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Automatic Sleep Spindle Detection Using SMOTE and Composite Features with SWT and Adaboost

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Abstract: Sleep Spindles contribute to diagnosing several brain-related diseases like sleep apnea, major depression, etc. Hence, sleep spindle detection from Electroencephalogram (EEG) has gained significant research interest in the bio-medical signaling field. Existing methods use template matching and machine learning algorithms for spindle detection. In the template matching methods, the additional and continuous tuning of the threshold creates an unnecessary computational burden. In the machine learning-based method, significant problems such as data imbalance and less discrimination due to fewer and inappropriate features are addressed. To address these issues, this research presents a novel automatic spindle recognition approach that uses the Synthetic Minority Oversampling Technique (SMOTE) to balance the dataset and integrates time-domain and frequency-domain information for effective feature extraction. The Synchrosqueezed Wavelet Transform (SWT) is utilized for accurate frequency domain feature extraction, while the Adaboost(Adaptive Boosting)algorithm is implemented for classification. This method, evaluated using the publicly accessible Montreal Archives of Sleep Studies Cohort 1 (MASS-C1) dataset, significantly outperforms existing methods like as SpindleU-Net, Convolutional MIL (Multiple Instance Learning), SST-RUSBoost (Synchrosqueezed Transform - Random Under-Sampling Boosting), and MuFF-E(Multi-Feature Fusion and Ensemble), with an F-score of 75%, Sensitivity of 78%, and Positive Predictive Value of 73%. The findings illustrate the superiority of the proposed method in addressing data imbalance and improving detection accuracy.

Keywords: Electroencephalogram, Sleep spindles, Synchrosqueezed wavelet transform, Sigma ratio, Sigma index, SMOTE, Adaboost.

1. Introduction

Sleep spindles are rhythmic bursts of oscillatory brain activity observed during stage NREM2 of sleep and are considered crucial for cognitive functions such as memory consolidation and neurocognitive performance [1, 2]. These spindles, characterized by frequencies ranging from 11-17 Hz and durations between 0.5-2 seconds, are often used as biomarkers for various neurological and psychiatric conditions, including autism, schizophrenia, epilepsy, and Parkinson's disease [3, 4]. Detecting these spindles accurately is essential in sleep studies and clinical applications, where they provide critical insights into sleep architecture and brain health. Electroencephalogram (EEG) signals are widely regarded as the gold standard for capturing such events due to their ability to monitor electrical activity in the brain with high temporal resolution [5, 6].

Traditional approaches to sleep spindle detection have evolved from manual to automated methods. Manual detection, which involves visual inspection of EEG signals by experts, is still regarded as reliable but suffers from significant limitations, such as subjectivity, inconsistency, and time-intensive processes [7]. Automated methods such as template matching, signal thresholding, and feature-based classification have been introduced to overcome these limitations [8]. Template-based methods segment EEG signals and classify spindles by matching their morphology to predefined templates, but their reliance on fixed thresholds often results in a lack of adaptability to individual variability [9]. More recently, machine learning approaches such as Random Forests, Support Vector Machines, and convolutional neural networks (CNNs) have been employed for spindle detection, leveraging large datasets and advanced algorithms [10, 11]. However, while these methods show promise, their practical application faces significant challenges [12].

Despite advancements, traditional and modern methods face persistent limitations. Manual detection is prone to inter-observer variability and is impractical for large-scale studies [13]. Template-based methods require extensive parameter tuning to accommodate the variability in EEG signals across individuals and experimental setups [14]. Machine learning methods, while powerful, suffer from imbalanced datasets, where spindles are often underrepresented compared to non-spindle events, leading to biased models and reduced sensitivity [15]. Moreover, existing feature extraction techniques often fail to fully capture the subtle time-frequency characteristics of spindles, which are critical for accurate classification [16]. Computational inefficiencies in many advanced models also hinder their use in real-time applications and resource-constrained environments, such as wearable devices [17, 18].

To address these challenges, this paper introduces a novel sleep spindle detection framework, SST-SMOTE-Adaboost, which integrates Synthetic Minority Oversampling Technique (SMOTE) for balancing imbalanced datasets, Synchrosqueezed Wavelet Transform (SWT) for precise time-frequency feature extraction, and the Adaboost algorithm for robust classification. SMOTE enhances the representation of minority spindle events by generating synthetic samples, mitigating the impact of class imbalance. SWT provides sharper time-frequency representations, allowing for better discrimination between spindles and other signal components. Finally, Adaboost combines multiple weak classifiers into a strong classifier, effectively handling complex decision boundaries in the data. The framework captures both time-domain features (e.g., RMS, TKE) and frequency-domain features (e.g., Sigma Index, Spindle Band Ratio), ensuring a comprehensive feature set for accurate detection.

The main contributions of the study as follows,

- Proposes a novel spindle detection framework combining SMOTE, SWT, and Adaboost.
- Introduces an enhanced feature extraction method integrating time-domain and frequency-domain features.
- Addresses the dataset imbalance issue using SMOTE for minority spindle class oversampling.
- Demonstrates superior performance on the MASS-C1 dataset compared to existing methods.
- Highlights practical implications for clinical and real-world EEG applications.

The rest of the paper is organized as follows: Section II reviews the related works on sleep spindle detection, highlighting traditional manual methods, template-based approaches, and recent advancements in machine learning techniques. Section III provides an in-depth description of the proposed SST-SMOTE-Adaboost framework, detailing the preprocessing steps, feature extraction methodology, and classification process. Section IV discusses the experimental setup, including the dataset, evaluation metrics, and results, presenting a comprehensive analysis of the framework's performance. Section V offers a detailed discussion of the findings, addressing the framework's strengths, limitations, and potential directions for future research. Finally, Section VI concludes the paper by summarizing the key contributions and the broader implications of the proposed method for sleep spindle detection and clinical applications.

2. Related work

The accurate identification of sleep spindles is crucial for diagnosing numerous neurological disorders. The landscape of spindle detection has evolved significantly, moving from manual methods to automated techniques, each with distinct advantages and shortcomings.

Manual Detection: Historically, spindle detection was predominantly manual, relying on visual inspection by experts, which was labor-intensive and subject to considerable variability. Wendt et al. [19] highlighted the limitations of this method, reporting inter-expert and intra-expert reliability F-measures of 61.6% and 72.7%, respectively. These discrepancies underscore the need for more consistent and automated methods.

Template-Based Detection: The first generation of automated spindle detection, entail segmenting the EEG signal and aligning each segment with a predetermined spindle template. Each segment is subsequently categorized as either spindle or non-spindle according to a predetermined threshold, which frequently necessitates human modification owing to the distinctive properties of EEG signals [20]. This strategy, albeit a progression towards automation, had considerable obstacles. The primary research gap identified was the necessity for frequent threshold modifications, which may add subjectivity and diminish reproducibility.

