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A Multimodal Approach Harnessing EEG and ECG Signals for Advanced Sleep Stage Classification

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Abstract: The categorisation of sleep stages is a crucial element in comprehending the impact of sleep patterns on one's well-being. This study introduces a new way for categorising the different phases of sleep. The methodology combines data from both electroencephalogram (EEG) and electrocardiogram (ECG) and utilises sophisticated feature extraction methods. The Ensemble Empirical Mode Decomposition (EEMD) technique is employed for analysing electroencephalogram (EEG) signals, whereas the time-frequency Heart Rate Variability (HRV) analysis is used for examining electrocardiogram (ECG) readings. Moreover, the method employs multiscale entropy to do nonlinear signal analysis. The proposed method employed a support vector machine technique for classification. This algorithm partitions each epoch into a total of five unique groups. The combination of electroencephalogram (EEG) and electrocardiogram (ECG) signals provides a full view of sleep physiology, enabling more precise classification of sleep stages. The experimental results offer compelling proof of the effectiveness of the suggested method, emphasising its potential to enhance the reliability of sleep monitoring systems. This could have significant implications for healthcare and overall well-being. After the simulation of proposed approach on the standard datasets like MASS-SS3 and ISRUC – S3, the average accuracy observed as 84.6% which is 4.3% more than the state-of-the-art methods. The novelty of the proposed method lies in its integration of EEG and ECG data to achieve a comprehensive analysis of sleep stages, utilizing EEMD for EEG and time-frequency HRV for ECG. Additionally, it incorporates multiscale entropy for nonlinear signal analysis, improving the sensitivity of the classification. The method employs a SVM to classify sleep into five distinct stages, enhancing accuracy and reliability in sleep monitoring, which could significantly benefit healthcare and individual well-being.

Keywords: Sleep stage classification, EEG, ECG, Empirical mode decomposition (EMD), Heart rate variability (HRV), Multiscale entropy, Feature extraction, Signal analysis, Sleep monitoring, Healthcare.

1. Introduction

Quality sleep is essential for optimal health, since it is crucial in the body's recuperation, memory formation, and overall state of wellness. Insufficient sleep can lead to several difficulties such as decreased reaction times, memory impairments, emotional disorders, and heightened vulnerability to illnesses [1, 2]. Regrettably, the incidence of sleep problems has been on the rise, affecting around 27% of the worldwide population, as reported by the World Health Organisation [3]. However, sleep issues often receive little attention from individuals. In such instances, such problems can be severe and occasionally irreversible. A contributing factor to the under recognition of sleep disorders is the limited comprehension regarding the nature of sleep and its associated standards. During the sleep cycle, the brain goes through different stages of activity, which are classified as wakefulness, non-rapid eye movement (NREM), and rapid eye movement (REM) sleep, following the guidelines established by the American Academy of Sleep Medicine (AASM) [4]. Additionally, the non-rapid eye movement (NREM) sleep is divided into three distinct stages, which are referred to as N1, N2, and N3. Disruptions in these stages can result in the development of illnesses such

as nocturnal frontal lobe epilepsy, insomnia, and REM sleep behaviour disorder. These types of abnormalities can be identified through the process of sleep staging, which is a commonly used diagnostic tool for diagnosing sleep disorders.

Polysomnography (PSG) is a method used to monitor sleep stages by measuring several physiological signals such as electromyogram (EMG), electrooculogram (EOG), electrocardiogram (ECG), electroencephalogram (EEG), oxygen saturation, and oral and nasal airflow [5]. The signals derived by polysomnography (PSG) provide unique insights into the physiological and neurological processes taking place in the brain and body during various sleep stages. Although the brain is constantly changing, it nonetheless manages to regulate the activities of many organs while we sleep. PSG signals, obtained from many sensors, unavoidably encompass interference from multiple sources. It is necessary for sleep professionals to jointly analyse these signals in order to determine sleep stages based on established criteria. Evaluating the quality of sleep by analysing staging information requires a thorough assessment of the complete sleep cycle. In addition, the night consists of many sleep stages that alternate repeatedly over relatively brief periods of time. An effective method of determining sleep stages requires a comprehensive strategy that takes into account various physiological signals and temporal intervals. The process of manually categorising sleep stages is thorough, monotonous, and requires a significant amount of time, even for individuals with expertise in the field. Therefore, the task of creating automated sleep staging systems is a difficult job.

Automated sleep staging systems have the potential to greatly improve the efficiency and precision of conventional sleep scoring and monitoring [6-8], hence offering improved assistance in detecting sleep disorders. Multiple studies have focused on creating automated methods for classifying sleep stages utilising powerful machine learning algorithms that extract information from physiological inputs. Nevertheless, the extraction of dependable features with accurate physiological inference or statistical significance from physiological signals can streamline architecture design and minimise the training procedure, necessitating a significantly smaller amount of data. Several research have suggested using single-mode analysis techniques that depend on EEG or ECG signals. These methods usually consist of obtaining spectral, temporal, and statistical characteristics, and then employing common machine-learning techniques such random forest (RF) [9], support vector machine (SVM) [10, 11], and linear discriminant analysis (LDA) [12] for sleep staging.

