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An automatic sleep-scoring system in elderly women with osteoporosis fractures using frequency localized finite orthogonal quadrature Fejer Korovkin kernels

Bharti Jogi Dakhale [b], Manish Sharma [a,*], Mohammad Arif [a], Kushagra Asthana [a], Ankit A. Bhurane [c], Ashwin G. Kothari [c], U. Rajendra Acharya [d,f,e]

[a] Department of Electrical and Computer Science Engineering, Institute of Infrastructure, Technology, Research and Management (IITRAM), Ahmedabad, India
[b] Department of Electonics and Communication, Indian Institute of Information Technology Nagpur, Maharashtra, India
[c] Department of Electronics and Communication, Visvesvaraya National Institute of Technology Nagpur, Maharashtra, India
[d] Department of Electronics and Computer Engineering, Ngee Ann Polytechnic, Singapore 639798, Singapore
[e] Department of Bioinformatics and Medical Engineering, Asia University, Taichung 41354, Taiwan
[f] Department of Biomedical Engineering, School of Science and Technology, Singapore 639798, Singapore

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ABSTRACT

Healthy sleep signifies a good physical and mental state of the body. However, factors such as inappropriate work schedules, medical complications, and others can make it difficult to get enough sleep, leading to various sleep disorders. The identification of these disorders requires sleep stage classification. Visual evaluation of sleep stages is time intensive, placing a significant strain on sleep experts and prone to human errors. As a result, it is crucial to develop machine learning algorithms to score sleep stages to acquire an accurate diagnosis. Hence, a new methodology for automated sleep stage classification is suggested using machine learning and filtering electroencephalogram (EEG) signals. The national sleep research resource's (NSRR) study of osteoporotic fractures (SOF) dataset comprising 453 subjects' polysomnograph (PSG) data is used in this study. Only two unipolar EEG derivations C4-A1 and C3-A2 are employed individually and jointly in this work. The EEG signals are decomposed into sub-bands using a frequency-localized finite orthogonal quadrature Fejer Korovkin wavelet filter bank. The wavelet-based entropy features are extracted from sub-bands. Subsequently, extracted features are classified using machine learning techniques. Our developed model obtained the highest classification accuracy of 81.3%, using an ensembled bagged trees classifier with a 10-fold cross-validation method and Cohen's Kappa coefficient of 0.72. The proposed model is accurate, dependable, and easy to implement and can be employed as an alternative to a PSG-based system at home with minimal resources. It is also ready to be tested on other EEG data to evaluate the sleep stages of healthy and unhealthy subjects.

1. Introduction

Sleep is essential for preserving one's mental and physical health. It is very important to get the correct amount of sleep to have a good quality of life [1]. An average adult needs 7–8 hours of sleep daily [2]. According to health professionals, when people are forced to sleep for an adequate amount of time, their daily alertness, response time, and mood increase significantly [3]. Early research [4] discovered that people who sleep fewer than 4 hours or more than 9 hours have a higher risk of coronary artery disease, cancer, or stroke than those who sleep an average of 7-8 hours. Clearly, our health is heavily influenced by the quality of sleep we obtain, and sleep problems may significantly impact our mental and physical well-being. The international classification of sleep disorders [5] classified it into the following categories: insomnia, parasomnia, central hypersomnia, sleep-related disorder, circadian rhythm sleep disorder, sleep-related movement disorders, and other disorders. Insomnia is shown to be the most common sleep disorder [6,7]. The disorder is characterized mostly by dissatisfaction with

* Corresponding author.
E-mail addresses: dakhalebharti@gmail.com (B.J. Dakhale), manishsharma.iitb@gmail.com (M. Sharma), mohammad.arif.18e@iitram.ac.in (M. Arif), kushagra.asthana.18e@iitram.ac.in (K. Asthana), ankitbhurane@ece.vnit.ac.in (A.A. Bhurane), ashwinkothari@ece.vnit.as.in (A.G. Kothari), aru@np.edu.sg (U. Rajendra Acharya).

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sleep length or quality, difficulty beginning or sustaining sleep, significant discomfort, and problems with daily functioning [8,7]. It has been related to adverse long-term health effects, such as impaired quality of life, low life expectancy, and psychological disorders [9]. Approximately 50% of all older people have trouble falling asleep which raises the risk of substantial co-occurring diseases, and mortality [10].

