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Automated phase A and phase B characterization of cyclic alternating patterns in sleep stages using optimal wavelet-based entropy features†

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Abstract

Humans spend significant portion of their time in the state of sleep, and therefore one's 'sleep health' is an important indicator of the overall health of an individual. Non-invasive methods such as electroencephalography (EEG) are utilized to evaluate the 'sleep health' as well as associated disorders such as nocturnal front lobe epilepsy, insomnia, and narcolepsy. A long-lasting periodic activity, known as cyclic alternating pattern (CAP), are observed in the EEG waveforms which reflect the cortical electrical activity during non-rapid eye movement (NREM) sleep. The CAP sequences involve various, continuing periods of phasic activation (phase-A) and deactivation (phase-B). The manual analysis of these signals are performed by clinicians, are prone to errors and may lead to wrong diagnosis. Hence automated systems which can detect the two phases (viz. Phase A and Phase B) and perform self-diagnosis accurately can completely eliminate any human involvement in the diagnosis. This work proposes the classification of two phases using a biorthogonal wavelet filter bank (BOWFB) and extraction of entropies from six sub-bands of BOWFB. The proposed work exhibited the highest average classification accuracy of 73.43% and area under receiver operating characteristic (AUC) of 0.80 with 10-fold cross-validation on the balanced dataset. Same proposed model yielded a maximum accuracy of 74.40 % with 10% hold-out validation with balanced dataset and average classification accuracy of 87.83% with unbalanced dataset using ensemble bagged tree classifier. The developed system can assist the medical practitioners to assess the person's cerebral activity and sleep quality accurately.

KEYWORDS:
EEG; Detection of phase A and phase B; Cyclic alternating pattern; Wavelets; Optimization problem; Machine learning; Filter design; Classification of signals

1 | INTRODUCTION

Sleep, an altered state of consciousness observed via reduced interactions, is an activity practised by the majority of life forms during one-third of their lifespan (Basics 2016). Sleep is needed for many brain functions, including interactions of neurons with each other to control the processes such as judgment, concentration, productivity, mental health, and performance (M. Terzano et al. 1985).

†This is an example for title footnote.
[0]**Abbreviations:** ANA, anti-nuclear antibodies; APC, antigen-presenting cells; IRF, interferon regulatory factor

Sleep estimation based on conventional rules, simplifies the complex architecture of this prominent semiconscious activity (Parrino, Milioli, Melpignano, & Trippi 2016). The dynamic stages of sleep transition show a natural cyclic behaviour, which could be interpreted from the macrostructure and microstructure patterns of electroencephalogram (EEG) events (Parrino, Ferri, Bruni, & Terzano 2012). At macrostructure level, any absolute sleep can be distinguished into two levels (i) rapid eye movement (REM) sleep and (ii) non-rapid eye movement (NREM) sleep (Schulz, Dirlich, Balteskonis, & Zulley 1980) that are immediately linked to the depth of the sleep. The human body is subjected to various physio-chemical changes during sleep that help to distinguish these stages. These changes can be recorded on the EEG signal with non-invasive electrodes placed along the scalp, which displays the electrical activity of the brain in the form of specific patterns. As per Rechtschaffen & Kale, criterion (Parrino et al. 2012) NREM further can be categorized into three sub-stages (S1, S2, S3). The classification is performed on twenty or thirty-second's windowed EEG. A trained expert annotates each epoch of 30s into one of the four stages (S1, S2, S3, REM) as per the EEG pattern. These stages tend to repeat in a cycle 20-25 minutes duration, with 18-20 cycles for a good sleep.

A suitable microstructure phasic event that further characterizes NREM sleep was introduced in 2001 called cyclic alternating patterns (CAP). The CAP can be defined as the periodic recurrent activity of pseudo-periodic phases, namely Phase A (phasic transients) followed by Phase B (background activities) (M. G. Terzano et al. 2002). The duration of a phase varies between 2-60s. A CAP sequence can be described as a series of two or more CAP cycles. For a healthy person, a CAP sequence lasts for 153s. A high value of CAP rate indicates the inferior quality of sleep. Hence, CAP can be regarded as the marker of arousal instability and measures the effort put in by the brain to sustain the sleep. The sleep pattern CAP is not only a qualitative representation of the stability and quality of sleep but also an indicator of major neurological disorders (Dhok et al. 2020). Any disturbance in this regularity, sleep disorders such as sleep apnea, narcolepsy, epileptic seizure, depression, anxiety, insomnia, which are responsible for depression and restlessness may occur, later leading to a significant reduction in productivity and capabilities of a human (Yeh & Shi 2018). Also, the presence of CAP helps to better evaluate the overall projections for the survival and recovery of coma patients (Kassab, Farooq, Diaz-Arrastia, & Van Ness 2007).