Although classic machine-learning algorithms have demonstrated great accuracy in sleep stage classification, there are still some unresolved difficulties. Previous research has mostly concentrated on single-mode signals, such as EEG, but other electrophysiological signals also offer useful insights during sleep. ECG signals have the ability to record autonomic nervous system (ANS) activity, which indicates cardiovascular functions during sleep. The incorporation of characteristics from several physiological signals has the potential to greatly enhance the accuracy of sleep staging. Although physiological signals have a role in determining sleep stages through many mechanisms, the precise influence of different types of signals has not been well studied. Furthermore, the study of the non-linear dynamics of these signals at various frequencies and time scales during sleep is an essential area that requires additional investigation. This research presents a novel approach for classifying sleep stages by integrating EEG and ECG information and utilising sophisticated feature extraction algorithms. The primary contributions are delineated as follows:

1. **Integration of EEG and ECG signals:** The method integrates both EEG and ECG signals, thereby capturing additional information pertinent to sleep stage classification and providing a comprehensive understanding of sleep physiology.
2. **Innovative feature extraction techniques**: The representation of underlying physiological phenomena is improved with Empirical Mode Decomposition (EMD) for EEG signals and Heart Rate Variability (HRV) analysis for ECG signals.
3. **Advanced non-linear signal analysis:** The method utilizes multiscale entropy for non-linear signal analysis, which enables the capture of intricate temporal dynamics in the signals and enhances comprehension of sleep patterns.

The remaining sections of the paper are structured as follows: Section 2, Literature Survey, examines current methodologies in the subject, with a particular focus on EEG-based techniques and their constraints. Section 3, Proposed Method, describes a new and innovative approach that combines EEG and ECG signals. It explains how Empirical Mode Decomposition (EMD) is used for EEG analysis and Heart Rate Variability (HRV) analysis is used for ECG analysis. Section 4, Results and Analysis, provides empirical results, which encompass specific information on the dataset, performance indicators,

and comparisons with established methodologies, both in terms of quantitative and qualitative aspects. Section 5, Conclusion, provides a concise overview of important findings, explores the consequences, and emphasises the advancements made by the suggested method in sleep stage categorisation methodologies.

2. Literature survey

The field of automatic sleep stage classification has attracted considerable attention because of its potential to enhance the diagnosis and treatment of sleep-related problems. The conventional method of manually evaluating sleep stages is both time-consuming and prone to inconsistencies across different raters. Machine learning approaches present a hopeful substitute by delivering impartial and reliable categorisation outcomes. This literature review examines different strategies used in automatic sleep stage categorisation, with a focus on feature extraction and classification techniques.

Abdollahi Gharbali et al. [13] specifically examined the role of distance-based characteristics in the classification of sleep stages. They utilised Itakura, Itakura-Saito, and COSH distances to extract a total of 32 features, which were then merged with conventional features. Their research showed that incorporating distance-based characteristics enhanced the precision of classification, especially in differentiating between REM and N1 sleep stages. However, incorporating distance-based features could lead to higher computational complexity.

Wang et al. [14] introduced a hybrid feature selection technique that utilises the entropy weight method to automate the process of sleep staging. A total of 185 characteristics were recovered from the PSG signals and subsequently subjected to a two-stage feature selection method. Their ensemble model, using support vector machines and other classifiers, attained an accuracy rate of 88.86%. This showcases the efficacy of their methodology in diminishing feature redundancy and enhancing classification performance. However, this method is very prone to over fitting issues for the multi-label data.

Tripathi et al. [15] created a hybrid machine learning classifier to diagnose bruxism by analysing physiological inputs. The ensemble expert system demonstrated great specificity and accuracy in sleep stage categorisation by integrating EEG, ECG, and EMG inputs, highlighting the efficacy of merging multiple physiological signals. This approach combines many physiological markers, may encounter difficulties in synchronising the data and managing the complexity of the model.

Karimzadeh et al. [16] proposed a new set of features for sleep stage scoring. These features are based on the Shannon entropy of the instantaneous analytical form envelope and EEG frequencies. The suggested characteristics, when employed alongside a distributed decision-tree classifier, attained commendable precision, showcasing the promise of resilient EEG phase extraction methodologies. The efficacy of innovative feature set may fluctuate depending on the quality of the signal and individual variations.

Zhang and Wu [17] created an unsupervised competitive convolutional neural network (C-CNN) to classify sleep stages. This approach tackles the difficulty of acquiring labelled data. The model, assessed on the UCD [18] and Sleep-EDF datasets [19], exhibited enhanced performance in comparison to baseline models, indicating the effectiveness of competitive learning in extracting features. However, the C-CNN does not have the ability to apply their findings to different situations.

Yan et al. [20] investigated the combination of several physiological signals from polysomnography (PSG), such as electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), and electrocardiography (ECG), in order to improve the accuracy of automated sleep grading. The researchers identified crucial characteristics from each signal modality and discovered that merging these characteristics enhanced the accuracy of classification. This study emphasised the significance of using many methods to gather complete and thorough sleep data. This method could make the process of extracting and interpreting features more complicated.

Tabar et al. [21] conducted a study on the application of low-dimensional feature spaces in automatic sleep staging. The objective was to decrease computational complexity while maintaining performance. The researchers utilised bootstrapping, Gini ranking, and mutual information-based feature selection techniques on EEG data. They discovered that a concise selection of features was able to accurately represent the whole feature space. Even though they try to decrease complexity by focussing on low-dimensional feature spaces, however this approach carries the risk of losing information.

Jia et al. [22] introduced a technique that uses multi-view spatial-temporal graph convolutional networks (GNNs) to classify sleep stages, with a focus on domain generalisation. This method utilises the geographical and temporal connections in sleep

data, providing a strong framework that can be applied effectively to other datasets. Utilising Graph Neural Networks (GNNs) enables the capture of intricate interconnections and enhances the accuracy of classification in diverse scenarios and with different individuals. SeqSleepNet, developed by H. Phan et al. [23], is an end-to-end hierarchical recurrent neural network specifically built for autonomous sleep staging using sequence-to-sequence methodology. This model analyses polysomnography data in a hierarchical fashion, initially prioritising short-term connections and then shifting to long-term connections. By employing a hierarchical technique, it becomes possible to record sleep dynamics with greater accuracy, resulting in superior performance in tasks related to sleep stage classification. When applying Graph Neural Networks (GNNs) to ECG data, a key problem arises from the challenge of representing the sequential nature of the time series within a graph structure. ECG signals are inherently temporal and continuous, making it difficult to capture critical temporal dependencies when transforming them into a graph format. Additionally, the choice of graph topology can significantly influence the model's performance, and improper representations may lead to loss of important information.