This estimate ranges from 24% to 42% of elderly persons suffering from sleep apnea conditions (SAS) [11,12]. SAS is characterized by recurring total or partial upper airway blockages during sleeping [13,14]. In addition, SAS-related sleep disruption and oxygen desaturation may be risk factors for cognitive impairment, particularly in the elderly [15,16]. Observing sleep structure is extremely important to detect these and other commonly occurring sleep disorders [17]. In 1968, Rechtschaffen and Kales [18] gave R&K sleep-stage scoring technique. According to it, sleep is divided into rapid eye movement (REM) and non-rapid eye movement (NREM). REM sleep accounts for 20%–25% of total sleep time, while for an adult person, NREM sleep accounts for 75%–80% of sleep duration. NREM is subdivided into four stages (S1, S2, S3, and S4). However, the recent scoring manual of the American academy of sleep medicine (AASM) [19], S3 and S4 stages are merged as N3, making a total of 3 subdivisions of NREM sleep N1, N2, and N3. In humans, 4–6 alternate cycles of REM and NREM sleep are observed during a typical sleep duration, with each cycle lasting between 90 to 110 minutes on average [20]. Polysomnography (PSG) is currently considered the best standard for analyzing and determining sleep quality [21,22]. PSG captures electroencephalogram (EEG), electromyography (EMG), electrooculography (EOG), electrocardiogram (ECG), and other electrophysiological data during sleep. After that, human professionals can visually analyze the PSG recordings and perform the sleep staging. As it is time-consuming and prone to human errors, attempts are made to develop a faster and simpler method. Accurate automatic sleep stage scoring techniques are being developed [23,24], with EEG data using single and multichannel [25,26]. Acharya et al. [27] conducted a comprehensive review of the literature on sleep stage classification. Shi et al. [28] conducted a study on 25 adult subjects, utilizing a two-stage multi-view algorithm followed by the k means clustering method using multi-channel EEG signals of the sleep apnea dataset and achieved an accuracy of 81.10%. Sharma et al. [29] performed a six-class sleep stage classification by employing a three-band time-frequency localized (TBTFL) wavelet filter bank (FB) approach. This study used an EEG channel from the sleep-EDF database. They obtained an overall classification accuracy of 91.7% for five classes using a support vector machine (SVM) classifier. Zhu et al. [30] presented an approach based on difference visibility graph for sleep stage classification. They achieved a classification accuracy (CA) of 88.9% for five-stage classification using 9 features and SVM classifier. Berthomier et al. [31] used a five-stage fuzzy logic-based iterative approach using a single EEG channel that resulted in a CA of 82.9% using only 12 healthy subjects. Liang et al. [32] developed an automated sleep grading using 20 healthy individuals' EEG data with multi-scale entropy (MSE) and a single EEG channel. A recurrent neural network (RNN) classifier was used in their study to conduct classification. EEG epochs were classified into five stages (Wake, REM, S1, S2, SWS). Mean squared error (MSE) alone demonstrated an overall sensitivity of 76.9% and a kappa value of 0.65. Redmond et al. [33] used ECG-derived respiration and HR statistics of 31 male subjects. They classified the data into Wake, Non-REM, and REM (WNR) classes, using linear discriminant analysis (LDA) and quadratic LDA with an accuracy of up to 76.1%. Tzimourta et al. [34] conducted an EEG-based study on the ISRUC-Sleep that contained 118 subjects, out of which they employed only 100 subjects and 87187 epochs. They used six EEG channels for five-stage sleep classification and achieved 75.3% accuracy. Hassan et al. [35], using adjustable Q-factor wavelet transform (TQWT), recently developed a new approach for splitting EEG signals into sub-bands(SBs). The random forest extracts spectral information from these TQWT SBs and classifies them. They reported CA of 97.5% to 90.38% for two-class and six-class sleep classification problems, respectively. However, they only considered 28 participants and 20,257 30-second EEG epochs. Although these studies evaluated diverse psychological signals from different datasets and demonstrated reasonably with a small number of subjects ranging from 8 to 118. As a result, a large-scale study with a large number of individuals is required to develop a credible sleep-scoring system. In this work, we used the study of osteoporotic fractures (SOF) dataset as it covers many individuals (461 in total). Hence, we choose this dataset for our study.

Table 1
Number and share of epochs for each stage used in the study.

Sleep Stage	Number of epochs	epochs %
W	182828	39.16%
N1	14156	3.03%
N2	158735	33.99%
N3	58690	12.57%
REM	52463	11.23%
Total	466872	100%

The salient features of the proposed study are as follows:

- Used a SOF database containing 461 women subjects suffering from osteoporosis. To the best of our knowledge, we are the first group to use database to score sleep stages in this study. Database is significantly larger than [36,37].
- We have used a new class of finite orthogonal quadrature Fejer Korovkin wavelet filter bank.
- Our model employed one or two unipolar EEG C4-A1, and C3-A2 making the system simple and easy to use compared to other systems developed using multimodal PSG signals [38–40].
- Only entropy features, namely Tsallis, wavelet, and Renyi Entropies, have been used to develop the model.
- We have used single and dual EEG channels.
- The suggested approach is efficient and may be used in real-time low-cost Internet of Things (IoT) configurations.

2. Material used

The osteoporotic fracture (SOF) dataset is publicly available on the national sleep research resource (NSRR) website [41,42]. The multicenter SOF repository contains 16 years of osteoporosis data collected during various visits of participants. As a result acted as the foundation for numerous studies concerning osteoporosis and aging in women aged 65 and older. NSRR, in collaboration with SOF Online, provided raw EDF data and a more comprehensive collection of PSG signals. The sleep study employed in our proposed work was conducted on 461 women participants aging between 65 and 89 years during 2002-2004. It is to be noted that the polysomnography data is available for 453 subjects because of the earlier data loss from the owner of the dataset making the annotations and raw data unavailable for eight subjects (508, 1050, 1681, 2461, 2729, 3698, 5332, 7411) of the study. Therefore, 12 electrode system containing Cz (reference), forehead (GND), C3, C4, A1, A2, left EOG, right EOG, 2 chin EMG, and 2 ECG (snaps), was used to acquire the data which were placed using the standard norms [43]. The proposed work used C3-A1, and C4-A2 dual EEG channels collected using gold disk electrodes C4 A1 and C3 A2, respectively, sampled at a frequency of 128 Hz. Additionally, all the standard procedures were followed to ensure the electrode quality before and after data collection [44,45]. The information on the total number of epochs for each sleep stage is shown in Table 1.