A more generic explanation of the Rechtschaffen and Kales (R-K criterion) (Rechtschaffen 1968), which was introduced to classify sleep in to seven discrete stages based on scoring rules and features identified from EEG and eye movement recordings are given below:

- **Wakefulness (W):** This stage has brain activity, and active muscle tone during this period which are observed as low voltage, mixed frequency and/or alpha waves on EEG recordings (Rechtschaffen 1968).
- **Movement Time (MT):** This stage, typically referred to as 'time-out' period, conceals the sleep patterns as it obscures the EEG activity because of increased movement of the subject (Ogilvie & Wilkinson 1988).
- **NREM sleep stage 1 (NS1):** First and shallow stage of sleep is indicated by slow brain activity, reduced eye movements and sudden sensational experiences of falling, followed by abrupt muscle spasms (Rechtschaffen 1968).
- **NREM sleep stage 2 (NS2):** In this stage, sleep begins, and arousals are intercepted by specific bursts of rapid brain wave activity, known as sleep spindles with 12-14 cycles per second, blended with sleep structures known as K-complexes. In this stage, body temperature and heart rate go down (Rechtschaffen 1968).
- **NREM sleep stage 3 (NS3):** The most recuperative sleep stage, also known as deep sleep, is observed with moderate amounts of high amplitude, slow-wave activity. Parasomnias such as sleepwalking, sleep talking and night terrors tend to occur in this stage (Rechtschaffen 1968).
- **NREM sleep stage 4 (NS4):** Prolonged deep sleep with increased mental uncertainty and many high amplitude slow-wave activity are detected in this stage (Rechtschaffen 1968).
- **REM sleep stage (REM):** Brain waves imitate activities of semiconscious state with rapid eye-rolling in different directions with abrupt twitches, are observed in this state. This stage (dreaming stage) recurs for about every 90-120 mins/day (Iranzo, Santamaria, & Tolosa 2009).

All of these EEG samples are recorded as clusters of 25-30s, which is carried out for 8-10 hours by certified personnel. Despite the explicitness of this R-K standard, subjective interpretation of the rules persists, leading to significant uncertainty in the visual introspection (Danker-Hopfe et al. 2001). Moreover, the rules stood true only for extensively niche patient age groups (Himanen & Hasan 2000). American Academy of Sleep Medicine (AASM) regrouped the deep sleep stage by merging NS4 to the trivial NS3 in 2007 (Berry et al. 2012) for eliminating ambiguity in the manual inspection of the recordings. According to the AASM manual, a minimum of 3 EEG samples from the frontal, central, and occipital regions are to be recorded (Berry et al. 2017).

In the context of all such frequency based activities observed in EEG signals (Dunand & Jallon 2002), CAP was postulated as an expression of a basic arousal modulator that explains majority of the sleep characteristics (Faust, Razaghi, Barika, Ciaccio, & Acharya 2019a). This representation which reflects the magnitude and distribution of standard sleep parameters (M. G. Terzano & Parrino 2000) is distinguished by cyclic periods of

cerebral activation (phase A) preceded with deactivation cycles (phase B) and separating two consecutive phases A cycles with a duration of < 1 min. Phase A and subsequent phase B in proximity describe a CAP cycle that further with at least two CAP cycles constitute a CAP sequence. The Fig.1 shows the phase A and Phase B in a CAP sequence with the activation phase-A duration is from 2 to 60 sec. The phase-A possesses heterogeneity of information with high amplitude and low amplitude EEG signal (Acharya et al. 2015a) which can be categorized into three different parts as:

- The A_1 sub-type is defined by delta wave for frequency range 0.5Hz to 4Hz with K-complexes and bursts.
- A_2 sub-type covers 20% to 50% of A-phase duration with high amplitude slow varying EEG waves and a drop in sleep stability.
- The A_3 sub-type represents the 50% duration of A-phase which consists of alpha-beta waves with varying frequency ranges.

In addition to the wave characterization in subtype A3, all the subtypes contains different frequency signatures in the EEG frequency bands as: delta (θ = [1, 4] Hz), theta (θ = [4, 8] Hz) , alpha (α = [8, 13] Hz) , sigma (σ = [13, 16] Hz) and beta (β = [16, 35] Hz) (Machado, Sales, Santos, Dourado, & Teixeira 2018).

Traditionally, the distinction of CAP phases performed by medical professionals, require substantial amount of time and experience in order to investigate the sleep disorder (Tatum 2014). Although sleep being a physiological phenomenon, CAP observed from the EEG recordings indicate sleep dysfunction and can be associated with multiple pathologies relevant to sleep (Al-Angari & Sahakian 2012; Sharma, Pachori, & Acharya 2017a). The CAP keeps track of individual's inactive state of brain and these neurological patterns are also responsible for any endogenous or exogenous disease recognition (Sharma, Dhere, Pachori, & Acharya 2017). Sleep-disordered breathing (SDB), insomnia, sleep movement disorders, periodic leg movements (PLM), restless leg syndrome (RLS), parasomnia such as REM behavioral disorder (RBD), nocturnal frontal lobe epilepsy (NFLE), and narcolepsy are reflected with high CAP rates (i.e., the ratio of NREM CAP to total NREM sleep) (Sharma & Pachori 2018). Therefore, the demand for a robust automated technique, which performs accurate diagnosis of individual's physiology and assists the medical practitioners is worthwhile.

So far, several approaches have been proposed for automated detection of the CAP components in literature (Acharya et al. 2015b; Faust, Razaghi, Barika, Ciaccio, & Acharya 2019b) of which majority have used spectral bands of the EEG signal and onset-offset separation of CAP phases (Dhok et al. 2020). Also, various classifiers are used to distinguish CAP parts after extracting features from sleep EEG signals (Karimzadeh, Seraj, Boostani, & Torabi-Nami 2015). Attempts have been made to detect and classify phase A using a *k*-nearest neighbor (KNN) classifier (Mendez et al. 2016), artificial neural networks (ANN) (Hartmann & Baumert 2019; Mariani et al. 2010) or finite state machines (FSM) (Mendonça, Fred, Mostafa, Morgado-Dias, & Ravelo-García 2018). Recently, Dhok et al. (Dhok et al. 2020) have proposed the classification of A and B phases using Wigner-ville based features. Karimzadeh et. al has assessed the performance of various features that could be used for CAP phase classification (Karimzadeh et al. 2015). A detailed analysis of various methods used are summarized on Table 1.

