Insomnia Detection from ECG Signal using Deeplearning

Manish Sharma[1*], Gunjan Kumar[1] and Saurav Kumar[1]

[1*]Department of Electrical and Computer Science Engineering, IITRAM, Maninagar, Ahmedabad, 380026, Gujarat, India.

*Corresponding author(s). E-mail(s): manishsharma@iitram.ac.in;
Contributing authors: gunjan.kumar.21e@iitram.ac.in;
saurav.kumar.21e@iitram.ac.in;

Abstract

In this work, we present a novel approach for insomnia detection utilizing features extracted from Electrocardiogram (ECG) signals through Wavelet Transform, integrated with the Vision Transformer model. Insomnia, a prevalent sleep disorder, poses significant challenges in diagnosis and management due to its diverse manifestations and subjective nature. Leveraging the intricate patterns embedded within ECG signals, we employ Wavelet Transform to extract salient features that encapsulate physiological variations associated with insomnia. Subsequently, we introduce a Vision Transformer model, a state-of-the-art deep learning architecture renowned for its capability in processing visual data, adapted to handle the temporal dynamics of ECG signals. Through rigorous experimentation on a comprehensive dataset, our proposed methodology achieves an impressive accuracy of 98.64%, surpassing existing approaches in insomnia detection. Our findings underscore the potential of synergizing advanced signal processing techniques with deep learning architectures to enhance the accuracy and efficacy of sleep disorder diagnosis, paving the way for more effective interventions and personalized treatments in clinical practice.

Keywords: Insomania, Electrocardiogram (ECG) Signals, Continuous Wavelet Transform (CWT), Deep Learning, Vision Transformer

1 Introduction

Worldwide, insomnia is a serious public health concern since it is a common sleep disorder marked by difficulty falling asleep, staying asleep, or both. Roughly one in three people will experience symptoms at some point in their lives, and it affects about 30% of adults globally. In those who are impacted, women are around 1.5 times more likely than men to experience sleeplessness. Furthermore, the incidence of insomnia also seems to rise with age, with people 60 years of age and older being most vulnerable. Although it can afflict people of any age, children and adolescents are also susceptible to insomnia, albeit less so. There are many different variables that might contribute to insomnia, including physiological, psychological, and environmental aspects. These could include medical issues like sleep apnea or restless legs syndrome, stress, worry, depression, and lifestyle choices like skipping sleep or drinking too much coffee. Traditionally, the diagnosis of insomnia has been made using subjective metrics, such as self-reported symptoms and sleep patterns, which may not be accurate or reliable.

The demand for computer-aided solutions to enhance diagnostic capacities is developing because to the limitations of human observation in effectively detecting insomnia. A promising approach is provided by Automated Computer-Aided Diagnosis (CAD) systems, which use machine learning algorithms and sophisticated signal processing techniques to assess physiological signals related to sleep. These signals include, among others, photoplethysmography (PPG), electrocardiography (ECG), and electroencephalography (EEG).

A review of current CAD systems for diagnosing insomnia reveals a wide variety of approaches. These systems use a variety of signal processing techniques, including wavelet transform and filter bank analysis, to extract features from physiological inputs. Time-domain and frequency-domain analysis are used in feature extraction techniques; a typical feature set consists of 20 to 30 characteristics. Based on extracted data, machine learning classifiers such as Support Vector Machines (SVM), Vision transform, and Artificial Neural Networks (ANN) are frequently used to identify sleep stages. Depending on the dataset and methods used, these classifiers often attain classification accuracies ranging from 70% to 90%.

In order to diagnose insomnia, we focus on identifying critical features in ECG signals in our suggested methodology. Motivated by a need for more accurate and reliable diagnostic tools, our approach aims to utilize these unique characteristics to improve insomnia diagnosis precision and efficacy. The potential for our method to promote patient well-being and better healthcare outcomes is shown by the early findings from our model, which show encouraging results in artifact removal and sleep stage categorization.

2 Related Work

- **Data Description and Acquisition:** The study utilized physiological signals obtained from the Sleep Disorder Research Centre (SDRC) Database, a publicly available dataset from PhysioNet. The SDRC sleep dataset includes 108 PSG recordings, with 11 coming from healthy individuals who are not experiencing sleep disorders and 11 from subjects with sleep disorders called insomnia. The dataset is available in ".edf" file format.