Adaptive Methods: To address the limitations of template-based methods, adaptive approaches were developed. These methods utilize historical knowledge of spindles to automate threshold adjustments [21, 22]. However, they often fail to fully account for the inherent variability in spindle morphology across individuals, which limit their effectiveness.

Recent Techniques: Recent advancements in sleep spindle detection have focused on enhancing the accuracy and efficiency of automated methods using various signal processing techniques and machine learning models. Kinoshita et al. [23] proposed an approach that integrates random under-sampling boosting (RUSBoost) with Synchrosqueezed Wavelet Transform (SWT) to mitigate data imbalance without necessitating further threshold adjustment. This strategy enhanced the management of imbalanced data; nevertheless, employing under-sampling may result in the loss of significant data, hence constraining the classifier's efficacy. Patti et al. [24] utilized a Multivariate Gaussian Mixture Model (MVGMM) for spindle detection, tailored to individual subject factors. This methodology sought to guarantee reliable, subject-agnostic detection; nevertheless, it frequently necessitated substantial parameter adjustment to optimize for various subjects, rendering it less feasible for widespread application. Wei L et al. [25, 26] developed Spindle-AI, employing a Random Forest algorithm to detect spindles in newborn EEG signals. Although it evaluates multiple features per epoch, the complexity of the model can result in computational inefficiencies and potential overfitting. Tsanas et al. [27] proposed a new methodology for the detection of sleep spindles from EEG signals. They used an intuitive appealing continuous wavelet transform (CWT) using the Morlet mother wavelet function. The CWT identifies the spindles based on the theory that the spindle frequency is significant in CWT coefficients. Further, a local weighted smoothing method was employed to refine the spindle signal segment.

J. You et al. [28] developed SpindleU-Net, an adaptive U-Net framework specifically designed for spindle detection in single-channel EEG, which includes an attention module to enhance feature extraction capabilities. This framework, however, may not fully leverage the spatial information available in multi-channel EEG, suggesting a potential area for further research. X. Sun et al. [29] introduced a convolutional multiple instance learning framework for sleep spindle detection, incorporating a label refinement strategy to improve spindle identification accuracy, though it relies heavily on the initial label accuracy. Z. Yang and J. Pan [30] focused on using CNNs for the automatic detection of sleep spindles to assess patients with acute disorders of consciousness, highlighting the need for further validation across diverse clinical conditions. Xian Zhao et al. [31] introduced a hybrid expert scheme for the automatic identification of micro-sleep event K-complexes, leveraging energy screening and morphology characterization techniques. This innovative approach was tested using the MASS-C1 dataset, which includes EEG recordings from 19 healthy adults. The evaluation of the system showed promising results, with the scheme achieving an average F-measure of 0.63, accompanied by a recall of 0.81 and a precision of 0.53. These metrics indicate the effectiveness of the hybrid approach in detecting sleep-specific EEG patterns. F. Andreotti et al. [32] examined the application of CNNs for automated sleep stage classification using polysomnographic signals such as EEG, EMG, and EOG. The research demonstrated that CNN models performed well, achieving a Cohen's Kappa score of 0.75 for healthy subjects and 0.64 for patients with sleep disorders. The study also addressed the challenge of limited data availability for rare conditions by implementing a transfer learning strategy, which involved pretraining on a large public dataset and fine-tuning on a smaller dataset specific to REM Behavior Disorder, resulting in a 24.4% improvement in classification accuracy.

2.1 Problem definition and novel approach clarification

The precise identification of sleep spindles is essential for diagnosing and understanding neurological diseases, yet current detection techniques face significant challenges. Automated methods, such as those proposed by Kinoshita et al. using RUSBoost combined with Synchrosqueezed Wavelet Transform, strive to manage data imbalance but risk losing crucial data which may diminish classifier effectiveness [23]. Patti et al.'s use of a Multivariate Gaussian Mixture Model aims for subject-agnostic detection but often requires extensive parameter tuning, making it impractical for broad application [24]. Methods incorporating complex algorithms like the Random Forest in Spindle-AI by Wei L et al. evaluate numerous features but suffer from potential computational inefficiencies and overfitting [25, 26]. Additionally, J. You et al.'s SpindleU-Net, though innovative with its attention module for enhanced feature extraction, does not fully exploit spatial information from multi-channel EEG, indicating a gap for further enhancement [28]. These varied approaches underscore the need for developing more efficient, accurate, and universally applicable methods for spindle detection in diverse clinical and research settings. The novel approach presented in this work addresses the limitations of existing sleep spindle detection methods by integrating SMOTE, Synchrosqueezed Wavelet Transform (SWT), and the Adaboost classifier to effectively manage data imbalances and enhance feature extraction without the loss of significant information. Unlike other methods that suffer from overfitting, require extensive parameter tuning, or fail to exploit multi-channel EEG data fully, this method maintains a balance between simplicity and performance, simplifying the detection process while ensuring high accuracy and robustness. By leveraging comprehensive time and frequency domain features and an adaptive classification strategy, this approach offers a scalable and effective solution for spindle detection in various clinical and research settings.

3. Proposed approach

3.1 Overview

This work proposed a new spindle detection mechanism that can improve detection performance and also solve the data imbalance problem in machine learning methods. It derives a new set of features to identify the sleep spindles from EEG signals. Two sets of features are derived from both time and frequency domains. Totally 12 features are used to describe each epoch, among which seven features belong to the time domain, and the remaining five features belong to the frequency domain. For classification, we employed a simple Adaboost algorithm and classified each epoch into two classes; a spindle and a non-spindle. Fig. 1 illustrates the proposed spindle detection framework, detailing preprocessing with SMOTE, feature extraction using SWT, and classification with the Adaboost algorithm.

3.2 Smote

Generally, the data imbalance problem occurs in datasets when they have imbalanced data, i.e., too much deviation between the number of samples of different classes. In such a dataset, the probability of output distribution induces a bias problem which results in poor detection performance. To sort out this problem, the dataset needs to be balanced before processing it for training. Towards such contribution, here we employed the most popular Synthetic Minority Oversampling Technique (SMOTE). When compared to the non-spindle events number in EEG signals the spindle events are lower, so the problem of class imbalance improves at learning algorithm and makes the detection task challenging. SMOTE addresses this problem and balances the dataset. SMOTE is an over-sampling method that induces extra samples for minor classes by creating some additional samples into the sample space. Additionally, the random number generator uses the random state as a seed. The working of SMOTE algorithm can be explored as follows.

