

where the TP, FP, TN, and FN indicate the true positives, false positives, true negatives, and false negatives cases, respectively. Such parameters are derived based on the confusion matrices at each fold test trail.

V. RESULTS AND DISCUSSION

A. Preprocessing and Feature Extraction

The 70 percent of the cardiac arrests are found in the time of insomnia. We used 3,200 ECG recordings including 1600 REM stage and 160 w stages. The duration of the experimental dataset is 3,200 minutes. We extracted the single ECG signal of the normal and insomnia in the sleep recording from *Physionet* for the detection of insomnia shown in *Figure 2*. Because single-channel recordings are easy and accurate to identify the diseases[61], [62], [63].We removed the noise of the subject using low pass filter. After filtration, we calculated the HRV of the signal from the subjects. The R peak to peak of the ECG signal from all subjects is shown in *Figure 3*. The variation of instantaneous both heart rate and RR intervals are called HRV. In the cardiac system, the heart rate varies due to age, disease, neuropathy, respiration, and heart load. After HRV, we calculated the power spectral density of the signal using the Welch method. This method converts the signal from the time domain into the frequency domain. However, Welch method is used in the estimation of power signals at different frequencies. The ECG feature extraction is one of the crucial plays in detecting the cardiovascular disorder. The span of ECG signal contains P-QRS-T waves. The extraction system takes out the amplitudes and time intervals between them which attain the proper operation of the heart.

Nowadays, various manuscripts define about the approaches used in converting the planned literature for extracting the feature of ECG signal. The crucial information in cardiac signal dispensation and their executed replications are elaborated as follows. The denoising method is applicable in the time period of prior dispensation of the response signal. For getting better results it is crucial that the signals are interrupted by noise and should be removed to get efficient outcomes. approaches used in these are base motion, frequency interruption, muscle movement and quick response. the limit of the frequency cannot affect the frequency limit for the ECG signal which can be removed by one of the efficient approaches that is simple band stop filter.

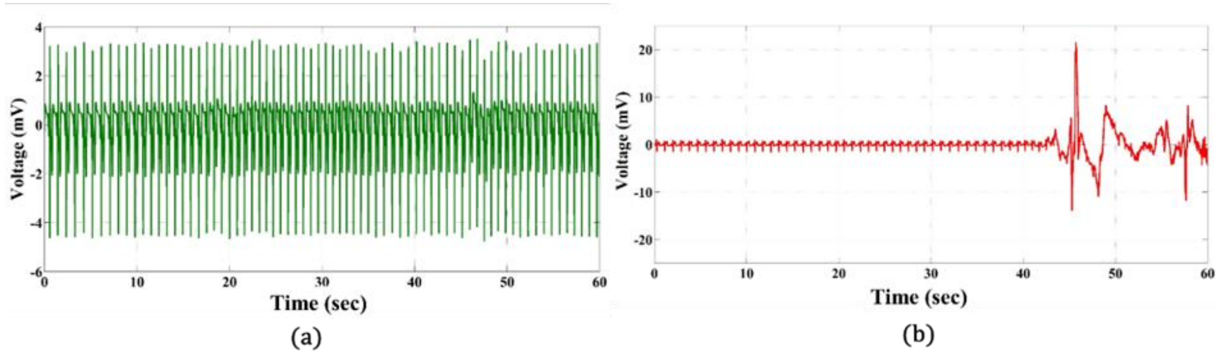

Figure 1. ECG Signal representation from the (a) normal and (b) Insomnia subjects.

