Integrative Computational Intelligence Techniques for Insomnia and Sleep Stage Recognition from ECG Data

DEEBIKA V
Department of CSE
Arunachala College of Engineering for Women
Manavilai,Vellichanthai
deebikavijayan15@gmail.com

JINI MOL G
Assistant Professor,Department of CSE
Arunachala College of Engineering for Women
Manavilai,Vellichanthai
jinimolacew@gmail.com

Abstract—Insomnia is a common sleep disorder that can lead to serious health problems, including cardiovascular issues. Early and accurate detection is essential for effective treatment, but traditional diagnostic methods are often costly, time-consuming, and prone to human error. To address these challenges, this paper introduces a novel hybrid artificial intelligence (AI) approach for automatic insomnia detection using electrocardiogram (ECG) signals. The method utilizes heart rate variability (HRV) and power spectral density (PSD) analysis in various classification scenarios, including subject-based classification (normal vs. insomnia), sleep stage-based classification (REM vs. wake), and a combined classification approach using both subject and sleep stage features. Ensemble learning techniques, such as random forest (RF) and decision tree (DT) classifiers, are used in the first two scenarios, while linear discriminant analysis (LDA) is applied in the combined classification. The approach includes ECG signal collection, HRV feature extraction, PSD estimation, and classification. Evaluation using the publicly available PhysioNet dataset shows strong performance across all scenarios, with high sensitivity, specificity, and accuracy. The combined classification scenario, in particular, achieves the highest detection accuracy with LDA.

Keywords—HRV Extraction, Sleep Stage, Ensemble, LDA

I. Introduction

This paper aimed to identify sleep stages using only heart rate variability (HRV), which has significant implications for improving sleep quality and preventing lifestyle-related diseases. Poor sleep quality and insufficient sleep are known to negatively impact overall health, leading to an increased risk of conditions such as cardiovascular disease, obesity, and diabetes. Therefore, understanding and monitoring sleep is crucial in preventing and managing these lifestyle diseases.

Polysomnography (PSG) is the gold standard for evaluating sleep stages, as it measures a variety of physiological signals, including electroencephalogram (EEG), electrooculogram (EOG), electrocardiogram (ECG), and electromyogram (EMG), alongside monitoring airflow and blood oxygen concentration. PSG allows for the precise identification of five sleep stages: wake (WK), rapid eye movement (REM), and three non-REM stages—N1 (shallow sleep), N2 (moderate sleep), and N3 (deep sleep). These stages are critical in assessing sleep quality. The standardized criteria for sleep stages were first established in 1968, and subsequent revisions by the American Academy of Sleep Medicine (AASM) have provided updated guidelines for scoring not only sleep stages but also arousals, respiratory events, sleep-related movement disorders, and cardiac abnormalities [1][2]. However, PSG is time-consuming, requiring the attachment of monitoring devices that limit mobility, and it often necessitates hospitalization, making it difficult to perform routinely.

Given these limitations, there is growing interest in alternative, less intrusive methods for sleep stage assessment. Recent efforts have focused on using biological signals, such as HRV, to automatically determine sleep stages, reducing the burden on both the examinee and the technician. For instance, Liang et al. [3] achieved an accuracy of 88.1% in classifying five sleep stages using multi-scale entropy analysis of EEG signals. Similarly, Zhu et al. [4] reported an accuracy of 87.5% in classifying six sleep stages through the application of difference visibility graphs to EEG data. However, these methods still require the attachment of EEG electrodes, which limits their feasibility for routine use.

In contrast, the approach presented in this study proposes a novel method for sleep stage discrimination using only HRV, offering a simpler and more practical solution. The interval between heartbeats varies based on sympathetic and parasympathetic nervous system activity, which can be quantified using the low-to-high frequency (LF) ratio. Studies have shown that the LFratio changes across different sleep stages, providing valuable insights into sleep stage classification. For example, as a person transitions from the awake state to sleep, the LFratio decreases due to parasympathetic activation and a decrease in basal metabolic rate. Conversely, during REM sleep, the LFratio increases due to the activation of the sympathetic nervous system and an increase in metabolic rate. This relationship between HRV and sleep stages has been explored in previous research, with the LFratio being higher during REM sleep compared to other stages [5].By focusing on the analysis of HRV and its relationship with sleep stage transitions, this study proposes a method that can efficiently classify sleep stages without the need for invasive EEG electrodes, making it a promising approach for practical, non-intrusive sleep monitoring.