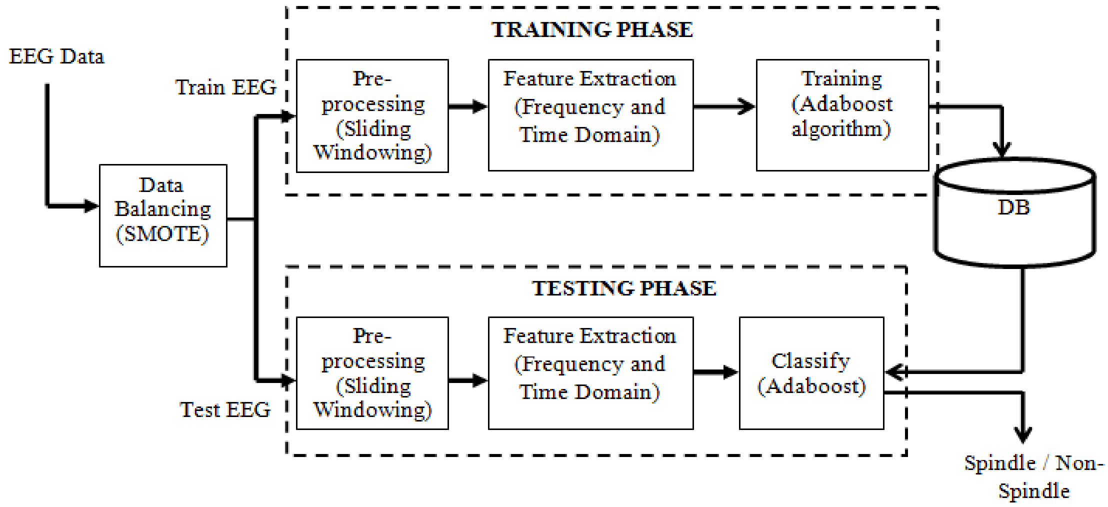

Figure. 1 Detailed schematic of working of the proposed spindle detection framework

Step 1: Consider the minority class set as M for each, the K-nearest neighbors of m derived by computing the Euclidean distance between m and every other sample in the set M.

Step 2: Consider N to be the sampling rate for every N example (i.e.,) randomly chosen for construction of a new set M1 using its K-nearest neighbor.

Step 3: For each sample, the below formula generates a new example that signifies the random number between 0 and 1.

3.3 Features extraction

After the completion of pre-processing through SMOTE, our method extracts two sets of features from each epoch, and they are namely time and frequency domain features. Under the time domain, we considered the epoch as direct input. In contrast, in the frequency domain, the epoch is initially transformed into the frequency domain through Synchrosqueezed Wavelet Transform (SWT), and then features are extracted. Here the size of each epoch is maintained at 0.5 seconds because the range of the Spindle lies between 0.5 seconds and 1.5 seconds. So to cover each epoch in the EEG signal, the size is fixed to 0.5 seconds. For a given EEG, the segmentation is done through a sliding window with an overlapping of 0.25 seconds between two successive epochs. The details of the feature are explored in the following sub-sections;

3.3.1. Time domain features

In the time domain, we extract totally seven features; they are namely Root Mean Square (RMS), Mean of Absolute Amplitude, Maximum Absolute Amplitude, Minimum Absolute Amplitude, Teager-Kaiser Energy (TKE), symmetry, and Anti-symmetry. Among these features, the first of four features are common features, and they can be extracted very easily. Next, the TKE is regarded as a nonlinear feature that can estimate the non-stationary signal's spontaneous energy. Generally, the TKE is applied to identify the sudden changes in the biological signals. The mathematical expression for TKE is shown asin Eq. (1).

$$TKE[n] = x[n]^2 - x[n-1]x[n+1] \tag{1}$$

Where $x[n]$ is regarded as the n^{th} sample in the epoch and $x[n-1]$ and $x[n+1]$ are $(n-1)^{th}$ and $(n+1)^{th}$ samples of the Pre-processed epoch of EEG signal. Next, symmetry (S) and Anti-symmetry $(\hat{S})$ of a signal signify the distribution along vertical or horizontal axes. If a signal is symmetrical about either the vertical axis or time origin, then it is called an even signal or symmetrical signal. Here, we use symmetry and Anti-symmetry properties to describe the Spindle and non-spindle events. Mathematically, they are expressed asin Eq. (2)

$$S = \frac{\sum_{i=0}^{N/2} p_+[i]}{N\left(max_{i=0}^{N/2}(p_+[i])\right)^2} \tag{2}$$

Where $p_+[i]$ represents the average of symmetric pairs of samples about the center of the epoch, calculated asin Eq. (3) and (4).

$$p_+[i] = \frac{x[N/2+i]+x[N/2-i]}{2} \tag{3}$$

And

$$\hat{S} = \frac{\sum_{i=0}^{N/2} n_-[i]}{N\left(max_{i=0}^{N/2}(n_-[i])\right)^2} \tag{4}$$

Where $n_-[i]$ is the difference between symmetric pairs of samples, defined asin Eq. (5)..

$$n_-[i] = \frac{x[N/2+i]-x[N/2-i]}{2} \tag{5}$$

Where $x[N/2+i]$ and $x[N/2-i]$ are $(\frac{N}{2}+1)^{th}$ and $(\frac{N}{2}-1)^{th}$ samples in the epoch of pre-processed EEG, and N is the total number of samples in each epoch. S

3.3.2. Frequency domain features

EEG signals are composed of several components, like sleep spindles, temporary waves, and background activities. Among these components, spindle waves are temporary waves that lie within the range of 11Hz and 16Hz. So, to determine the spindles from the EEG signal, we need to estimate the accurate frequency of spindles which is a challenging task. Towards such contribution several time-frequency transformation techniques have been applied in the past, namely Wavelet Transform (W.T.), S-Transform, Continuous Wavelet Transform (CWT), and Empirical Mode Decomposition (EMD), etc. Among these transformations, CWT is one of the effective transformation techniques which can analyze the multi-resolution components of an EEG signal. CWT is regarded as an output of cross correlation between signal and mother wavelet as followsin Eq. (6).

$$W_S(a,b) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{|a|}} s(t)\psi^*\left(\frac{t-b}{a}\right) dt \tag{6}$$