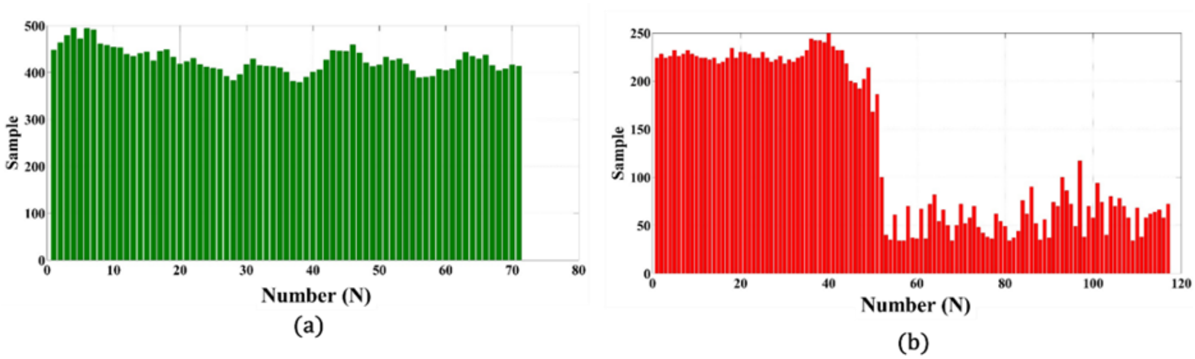

Figure 2.Peak to peak R signal of the ECG signal from the (a) normal and (b) Insomnia subjects.

B. Subject-based Classification Scenario

In this scenario, DT and RF classifiers are used achieving the classification based on the normal and insomnia binary classification scenario. To show an example evaluation result, we designed three models which are the results of the random sampling and two verifying techniques: 2nd and 5th fold cross validation. The evaluation results of this scenario are recorded in Table IV. The average performance of the subject-based classification scenario is recoded to be F1-score of 85.55%, precision of 86.18%, recall of 85.41%, specificity of 81.30%, and overall accuracy of 85.41%. From *Table IV*, it is clearly shown that both DT and RF could achieve much similar results with slightly better performance in the RF classifier. The result varying is due to the DT and RF training algorithms that depends on the internal weights fine-tuning during the training process.

Table IV. PERFORMANCE (%) OF THE SUBJECT-BASED CLASSIFICATION SCENARIO

Models	Method	F1	Precision	Sensitivity	Specificity	Accuracy
Random Sampling	DT	83.70	85.20	83.20	82.80	83.20
2-Fold		85.80	85.70	85.90	78.20	85.90
5-Fold		86.10	86.10	86.20	78.70	86.20
Random Sampling	**RF**	84.40	86.90	83.80	87.00	83.80
2-Fold		86.40	86.40	86.50	80.20	86.50
5-Fold		**86.90**	**86.80**	**86.90**	**80.90**	**86.90**
Ensemble Result	Mean	85.55	86.18	85.41	81.30	85.41
	±SD	1.12	0.59	1.39	2.95	1.39

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C. Sleep Stage-based Classification Scenario

Similarly, both DT and RF classifiers are used to classify the sleep stage-based into REM Vs. w stages. Also, the same evaluation strategy is designed to evaluate the performance of this scenario: random sampling and randomly two-fold tests are selected [78]. The *Table V* presented the individual and ensemble performance of the sleep stage-based classification scenario using DT and RF classifier. The highest performance of the DT classifier is recorded to 87% for all metrics except the specificity it is estimated by 85.0%. Using the RF classifier, the evaluation performance is much better achieved by 88.0% for F1 and precision, 87.90% for sensitivity and accuracy, and 86.80% for specificity.