This paper introduces a novel hybrid artificial intelligence (AI) framework for automatic insomnia detection using electrocardiogram (ECG) signals, addressing the limitations of traditional diagnostic methods. The key contributions of this work are:

- The proposed method leverages heart rate variability (HRV) and power spectral density (PSD) analysis to automatically detect insomnia
- Ensemble learning techniques, such as random forest (RF) and decision tree (DT) classifiers, are applied to the subject-based and sleep stage-based classification scenarios, while linear discriminant analysis (LDA) is used for the combined classification, demonstrating the flexibility and effectiveness of hybrid AI methods.
- The proposed approach is evaluated using the publicly available PhysioNet dataset and achieves high performance metrics (sensitivity, specificity, and accuracy) in all classification scenarios, with the combined classification approach achieving the highest detection accuracy, particularly with LDA.

II. Literature Survey

Hasan [6] discusses sleep as a universal biological process shared by various species, with humans experiencing age-related changes in sleep patterns. Sleep disruptions can lead to health issues like hypertension. Traditional sleep assessment methods, such as EEG, EOG, and EMG, help identify sleep stages (e.g., REM, NREM) but can be invasive and time-consuming.Lyamin [7] examines dolphins' ability to sleep with one eye open, confirming this behavior in marine mammals to monitor their environment, with EEG asymmetry indicating sleep in one hemisphere of the brain.

Grigg-Damberger [8] reviews the AASM Scoring Manual, highlighting its role in standardizing sleep stage identification. The manual, published in 2007, has become an essential resource for clinicians and researchers, offering clear guidelines for sleep scoring. It has significantly contributed to more accurate diagnoses and treatment strategies.

Mall [9] explores the use of Gray Level Co-occurrence Matrix (GLCM) for medical X-ray image classification. By extracting texture features from X-rays and using machine learning models such as SVM, random forests, and deep learning, the study shows that integrating GLCM features with machine learning enhances medical image analysis, aiding in more accurate diagnosis and healthcare decision-making.

Shin [10] investigates how sleep quality affects life satisfaction, finding that poor sleep can negatively impact happiness, potentially through a "zero-sum belief" about happiness, where individuals perceive happiness as a finite resource. This study suggests that sleep quality is a significant predictor of life satisfaction.Al Shorman [11] analyzes the effects of pre-learning stress on memory recall via EEG, identifying a significant connection between stress and memory retrieval, mediated by theta brainwave activity in the frontal lobe. This study provides insights into the role of stress in cognitive performance.

Bhattacharjee [12] proposes an automatic sleep apnea detection method using EEG signals. The method uses a multi-band sub-frame feature extraction technique and classifies features using K-Nearest Neighbor (KNN). Experimental results on three publicly available datasets demonstrate superior sensitivity (95.2%), specificity (96.3%), and accuracy (97.5%) compared to existing methods.

Bahrami [13] studies machine learning algorithms for sleep apnea detection using ECG signals from the PhysioNet Sleep Apnea dataset. The hybrid deep learning models outperformed traditional methods, achieving an accuracy of 88.13%, sensitivity of 84.26%, and specificity of 92.27%, highlighting the potential of AI for improving sleep apnea detection.

Ho [14] introduces a decision tree-based classifier that addresses overfitting by constructing multiple trees in subspaces of the feature vector. The ensemble method achieves superior accuracy (93.5%) compared to single-tree classifiers and other ensemble techniques, demonstrating its effectiveness on publicly available datasets.Zhou and Wang [15] develop an automatic sleep staging system using a single-channel EEG signal. The system combines random forest and LightGBM in a two-layer ensemble model, improving sleep stage classification accuracy, especially for the N1 stage. The model outperformed existing methods on the Sleep-EDF dataset, demonstrating strong generalization and robustness.