Where b signifies the translation parameter and a signifies the scaling parameter. ψ is the mother wavelet, and $\psi^*$is a complex conjugate of ψ, t is the time, and $W_s(a,b)$ is the representation of a signal in time scale. The temporal length of wavelength used in the cross-correlation is different for different frequencies. To improve the frequency localization generally, longer wavelets are used frequencies which are low at the expense of time localization. On the other hand, shorter wavelets are used for high frequencies to enhance the time localization at the cost of frequency localization. We can use CWT to analyze a wide range of signals.SWT is an extended version of CWT that reduces the quantity of spectral smearing linked with the time-frequency transform such that it enhances the readability but no improvisation in the power of localization. For an SWT computation of a signal, starting with CWT, the next step is to compute Instantaneous Frequencies (I.F.s) and their reassignment. SWT assumes the representation of the signal as a sum of a finite number of harmonic components and some random noise, asin Eq. (7).

$$s(t) = \sum_{k=1}^{K} A_k(t) \cos\left(\theta_k(t) + \eta(t)\right) \tag{7}$$

Where θ_k and A_k are the phase and amplitude ofk^{th} signal component, η is some random noise, and K represents the total number of samples present in the signal. Then the instantaneous frequency (let it bef_k) of each component is derived asin Eq. (8).

$$f_k(t) = \frac{1}{2\pi}\frac{d\theta_k(t)}{dt} \tag{8}$$

However, most of the smearing happens on the frequency axis, and the instantaneous frequency can be directly computed from CWT Time-scale representation as follows

$$f_s(a,b) = \frac{1}{2\pi j W_s(a,b)}\frac{\partial}{\partial b} W_s(a,b) \tag{9}$$

So the above Eq.(9) transforms the signal representation from Time-Scale to time-frequency. Based on the attributes, the SWT is computed asin Eq. (10).

$$S(t,f) = \int_{-\infty}^{\infty} W_s(a,b)\frac{1}{\delta} h\left(\frac{f - f_s(a,b)}{\delta}\right) da \tag{10}$$

Where f denotes frequency, $h(t)$ is a function with $\int h(t)dt = 1$ and $S(t,f)$ is called the SWT coefficient. Squeezed CWT is produced out of this transformation as the rapid frequency bands will beallotted to the CWT time-frequency region Centroid. This reassignment of the frequency generates a structured output than the CWT.

Once the SWT array is obtained for each epoch, then we compute totally five features, namely Sigma Index (S.I.) and Sigma Ratio (S.R.) Alpha Band Ratio (α_{BR}), Sleep Spindle Band Ratio (SS_{BR}), and Relative Spindle Power (RSP). The definitions of these parameters or explode are as follows;

A. Sigma Index (S.I.): S.I. is obtained by dividingthe mean power of the spindle range (11-16Hz) with the frequency range average power around the frequency range of the spindle. The Sigma index is mathematically expressed asin Eq. (11).

$$SI(t) = \frac{mean(|F_3(x)|)}{mean(|F_1(x)|) + mean(|F_2(x)|)} \tag{11}$$

Where $F_1(x)$, $F_2(x)$, and $F_3(x)$ are the frequency ranges of three bands of EEG signal such as 4-10 Hz, 20-40Hz, and 11-16Hz respectively.

B. Sigma Ratio (S.R.): S.R. is the proportion of maximum power of the range of frequency of the spindle (11-16Hz) to the frequency range maximum power around the range of spindle. S.R. is mathematically expressed as in Eq. (12).

$$SR(t) = \frac{max(|F_3(x)|)}{max(|F_1(x)|) + max(|F_2(x)|)} \tag{12}$$

Where $|F_3(x)|$ represents the absolute power within the spindle frequency range (11-16Hz), $|F_1(x)|$ and $|F_2(x)|$ are the absolute powers within the adjacent lower and higher frequency ranges, respectively.

C. Related Spindle Power (RSP): RSP is obtained as the fraction of the power of the frequency of the spindle (11-16Hz) to the entire signal frequency. Mathematically it is expressed as followsin Eq. (13).

$$RSP(t) = \frac{\int_{11}^{16} S(t,f)}{\int_{0.5}^{40} S(t,f)} \tag{13}$$

Where $\int_{11}^{16} S(t,f)$ is the power of the SWT coefficient of t^{th} sample in the spindle frequency range and $\int_{0.5}^{40} S(t,f)$ is the power of the SWT coefficient of t^{th} sample in the entire signal's frequency range.

D. Alpha band ratio ($\boldsymbol{\alpha_{BR}}$): α_{BR} issue is the ratio of root mean square (RMS)value of the amplitude in the band of Alpha (8-11Hz) to the overall RMS value of amplitude of the epoch in the pre-processed Epoch of EEG Signal. Mathematically, α_{BR} is expressed as in Eq. (14).

$$\alpha_{BR} = \frac{RMS(f_{\alpha}(t,f))}{RMS(f_{sp}(t,f))} \quad (14)$$

Where $f_{\alpha}(t,f)$ and $f_s(t,f)$ are the amplitudes of samples in the alpha band and spindle band respectively.

E. Sleep Spindle Band Ratio (SS_{BR}): The Sleep Spindle Band Ratio (SS_{BR}) is defined as the ratio of the root mean square (RMS) value of the amplitude within the spindle frequency band (10.5-16Hz) to the RMS value of the amplitude across the entire frequency range of the EEG epoch. This ratio emphasizes the significance of spindle-specific activity relative to the overall EEG activity within an epoch, making it a valuable metric for identifying sleep spindles. Mathematically, SS_{BR} is expressed as in Eq. (15):

$$SS_{BR} = \frac{RMS(f_{sp}(t,f))}{RMS(f_s(t,f))} \quad (15)$$

Where $f_{sp}(t,f)$represents the amplitude of samples within the spindle frequency band (10.5-16Hz), and $f_s(t,f)$represents the amplitude of samples across the entire frequency range of the EEG.

3.4 Classification

For classification, we used an Adaboost algorithm which is simple and effective in nature. Initially, the detection system is trained and then subjected to testing. Algorithm 1 shows the process of training, and Algorithm 2 shows the process of testing. After segmenting the EGG into different epochs, each epoch is processed for feature extraction, and the obtained feature Vector is used to train the system. In algorithm 1, K represents the number of subjects used for training. For the EEG signal of *the* k^{th} subject, the sliding window is applied to the segment and then the feature vector is constructed as $\boldsymbol{X}^{(k)} \in \mathcal{R}^{N_k \times q} (k = 1,2, \dots, K)$ where q and N_k are the number of input variables and features extracted from k^{th} subject's EEG. Next, a label vector is formulated as $y^{(k)} \in \boldsymbol{y}^{N_k} (\boldsymbol{y} \in \{-1,1\})$ in which -1 is annotated for non-spindle and 1 is annotated for Spindle. Here the feature vector $\boldsymbol{X}^{(k)}$and label vector $y^{(k)}$ are merged into a single vector as $\boldsymbol{D} = \{X, y\}$ finally classified with the training $\boldsymbol{D}$.