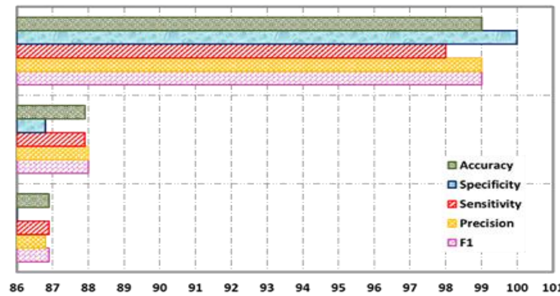
Table V. PERFORMANCE (%) OF THE SLEEP STAGE-BASED CLASSIFICATION SCENARIO

Models	Method	F1	Precision	Sensitivity	Specificity	Accuracy
Random Sampling	DT	24.40	17.30	41.50	58.50	41.50
2-Fold	DT	86.50	86.50	86.60	84.40	86.60
5-Fold	DT	87.00	87.00	87.00	85.00	87.00
Random Sampling	**RF**	75.90	84.60	76.20	83.00	76.20
2-Fold	**RF**	87.60	87.60	87.60	86.30	87.60
5-Fold	**RF**	**88.00**	**88.00**	**87.90**	**86.80**	**87.90**
Ensemble Result	Mean	74.90	75.16	77.80	80.66	77.80
	±SD	22.96	25.90	16.73	9.99	16.73

The unsupervised learning architecture was applicable in the literature using the recognition of sleep stage[64]. Boe *et al.* [65] utilized a multimodal devices assessing hand hastening, ECG, and Acti Watch for the diagnostic sleep stage such as *w*, REM, and NREM. Bajaj *et al.* [66] intended a programmed scheme for the diagnostic sleep stage by means of time occurrence pictures of the EEG indications. Mitsukura *et al.* [67] argued that ECG degree dimension are obliging and informal to sleep stage checking.

D. Combined Classification Scenario

In this scenario, the features of subject-based (i.e., normal Vs. insomnia) and sleep stage-based (REM Vs. W. stage) scenarios are combined together. Then, LDA classifier is used for the classification purpose. Figure 4 shows the average evaluation results in similar way of the first and second scenarios. The best classification performance is achieved in terms of F1, precision, sensitivity, specificity, accuracy to be99.0%, 99.0%, 98.0%, 100%, and 99.0%, respectively. This means the hybrid model via LDA could achieve the best accuracy compared with other scenarios.



	Subject-based Scenario	Sleep Stage-based Scenario	Combined Hybrid Scenario
Accuracy	86.9	87.9	99
Specificity	80.9	86.8	100
Sensitivity	86.9	87.9	98
Precision	86.8	88	99
F1	86.9	88	99

Figure 3. Ensemble evaluation performance comparison among the three proposed classification scenarios.

E. Comparison Study with the Existing Works

The earlier approaches used in the insomnia detection is not that efficient as some can detect sleep stages and some can diagnose subjects. The approach used in the manuscript give three types of classification i.e., sleep stages classification, subject classification and combined classification of sleep stages and subjects. The technique also gives the maximum accuracy by using LDA classifier as described above. The accuracy for LDA classifier for combined classification is 99% which is better than the approach used earlier. The unsupervised learning architecture (deep belief nets and concealed Markov prototypical) had applied for the identification of sleep stage [64]. Boe et al. [65] had applied the multi scheme sensor scheme estimating random eye movement, non-random eye movement for sleep detection. Here, we considered a programmed scheme for the diagnostic Sleep Stage by means of period occurrence imageries of the EEG signals. Mitsukura et al. [67] argued that rate of heart are obliging & informal to sleep stage nursing. They calculated positively four stages with accuracy of 66% of the system. In the proposed work, the LDA classifier's model random sampling is highest in performance to other models of RF classifier.

TABLE VI. COMPARISON STUDY WITH THE EXISTING METHODS FOR INSOMNIA SLEEP DISORDER AND SLEEP STAGE CLASSIFICATION

Reference	Detection	Classifier	Accuracy (%)
Abdullah *et al.* [68]	Insomnia	FNN	81.00
Shahin *et al.* [69]	Insomnia	DNN	90.00
Hassan *et al.* [70]	Sleep Stage	AB	94.00
Zhang *et al.* [71]	Sleep Stage	OCNN	88.00
Zhou *et al.* [72]	Sleep Stage	RF, LGB	91.00
Proposed Work	**Insomnia and Sleep Stage**	**Ensemble (Subject-based)**	**86.90**
		Ensemble (Sleep Stage-based)	**87.90**
		LDA (Combined)	**99.00**