In their study, J. Fan et al. [24] propose a novel sleep staging approach using electrooculogram (EOG) signals, which are more convenient to acquire than the EEG. A two-scale convolutional neural network first extracts epoch-wise temporary-equivalent features from raw EOG signals. A recurrent neural network then captures the long-term sequential information. Z. Zia et al. [25] propose a SalientSleepNet, a multimodal salient wave detection network for sleep staging. Specifically, SalientSleepNet is a temporal fully convolutional network based on the U2-Net architecture that is originally proposed for salient object detection in computer vision. It is mainly composed of two independent U2-like streams to extract the salient features from multimodal data, respectively. Meanwhile, the multi-scale extraction module is designed to capture multi-scale transition rules among sleep stages. Besides, the multimodal attention module is proposed to adaptively capture valuable information from multimodal data for the specific sleep stage. Deep learning architectures may require extensive datasets and processing resources, which can restrict their practical use in real-world scenarios.

Jia et al. [26] presented GraphSleepNet, a spatial-temporal graph convolutional network designed for sleep stage classification, as a continuation of their prior research. This model enhances the graph-based approach by dynamically adjusting to the geographical and temporal attributes of the sleep data. This network's versatility enables enhanced performance and generalisation across diverse datasets and subjects. However, the Graph Sleep Net may result in increased processing burden and varying performance levels according on the complexity of the dataset.

3. Proposed approach

The suggested approach utilises multimodal signals to assess the sleep stage by analysing both the electrocardiogram (ECG) and electroencephalogram (EEG). The proposed methodology consists of three distinct parts. This method primarily concentrated on extracting non-linear characteristics from ECG/EEG using multiscale entropy in the initial step. The suggested method obtains characteristics from many scale ranges and frequency ranges. In the second phase, two distinct techniques are employed to extract features from ECG and EEG data. The suggested method utilises two sophisticated feature extraction algorithms to analyse both EEG and ECG signals, resulting in improved sleep stage categorisation. The Ensemble Empirical Mode Decomposition (EEMD) method is employed to extract characteristics from EEG signals, whereas Heart Rate Variability (HRV) analysis is used to extract characteristics from ECG signals. The integrated method improves the reliability of sleep stage categorisation by including extensive physiological data. Using both EEG and ECG characteristics enhances the accuracy of classification by considering both central and peripheral physiological alterations that occur during sleep. In addition, the technique offers a comprehensive perspective on sleep patterns by examining both cerebral activity and variations in heart rate, resulting in more dependable and intricate assessment of sleep stages. Fig. 1 displays the

Table.1 notations

Notation	Meaning
$s(i)$	i^{th} segment
$d_{s_m(j)}^{s_m(i)}$	distance between two different vectors $s_m(i)$ and $s_m(j)$
P^m	Probability density
$Q_j^m(r)$	Density
$Q^m(r)$	Vector
SE	Sample Entropy
r_n	Residue after extracting IMFS
IMF_i	i^{th} intrinsic mode function
$m(t)$	Envelope
$w_k(t)$	White Gaussian Noise

comprehensive block diagram of the proposed system. Table 1 shows the notations.

3.1. Multi-scale entropy

Sample entropy is generally used for the short-time series analysis of a signal which determines the entropy rate for specific applications [25]. According to the definition of Grassberger and Procaccia [26], sample entropy is considered as a regular statistical measure, treated as an enhanced version of entropy method [27, 28]. In the computation of sample entropy, two parameters namely threshold and embedding dimension are important to determine [29, 30]. For a given data sequence $s(n) = [s(1), s(2), \dots, s(N)]$, the sample entropy is computed as follows; initially a m-dimensional vector is reconstructed as $s_m(i)(i = 1,2,3, \dots N - m + 1)$ as

$$s_m(i) = [s(i), s(i+1), \dots, s(i+m-1)] \quad (1)$$

Then compute the distance between two different vectors namely $s_m(i)$ and $s_m(j)$ which is determined as the maximum distance between every two elements in the two distinct vectors, i.e.,

$$d_{s_m(j)}^{s_m(i)} = max\left|s_{i+k} - s_{j+k}\right|, 0 \le k < m-1 \quad (2)$$

For every vector $s_m(i)$, compute the probability of any vector which is close to the given vector, as

$$P_i^m(r) = P_i/N - m - 1 \quad (3)$$

Where P_i signifies the total vectors count that satisfy the condition $d_{s_m(j)}^{s_m(i)} \le r, i \ne j$. Next P^m denotes the density which is computed as accumulated average of maximum distance between vectors, as $P^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} P_i^m(r)$