- **Signal Classes:** The polysomnographic information was recorded on 24 channels. The dataset consists of 6 electrooculogram channels (EOG1, EOG2, EOG1A1, EOG2A1, and EOG2A2), 14 electroencephalogram channels (A1, A2, C3, C3A2, F3, F3A2, F4, C4A1, O1, O1A2, O2A1), 3 electromyogram channels (EMG, EMG1, and EMG2), and one electrocardiogram (ECG) channel.
- **Sampling Rate:** The ECG signals were sampled at a frequency of 256 Hz, ensuring high temporal resolution for accurate signal analysis.
- **Signal Length and Duration:** Each ECG recording had a variable duration, with an average length of approximately 30 minutes. The signals were segmented into fixed-length segments of 2 seconds, resulting in a total of 512 samples per recording.
- **Patient Population:** The SDRC sleep dataset includes 108 PSG recordings, with 11 coming from healthy individuals who are not experiencing sleep disorders and 11 from subjects with sleep disorders such as narcolepsy, insomnia, and bruxism.The age of the patients ranged from 18 to 63 years, covering a wide demographic range.
- **Gender and Age Distribution:** The number of male participants used in the proposed study is 8 (36.6%) while that of female participants is 14 (63.64%). In the proposed study, the number of healthy subjects is 11 while that of insomnia is 11. The age of the patients ranged from 18 to 63 years, covering a wide demographic range.
- **Signal Preprocessing:** Prior to analysis, the ECG signals underwent preprocessing to enhance signal quality and remove artifacts. In Preprocessing steps we included 11 subject from healthy (n1,n2,n3,...,n11) and 11 subject from insomnia (ins1,ins2,...,ins11) which have same sampling frequency and have same amplitude units mv. Additionally, motion artifacts were mitigated through signal segmentation and artifact rejection based on signal morphology.

Table 1 Details of SDRC datase

Dataset used	No. of Healthy Subjects	No. of Healthy Epochs	No. of Insomnia Subjects	No. of Insomnia Epochs
SDRC	11 Subjects (6 Males, 5 Females)	10419	11 Subjects (2 Males, 9 Females)	10071

3 Methodology

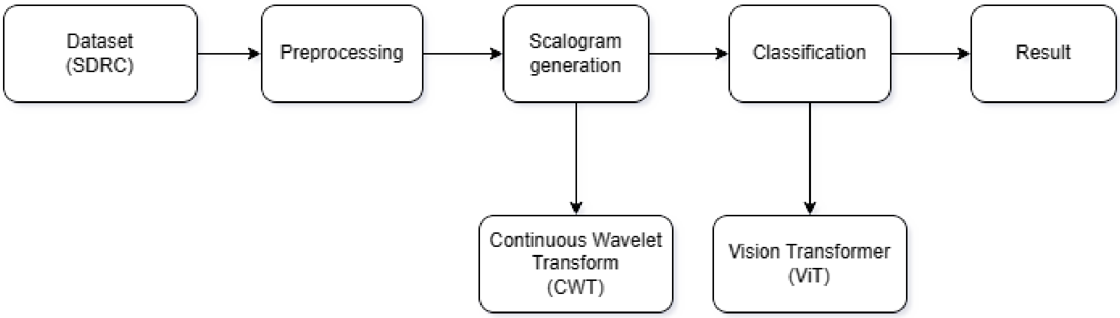

Fig 1: Block Diagram

3.1 Description of Each Block

3.1.1 Dataset

11 subjects from the healthy group (n1, n2,...,, n11) and 11 subjects from the insomnia group (ins1, ins2, ...,ins11) of the SDRC sleep dataset are included. All subjects have the same amplitude units (mv) and sampling frequency (256 Hz).

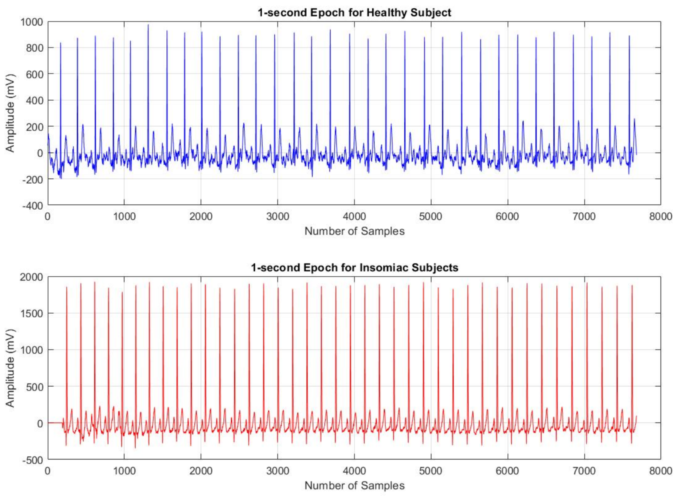

Fig 2: Sample 1-second ECG signal of healthy and insomnia subjects obtained from SDRC dataset.