Next, algorithm 2 shows the process of testing, i.e., the detection of spindles. Similar to training, initially, the EEG signal is segmented through a sliding window, and then features are extracted from each segment. Next, the labels are predicted using features of the test epoch and trained epochs. Further, the successive spindle candidates are marked, and then a search process is employed to find out the spindle candidate whose duration is more than 0.5 seconds.

Algorithm 1: Training of the Classifier
Input: The EEG recordings acquired from K subjects **Output:** Trained Classifier ***C*** with data D
1. for $k = 1,2, \dots, K$ do 2. Apply a sliding window to segment each EEG 3. Extract time domain and frequency domain features from each epoch 4. Formulate all features into a single feature vector $\boldsymbol{X}^{(k)}$ 5. Formulate a label vector $y^{(k)}$ 6. end for 7. Form a new Feature matrix $\boldsymbol{X}$ by merging all feature vectors $\boldsymbol{X}_{Tr}^{(k)}$ 8. Form a new Label matrix $\boldsymbol{y}$ by merging all label vector $y_{Tr}^{(k)}$ 9. Form a complete dataset as $\boldsymbol{D} = \{X, y\}$ 10. Train the classifier ***C*** with ***D***

Algorithm 2: Testing the classifier
Input: EEG recording acquired from one subject and trained classifier **Output:** Identified spindles
1. Apply a sliding window to segment the EEG recording 2. Extract time feature along with frequency domain from each epoch 3. Formulate all features into a single feature vector $\boldsymbol{X}_{.T.s}$ 4. Predict the label $\hat{y}$ with the help of ***C*** and $\boldsymbol{X}_{.T.s}$ 5. Mark the duration of Spindles where the test result had shown +1. 6. Search the spindles that successive duration is more than 0.5s.

4. Simulation experiments

This section explores the usefulness of the proposed method by validating it over a standard open-access database, Montreal Archives of sleep studies cohort 1 (MASS-C1) [31]. This dataset has a total of five subsets (S.S.) of PSG recordings. For the experimental validation of our proposed method, we used only one subset, i.e., SS2(Subset 2). In this section, first, we explore the details of the dataset and simulation setup. Next, the details of the evaluation and the obtained performance metrics are discussed.

4.1 Classification

The SS2 (Subset 2)of MASS-C1 consists of a total of 19 PSG (Polysomnography)recordings which were acquired with the help of nineteen subjects, among which eight are male, and eleven are female. The approximate age of subjects lies within the range of 18 to 33 years, and the collection is carried out according to the standard 10-20 system. Each PSG recording consists of totally five types of signals, namely Respiratory data, EMG (Electromyography), ECG (Electrocardiogram), EOG (Electrooculography), and EEG. The SS2 consists of sleep events marked by experts, such as k-complexes and sleep spindles. Experts 1 considered all the subjects and scored the k-complexes and sleep spindles, while Expert 2 considered only 15 out of 19 subjects and scored only sleep spindles. Sleep stage scoring followed purely R&K rules and scored the every 20 seconds duration PSG.Table 1 presents the individual and common sleep spindles identified for each subject, showing the overlap between annotations by different experts and highlighting the distribution of spindles across subjects.

In this dataset, two experts followed two different strategies for scoring the sleep spindles independently on channel C3. The first expert strictly followed R& K rules and annotated sleep spindles, while the second expert approached a wide frequency band-based scoring, which is different from R& K rule. Moreover, the recordings of the second expert are only 15 and excluded the recordings belonging to subjects 4, 8, 15, and 16.

To avoid such confusion in the selection of recordings as ground truths, we considered the common recordings that were finalized by both experts. The summarized number of standard and individual sleep spindles is shown in table.1 where S1 and S2 signify the sleep spindles scored by 1st and 2nd experts, respectively, and signify the common sleep spindles of 1st and 2nd experts. Hence, the total number of common sleep spindles is observed as 9066, and non-spindles are observed as 1,50,000, which declares a huge data imbalance between spindles and non-spindles. Fig. 2 presents an example of a sleep spindle waveform, showcasing its characteristic oscillatory pattern with frequencies ranging from 11 to 17 Hz and a duration of 0.5 to 2 seconds.

4.2 Performance analysis

Under the performance assessment, this work is evaluated through the computation of spindle detection event-by-event [32]. Considering SS_P (detected sleep spindles) and SS_G(ground truth sleep spindles) as the sleep spindles detected by the proposed approach and ground truth, respectively, the performance is measured as an

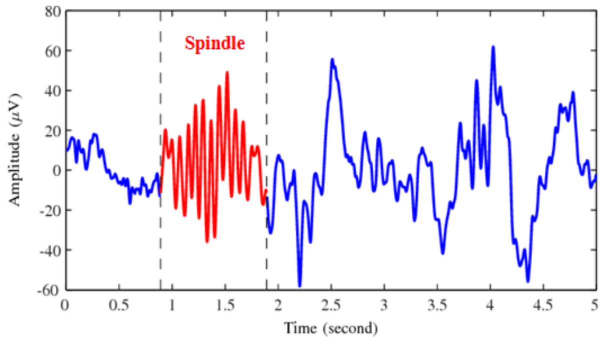

Figure. 2 Samples Sleep Spindle waveform

Table. 1 Individual and Common sleep spindles in each subject

Subject	D1	D2	$D1 \cap D2$	Subject	D1	D2	$D1 \cap D2$
S1	901	1979	980	S11	563	1020	557
S2	1095	1797	1084	S12	655	923	620
S3	130	246	128	S13	641	996	619
S5	314	644	313	S14	666	1133	645
S6	133	258	132	S17	428	700	422
S7	840	1291	794	S18	1075	1390	984
S9	765	1298	756	S19	294	475	294
S10	748	1406	736				