The proposed study utilized an optimal biorthogonal wavelet filter bank (BOWFB) for separation of unknown CAP phases A and B. The BOWFBs is designed using mean-squared frequency spread. The optimal filters comprise the desired vanishing moments (VMs), and minimum frequency spread. Parametrization is not considered in the convex semidefinite programming (SDP) problem, which helps to find the filter co-coefficients in time domain directly. The motivation behind using BOWFB is its superior performance in diverse applications such as image processing (Heller, Nguyen, Singh, & Carey 1995), signal analysis (Zhang, Desai, & Peng 1999), seismology (Ma & Yang 2001) and economic data analysis (Schleicher et al. 2002). Several preliminary experiments showed decent classification accuracy and recall for the detection of CAP phase A and B. The salient features of the proposed study are as follows:

- BOWFB and entropy-based features are used for the classification of CAP phases.
- The classification is performed using both balanced and unbalanced dataset obtained from six normal patients.
- The balanced dataset is prepared by randomly selecting an equal number of phase-wise data samples from CAP phases across the patients.
- The proposed method employed only 12 features for the identification, whereas the other methods employed (Dhok et al. 2020) more number of features.
- The proposed technique does not require any pre/post-processing methods.
- The robustness of the model is ensured by using 10 fold cross-validation (CV) and hold-out validation (HoV).

TABLE 1 Summary of automated phase classification of patterns of sleep stages developed using CAP EEG signals.

Author	Approach	Number of Samples	Performance Parameters
Mendez et al. (Mendez et al. 2016)	KNN Classifier	Unbalanced A phases: 3963	ACC = 80.00% SPE = 80.00% SEN = 70.00%
Navona et al. (Navona et al. 2002)	Thresholding	Unbalanced	ACC = 77.00% SPE = 90.00% SEN = 84.00%
Mariani et al. (Mariani et al. 2013)	ANN Classifier + EEG Segmentation	Unbalanced	ACC = 87.19 $\pm$ 2.48% SPE = 90.49 $\pm$ 2.80% SEN = 69.55 $\pm$ 6.60%
Mariani et al. (Mariani et al. 2012)	SVM, LDA, AdaBoost and ANN	Unbalanced A-phase: 26305 B-phase: 214,124	ACC = 84.90 $\pm$ 4.80% SPE = 86.60 $\pm$ 6.30% SEN = 72.50 $\pm$ 10.90%
Hartmann et al. (Hartmann & Baumert 2019)	Variable LSTM Network	Both Balanced and Unbalanced	ACC = 82.42 $\pm$ 6.59% SPE = 83.90 $\pm$ 8.95% SEN = 75.28 $\pm$ 12.00%
Dhok et al. (Dhok et al. 2020)	Wigner-Ville + Rényi entropy + SVM	Balanced 9306 (A phase: 4653 B phase: 4653)	ACC = 72.35$\pm$ 0.20% SPE = 69.19$\pm$ 0.30% SEN = 76.76 $\pm$ 0.20%
		Unbalanced 71862	ACC = 87.45$\pm$ 0.20% SPE = 52.09$\pm$ 0.10% SEN = 87.75$\pm$ 0.20%
This work	BOWFB +APE+TSE + EBT	Balanced with 10 fold CV 9306 (A phase: 4653 B phase: 4653)	ACC = 73.43 $\pm$ 0.50 % SPE = 70.95$\pm$0.60 % SEN = 76.59$\pm$0.40 %
		Balanced with 10% HoV 930	ACC = 74.4% SPE = 81.29 % SEN = 67.53 %
		Unbalanced 71862	ACC = 87.50% SPE = 51.89 % SEN = 87.53 %

2 | MATERIALS AND METHODS

2.1 | Dataset

The CAP sleep database was acquired from PhysioNet repository (Goldberger et al. 2000) for this study. The polysomnographic (PSG) signals obtained at the Sleep Disorders Center of the Maggiore Hospital, Italy were used to create this dataset (Hartmann & Baumert 2019). Total of 108 recordings were collected during the night for 9-10 hours. The recordings contained three channels of electroencephalogram (EEG), electro-oculogram (EOG) and electromyogram (EMG) signals sampled at various sampling frequencies such as 128Hz, 256, Hz and 512Hz respectively. The 10-20 international electrode system was used for EEG recording. In this study, we have used only single-channel EEG (C4-A1 or C3-A2) recordings sampled at 512 Hz collected from 6 healthy subjects. We have created a balanced dataset from C4-A1 or C3-A2 EEG signals. Subsequently, we segmented EEG signals into clusters of 2 seconds, the REM sleep stages of the EEG recordings were discarded, and only NREM stages were considered. The subjects were chosen based on their neurological stability to avoid the effects of uncertainties in the data for classification. The annotated balanced dataset consisted of 9306 signals with phase A and phase B having equal number of samples, as shown in Fig.2 and 3, respectively. The EEG signal in Phase-A and Phase-B consisted of 1024 samples.