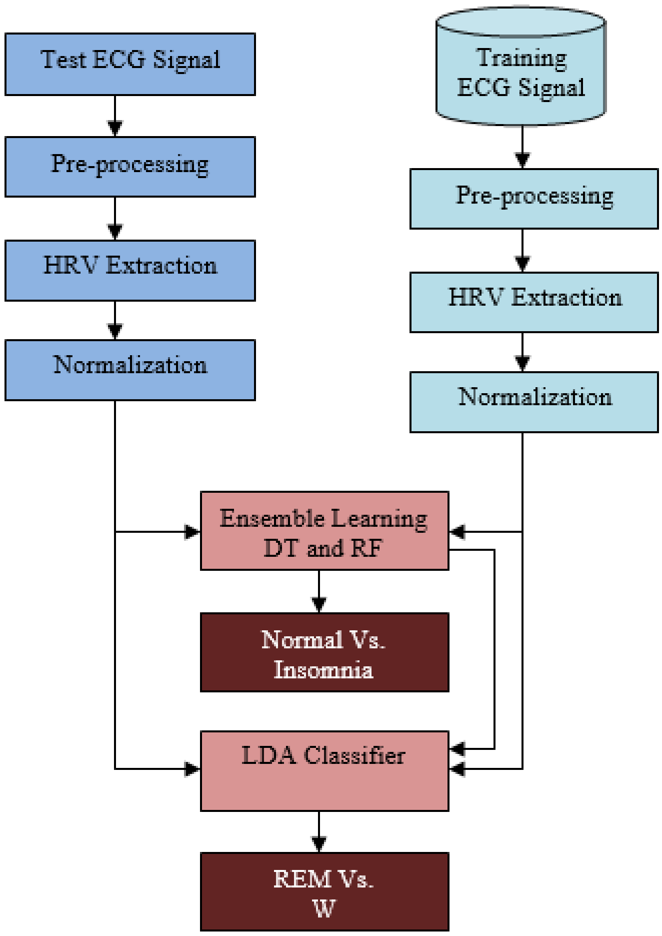

Figure. 1 Work flow of proposed system

III. Proposed Methodology

The proposed workflow for automatic insomnia detection using ECG signals as shown in fig, 1, begins with the collection of raw ECG data, followed by pre-processing to remove noise and artifacts. After cleaning, Heart Rate Variability (HRV) features are extracted, which provide insight into autonomic nervous system activity. These features are then normalized to ensure consistent scaling before being fed into machine learning models for classification. The workflow includes two primary classification scenarios: normal vs. insomnia and REM vs. wake (RWM vs. W). In the first scenario, an ensemble learning approach using Decision Tree (DT) and Random Forest (RF) classifiers is applied to distinguish between normal and insomnia states. For the sleep stage classification (RWM vs. W), Linear Discriminant Analysis (LDA) is used to effectively separate the two classes. This approach offers a streamlined, automated method for insomnia detection, improving diagnostic efficiency without the need for complex and expensive tools.

A. DATASET

In this work, sleep ECG signals are extracted from the publicly available PhysioNet dataset [16] to develop an insomnia detection framework. The PhysioNet dataset includes various waveform signals, such as EEG, ECG, EOG, EMG, and respiration data.