3. Fejér-Korovkin (FK) wavelet filters

FK is a family of quadrature filters that are well suited for applications requiring optimal asymptotic frequency localization (γ_p). However, the wavelet filters using finite length filters lose information at

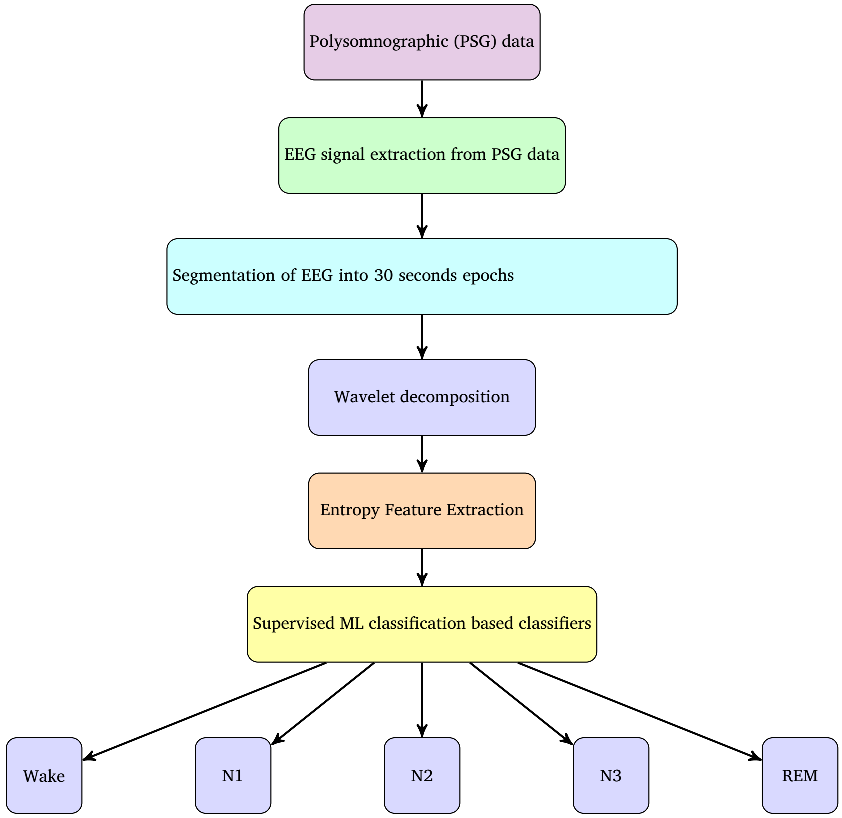

Fig. 1. Flowchart illustrating the methods used.

high frequencies. FK is known to have better symmetry and comparatively lesser smoothness than Daubechies wavelets. Further, they have a nonlinear phase and a frequency response that becomes ideal as the support increases. FK filters excel in parameter extraction for signal classification [46]. As detailed in the subsequent section, we have used a 5-level FK wavelet decomposition to obtain six subbands of EEG signals.

4. Methodology

Fig. 1 represents the steps involved in sleep scoring. The subsection that follows explains the various steps involved in the automated sleep stages classification.

4.1. EEG extraction and segmentation

The data contains 466872 EEG epochs of duration 30 sec from 453 subjects. The data is unbalanced because the amount of epochs that contribute to each sleep stage varies greatly, with W (wake) stage having the highest and N1 stage having the lowest number of epochs, equals to 39.16% and 3.03% of the total number of epochs available for sleep stage classification, respectively. A full sleep cycle broadly comprises three phases: W (wakefulness): stage 1, NREM: stages-2-5, and REM: stage 6. Previously, the sleep research community utilized the Rechtschaffen and Kales (R and K) [18] criteria, which were widely used from 1968 until 2007 for scoring sleep into 6 stages (W, S1, S2, S3, S4, REM). Later, the American academy of sleep medicine (AASM) [19]) upgraded sleep classification rules and concluded that stages S3 and S4 jointly contribute to a single stage(N3). As a result, complete sleep has been divided into five stages W, N1, N2, N3, and REM. In this study, we utilized AASM criteria for sleep stage classification.

4.2. Filtering

In this study, we have utilized the Fejér-Korovkin orthogonal wavelet filter of length-18. The filter bank is constructed using a new approach to constructing finite orthogonal quadrature filters using convolution kernels [47].