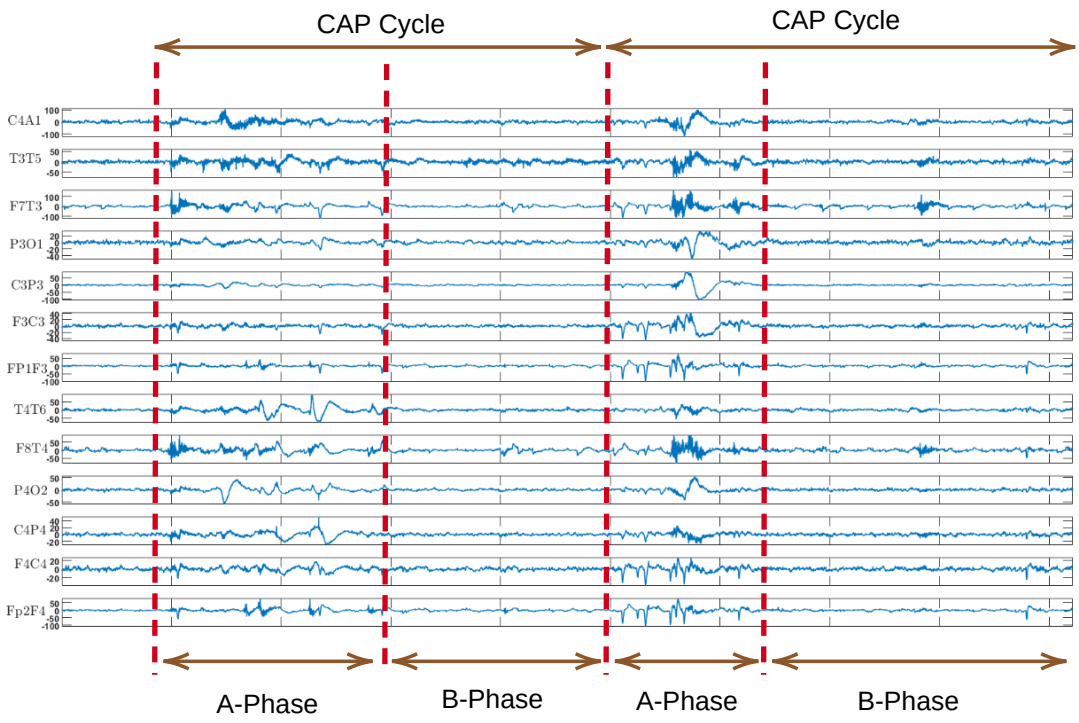

FIGURE 1 A typical CAP waveform recorded from different electrodes.

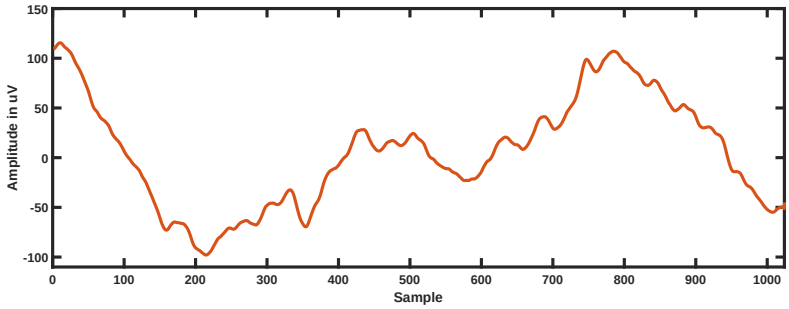

FIGURE 2 Phase-A waveform.

The details of patient-wise number of samples used for balanced and unbalanced datasets are summarised in Table 2 and 3 respectively. For consistency, the samples are randomly and equally extracted from the patients (Dhok et al. 2020).

2.2 | Process Overview

Fig.4 describes the proposed process flow employed in this study. The balanced EEG signal segmented in to raw CAP EEG signals into 2 seconds epochs with 1024 data points. The time segmented signals are later decomposed into six sub-bands using the root mean square bandwidth (RMSBW) biorthogonal wavelet filter bank (BOWFB). The entropy features are extracted from each sub-bands of the BOWFB filter bank. The phases A and B are classified using different classifiers such as linear support vector machine(SVM), logistic regression, quadratic SVM, Gaussian SVM and ensemble boosted tree (EBT). The most optimal performing classifier is then employed in the proposed study work, and 10-fold cross validation and hold-out validations are implemented to avoid the over-fitting problem.

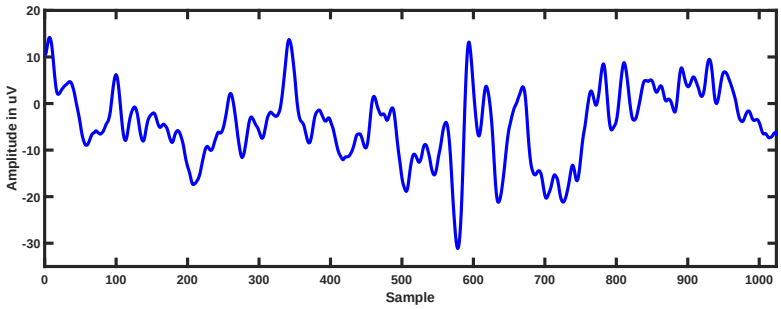

FIGURE 3 Phase-B waveform.

TABLE 2 Patient-wise number of samples used in balanced dataset.

Phase	Patient-wise number of samples						Total
	n1	n2	n3	n5	n10	n11	
A	1062	981	852	471	477	810	**4653**
B	1062	981	852	471	477	810	**4653**
Total (A+B)	2124	1962	1704	942	954	1620	**9306**

TABLE 3 Patient-wise number of samples used in the unbalanced dataset.