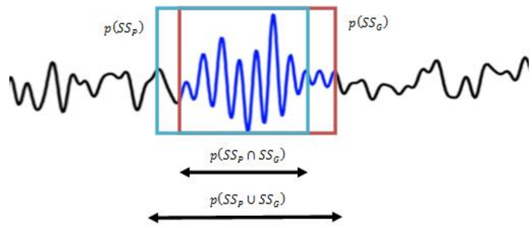

Figure. 3 Spindle portion detected by proposed method and Ground Truth

Overlap Score (O.S.). O.S. is defined as a ratio of the common intersected portion between SS_P and SS_G and an overall portion of SS_PandSS_G. Fig. 3 shows an example computation of O.S. Consider $p(SS_P \cap SS_G)$ and $p(SS_P \cup SS_G)$ be the common intersected portion and overall spindle portion between$SS_P$and SS_G, respectively, and then the O.S. is measured as

$$OS = \frac{p(SS_P \cap SS_G)}{p(SS_P \cup SS_G)} \quad (16)$$

Fig. 3 illustrates the spindle portions detected by the proposed method compared to the Ground Truth, highlighting the overlap and differences in spindle detection accuracy. The detection performance is evaluated by comparing the resulting O.S. with a predetermined threshold. If the overlap score of a spindle exceeds the established threshold, it is classified as a True Positive (T.P.); otherwise, it is categorized as a False Positive (F.P.) or False Negative (F.N.). The threshold value is established at 0.2, drawing inspiration from previous methodologies [32]. The performance is evaluated using three metrics: Sensitivity (True Positive Rate), Positive Predictive Value, and F-score. They are mathematically represented as

$$TPR = \frac{TP}{TP+FN} \tag{17}$$

$$PPV = \frac{TP}{TP+FP} \tag{18}$$

$$F-score = \frac{2TP}{2TP+FP+FN} \tag{19}$$

Of the total available spindles, 70% of the spindles are used for training, and the remaining 30% are used for testing. So, out of 9066, 6300 are used for training, and 2766 are used for testing. The classification results are presented in Table 2 as a confusion matrix, summarizing the True Positives, False Negatives, and False Positives for spindle detection by the proposed method.On the basis of these results, the TPR, PPV (Positive Predictive Value), and F-score of spindles are identified as 83.1100%, 71.5700%, and 77.2400%, respectively. In the confusion matrix, we didn't mention the True negatives because the non-spindles count was enormous when compared with spindles.

Figs 4-6 collectively compare the three methods based on Sensitivity, Positive Predictive Value, and F-score, respectively, demonstrating SWT's overall effectiveness in sleep spindle detection. In this case study, we considered the entire 12 features (features of the time and frequency domains). But, the frequency domain features are derived through different frequency domain transformation techniques such as Wavelet Transform (W.T.), CWT, and SWT. Among the three transformation methods, SWT had shown better performance than CWT and W.T. On average, the Sensitivity of SWT, CWT, and W.T. is observed as 78.90%, 74.37%, and 73.9%, respectively. Next, the average PPV of SWT, CWT, and W.T. is observed as 73.20%, 68.40%, and 68.13%, respectively. Finally, the average F-score of SWT, CWT, and W.T. is observed as 75.2000%, 70.8571%, and 70.4160%, respectively. Further, among the different subjects, the maximum detection performance is achieved in almost all subjects except at 3, 5, and 14. The minimum and maximum F-scores are attained by SWT at subject 3 and subject 9, respectively, as they are approximately 60.2000% and 88.9600%. The main reason we found behind the lower detection rate at the 3rd, 5th, and 14th subjects is the domination of the background signal's amplitude over the sleep spindle signal's amplitude.

Table. 2 Confusion matrix for the detected spindle results

		Predicted	
		Spindle	**Non-spindle**
Actual	**Spindle**	2820 (T.P.)	573 (F.N.)
	Non-Spindle	1120 (F.P.)	- (T.N.)

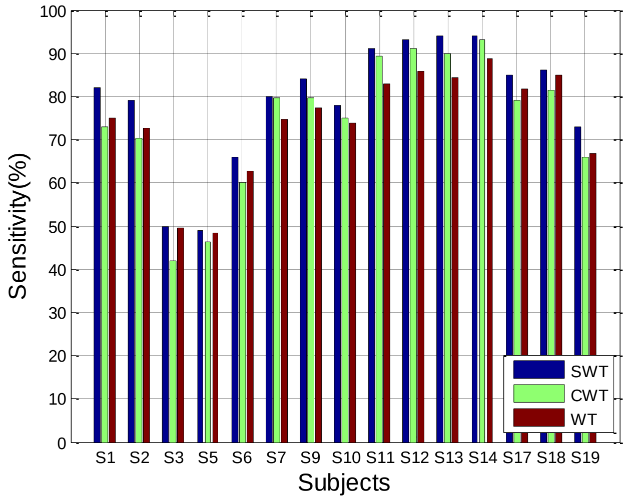

Figure. 4 Sensitivity comparison between W.T., CWT, and SWT in different subjects

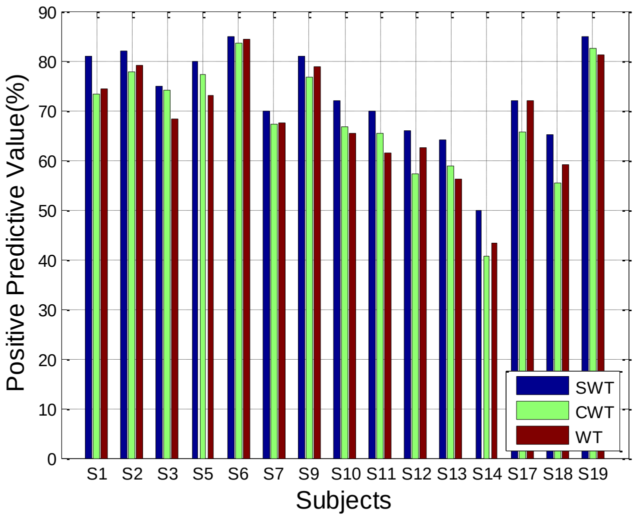

Figure. 5 PPV comparison between W.T., CWT, and SWT in different subjects

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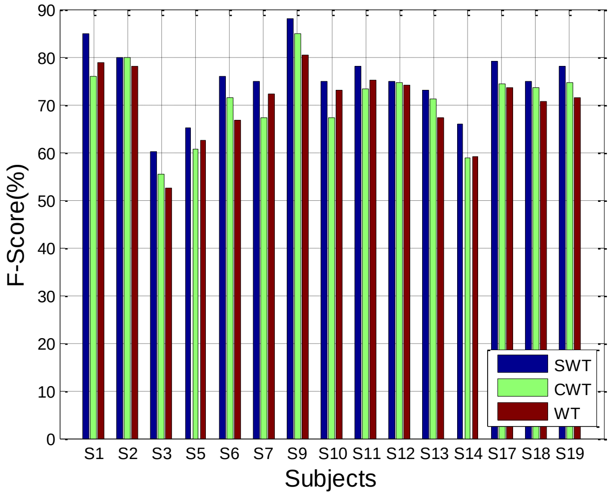