4.3. Wavelet decomposition

EEG signal is non-stationary; hence Fourier transform-based algorithms are unable to analyze data. The use of wavelet bases to analyze non-stationary EEG signals has been beneficial, and several successful attempts have already been made to classify bio-signals using orthogonal filter banks [48,49]. In this study, an orthogonal wavelet filter bank is used to identify EEG epochs that belong to a specific group. The above mentioned wavelet filter bank is used to decompose each epoch into six sub-bands. As a result of five-level decompositions, six sub-bands of EEG epochs are obtained with frequency ranges of 0-4 Hz (A),4-8 Hz (D5), and 8-16 Hz (D4), 16-32 Hz (D3), 32-64 (D2), 64-128 (D1). The lower frequency range 0-4 Hz (A) is referred to as approximate coefficient (A) [50], whereas the other bands with higher frequencies are referred to as detailed coefficients (D1, D2, D3, D4, and D5). Moreover, these sub-bands are used to extract different features.

4.4. Features extraction

We extracted different features from the sub-bands gained after the decomposition of epochs. Extracted features are used for classifying sleep into five different classes and are briefly explained below:

- Tsallis Entropy: Tsallis entropy [51] is a generalization of Boltzmann-Gibbs theory, and has a similar form as the Havrda–Charvát structural α-entropy proposed in 1967 [52]. Tsallis proposed a real parameter, an entropic expression, expressed with an index q. S forms the basis of nonextensive statistical mechanics, which modifies Boltzmann-Gibbs's theory. Tsallis statics proved to be of great help in a broad variety of phenomena in fields like physics, biology, medicines, etc. It is defined as,

Table 2
Statistical analysis for C3-A2 and C4-A1 channels combined.

Feature	Sub-band	Rank	W (mean± std)	N1 (mean± std)	N2 (mean± std)	N3 (mean± std)	REM (mean± std)
	Sb-1	3	−1.7587e+7 ± 1.2337e+8	−1.4546e+7 ± 1.0045e+8	−1.6116e+7 ± 1.1804e+8	−2.1268e+7 ± 1.4579e+8	−2.2573e+7 ± 1.5221e+8
	Sb-2	18	−4.5121e+6 ± 7.1023e+7	−7.6227e+05 ± 1.0608e+7	−2.9435e+06 ± 5.0825e+7	−4.9141e+6 ± 7.4129e+7	−5.1646e+6 ± 7.6277e+7
Tsallis	Sb-3	5	−4.4528e+5 ± 7.9434e+6	−3.3510e+5 ± 3.2650e+6	−4.1969e+5 ± 8.3077e+6	−4.7804e+5 ± 5.3511e+6	−5.0386e+5 ± 5.6492e+6
Entropy	Sb-4	15	−5.9184e+5 ± 9.4562e+6	−4.1349e+5 ± 5.7994e+6	−5.5923e+5 ± 9.6178e+6	−7.6432e+5 ± 1.0290e+7	−8.2076e+5 ± 1.0869e+7
	Sb-5	1	−1.0072e+6 ± 1.9138e+7	−6.9659e+5 ± 1.1783e+7	−9.8638e+5 ± 1.9902e+7	−1.5970e+6 ± 3.0025e+7	−1.7399e+6 ± 3.1735e+7
	Sb-6	14	−1.3586e+6 ± 1.8210e+7	−1.0787e+6 ± 1.4706e+7	−1.3207e+6 ± 1.8413e+7	−1.8004e+6 ± 2.2575e+7	−1.9415e+6 ± 2.3822e+7
	Sb-1	4	−2.0455e+8 ± 1.6708e+9	−1.6585e+8 ± 1.3536e+9	−1.8711e+8 ± 1.5979e+9	−2.5458e+8 ± 1.9715e+9	−2.7152e+8 ± 2.0587e+9
	Sb-2	12	−5.5184e+7 ± 9.4651e+8	−7.7542e+06 ± 1.2555e+8	−3.4874e+7 ± 6.7263e+8	−6.0471e+7 ± 9.9035e+8	−6.3671e+7 ± 1.0191e+9
Wavelet	Sb-3	16	−4.2054e+6 ± 1.0062e+8	−2.9222e+6 ± 3.6066e+7	−3.9849e+6 ± 1.0576e+8	−4.5171e+6 ± 6.1429e+7	−48289e+6 ± 6.4885e+7
Entropy	Sb-4	11	−5.9111e+6 ± 1.1741e+8	−3.8569e+6 ± 6.9604e+7	−5.6053e+6 ± 1.1978e+8	−7.8730e+6 ± 1.2420e+8	−8.5539e+6 ± 1.3122e+8
	Sb-5	7	−1.0908e+7 ± 2.4936e+8	−7.0821e+6 ± 1.4828e+8	−1.0776e+7 ± 2.6008e+8	−1.8425e+7 ± 3.9566e+8	−2.0221e+7 ± 4.1826e+8
	Sb-6	10	−1.4283e+7 ± 2.3123e+8	−1.0909e+7 ± 1.8462e+8	−1.3924e+7 ± 2.3419e+8	−1.9621e+7 ± 2.8556e+8	−2.1334e+7 ± 3.0146e+8
	Sb-1	9	−16.3788 ± 1.9858	−16.5237 ± 1.7679	−16.2864 ± 1.9694	−16.4006 ± 1.9574	−16.4141 ± 1.9722
	Sb-2	6	−14.3358 ± 2.2600	−14.4127 ± 2.0292	−14.2662 ± 2.2283	−14.3143 ± 2.2408	−14.2972 ± 2.2425
Renyi	Sb-3	2	−14.4141 ± 1.7150	−14.4825 ± 1.6082	−14.3685 ± 1.6807	−14.4325 ± 1.7036	−14.4062 ± 1.7138
Entropy	Sb-4	13	−14.4546 ± 1.5416	−14.5085 ± 1.4065	−14.4160 ± 1.5132	−14.5178 ± 1.5506	−14.4924 ± 1.5659
	Sb-5	8	−14.4548 ± 1.8641	−14.5626 ± 1.6824	−14.4072 ± 1.8535	−14.5244 ± 1.8885	−14.5272 ± 1.9031
	Sb-6	17	−14.4177 ± 2.1937	−14.6160 ± 1.9689	−14.3526 ± 2.1954	−14.4632 ± 2.2135	−14.4756 ± 2.2246