Patient Name	Number of samples		
	A	B	Total
n1	1915	12930	14845
n2	1474	10575	12049
n3	1063	10125	11188
n5	1841	11475	13316
n10	1307	8550	9857
n11	1452	9225	10677

The complete experiment was performed on the Desktop computer on MATLAB 2016B licenses version with hardware of Intel 7 (i7 microprocessor), 16 Gigabyte Random Access Memory, and 1 Terabyte hard-disk. The simulation process was performed as a single task operation.

2.3 | Wavelet Decomposition

Essentially, wavelets manifest considerable joint duration-bandwidth localization property which enabled the approach it to find application in various healthcare applications using physiological signals (Sharma, Dhere, Pachori, & Gadre 2017; Sharma, Pachori, & Acharya 2017b; Sharma, Sharma, Pachori, & Acharya 2018b; Sharma, Singh, Kumar, Tan, & Acharya 2019). Additionally, due to the non stationary behavior of EEG signals, wavelets of such signals contain both —steady and transient patterns (Sharma & Acharya 2019; Sharma, Goyal, Achuth, & Acharya 2018; Sharma, Tan, & Acharya 2019). A quality time-frequency optimized filter can potentially extract most significant features from these signals, thereby increasing the accuracy of the system (Sharma, Achuth, Deb, Puthankattil, & Acharya 2018; Sharma, Tan, & Acharya 2018). In this work, a wavelet decomposition method is implemented using a stopband energy optimized filter bank for the decomposition of the EEG phases. The implemented method utilized an optimal wavelet based features for the classification of phase A and B of CAP EEG signals which is novelty of this work. The frequency responses of low-pass and high-pass filters of this optimal wavelet filter bank is shown in Figure 5 and Figure 6. A few studies (Sharma, Bhurane, & Acharya 2018) have employed the wavelet-based features for the classification task, however, optimally localized wavelets have never been implemented to solve the fore-mentioned challenges. Non-optimal Daubchies wavelets have been used earlier (Al-Qazzaz, Hamid Bin Mohd Ali, Ahmad, Islam, & Escudero 2015). Hence, this proposed methodology provided an accurate, robust, and simple system for CAP EEG signal classification.

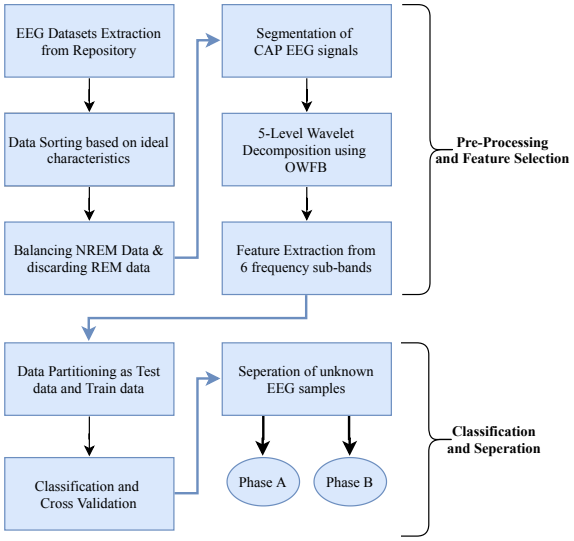

FIGURE 4 Architecture of proposed algorithm.

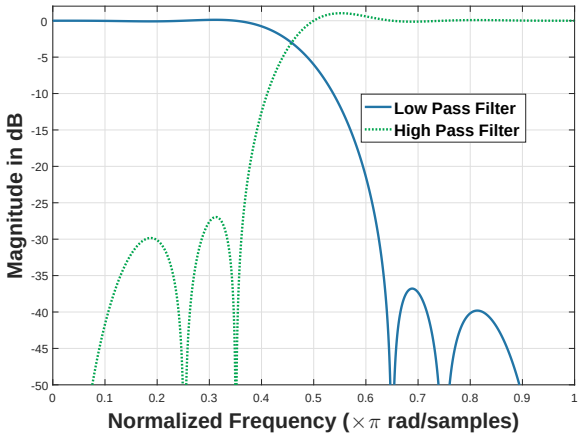

FIGURE 5 Frequency responses of optimal filters of wavelet filter bank.

The EEG epochs are decomposed into 6 sub-bands (SBs) (i.e., 5-level) by using wavelet decomposition technique. The frequency components having important characteristics are withheld by using five level decomposition technique (Sharma & Acharya 2018 2021; Sharma, Sharma, Pachori, & Acharya 2018a 2018c) which delivered exceptional performance. Out of 6 sub-bands, 5 sub-bands (WSBs) from SB2 to SB6 are detailed and one sub-band is approximate coeeficients.

2.4 | Feature computation

The entropy based features are computed from each of the 6 sub-bands obtained in the previous step. These features are approximate entropy (APE) (Pincus 1991), and Tsallis entropy (Tsallis 1988).

The APE feature helps to evaluate the unpredictable fluctuations in the EEG signals. It gives less value for multiple repetitive patterns. Similarly, Tsallis entropy captures the intrinsic fluctuations in the signals. Thus, it quantifies the amount of multiresolution patterns in the EEG data.