Similarly, for the other dimensional vector $s_m(j)$, the density and vector count are computed as

$$Q_j^m(r) = Q_j/N - m - 1 \quad (4)$$

And

$$Q^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} Q_j^m(r) \quad (5)$$

Then the sample entropy is computed as

$$SE = -log\left(\frac{Q(r)}{P(r)}\right) \quad (6)$$

Where $Q(r)$ and $P(r)$ denotes the total template matches count in the m-dimensional state space with specific tolerance r. They are computed as

$$P(r)or\ Q(r) = \frac{[(N-m-1)(N-m)]P^m(r)or\ Q(r)}{2} \quad (7)$$

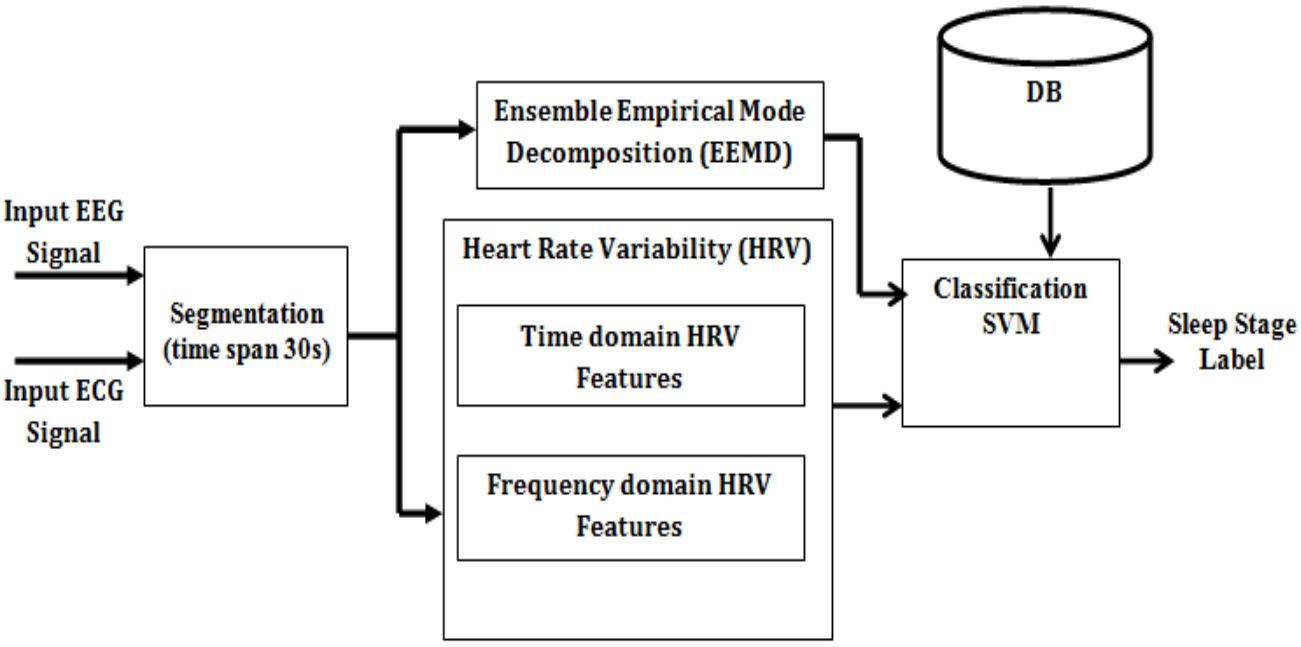

Figure.1 Overall Block diagram of proposed system

3.2. EEG features extraction

A total of 24 features are extracted from EEG signal from its two frequency bands namely delta ([1-3 Hz]) and Alpha (8 – 13 Hz). Totally six channels are considered here for every EEG, they are namely F3 channel, F4 channel, C3 channel, C4 channel, O1 channel and O2 channel. Among the 24 features, 12 are Statistical features which are derived based on Mean Square Error (MSE) of corresponding channel and the remaining 12 are intrinsic mode functions derived from EEMD process. The complete details about EMD, EEMD followed by features extraction are outlined here.

3.2.1. Empirical Mode Decomposition (EMD)

EMD is a method designed to analyze non-linear and non-stationary time series data. It decomposes a signal into a set of IMFs, which are simpler components that represent different frequency bands present in the original signal. The IMFs are derived through an iterative sifting process, where each IMF must satisfy specific properties:

- The number of extrema (maxima and minima) and the number of zero crossings must either be equal or differ at most by one.
- The mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero at any point.

EMD decomposes a signal $x(t)$ into a set of Intrinsic Mode Functions (IMFs) and a residue. The general formula for EMD decomposition is:

$$x(t) = \sum_{i=1}^{n} IMF_i(t) + r_n(t) \quad (8)$$

Where$IMF_i(t)$ are the intrinsic mode functions, and $r_n(t$ is the residue after extracting *n* IMFs.

Sifting Process in EMD

1. The sifting process involves the following steps:
2. Identify all the local extrema (maxima and minima) of the signal $x(t)$
3. Interpolate between the local maxima to form an upper envelope $e_{max}(t)$
4. Interpolate between the local minima to form a lower envelope $e_{min}(t)$
5. Compute the mean envelope $m(t) = \frac{e_{max}(t)+e_{min}(t)}{2}$
6. Extract the detail $h(t) = x(t) - m(t)$
7. Iterate on $h(t)$until it satisfies the IMF conditions, then treat $h(t)$ as the first IMF.

3.2.2. Ensemble EMD (EEMD)

The primary concern of Empirical Mode Decomposition (EMD) is the phenomenon of mode mixing, which occurs when distinct signal components are not effectively separated, resulting in the presence of numerous physical modes within a single Intrinsic Mode Function (IMF). This might complicate the interpretation of International Monetary Funds (IMFs) and reduce their significance. The Ensemble Empirical Mode Decomposition (EEMD) is an enhanced version of the Empirical Mode Decomposition (EMD) technique. It addresses the issue of mode mixing by including a noise-assisted data processing approach. The process involves introducing white noise to the initial signal and subsequently applying Empirical Mode Decomposition (EMD) on the noisy signal repeatedly. The primary benefits of EEDM are manifold; they include

Minimising Mode Interference: The Ensemble Empirical Mode Decomposition (EEMD) method successfully mitigates the problem of mode mixing, which is a prevalent issue in the conventional Empirical Mode Decomposition (EMD) technique where distinct frequency components are not well separated. EEMD, by taking the average of many noisy decompositions, guarantees that each IMF accurately represents a specific frequency range of the EEG signal. This results in components that are more distinct and easier to read.