Figure. 6 F-score comparison between W.T., CWT, and SWT in different subjects

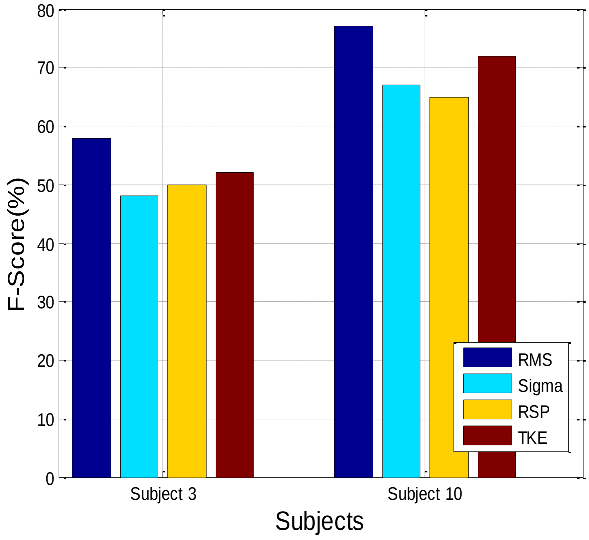

Figure. 9 F-score comparison between subject 3 and subject 10 at different features

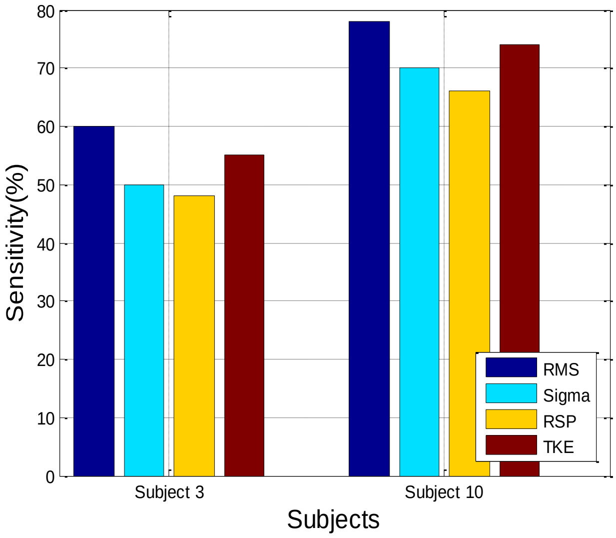

Figure. 7 Sensitivity comparison between subject 3 and subject 10 at different features

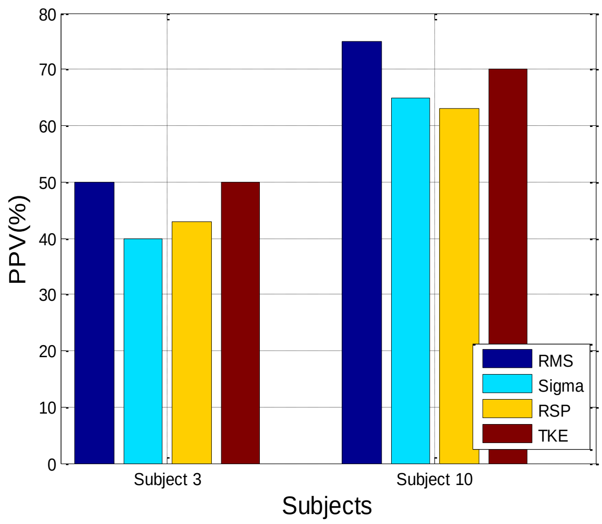

Figure. 8 PPV comparison between subject 3 and subject 10 at different features

Table. 3 Performance comparison over the MASS-C1 database

Method	PPV (%)	TPR (%)	F-Score (%)
SST-RUSBoost [23]	61.2000	77.0000	70.0000
MVGMM [24]	60.7800	74.0000	69.0000
Hybrid Expert Scheme [31]	53.0000	81.0000	63.0000
SST-SMOTE-Adaboost (Proposed)	73.2000	78.9000	75.9868

Figs. 7-9 presents the impact of feature subjects on spindle detection through Sensitivity, PPV, and F-score, respectively. From the results, it was noticed that better performance was achieved for the recordings of subject 10 than for the recordings of subject 3. The average Sensitivity of subject 3 is noticed as 53.20%, while for subject 10, it is noticed as 72%. Similarly, the PPV is observed as 45.75% and 68.25% for subjects 3 and 10, respectively. Finally, the average F-score of subjects 3 and 10 is noticed as 52% and 72.5%, respectively. Further, among the four features, better detection is observed at RMS. The average F-score attained when RMS is the only feature considered is noticed as 68.50%, while for remaining features, it is observed as 49.1667%, 55.8333%, and 62.1667% for Sigma, RSP, and TKE, respectively in Table 3.

Table 3 presents a comparative performance analysis of various sleep spindle detection methods

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Figure. 10 Performance comparison of Sleep Spindle Detection Methods Using the MASS-C1 database

validated on the MASS-C1 database, focusing on Positive Predictive Value (PPV), True Positive Rate (TPR), and F-Score metrics. The SST-RUSBoost method combines Synchrosqueezed Wavelet Transform with Random Under-Sampling Boosting to address data imbalances, achieving a PPV of 61.2%, a TPR of 77.0%, and an F-Score of 70.0%. Despite its advancements, the reliance on under-sampling can lead to significant data loss, potentially impacting overall accuracy. The MVGMM approach uses Multivariate Gaussian Mixture Models, records a PPV of 60.78%, a TPR of 74.0%, and an F-Score of 69.0%, showing solid performance but potentially less effectiveness in highly imbalanced datasets. The Hybrid Expert Scheme demonstrates strong sensitivity with a TPR of 81.0% but achieves a lower precision at 53.0%, resulting in an F-Score of 63.0%, which indicates a propensity to identify more false positives while capturing true events. The proposed SST-SMOTE-Adaboost method integrates Synthetic Minority Over-sampling Technique (SMOTE) with Adaboost classification to balance imbalanced datasets and enhance detection accuracy. It outperforms other methods with a PPV of 73.2%, a TPR of 78.9%, and an F-Score of approximately 76.0%, demonstrating its efficacy as a robust and reliable tool for sleep spindle detection, as shown in Fig. 10. Overall, the SST-SMOTE-Adaboost method demonstrates the highest performance in terms of F-Score, indicating a well-balanced trade-off between precision and sensitivity. This superior performance illustrates the effectiveness of integrating advanced sampling techniques and ensemble learning in handling the challenges of sleep spindle detection in EEG analysis.