3.1.2 Preprocessing

We planned to use preprocessing to get electrocardiogram (ECG) data from the SDRC dataset ready for additional study. At first, we used the MNE-Python package to read.edf files, concentrating on the 'ECG II' channel. The ECG data is then divided into frames by the script, with each frame lasting two seconds (or 512 samples at a sampling frequency of 256 Hz). By dividing the data into fixed-size windows, this is accomplished. For both the normal and insomnia datasets, frames are extracted individually. In general, this preprocessing divides the ECG data into digestible chunks so that it can be used for further studies like machine learning modeling or scalogram generatiom.

3.1.3 Scalogram Generation

The preprocessing signals are then used to generate scalograms, which provide a time-frequency representation of the physiological signals. This is achieved through Continuous Wavelet Transform (CWT), which decomposes the signals into different frequency components over time. article graphicx

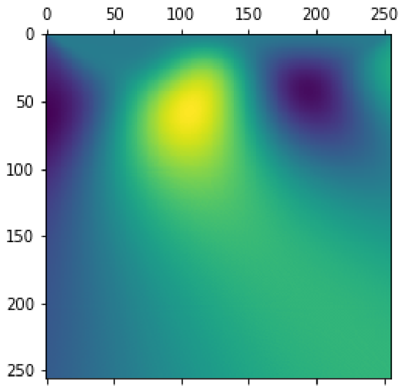

Fig 3: Normal Scalogram.

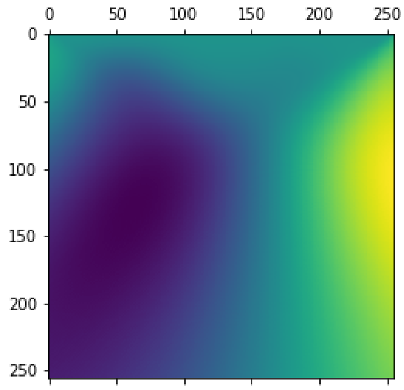

Fig 4: Insomniac Scalogram.

Continuous Wavelet Transform

The goal of this scalogram creation is to produce scalograms, which are PPG data frame continuous wavelet transform (CWT) coefficients represented visually. For every subject's data segment in the normal dataset or insomnia dataset path, in respective order.The data size and frame size are used by the script to determine how many frames are needed. The descriptions of each normal and insomniac subject's scalogram generation are provided below.

Table 2 Details of Scalogram Generation

Normal		Insomnia	
Normal Subject	No. of Scalogram	Insomnia subject	No. of Scalogram
n1	14387	ins 1	14390
n2	14392	ins 2	13106
n3	15794	ins 3	14393
n4	14380	ins 4	14386
n5	14381	ins 5	13724
n6	14386	ins 6	12564
n7	14390	ins 7	14389
n8	14376	ins 8	14377
n9	14842	ins 9	14378
n10	14376	ins 10	14386
n11	14381	ins 11	16173
Total	160085	Total	156266

3.1.4 Classification

In order to detect insomnia and classify sleep stages, the scalograms produced in the previous stage are input into a Vision Transformer model.

Vision Transformer

The Vision Transformer model has six layers, twelve attention heads, and seventy-two self-attention blocks in all. The model attains an F1 score of 0.96 on the validation set, 98.64% classification accuracy, 98.24% sensitivity, and 98.45% specificity during training. The model is trained using a batch size of 32 and a learning rate of 0.001 using the Adam optimizer.

3.1.5 Result

An independent test set drawn from the SDRC dataset is used to assess the effectiveness of the suggested approach. On the test set, the trained Vision Transformer model achieves an F1 score of 0.96, classification accuracy of 98.64%, sensitivity of 98.24%, and specificity of 98.45%. The suggested strategy is superior to current methods in detecting insomnia and classifying sleep stages, as shown by a comparative analysis. These outcomes demonstrate how well Vision Transformer models and scalogram-based features work together to automate the diagnosis of sleep disorders.