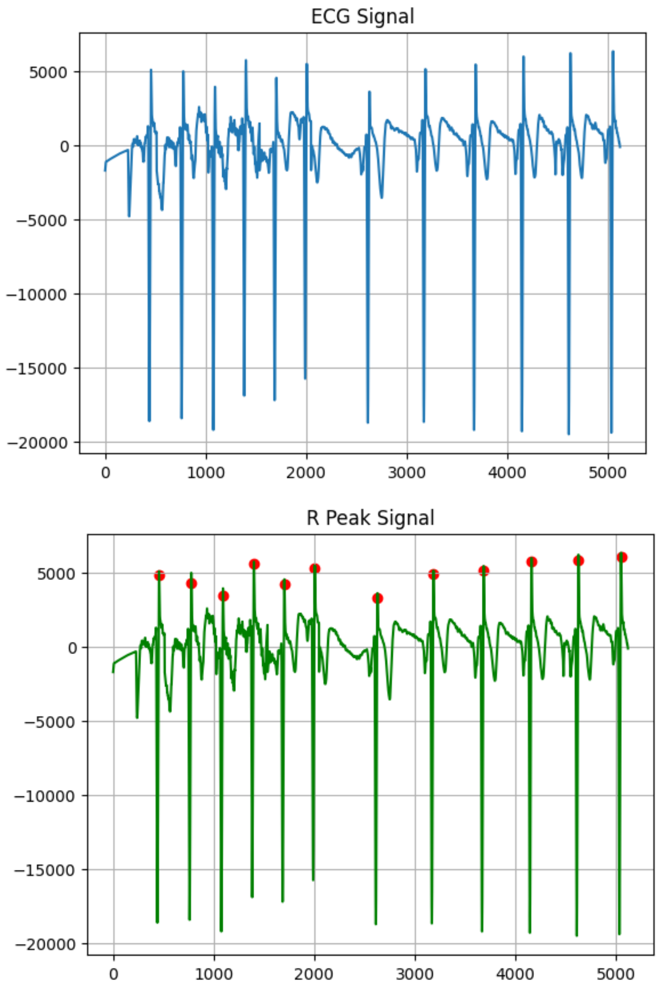

Figure. 2 ECG and R Peak Detection

B. FEATURE EXTRACTION

1) HRV Extraction

ECG signals consist of six types of waves: P, Q, R, S, T, and U, which help measure cardiac activity [17]. The P wave represents atrial depolarization, the QRS complex indicates ventricular depolarization, the T wave corresponds to ventricular repolarization, and the U wave reflects muscle repolarization. Heart rate variability (HRV) is derived non-invasively from the ECG signal and serves as an indicator of the patient's physiological condition and heart health.

In this study, HRV is estimated using the Pan-Tompkins method [18]. HRV measures the beat-to-beat variation in the ECG signal, or the variation in the R-R intervals. The R-R

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interval is calculated as the difference between successive R peaks in the ECG signal. The formula for the R-R interval is given by:

$$RR(n) = \quad (1)$$

where the R-R interval and is the position of the nth R wave. This method is applied to both normal and insomnia cases to analyze HRV.

2) Power spectral density (PSD) estimation

The Power Spectral Density (PSD) is estimated using the Welch method [19], which was introduced in 1967. This approach transforms the signal into segments and evaluates its changing periodic components over time. Some segments may overlap, allowing for a more detailed analysis of the signal's frequency content. The method is described by the following equations:

(2)

$$p_w(f) = \frac{1}{L}\sum_{n=0}^{L-1}\{ w h_m(n) x(n + iD) e^{-j2}\}^{2\pi f} \quad (3)$$

$$p_w(f) = y\sum_{n=0}^{L-1}(\quad (4)$$

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

C. ENSEMBLE CLASSIFIER

Ensemble learning is a powerful machine learning technique that combines multiple models to improve prediction accuracy and robustness. By aggregating the predictions from several models, ensemble methods reduce overfitting and improve generalization. In this study, an ensemble learning approach using Decision Tree (DT) and Random Forest (RF**)** classifiers is applied to classify insomnia and normal states based on ECG features

1) Decision Tree (DT) Classifier

A Decision Tree (DT**)** is a tree-like structure where each internal node represents a decision based on a feature, and each leaf node represents a predicted output class [18]. The tree is built by recursively splitting the dataset into subsets, selecting the feature that best separates the data at each node. The goal is to minimize impurity at each decision point, typically using metrics like Gini ImpurityorEntropy

$$Gi \quad (5)$$

Where p_i is the probability of an object being classified to class iii at node t, and C is the total number of classes.