Management EEG signals possess inherent non-stationarity and non-linearity. The EEMD method is particularly suitable for analysing such signals because it does not make any assumptions about linearity or stationarity. The signal is decomposed in an adaptive manner, considering its inherent qualities. This enables precise extraction of features that accurately represent the changing nature of brain activity.

EEMD enhances the representation of EEG signals by breaking them down into Intrinsic Mode Functions (IMFs), resulting in a multi-scale depiction of the signal. This is especially advantageous in sleep studies, as distinct sleep stages are distinguished by certain frequency ranges (for example, delta waves in deep sleep and theta waves in light sleep). Empirical Mode Decomposition (EEMD) enables the separation and examination of these frequency bands, enhancing the precision of sleep stage classification. The noise-adding method in Ensemble Empirical Mode Decomposition (EEMD) improves the signal's noise robustness by evenly distributing its energy over several frequency scales. This, in turn, promotes the separation of intrinsic modes. This enhances the

Table 2. Features Extracted from EEG signal

No.	Feature	No.	Feature	No.	Feature
Delta (δ): ([1- 3 Hz])					
1.	F3 - IMF_{δ}	**2.**	F3 - MSE_{δ}	**3.**	F4 - IMF_{δ}
4.	F4 - MSE_{δ}	**5.**	C3 - IMF_{δ}	**6.**	C3 - MSE_{δ}
7.	C4 - IMF_{δ}	**6.**	C4 - MSE_{δ}	**9.**	O1 - IMF_{δ}
10.	O1 - MSE_{δ}	**11.**	O2 - IMF_{δ}	**12.**	O2 - MSE_{δ}
Alpha (α): ([8- 13 Hz])					
13.	F3 - IMF_{α}	**14.**	F3 - MSE_{α}	**15.**	F4 - IMF_{α}
16.	F4 - MSE_{α}	**17.**	C3 - IMF_{α}	**18.**	C3 - MSE_{α}
19.	C4 - IMF_{α}	**20.**	C4 - MSE_{α}	**21.**	O1 - IMF_{α}
22.	O1 - MSE_{α}	**23.**	O2 - IMF_{α}	**24.**	O2 - MSE_{α}

resilience of the breakdown to noise, which is a crucial factor to consider in EEG analysis, as signal noise can be widespread.

The steps involved in EEMD are:

1. Add White Noise: Add a different realization of white noise to the original signal. This helps in spreading the signal's energy uniformly across different frequency scales.

$$x_k(t) = x(t) + w_k(t) \tag{9}$$

Where k k ranges from 1 to K, the total number of noise realizations

2. Decompose the Noisy Signal: Apply the EMD process to the noisy signal to decompose it into its IMFs.

$$x_k(t) = \sum_{i=1}^{n} IMF_{ik}(t) + r_{nk}(t) \tag{10}$$

Where $IMF_{ik}(t)$ are the IMFs of the noisy signal $x_k(t)$.

3. Repeat: Repeat the process multiple times (with different noise realizations) to create an ensemble of IMFs for each noisy signal.

4. Ensemble Averaging: Compute the ensemble average of the corresponding IMFs from all the trials. This averaging process helps cancel out the added noise while retaining the true signal components, resulting in a more stable and reliable set of IMFs

$$IMF_i(t) = \frac{1}{K}\sum_{k=1}^{K} IMF_{ik}(t) \tag{11}$$

This averaging process cancels out the added noise, retaining the true signal components. Table 2 Leverages the total 24 features extracted from EEG signal in two frequency band.

3.3. ECG features extraction

Heart Rate Variability (HRV) is a key measure derived from Electrocardiogram (ECG) signals that reflects the variations in time intervals between consecutive heartbeats. It is widely used for assessing autonomic nervous system function and overall heart health. Feature extraction from ECG signals for HRV analysis can be categorized into time domain and frequency domain methods. Sine both domains have significant contribution in representing the sleep abnormalities, we considered both in our work.

3.3.1. Time domain HRV

Time domain features are statistical measures computed directly from the time intervals between successive R-peaks (RR intervals) in the ECG signal. Time domain HRV features are simple to compute and interpret, making them useful for real-time monitoring and basic HRV assessments. Common time domain HRV features include RRMean, Standard Deviation of NN Intervals (SDNN), Root Mean Square of Successive Differences (RMSSD), and pNN50 [27]. They are described as follows.

Mean RR Interval (RR mean): The average time between successive R-peaks.

$$RRMean = \frac{1}{N}\sum_{i=1}^{N} RR_i \tag{12}$$

Standard Deviation of NN Intervals (SDNN): The standard deviation of all NN (normal-to-normal) intervals, representing overall HRV.

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_i - RRMean)^2} \tag{13}$$

Root Mean Square of Successive Differences (RMSSD): The square root of the mean of the squares of successive differences between adjacent NN intervals, indicating short-term HRV.

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_{i+1} - RR_i)^2} \tag{14}$$

pNN50: The proportion of successive RR intervals that differ by more than 50 ms.

$$pNN50 = \frac{Number\ of\ Intervals\ with\ |RR_{i+1} - RR_i| > 50ms}{N} \quad (15)$$

Heart rate reflects the dynamic activities of the Parasympathetic Nervous System (PNS) and Sympathetic Nervous System (SNS), correlates with respiratory frequency, and offers insights into cardiac activity during sleep.