- Approximate entropy (APE): Let, $n_{im}(r)$ be the number of subsequences in a pattern set $P_m = \{p_m(i)\}$ of S. For an N length sequence S, pattern length m and similarity criterion r, let $C_{im}(r) = \frac{n_{im}(r)}{N-m+1}$, where n_{im} is the number of similar patterns between P_m and $p_m(i)$. The

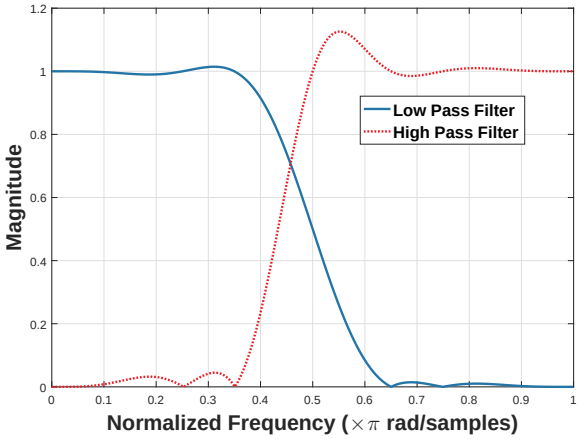

FIGURE 6 Frequency responses of optimal filters of wavelet filter bank.

approximate entropy is defined as the (Pincus 1991).

$$APE(S,m,r) = \ln\left[\frac{C_m(r)}{C_{m+1}(r)}\right] \tag{1}$$

where, $C_m(r)$ is the average of $C_{im}(r)$,

- Tsallis entropy (TSE): It can be interpreted as an extension of the standard Boltzmann/Gibbs entropy (Tsallis 1988). It is given by S_q,

$$TSE = \frac{1-\sum_{i=1}^{n} p_i^q}{q-1} \tag{2}$$

Here, q is the Tsallis parameter.

2.5 | Classification and Performance Evaluation

We have used many supervised learning classifiers to select the optimum performing classifier. In EBT classifier, several base estimators are combined to obtain robust performance and improved accuracy of the classifier. It works on the principle of increasing the weight of misclassified data points (Freund & Schapire 1996). There are two methods of ensemble estimation: averaging and boosting method. The main advantage of adaboot method is that it does not overfits quickly and therefore more suitable for classification. The Adaboost EBT classifier is a weighted classifier constructed using several classifiers. These weights w_i are optimized over i iterations to minimize the expression (Dietterich 2000),

$$\sum_i exp\left(-y_i \sum_l w_l h_l(x_i)\right) \tag{3}$$

where h denotes individual classifiers, x are the feature vectors and y indicates the set of classes. A ten-fold cross-validation technique is used to overcome the over-fitting problem.

3 | RESULTS

In this work, we have employed hold-out validation and 10-fold cross validation. Hold-out validation is a form of cross-validation which performs a single run test (Kohavi et al. 1995) over the sample data after separating the training and test data. The random sampling is carried out while the hold-out validation is carried out. For the classification, we used various supervised machine learning algorithms, and obtained the highest classification performance with EBT classifier. The training time is found to be 53s with prediction speed of 9000 observations per second. In order to overcome the problem of over-fitting, hold-out as well as 10-fold cross-validations are implemented. The confusion matrix with 10-fold CV using EBT classifier is shown in Table. 4 for the balanced data. The optimal parameters set to obtain the highest classification performance are provided in Table 5. In Table 6, the performance , in terms of accuracy, sensitivity, specificity and F1-score are shown. The EBT classifier yielded the highest accuracy of 73.4% with 10-fold CV for the balanced data. The receiver operating characteristics (ROC) curve is shown in Fig.7 which yielded the area under the ROC (AUC) of 0.81 for our developed model. The classification performance of other classifiers namely linear SVM, logistic regression, quadratic SVM and Gaussian SVM is reported are reported in Table 7 for the balanced data.

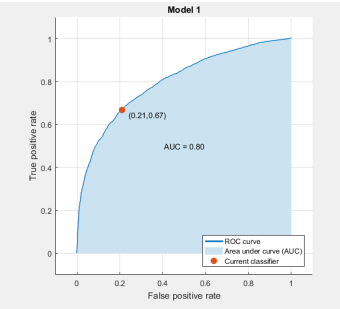

FIGURE 7 Receiver operating characteristics curve obtained for EBT classifier.

In order to evaluate the robustness of the implemented model, along with 10-fold cross-validation and hold-out validation are implemented at distinct levels ranging from 5% to 30% at regular intervals. The classification accuracies obtained for various percentage of hold-outs is shown in Figure 8. The summary of performance for various % of hold out is presented in Table 8. It can be noted from Table 8 that most of % of hold-outs have yielded consistent results. This method of validation is used when the sample data of EEG signals is high (Sharma, Bhurane, & Acharya 2018).

TABLE 4 Confusion matrix for EBT classifier with 10 fold CV.

	A phase	B phase
A phase	3135	1518
B phase	958	3695

TABLE 5 Specifications of EBT classifier to obtain optimal performance.

SN	Parameter	Value
1.	Ensemble Method	AdaBoost
2.	Learner type	Decision tree
3.	Maximum number of splits	30
4.	Number of learners	40
5.	Learning rate	0.1

TABLE 6 Results obtained by the proposed approach for balanced data.

Measure	Value
Accuracy	0.7343
Sensitivity	0.7659
Specificity	0.7095
F1 Score	0.7173

TABLE 7 Accuracy (%) obtained using of various machine learning classifiers with 10 fold CV.