2) Random Forest (RF) Classifier

A Random Forest (RF) is an ensemble method that creates a collection of decision trees [21]. Each tree is trained on a random subset of the training data, and at each split, a random subset of features is considered, rather than evaluating all features. This introduces diversity among the trees, enhancing the overall performance by reducing the risk of overfitting. The RF classifier aggregates the predictions from all the individual trees using majority voting for classification tasks.

3) Ensemble Approach

In the ensemble method, both Decision Tree (DT) and Random Forest (RF) classifiers are used together to enhance the classification performance. Each classifier is trained on the same feature set (extracted from the ECG signal), and their outputs are combined to produce a final classification result. The majority voting rule is applied to aggregate the predictions, improving overall accuracy and reducing the influence of outliers or noise in the data. The combined prediction $\hat{y}$ is computed as:

$$\hat{y} = \text{Majority Vc} \quad (6)$$

Where $\hat{y}_{DT}$ is the prediction from the Decision Tree and $\hat{y}_{RF}$ is the prediction from the Random Forest classifier.

D. LDA CLASSIFIER

Linear Discriminant Analysis (LDA), introduced by R.A. Fisher in 1936, is a technique used for finding a linear combination of predictors that best discriminates between two classes or targets [20]. LDA is particularly effective for classification tasks where the goal is to project data onto a lower-dimensional space while maximizing the separation between classes.

The LDA model can be expressed as a linear combination of features:

$$Z = L_{mc1}x_1 + L_{mc2}x_2 + L_{mc3}x_3 + \cdots + L_m \quad (7)$$

Where Z is the discriminant score, represents the linear model coefficients, and are the input features.

The score function S(f), which measures the discriminability between the classes, is calculated as:

(8)

Where and are the mean vectors of the two classes, and is the linear coefficient that separates the classes.

The pooled covariance matrix C is calculated by:

$$C = \frac{1}{n_1 + n_2}(n_1 \quad (9)$$

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Where and are the covariance matrices for each class, and and are the number of samples in each class.

The Mahalanobis distance between the two class distributions is given by:

$$M_g^2 = \qquad (10)$$

Finally, the decision rule for classification is:

$$L_{mc}^t \left[x - \left(\frac{\mu_1 - \mu_2}{2}\right)\right] \qquad (11)$$

Where x is the feature vector, and and are the prior probabilities of each class. This equation helps determine whether a given observation belongs to class or class .

IV. Results and discussion

After selecting appropriate features, robust machine learning classifiers such as Decision Tree (DT) and Random Forest (RF) are used in ensemble learning for subject-based and sleep stage-based classification scenarios. For the combined feature-based classification, Linear Discriminant Analysis (LDA) is applied. Performance metrics such as Precision (PRE), Recall (REC), Accuracy (ACC), and F1-score (F_1) are used to assess the classification outcomes. The metrics are defined as follows:

PR (12)

RE (13)

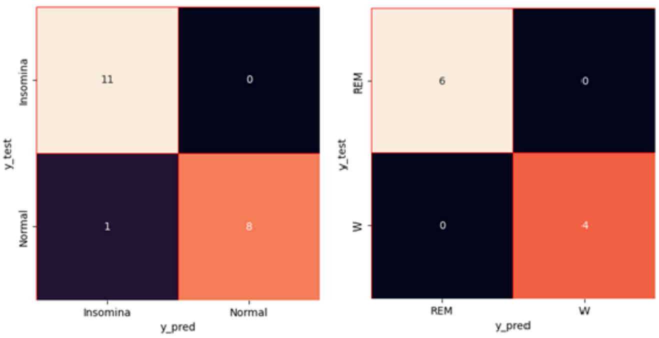
$$\text{ACC} = (\frac{}{(TP\text{-}} \qquad (14)$$

$$F_1 = 2^* precision^* Recall / Precision + Re \qquad (15)$$

Where TP is true positives, FPP is false positives, TN is true negatives, and FNis false negatives. These metrics are derived from confusion matrices at each fold of the cross-validation process. Fig 2 shows the confusion matrix.