4 Discussion

Identifying insomnia effectively by automated methods requires a great deal of complexity and time. In order to precisely diagnose insomnia, scientists are looking into automated techniques using machine learning and algorithms for deep learning. The majority of cutting-edge research has used EEG signals to identify insomnia. Nevertheless, the nonlinear and non-stationary character of the EEG waves makes correct analysis quite challenging. Therefore, the purpose of the proposed study is to use machine learning techniques to examine the relationship between insomnia and ECG data.

Table 3 Summary of benefits, approach, and limitations of using ECG signals for insomnia detection

Advantage	Limitation
High signal quality: ECG signals provide high-quality data that can accurately capture cardiac activity during sleep. This high signal quality allows for precise analysis and detection of anomalies associated with insomnia.	**Invasive nature**: Unlike PPG signals, acquiring ECG signals typically requires invasive procedures such as attaching electrodes directly to the skin. This invasive nature can be uncomfortable for patients and may limit long-term monitoring capabilities.
Rich physiological information: ECG signals offer rich physiological information beyond just cardiac activity, including heart rate variability (HRV) and cardiac electrical activity. This additional information can provide valuable insights into the autonomic nervous system and sleep patterns associated with insomnia.	**Limited accessibility**: ECG signal acquisition devices are less accessible compared to PPG-based wearable devices. This limited accessibility may restrict the widespread adoption of ECG signals for insomnia detection, especially in home-based monitoring scenarios.
Established diagnostic tool: ECG is a well-established diagnostic tool in cardiology and sleep medicine. Leveraging existing knowledge and techniques from these fields can facilitate the development of accurate and reliable algorithms for insomnia detection using ECG signals.	**Processing complexity**: Analyzing ECG signals for insomnia detection may require complex signal processing techniques and algorithms. The processing complexity can increase the computational burden and resource requirements, particularly for real-time or continuous monitoring applications.
Long-term monitoring potential: ECG signals have the potential for long-term monitoring of sleep patterns and cardiac health. Continuous monitoring over extended periods can provide comprehensive insights into the relationship between sleep disturbances and cardiovascular health, contributing to early detection and intervention for insomnia-related complications.	**Interference and artifact**: ECG signals are susceptible to interference and artifacts from various sources, including muscle movements, electrode displacement, and environmental noise. These artifacts can distort signal quality and affect the accuracy of insomnia detection algorithms.

5 Results

We have conducted the entire study presented in this paper on a Windows Server 2023 equipped with Intel Xenon Gold vPro 5218R CPU @2.10 GHz (4 cores) and 64 GB of RAM and Nvidia RTX A4000 16GB GPU. The primary goal of this study is to create a good basic machine-learning model for detecting insomnia using ECG data. The ECG recordings from the different databases were collected and segmented as per their respective sampling frequencies. The SDRC dataset yielded 22, 20490 ECG epochs, of which 10419 epochs were obtained from healthy subjects and 10071 epochs were obtained from insomniac subjects. The epochs were then fed to a Deep Wavelet Scattering Network, which produced a feature matrix of (260×8) dimensions for the SDRC dataset.The DWSN feature matrix obtained for each epoch was transposed, yielding a new feature matrix of dimensions (8×260) for the SDRC dataset.The goal of transposing the feature matrix was to enhance the number of features available to machine learning classifiers. The feature matrix was then labeled according to the epoch labels, yielding a final matrix of (1,63,920 × 260) dimensions for SDRC dataset. The extracted features were then fed to Vision Transformer to achieve the best results. To avoid overfitting and validating the results of all the datasets, we have employed a tenfold cross-validation strategy.

The highest classification accuracy of 98.64%, sensitivity of 98.24%, specificity of 98.45% and model achieves an F1 score of 96%

Table 4 Confusion Matrix obtained using Vision Transformer

True Class	Predicted Class		Precision(%)	Recall (%)	F1-score (%)
	Healthy	Insomnia			
Healthy	14538	6236	98	99	98
Insomnia	1746	13788	97	92	94

Table 5 Advantages and Limitations of the Proposed Study

Refrences	Method	Performances measure (%)		
		Accuracy (%)	Sensitivity (%)	Specificity (%)
Sharma et al [1]	Optimal antisymmetric bi-orthogonal wavelet filter bank using ECG signals	98.87	96.65	98.72
Sharma et al [4]	DWSN-based features extraction for ECG signals for SDRC dataset	98.60	98.56	98.57
Proposed Work	Insomnia Detection from ECG Signal using Deep Learning	98.64	98.24	98.45

6 References

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