$$S_q = \frac{n}{q-1}(1 - \sum_i z_i^q)$$

Here n is a positive constant, and z_i is a discrete collection of probabilities with the condition:

$$\sum_i z_i = 1$$

- Wavelet Entropy: Wavelet Entropy (WE) [53] is a unique tool for analyzing non-stationary signals' transitory properties in time and frequency domain. It has been useful in finding valuable clinical information in physiological signals like ECG, EEG and intracranial pressure recordings. For example, for a signal $P(x)$ the wavelet entropy is calculated as:

$$WE = -\sum (P(x)\log(P(x)))$$

where the $\log$ is defined with base 10.
- Renyi entropy: It is a measure of a system's heterogeneity and unpredictability. Rényi entropy generalizes majorly four entropies: Hartley entropy, Shannon entropy, collision entropy, and min-entropy [54,55]. Mathematically, it is represented as:

$$RenE_i = -\log(\sum_{n\in z} |p(x)|^2)$$

where $p(x)$ is a signal sequence.

4.5. Classification

The wavelet-based entropy features extracted from both the unipolar channels C4-A1 and C3-A2 are fed to various machine learning classifiers such as k-nearest neighbors (KNN) [56], decision trees [57,58], ensemble bagged trees (EBT) [59], logistic regression [60], support vector machines (SVM) [57], discriminant analysis and Naive Bayes [61]. A 10-fold CV method is applied during the training of the model, in which whole data is divided into ten equal sub-parts of 46687 epochs. Out of which, nine sub-parts (420183 epochs) are utilized for model training, while the remaining one sub-part (46687 epochs) is used for testing. The cycle is repeated ten times by taking each sub-part for testing. Among all the classifiers tested in this study, EBT outperformed others. It uses the bagging predictors technique for creating numerous versions of a predictor and then combining them into a single aggregated prediction by making bootstrap duplicates of the learning set and using these as a new learning set. The EBT combines the predictions of many decision trees into a single aggregated prediction. Bagged decision trees perform well because each decision tree is fitted on a different training dataset, allowing each decision tree to have minute differences resulting in an ensemble of diverse models that helps in making better predictions as the trees have less correlation among predictions and hence low prediction errors. The EBT classifier used in the proposed work utilizes 30 decision trees and has a prediction speed of 22000 obs/sec.

5. Results

The proposed work is executed on a machine with 16 GB RAM and Intel(R) Xeon(R) 3.50 GHz processor with MATLAB R2020a installed. In this study, the ensembled bagged trees classifier produced the highest classification accuracy for classifying five sleep stages W, N1, N2, N3, and REM. Statistical analysis of ranking features like, mean value, and standard deviation for all 5 stages with respect to each sub-band is given in Table 2. We used the analysis of variance (ANOVA) technique to examine the extracted features. The features were ranked using the minimum redundancy maximum relevance (MRMR) method [62]. The p-value corresponding to each sub-band is zero, which indicates that all the features used in this study are statistically significant. It can also be noted that sub-band 5 of Tsallis entropy is ranked 1, which indicates that it is the most significant feature among all the features used in this study.

From Table 1, it can be observed that among the top 5 ranks top 3 are from Tsallis entropy. The dataset is unbalanced, therefore, only classification accuracy may not be a good indicator of classification performance. Hence Cohen's kappa coefficient (K) is also calculated to analyze results. A classification performance in terms of accuracy, precision, recall, and Cohen's kappa of both the unipolar channels with all features extracted are given in Tables 3, 4 and 5.

Table 3 shows that unipolar channel C3-A2 yielded the best classification accuracy of 75.80% and kappa value of 0.64505 using Tsallis entropy with a 10-fold cross-validation method.

Table 4 shows that unipolar channel C4-A1 yielded the best classification accuracy of 75.87% and kappa value of 0.645605 using Tsallis entropy with a 10-fold cross-validation method.