3.3.2. Frequency domain HRV

Frequency domain features are derived by analyzing the power spectral density of the RR intervals, providing information about how power is distributed across different frequency bands. Frequency domain features provide deeper insights into autonomic regulation and physiological processes, useful for more detailed clinical analysis Common frequency domain HRV features include:

Low-Frequency Power (LF): Power in the low-frequency range (0.04 to 0.15 Hz), associated with both sympathetic and parasympathetic activity.

High-Frequency Power (HF): Power in the high-frequency range (0.15 to 0.4 Hz), primarily reflecting parasympathetic activity (respiratory sinus arrhythmia).

LF/HF Ratio: The ratio of LF to HF power, indicating the balance between sympathetic and parasympathetic acTotal Power: The total power of the spectrum within the frequency range (usually up to 0.4 Hz).

Total Power: The total power of the spectrum within the frequency range (usually up to 0.4 Hz).

Faster periodicities in heart rate patterns are captured by low-frequency (LF) power (0.04-0.15 Hz) and high-frequency (HF) power (0.15-0.4 Hz). LF power (0.04-0.15 Hz) and HF power (0.15-0.4 Hz) are associated with the regulation of the SNS and PNS, respectively [28]. The LF/HF ratio is used to assess changes in autonomic function between sleep stages and generally increases with heightened SNS activity during the transition from NREM to REM sleep. This ratio captures subtle changes in cardiac dynamics across different sleep stages [29].

4. Experimental analysis

4.1. Datasets and simulation setup

To assess the effectiveness of the suggested approach for categorising sleep stages, two openly accessible polysomnography (PSG) datasets containing both EEG and ECG recordings are utilised. These datasets are the ISRUC-S3 dataset [30] and the MASS-SS3 dataset [31]. Every recording from both datasets was divided into 30-second epochs and visually classified into five sleep stages: Awake, NREM (N1, N2, and N3), and REM sleep. The evaluation was carried out by specialists in sleep, following the protocols established by the American Academy of Sleep Medicine (AASM).

The ISRUC-S3 dataset is a component of the ISRUC-Sleep database, which is specifically created for the purpose of sleep stage classification. The dataset contains extensive polysomnography (PSG) data from various individuals, making it an asset for the development and assessment of sleep staging algorithms. The ISRUC-S3 dataset comprises recordings obtained from patients exhibiting symptoms indicative of sleep disorders. The system comprises several EEG channels, ECG, EOG (electrooculogram), and EMG (electromyogram). The American Academy of Sleep Medicine (AASM) criteria are used to annotate sleep stages, which include Wake (W), Non-REM stages (N1, N2, N3), and REM sleep.

The MASS-SS3 dataset is a comprehensive collection of data specifically designed for sleep research, known as the Montreal Archive of Sleep Studies (MASS). The MASS-SS3 subset is a meticulously selected component of the MASS dataset that is specifically tailored for sleep stage categorisation and other relevant research purposes.

The MASS-SS3 dataset comprises polysomnography (PSG) recordings obtained from various people, with an emphasis on those who are in good health. The system includes several EEG channels, such as F3-A2, F4-A1, C3-A2, C4-A1, O1-A2, and O2-A1, as well as ECG, EOG, and EMG. The American Academy of Sleep Medicine (AASM) criteria are used to annotate sleep stages, which include Wake (W), Non-REM stages (N1, N2, N3), and REM sleep.

Data pretreatment is a crucial step that needs to be done before feature extraction. Eliminating artefacts and noise improves the quality of extracted features, hence guaranteeing the precision of classification. After performing preprocessing steps on the EEG and ECG data in the ISRUC-S3 cohort, a total of 6827 epochs were obtained. Out of the total number of epochs, 974 were classified as the W stage, 775 as N1, 2298 as N2, 1779 as N3, and 1001 as REM. In contrast, the MASS-SS3 dataset yielded a total of 55852 epochs. The dataset contains 5844 epochs classified as W stage, 4526 as N1, 27946 as N2, 7378 as N3, and 10158 as REM stage.

4.2. Performance metrics

Further the performance is assessed through three performance metrics namely Cohen Kappa (κ) [32], F1-score and Accuracy. For a given True Positives (TPs), False Positives (FPs), True Negatives (TNs) and False Negatives (FNs), the Accuracy, kappa coefficient and F-score are measured as follows;

$$Recall_i = \frac{TP_i}{TP_i+FN_i} \quad (16)$$

$$Precision_i = \frac{TP_i}{TP_i+FP_i} \quad (17)$$

$$F1-Score_i = \frac{2*Recall_i*Precision_i}{Recall_i+Precision_i} \quad (18)$$

$$Accuracy = \frac{TP_i+TN_i}{TP_i+TN_i+FP_i+FN_i} \quad (19)$$

4.3. Results

The following results provide a detailed comparison of the percentage distribution of performance metrics like precision, recall and F1-score across various sleep stages (Wake, N1, N2, N3, REM) for ECG, EEG, and a combination of ECG+EEG signals.

In Fig. 2, the Wake stage shows a high signal percentage, with approximately 70% for ECG and 80% for EEG. The N1 stage shows a significant drop in ECG percentage to around 10%, while EEG remains at about 50%. For the N2 stage, both ECG and EEG percentages are relatively high, around 50% and 80%, respectively. The N3 stage, representing deep sleep, has the highest ECG percentage at 90% and a substantial EEG percentage of 70%. The REM stage also exhibits high signal percentages, with both ECG and EEG around 70-80%.

In Fig.3, the Wake stage again shows high signal percentages, with ECG at approximately 80% and EEG at 90%. The N1 stage displays a high percentage for both ECG and EEG, around 70% and 80%, respectively. The N2 stage maintains a high percentage, with ECG and EEG both around 80%. The N3 stage continues to show the highest signal percentages, with ECG at 90% and EEG at 80%, indicating intense physiological activity during deep sleep. The REM stage shows high percentages as well, with ECG at 70% and EEG at 80%.