FNN: Feed Forward Neural Network, **DNN:** Deep Neural Network, **AB**: Adaptive Boosting, **OCNN**: Orthogonal Convolutional Neural Network, **RF:** Random Forest, **LGB**: Light GBM, **LDA**: Linear Discriminator Analysis, **DT:** Decision Tree

We also compare our method with some insomnia and sleep stage detection methods. The data from those methods include EEG and ECG with different classifiers such as Feed Forward Neural Network (FNN), K-means, Deep Neural Network (DNN), Adaptive Boosting (AB), Orthogonal Convolutional Neural Network (OCNN), RF, and Light GBM (LGB). The Table VI revealed that our model has better performance than other selected models of insomnia and sleep stage classifications. Besides, our method can reach higher sensitivity, specificity and accuracy. The advantages of the proposed approach are that it can automatically accurately detect the insomnia disorder in the very early stage so as to prevent the patient from any cardiovascular disorder and also brain stroke. The automatic detection approach is less time consuming and gives the accurate precision by giving the classification for combined subjects as well as sleep stages. Accurate detection of insomnia disorder is a crucial step for disease analysis in the early stages.

F. Applications of the Proposed Work

The planned effort presented a submission for the identification of insomnia using ECG recording. This manuscript will deliver additional accurate and effective detection systems of insomnia for therapeutic applications. The maximum significant submission of the proposed work is to identify cerebral patients fast and accurately. It also detects the patients with sleep stage to help doctors for the treatment. The current effort has approximately limited that the planned information from the *Physio Net* web was ancient and minor for the estimation. Furthermore, would be obligatory for a great amount of actual information to examine the current effort for greater precision. In the future, we will use diverse sleep disorders like bruxism, narcolepsy, etc. to design a common detective system for all sleep disorders using other physiological signal.

VI. CONCLUSION

We conclude that it is possible to determine sleep disorders based on sleep quality features from 30-seconds epoch of the ECG signal. This approach is proven reliable in modeling sleep disorders without preoccupied with a multichannel signal of PSG. Moreover, it also easy to be implemented in an embedded hardware device. On the other hand, atrial fibrillation and other heart rhythm disorders are prevalent in the elderly population. It might have an impact on the HRV analysis. However, HRV able to assess sympathetic and parasympathetic influences on disease states. Hence, in further analysis, HRV can be improved following the intervention, and thus it has the ability to assess autonomic dysfunction in the elderly's heart rhythm disorders, such as atrial fibrillation, arrhythmias, and ventricular arrhythmias. In future, we intend to observe the autonomic dysfunction in the elderly via HRV intervention. Insomnia is a highly predominant health issue in globally. In this present work, we have developed a machine learning classification method to detect insomnia with sleep stages using a single sleep ECG recording (with 72 male and 28 female samples). The results show that the RF classification is best in the subject classification (Kindly refer Table IV, pg.no.5 in the main manuscript). The Decision Tree (DT), Random Forest (RF) and Linear Discriminant Analysis (LDA) classification approaches have been incorporated to enhance the accuracy (kindly refer Table IV, V and VI on page no. 5, 6 in the main manuscript). In addition, the DT classifier accuracy is found to be 94%, RF to be 96% and LDA classifier is highest in combine accuracy (99 %) with the subject (normal and insomnia) and its sleep stage (wake up and random eye movement). Therefore, we summarize that the LDA classifier can be utilized in the detection of insomnia due to its maximum accuracy (99%). Therefore, it will be easy and more effective the detection of insomnia sleep disorder with its sleep stages as discussed above. So, we can say that the proposed method (LDA) is better than other insomnia detection methods. Furthermore, the future research from this work can be extended to detect narcolepsy, bruxism and nocturnal frontal lobe epilepsy using single channel/multichannel of the sleep recordings.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest to publish such research findings.

AKNOWLEDGEMENT

The research fund was supported by the Sejong University under the project number 20220224.

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