For better overall classification accuracy, we jointly used features obtained from both the unipolar channels (C3-A2 + C4-A1). From Table 5, it is clear that Tsallis entropy outperformed the other two in terms of both accuracy and kappa value by obtaining average accuracy of 79.70% and a kappa value of 0.702274. The confusion matrices corresponding toboth the channesl for Tsallis Entropy are given in Tables 6 and 7.

The best result for the proposed methodology is achieved when all the features used together for C3-A2 and C4-A1 EEG channels. The overall classification accuracy achieved in our work is 81.3% by the EBT classifier and a high Cohen's kappa value of 0.724551. The confusion

Table 3
Sleep stage classification was performed using C3-A2 EEG channel with 10-fold cross-validation.

Features	Sleep Stages	Accuracy (%)	Precision	Recall	Cohen's kappa (K)	Average accuracy (%)
Tsallis Entropy	W	90.52	0.85	0.91	**0.645605**	**75.80**
	N1	96.84	0.26	0.02		
	N2	81.05	0.69	0.79		
	N3	92.65	0.75	0.62		
	R	90.54	0.6	0.46		
Wavelet Entropy	W	90.02	0.85	0.91	0.631465	74.93
	N1	96.84	0.24	0.02		
	N2	80.41	0.69	0.78		
	N3	92.36	0.74	0.6		
	R	90.23	0.59	0.44		
Renyi entropy	W	85.30	0.78	0.87	0.497474	66.22
	N1	96.86	0.09	0.004		
	N2	73.41	0.59	0.7		
	N3	89.03	0.59	0.43		
	R	87.83	0.43	0.25		

Table 4
Sleep stage classification was performed using C4-A1 EEG channel with 10-fold cross-validation.

Features	Sleep Stages	Accuracy (%)	Precision	Recall	Cohen's kappa (K)	Average accuracy (%)
Tsallis Entropy	W	90.28	0.85	0.91	**0.645605**	**75.87**
	N1	96.85	0.29	0.02		
	N2	81.23	0.7	0.79		
	N3	92.76	0.76	0.63		
	R	90.62	0.61	0.46		
Wavelet Entropy	W	89.85	0.84	0.91	0.634959	75.18
	N1	96.85	0.26	0.02		
	N2	80.69	0.69	0.79		
	N3	92.55	0.75	0.61		
	R	90.42	0.6	0.44		
Rényi entropy	W	85.10	0.78	0.87	0.496267	66.15
	N1	96.88	0.16	0.006		
	N2	73.27	0.59	0.71		
	N3	89.13	0.59	0.43		
	R	87.91	0.43	0.25		

Table 5
Sleep stage classification performed using C3-A2 and C4-A1 EEG channels jointly with 10-fold cross-validation.

Features Used	Sleep Stages	Accuracy(%)	Precision	Recall	Cohen's kappa (K)	Average accuracy (%)
Tsallis Entropy	W	92.10	0.87	0.93	**0.702274**	**79.70**
	N1	96.94	0.43	0.03		
	N2	84	0.73	0.83		
	N3	93.87	0.81	0.68		
	R	92.50	0.71	0.56		
Wavelet entropy	W	91.69	0.87	0.93	0.690232	78.90
	N1	96.93	0.4	0.02		
	N2	83.41	0.73	0.82		
	N3	93.61	0.8	0.66		
	R	92.18	0.7	0.54		
Renyi entropy	W	87.39	0.81	0.89	0.551507	69.85
	N1	96.94	0.33	0.007		
	N2	76.06	0.62	0.75		
	N3	90.21	0.65	0.48		
	R	89.10	0.53	0.3		

matrix obtained after the classification of sleep stages using the EBT classifier is shown in Table 8.

6. Discussion

Three entropy-based features namely Tsallis, wavelet, and Renyi entropies, were employed individually and jointly. Tables 3, 4, and 5 clearly show that Tsallis performed better than the other two for both unipolar channels. Our model achieved an accuracy of 79.24% for the C4-A1 and 79.19% for the C3-A2 channel. We observed that the model's overall accuracy increased to 81.3% when we jointly used both the channels and used all the features together. We also achieved a high value of kappa, of 0.724551. Zhang et al. [63] studied the sleep heart health study (SHHS) dataset for automated sleep scoring using deep neural networks. They obtained the F1 score of 0.68 and a kappa of 0.55 when trained with SHHS dataset and tested with SOF dataset.

PSG techniques for scoring sleep stages and diagnosing sleep disorders require multiple electrodes to record various psychological signals (like EEG, EMG, EOG, ECG) [64,40]. Additionally, the sleep recordings must be done in a dedicated sleep center or hospital overnight. Furthermore, the changed sleeping environment and the time-consuming process of PSG recording techniques might cause inconvenience to especially elderly people who are more likely to suffer from sleep disorders [65]. Hence, the model proposed in this study is highly required as it

Table 6
Confusion matrix for features obtained for C3-A2.

Overall Accuracy = 79.19%					Cohen's kappa = 0.694401	
True Class	Predicted Class					F1 score
	Wake	N1	N2	N3	R	
Wake	172037	120	7507	216	2939	0.91
N1	4943	241	6550	37	2385	0.03
N2	10941	149	132232	9245	6168	0.77
N3	986	3	19638	37891	172	0.71
R	6773	76	17878	405	27331	0.60

Table 7
Confusion matrix for features obtained from C4-A1.