Fig. 4 mirrors the trends observed in the previous figures. The Wake stage shows high percentages, with ECG at 70% and EEG at 80%. The N1 stage has ECG and EEG percentages around 70% and 80%, respectively. The N2 stage shows high percentages, with both ECG and EEG around 80%. The N3 stage again has the highest percentages, with ECG at 90%

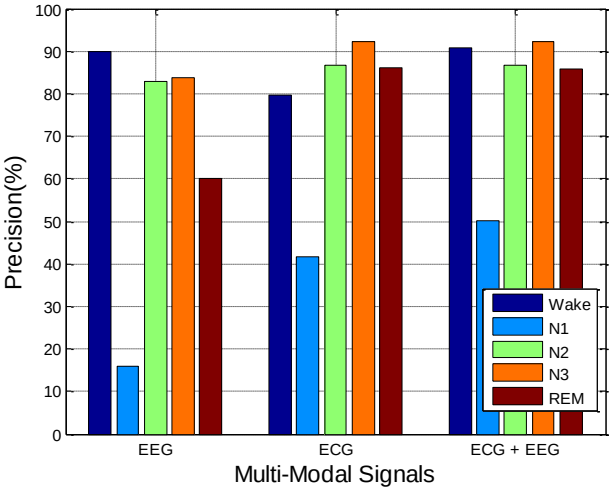

Figure.2 Precision of proposed approach for different sleep stages

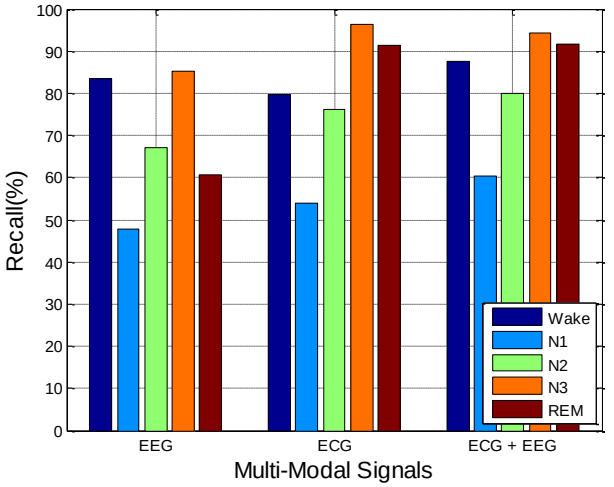

Figure.3 Recall of proposed approach for different sleep stages

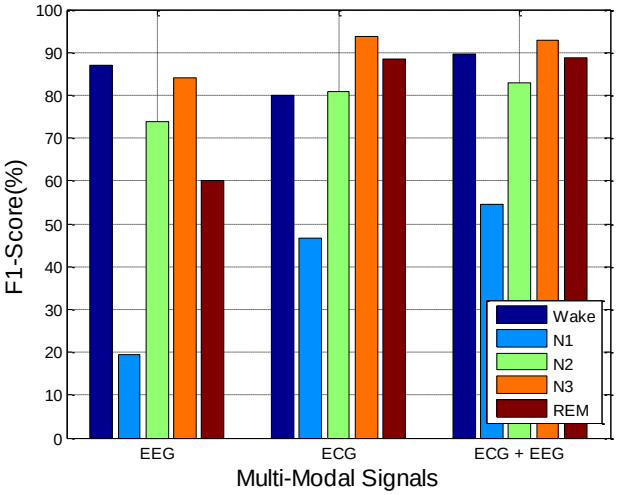

Figure. 4 F1-Score of proposed approach for different sleep stages

and EEG at 80%. The REM stage exhibits high signal percentages, with ECG at 70% and EEG at 80%. Overall, the figures consistently show that the N3 sleep stage, associated with deep sleep, has the highest signal percentages for both ECG and EEG. This indicates a significant increase in physiological activity during this stage. The REM stage also shows high percentages, reflecting active brain function. The N1 and N2 stages have moderate to high percentages, indicating a progression in sleep depth and corresponding physiological activity.

Wakefulness and REM sleep share similar EEG patterns characterized by low amplitude, mixed frequency waves, while NREM sleep displays slower, more synchronized waves. REM sleep and wakefulness are more similar in EEG patterns compared to NREM sleep. The heart rate during NREM sleep is slightly lower compared to wakefulness, and REM sleep may show variability in heart rate due to irregular breathing patterns and occasional increases in heart rate associated with vivid dreaming. Wakefulness typically shows a regular heart rate with normal variability. Combining ECG with EEG allows for a more comprehensive understanding of sleep physiology. For example, during REM sleep, the combination of irregular breathing patterns in ECG and the EEG patterns resembling wakefulness help differentiate it from other sleep stages. In contrast, NREM sleep shows slower EEG patterns along with a slight decrease in heart rate, indicating deeper relaxation compared to wakefulness

Figs. 5 and 6 shows the Comparison between proposed and existing methods at different datasets through accuracy and kappa coefficient respectively. Based on the comparison, the newly proposed approach stands out by considering both EEG and ECG signals, providing a more comprehensive view of sleep physiology. This approach potentially captures additional information about cardiac activity that can enhance the accuracy of sleep stage classification. P. Memer *et al.* [9], A. Alickovic *et al.* [10] and J. Fan *et al.* [24] propose a novel sleep staging method that utilizes EOG signals, which are more convenient to acquire than EEG signals. Their approach employs a two-scale convolutional neural network to extract temporary features from raw EOG data, followed by a recurrent neural network to capture long-term sequential information. However, a potential drawback is that EOG signals may not provide as rich a set of information regarding sleep stages compared to EEG signals, which could lead to reduced accuracy in classification. Additionally, the reliance on specific network architectures may limit the generalizability of the model to diverse datasets