Classifier	Accuracy in %
Linear SVM	71.8
Logistic Regression	72
Quadratic SVM	71.3
Gaussian SVM	74.3
EBT	73.4

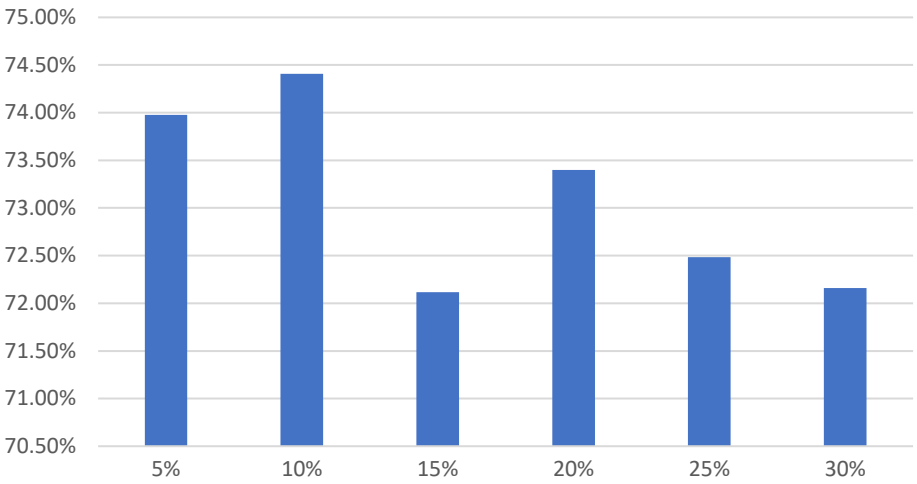

FIGURE 8 Classification accuracy (%) for various percentage of hold-outs.
(Here, X-axis denotes the percentage hold-out and Y-axis denotes the percentage accuracy.)

TABLE 8 Summary of performance (%) for various percentage of hold-outs.

% Hold-out	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 Score (%)
5%	73.978	66.524	81.466	71.926
10%	74.409	67.527	81.290	72.517
15%	72.115	65.136	79.083	70.008
20%	73.4	71.08	75.83	72.80
25%	72.485	66.638	78.332	70.776
30%	72.161	66.452	77.865	70.468

4 | DISCUSSION

The features are ranked using student's t-test and is tabulated in Table 9. The normalized box plots of APE and features corresponding to all six WSBs are given in Figure 9 and Figure 10 respectively.

It can be noted from Table 1 that our model has performed better than other published works in terms of ACC and F1 scores for the balanced data. Recently, Dohk et al.(Dhok et al. 2020) developed a model using Wigner-Ville-based features, and reported an accuracy of $72.35 \pm 0.20\%$ and $87.45 \pm 0.20\%$ for the balanced and unbalanced data respectively. (Dhok et al. 2020). Further, we have used only 12 features, whereas Dhok et al. have used a total of 121 features. From our results in Table 1 it can be noticed that the variation in ACC, SPE, and SEN is considerably lower, when compared to the studies previously published using the same CAP Sleep database (Mariani et al. 2011). Further, using the unbalanced dataset the

TABLE 9 Statistical details (mean, standard deviation, ranking and p-values)

SB#	Feature											
	APE						TSE					
	Phase-A		Phase-B		R	p	Phase-A		Phase-B		R	p
	μ_a	σ_a	μ_b	σ_b			μ_a	σ_a	μ_b	σ_b		
1	0.59	0.20	0.53	0.22	5	5.71E-56	-650396.41	1389489.55	-1368622.74	3384083.46	6	2.65E-177
2	2.14	0.10	2.10	0.14	3	5.12E-74	-2.92	27.14	-20.59	94.27	7	5.27E-147
3	2.16	0.09	2.12	0.14	2	2.75E-66	-87.81	868.46	-745.29	3889.86	9	9.08E-166
4	1.95	0.08	1.92	0.12	4	7.95E-50	-837.67	5571.68	-6110.27	33264.13	10	1.66E-124
5	2.15	0.08	2.14	0.09	11	3.99E-10	-6463.05	16034.83	-20042.35	73026.37	8	6.32E-241
6	1.76	0.08	1.76	0.09	12	0.851109939	-30425.49	35270.64	-52035.20	60538.24	1	3.53E-200

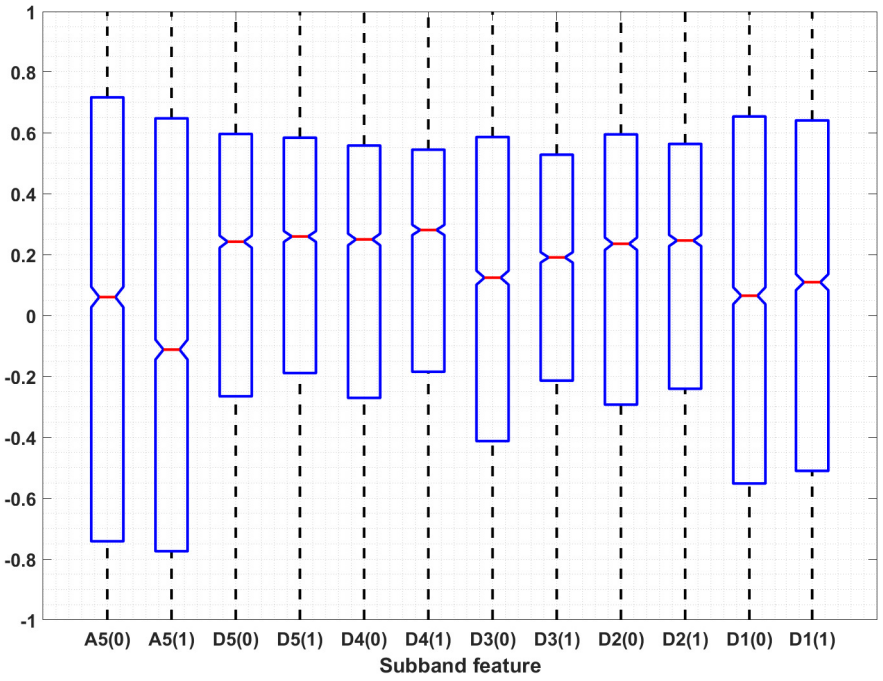

FIGURE 9 Normalized box plots for APE features.