Overall Accuracy = 79.24%					Cohen's kappa = 0.694553	
True Class	Predicted Class					F1 score
	Wake	N1	N2	N3	R	
Wake	171761	104	7754	207	2993	0.91
N1	4881	251	6585	26	2413	0.03
N2	11222	186	132264	9195	5868	0.77
N3	919	1	19484	38147	139	0.72
R	7073	62	17470	349	27509	0.60

Table 8
Confusion matrix for feature obtained from fused C3-A2 C4-A1 channel.

Overall Accuracy = 81.3%					Cohen's kappa = 0.724551	
True Class	Predicted Class					F1 score
	Wake	N1	N2	N3	R	
Wake	173487	111	6662	152	2407	0.92
N1	4889	306	6665	23	2273	0.04
N2	10149	161	135550	8110	4765	0.79
N3	827	0	18016	39738	109	0.74
R	5975	66	15791	355	30276	0.66

only uses one or two EEG channels which can offer reliable findings similar to manual PSG-based sleep scoring methods which are easy to use, take less time, are economical, and handy for the patients. Only three features, namely Tsallis entropy, wavelet entropy, and Renyi entropy, are extracted from six sub-bands each and fed to different classifiers to achieve the best classification accuracy using EBT classifier.

Wilcoxon signed-rank test [66] [67] is performed to compare the performance of classifiers, uses the results at each fold as a trial. Each trial, it computes the performance of the two classifiers. The absolute values of differences are then ranked. The ranks are summed up separately for positive and negative ranks. The minimum of the summations is compared to a critical value V_α. If the minimum value is less than V_α, the null hypothesis that the two classifiers perform equally can be rejected at a certain α confidence level. (See Table 9.)

The sum of positive ranks is 55, and negative ranks are 0. For N=10 (where N is number of folds), V_α was identified as 10 at a confidence level $\alpha = 0.05$. The minimum sum of ranks is 0, that is less than $V_\alpha =$ 10, we can reject the null hypothesis that the two classifiers performed equally with confidence level $\alpha = 0.05$.

The other studies [35][30] used a wide variety of statistical features (more than 40) to achieve good classification performance. Moreover, we used 466872 epochs to train our model 10-fold CV to avoid overfitting of the model, most state-of-the-art techniques employed fewer epochs for their models, with 50% epochs for training and 50% for testing [68]. To the best of our knowledge, this is the first study conducted on the SOF dataset, hence there is no available to compare the proposed model with other studies. However, a comparison of the classification performances of various models developed using different datasets is given in Table 10. It can be noted that although Sharma et al. [69] achieved higher accuracy than the proposed model, they conducted the study on a number of subjects from a different database. The novelty of work is that it can be utilized to score sleep stages of old age subjects who regularly suffer from irregular sleeping patterns at night, quickly and automatically. Since, all the subjects in the SOF dataset are women between 65-89 years with osteoporotic fractures, the model can also be used for gender-based sleep research as women are thought to require more sleep than men [70].

The main features of the study are,

1. To the best of our knowledge, this is the first study that used the SOF database 453 EDF files.
2. The proposed methodology used a novel FK wavelet filter bank to identify sleep stages with EEG data.
3. The proposed model yielded high Cohen's Kappa coefficient values of 0.724551.
4. Automated sleep stages detection is developed.
5. We used a new family of optimum wavelet filters.

The limitations of this study are as follows:

- We used 453 subjects' data out of 461 subjects, as 8 files were unavailable for the study.
- Placing many electrodes on a human scalp is a difficult task and can occasionally cause discomfort to the patients. Hence some patients can feel uneasy during the EEG recording.
- The least classification accuracy is achieved for the N1 sleep stage due to the availability of fewer data stage. It only contributes about 3.03% of the total 466872 epochs used for the study.

7. Future aspects

Internet of things (IoT) in healthcare is proving to be an elixir as the patient-doctor interaction is not limited to the number of visits. With this emerging technology, the doctor can continuously monitor a patient remotely without any contact, due to the sudden spike of COVID-19. This progress is also due to advancements in cloud computing, machine learning, and biological sensors. These technological advancements have now made personal healthcare practically possible. EEG, ECG, and PSG signals may now be acquired as user-friendly using smart devices. After that, computer-assisted detection methods can be used to identify any anomalies or obscene patterns in data and provide assistance to clinicians to make an accurate diagnosis.

The proposed method can be employed as an IoT-based sleep stage detection system. The psychological signals can be collected from a patient through simple sensors (like in two EEG channels), and a smartphone app can collect them. Further, the information be uploaded to a cloud server with the help of a gateway where our model is placed. The outcome of the model can be sent to a doctor, and the sleep stage can be classified in real-time, guiding the patient with appropriate advice in case of any abnormality. (See Fig. 2.)