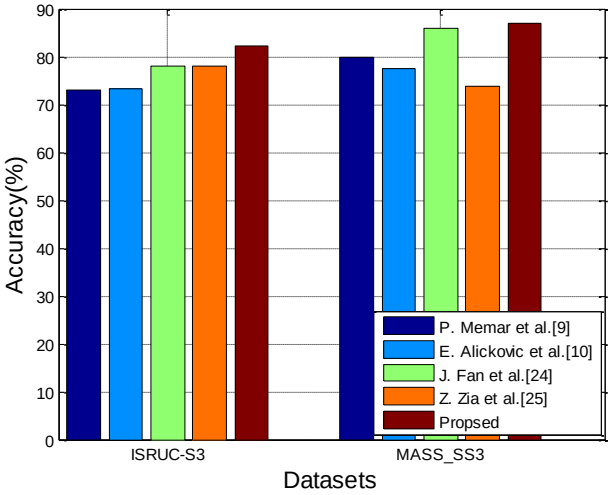

Figure. 5 Accuracy Comparison between proposed and existing methods at different datasets

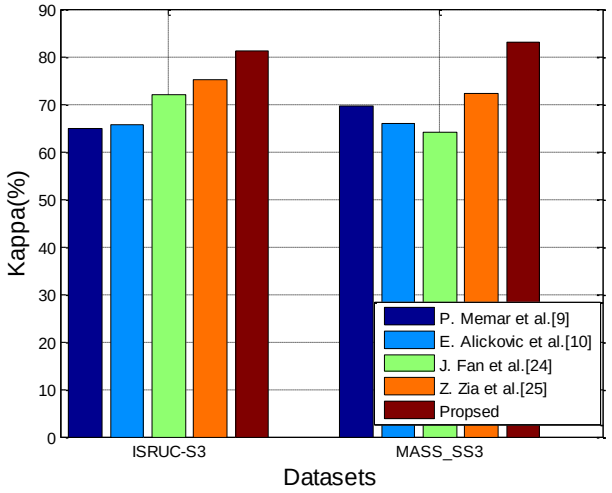

Figure. 6 Kappa Coefficient Comparison between proposed and existing methods at different datasets

or varying sleep patterns. Hence, they experienced only the accuracy around 70%. Next, Z. Zia *et al.* [25] propose SalientSleepNet, a multimodal salient wave detection network for sleep staging, based on the U2-Net architecture originally designed for salient object detection in computer vision. The model features two independent U2-like streams for extracting salient features from multimodal data, along with a multi-scale extraction module to identify transition rules among sleep stages and a multimodal attention module to selectively capture relevant information. A potential drawback is the complexity of the architecture, which may require substantial computational resources and tuning, potentially limiting its practical applicability in real-time sleep monitoring systems. However, none of these methods considered the additional information provided by ECG signals and mainly relied on EEG features alone for sleep stage classification. Unlike the previous

articles that primarily focus on EEG features, the new method utilizes two different feature extraction techniques: EMD for EEG signals and HRV for ECG signals. This indicates a more sophisticated feature extraction process, which may lead to better representation of the underlying physiological phenomena associated with different sleep stages. In addition, the proposed method introduces novel non-linear signal analysis techniques, particularly multiscale entropy, which can capture complex temporal dynamics in the EEG and ECG signals. This suggests a more advanced approach to feature representation and classification, potentially leading to improved accuracy in sleep stage scoring.In summary, the proposed method presents a promising advancement in sleep stage classification by integrating EEG and ECG signals and employing advanced feature extraction techniques and non-linear signal analysis methods. This comprehensive approach has the potential to improve the accuracy of sleep stage scoring compared to the state-of-the-art methods. The average accuracy of proposed approach in observed as 84.6% whereas for previous methods it is observed as 76.45%, 75.45%, 81.2% and 83.1% by P. Memer *et al.* [9], A. Alickovic*et al.* [10], J. Fan *et al.* [24] and Z. Zia *et al.* [25] respectively. Similarly, the average kappa coefficient is observed as 67.25%, 65.8000%, 71.80%, 70.85 and 73.75% by P. Memer *et al.* [9], A. Alickovic*et al.* [10], J. Fan *et al.* [24], Z. Zia *et al.* [25] and proposed methods respectively.

5. Conclusion

The suggested method represents a notable progress in the domain of sleep stage classification, as it combines EEG and ECG signals and employs cutting-edge techniques for extracting features, such as EMD and HRV. By combining both EEG and ECG information, the technique has the potential to improve the accuracy of sleep stage scoring by collecting a more thorough understanding of sleep physiology. Furthermore, the utilisation of advanced non-linear signal analysis techniques, such as multiscale entropy, enhances the ability to capture complex temporal dynamics in the signals. The method's capacity to enhance the advancement of more dependable and exact sleep monitoring systems is apparent in the achieved outcomes, which exhibit its efficacy in precisely evaluating sleep stages. Overall, this approach has the capacity to enhance our understanding of sleep patterns and their impact on health and well-being. On average, the proposed method achieved an improvement of 3.5% in accuracy and 2.64% in the kappa coefficient compared to state-of-the-art methods.

Conflicts of Interest

Authors declare that they have no conflict of interest.

Author Contributions

The authors confirm contribution to the paper as follows Conceptualization, Design, Analysis and Development work done by Voruchu Sai Babu. Implementation, Validation and proofreading work done by A.Ramakrishna. Both the authors reviewed the results and approved the final version of the manuscript.

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