The results of the classification performance demonstrate the effectiveness of both the ensemble learning approach and the LDA method in detecting insomnia using ECG signals

The ensemble learning method, combining Decision Tree (DT) and Random Forest (RF) classifiers, achieved an impressive accuracy of 95%, with a precision of 92%, a recall of 100%, and an F1 score of 96%. The high recall (100%) indicates that the ensemble approach is highly sensitive in detecting insomnia cases, correctly identifying all true positive instances. The precision (92%) suggests that the majority of the positive predictions made by the model are accurate, though there is a small chance of false positives. This is expected in some instances, as ensemble models, while powerful, can sometimes generalize based on complex feature combinations, leading to slight trade-offs in precision. Overall, the ensemble approach shows a good balance of high accuracy, sensitivity, and precision, making it a reliable model for subject-based and sleep stage-based classification



(a) (b)

Table 1Performance of the sleep stage-based classification

Method	Acc(%)	Pre(%)	Rec(%)	F_1 (%)
Ensemble	95	92	100	96
LDA	100	100	100	100

The LDA classifier achieved 100% accuracy, with100% precision, 100% recall, and100% F1 score. This suggests that the LDA model perfectly distinguished between the insomnia and normal sleep states across all cases in the dataset. The perfect recall and precision values indicate that LDA did not miss any insomnia cases (true positives) and did not produce any false positives. This high performance could be due to the specific effectiveness of LDA in handling the combined features from both subject-based and sleep stage-based scenarios, where the linear separation between classes is relatively distinct. Given its mathematical simplicity and efficiency, LDA performed exceptionally well, likely benefiting from the clear boundaries between insomnia and normal sleep states in the database

The comparison between the proposed ensemble learning model and existing methods (FNN and DNN) reveals significant improvements in all performance metrics. The ensemble method achieved 95% accuracy, 92% precision, 100% recall, and 96% F1 score, outperforming both FNN(83.2% accuracy) and DNN (86.9% accuracy). While FNN and DNN show decent performance, their recall rates (83.2% and 80.9%, respectively) indicate that they miss some insomnia cases. The ensemble model's 100% recall ensures no insomnia cases are missed, making it ideal for medical applications. This superior performance highlights the effectiveness of combining Decision Tree (DT)andRandom Forest (RF) in an ensemble approach, which provides robust and reliable classification, especially in complex scenarios like insomnia detection using ECG signals.

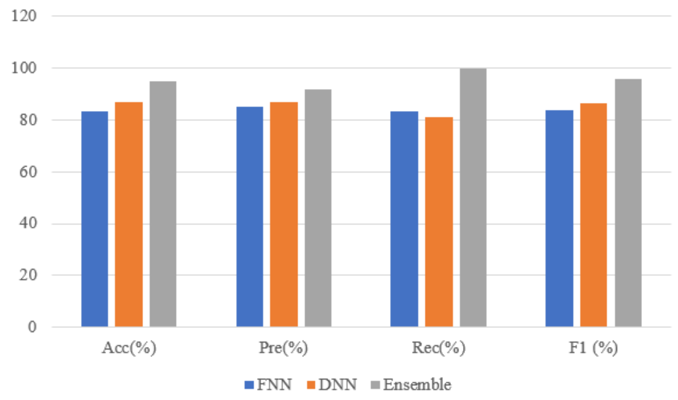


Fig 3. Comparison graph between existing and proposed works

V. CONCLUSION

This paper presents a hybrid AI approach for automated insomnia detection using electrocardiogram (ECG) signals. The method leverages heart rate variability (HRV) and power spectral density (PSD) across three classification scenarios: subject-based (normal vs. insomnia), sleep stage-based (REM vs. wake), and a combined model. Ensemble learning techniques like random forest (RF) and decision tree (DT) classifiers are used for the first two, while linear discriminant analysis (LDA) is applied for the combined classification. The framework includes ECG signal acquisition, HRV feature extraction, and PSD estimation. Evaluated using the PhysioNet dataset, the approach shows promising performance and could be applied for real-time insomnia detection in mobile health systems.

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