Table. 4 Performance comparison over different database

Method	Dataset	TPR	F-Score
DOSED30 [33]	Varies by age cohort	-	0.567
SpindleNet20 [34]	DREAMS	-	0.48
CNN/RNN Model [35]	MrOS Sleep Study	-	0.77
SpindleCatcher [36]	MASS dataset	0.707	0.681
SpindleU-Net [37]	DREAMS	-	0.739
Sparse Optimization Method [38]	General EEG database	-	0.633
SST-SMOTE-Adaboost (Proposed)	MASS-C1	0.789	0.759

The comparative analysis presented in Table 4 evaluates various sleep spindle detection methods across different datasets, primarily focusing on their TPR and F1 scores. Chambon et al. [33] introduced DOSED30, a deep learning model that achieved an F1 score of about 0.75, 0.50, and 0.45 across young, middle-aged, and older cohorts respectively, showcasing its performance variability across different age groups. Kulkarni et al. [34] developed SpindleNet20, which delivered an F1 score of 0.48 when evaluated on the DREAMS dataset, indicating the model's capabilities and limitations in real-time spindle detection in a standardized setting. Carvelli et al. [35] presented a CNN/RNN-based model for leg movement (LM) detection, reporting an F1 score of 0.77 on 348 PSGs from the MrOS sleep study, demonstrating the model's effectiveness in a specific sleep study context. Yang and Pan [36] explored the automatic detection of sleep spindles in patients with acute disorders of consciousness, achieving an F1 score of 0.794 on the MASS2 dataset and 0.681 on a patient-specific dataset, suggesting potential clinical applications in prognostic contexts. You et al. [37] described SpindleU-Net, an adaptive U-Net framework for sleep spindle detection in single-channel EEG, achieving an F1 score of 0.739 on the DREAMS dataset, illustrating the benefits of incorporating an attention module in spindle detection. Fang et al. [38] proposed a novel EEG signal decomposition approach using sparse optimization to detect sleep spindles, obtaining an average F1 score of 0.633, which highlights the potential of using advanced mathematical techniques in EEG analysis. Overall, these results demonstrate the varied efficacy of different detection methods across multiple datasets, underlining the ongoing advancements in the application of machine learning to sleep research.

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Table. 5 Computational complexity and performance comparison of SWT/SMOTE with STFT/ROS

Metric	SWT	STFT	SMOTE	ROS
Complexity	$O(N \cdot logN)$	$O(N \cdot logN)$	$O(N^2 \cdot d)$	$O(N)$
Overhead	High (Reassignment Step)	Moderate	High (Pairwise Distance)	Minimal
Accuracy Impact	High (Sharp Localization)	Moderate (Coarser)	High (Synthetic Diversity)	Low (Duplicate Risk)
Suitability	Best for small datasets	Suitable for quick analysis	Best for imbalanced data	Suitable for small datasets

4.3 Computational complexity

The computational complexity of the proposed sleep spindle detection framework plays a crucial role in determining its scalability and applicability in real-world scenarios, as shown in Table 5. While methods such as Synchrosqueezed Wavelet Transform (SWT) and Synthetic Minority Oversampling Technique (SMOTE) provide improved accuracy through enhanced frequency resolution and effective handling of class imbalance, they come at the cost of increased computational requirements. This overhead may limit their use in resource-constrained environments like wearable devices or real-time systems. To understand the trade-offs, a comparison is presented between SWT and SMOTE with simpler approaches such as Short-Time Fourier Transform (STFT) for frequency-domain analysis and Random Over-Sampling (ROS) for data balancing. The table 5 outlines the differences in computational complexity, overhead, accuracy impact, and suitability for various applications.

5. Discussion

The proposed SST-SMOTE-Adaboost framework for sleep spindle detection demonstrates significant promise in improving the accuracy and reliability of spindle identification in EEG signals. By combining the Synthetic Minority Oversampling Technique (SMOTE) to address data imbalance, Synchrosqueezed Wavelet Transform (SWT) for precise feature extraction, and the Adaboost algorithm for robust classification, the method achieved impressive results. Validated on the MASS-C1 dataset, the framework delivered an F-score of 75%, a Sensitivity of 78%, and a Positive Predictive Value (PPV) of 73%, outperforming existing methods like SST-RUSBoost and MVGMM. The integration of time-domain and frequency-domain features, facilitated by the sharp time-frequency representation of SWT, was particularly effective in reducing ambiguity between spindle and non-spindle events, contributing significantly to the detection performance.

The study also highlighted variability in detection performance across subjects. While some subjects, such as S9, achieved high F-scores (~88.96%), others, like S3 and S5, demonstrated lower detection rates (~60.2%). This variability was attributed to differences in EEG signal characteristics, with some subjects exhibiting a higher dominance of background signals over spindle activity. Compared to other methods, such as the Hybrid Expert Scheme, which showed higher sensitivity (81%) but suffered from lower precision due to false positives, the proposed approach struck a better balance between sensitivity and precision, making it a reliable tool for spindle detection. However, the study was conducted on a single-channel EEG (C3), limiting the potential to fully leverage spatial information available in multi-channel recordings.

The study's limitations include the lack of real-world applicability analysis, as it was validated only on the curated MASS-C1 dataset, which may not represent noisy, real-world data, and its demographic homogeneity limits generalizability. Computational complexity from SWT poses challenges for deployment in wearable devices, and its single-channel focus restricts multi-channel applications. Future work should validate the method on diverse, real-world datasets, optimize computational efficiency, incorporate multi-channel EEG analysis, and explore deployment in wearable devices for real-time monitoring, enhancing its robustness and scalability.

6. Conclusion

In conclusion, the proposed SST-SMOTE-Adaboost framework demonstrates significant advancements in the automated detection of sleep spindles from EEG signals, addressing key challenges like data imbalance and inadequate feature representation. By integrating SMOTE for balancing datasets, Synchrosqueezed Wavelet Transform (SWT) for precise feature extraction, and the Adaboost algorithm for classification, the method achieved superior performance, with an F-score of

75%, Sensitivity of 78%, and Positive Predictive Value (PPV) of 73% on the MASS-C1 dataset. These results outperform existing approaches such as SST-RUSBoost, MVGMM, and Hybrid Expert Scheme, showcasing the method's robustness and reliability. The integration of time-domain and frequency-domain features enhanced the discrimination between spindle and non-spindle events, while SWT provided sharper time-frequency representations for better detection accuracy. Despite variability in performance across subjects, the framework consistently demonstrated improved detection rates compared to traditional methods. Overall, the results highlight the potential of this approach as a reliable tool for sleep spindle detection, paving the way for its application in clinical and research settings with further optimizations and validations.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization and Design by Voruchu Sai Babu, Development and implementation by A. Ramakrishna and Validation and proofread by Dustakar Surendra Rao.

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