8. Conclusion

In the proposed work, we have developed a wavelet-based sleep-scoring system for elderly women with osteoporotic fractures using two unipolar EEG channels (C4-A1 and C3-A2). For five-stage sleep classification, EEG channels are used separately and in combination, and reported higher performance with a combination of both channels. We used an optimal orthogonal wavelet filter bank class to obtain six EEG signal sub-bands using 453 subjects. The entropy-based features are used to develop the model. Tsallis entropy outperformed the other two entropy features and gave better results for individual and combined channels. We have used ensembled bagged trees classifier ten-fold cross-validation method. Our developed model is accurate, and requires two channels. As a result, in the future, this model may be implemented on an IoT-based sleep stage detection system, minimizing the pain of the

Table 9
Wilcoxon signed-rank test for different channels.

	Fold number	1	2	3	4	5	6	7	8	9	10	
C3	Fine tree (%)	71	70.57	70.65	70.43	70.37	70.56	70.7	70.36	70.36	70.62	
	Ensembled bagged tree (%)	79.42	79.26	79.2	79.16	79.42	79.26	78.99	79.12	78.87	79.42	Sum of rank = +55
	Difference (%)	+8.42	+8.69	+8.55	+8.73	+9.05	+8.7	+8.29	+8.76	+8.51	+8.8	
	Rank	+2	+5	+4	+7	+10	+6	+1	+8	+3	+9	
C4	Fine tree	70.35	70.15	70.86	70.13	70.29	70.42	70.47	70.3	70.23	70.49	
	Ensembled bagged tree	79.49	79.26	79.99	79.2	79.27	79.88	78.24	79.2	78.39	79.69	Sum of rank = +55
	Difference	+9.14	+9.11	+9.13	+9.07	+8.98	+8.46	+8.77	+8.9	+9.16	+9.2	
	Rank	+8	+6	+7	+5	+4	+1	+2	+3	+9	+10	
C3 and C4	Fine KNN	71.38	71.22	71.28	71.44	70.94	71.37	71.46	71.37	71.45	71.5	
	Ensembled bagged tree	81.5	81.29	81.26	81.03	81.32	81.28	81.68	80.74	81.35	81.54	Sum of rank = +55
channel combined	Difference	+10.12	+10.07	+9.98	+9.59	+10.38	+9.91	+10.22	+9.37	+9.9	+10.04	
	Rank	+8	+7	+5	+2	+10	+4	+9	+1	+3	+6	

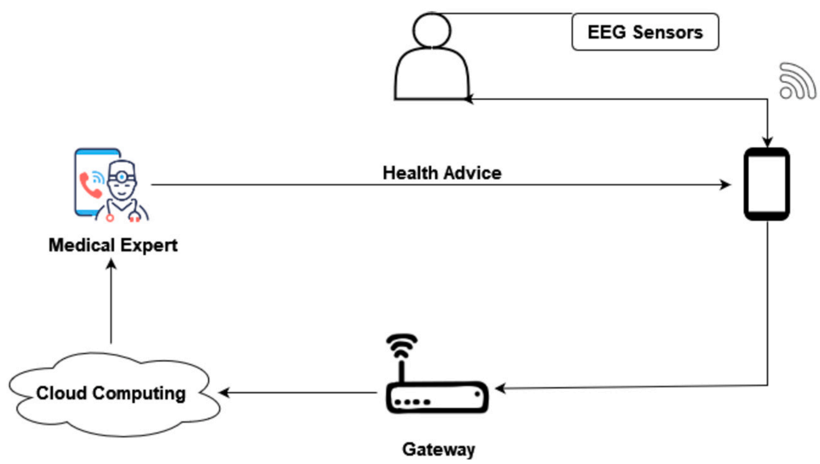

Fig. 2. Flow chart of an IoT-based sleep stage detection system.

Table 10
Summary of the state-of-the-art automated sleep stage classification studies conducted.

Work	Description	Accuracy
Shi et al. [28]	• **Classes:** 2 stage • **Subjects:** 25 • **Signals:** Two EEG (C3-A2 and C4-A1) • **Dataset:** St. Vincent's University Hospital and University College Dublin	81.10%
Sharma et al. [69]	• **Classes:** 6 stage classification • **Subjects:** 108 • **Signals:** Two EEG(C4-A1 and F4-C4) • **Dataset:** Cyclic alternating pattern (CAP)	85.3%
Güneş et al. [71]	• **Classes:** 5 stage classification • **Subjects:** 5 • **Signals:** Single EEG (C4-A1) • **Dataset:** Sleep laboratory of Meram Medicine Faculty of Selcuk University	82.15%
Tzimourta et al. [34]	• **Classes:** 5 stage classification • **Subjects:** 100 • **Signals:** Six EEG (F3-A2,C4-A1,C3-A2, O1-A2,O2-A1,F4-A1) • **Dataset:** SRUC-Sleep	75.3%
Helland et al. [40]	• **Classes:** 5 stage classification • **Subjects:** 10 • **Signals:** EEG, ECG and respiratory signals • **Dataset:** Siesta database	80%
Proposed work	• **Classes:** 5 stage classification • **Subjects:** 453 • **Signals:** Two EEG (C4-A1, C3-A2)	81.3%

patient coming to a specialized sleep laboratory and the arduous chore for doctors to score sleep manually.

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Declaration of competing interest

None.

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