model attained ACC of 87.5% which is higher than other models mentioned in Table 1. Mendonça et al. (MendonÇa., Fred., Mostafa., Morgado-Dias., & Ravelo-García. 2018) also used some handcrafted features also with machine learning classifiers and obtained an accuracy of 79% which is significantly lesser than our study. One of the advantages of this study is that the feature extraction is free of any pre-processing stage similar unlike other previous works. Our results were obtained for just 12 features as compared to 121 features used by Dhok et al. (Dhok et al. 2020). The main limitation of the study is that we have analyzed only healthy subjects; therefore, the proper-ties of A-phases for pathological cases like insomnia or sleep apnea remains unexplored. Also, in this study we have considered 9306 balanced samples. For better robustness higher number of samples can be considered. In future, linear features can be explored using the same method. Also, deep learning techniques including convolutions neural network (CNN) may be used. A subject specific testing is also carried out along with the analysis of combined (non-subject specific) datasets. The classification performance parameters for each of the subjects are shown in Table 10. It is evident that the highest classification accuracy of 81.34% is attained for subject N3.

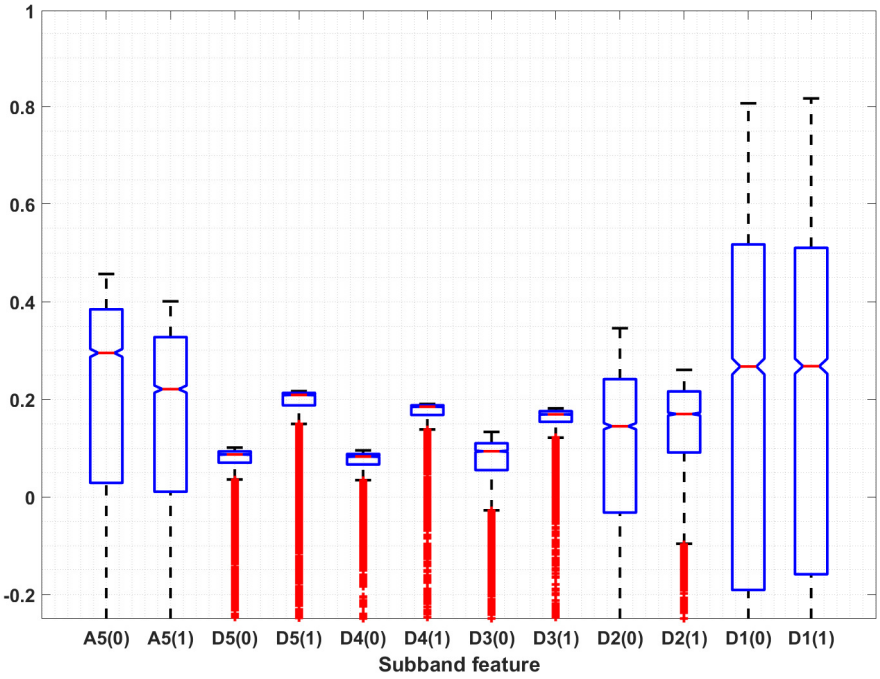

FIGURE 10 Normalized box plots for TSE features.

TABLE 10 Subject specific testing performance (%) for various percentage of 10 fold cross validation

% Subject	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision(%)	F1 Score (%)
N1	76.17702	70.056497	82.297552	79.82833	74.62387
N2	72.17125	65.341488	79.001019	75.67887	70.13129
N3	81.34038	76.938967	84.741784	83.26898	80.43524
N5	77.17622	74.309979	80.042463	78.82883	76.50273
N10	61.11111	65.408805	56.813417	60.23166	62.71357
N11	72.34568	73.333333	71.358025	71.91283	72.61614

5 | CONCLUSION

Periodic and transitory disturbances, observed in brain activity during sleep, have significant link to several neurological ailments. Medical practitioners have started the identification of various diseases such as insomnia, depression, sleep apnea, narcolepsy, etc. using this disturbances in CAP phases of EEG signals when the subject is in quiescency state. The proposed study has attempted to increase the reliability, and decrease the diagnosis time required for automated bifurcation of CAP phases derived from the EEG signals. The effective analysis of sleep quality is better analyzed from the CAP using which one may diagnose various diseases such as insomnia, depression, sleep apnea, and narcolepsy. The proposed classification of activation and deactivation phases of CAP-EEG signals is conducted using wavelet-based entropy features. After the extraction of wavelet-based features, the features are fed to the various machine learning algorithms. The EBT based classifier yielded the highest classification accuracy of 74.5% with holdout 20% validation. The same model yielded an accuracy of 74.3 % with ten-fold cross validation. Our proposed model provides faster diagnosis as it uses fewer features (only twelve) to provide highest accuracy. This model can help medical professionals to examine the CAP phases easily, and in future may be extended to diagnose other sleep related ailments like insomnia, sleep apnea, nacrolepsy, hypersomnia, sleep walking etc accurately.

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