A Comparison of Different Machine Learning Algorithms Using Single Channel EEG Signal for Classifying Human Sleep Stages

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Abstract — In recent years, the estimation of human sleep disorders from Electroencephalogram (EEG) signals have played an important role in developing automatic detection of sleep stages. A few methods exist in the market presently towards this aim. However, sleep physicians may not have full assurance and consideration in such methods due to concerns associated with systems accuracy, sensitivity and specificity. This paper presents a novel and efficient technique that can be implemented in a microcontroller device to identify sleep stages in an effort to assist physicians in the diagnosis and treatment of related sleep disorders by enhancing the accuracy of the developed algorithm using a single channel of EEG signals. First, the dataset of EEG signal is filtered and decomposed into delta, theta, alpha, beta and gamma sub-bands using Butterworth band-pass filters. Second, a set of sample statistical discriminating features are derived from each frequency band. Finally, sleep stages consisting of Wakefulness, Rapid Eye Movement (REM) and Non-Rapid Eye Movement (NREM) are classified using several supervised machine learning classifiers including multi-class Support Vector Machines (SVM), Decision Trees (DT), Neural Networks (NN), K-Nearest Neighbors (KNN) and Naive Bayes (NB). This paper combines REM with Stage 1 NREM due to data similarities. Performance is then compared based on single channel EEG signals that were obtained from 20 healthy subjects. The results show that the proposed technique using DT classifier efficiently achieves high accuracy of 97.30% in differentiating sleeps stages. Also, a comparison of our method with some recent available works in the literature reiterates the high classification accuracy performance.

Keywords- EEG, sleep stages, EEG sub-bands, Machine Learning Algorithms, Butterworth band-pass filter.

I. INTRODUCTION

A. Background

Sleep is the primary function of the brain that has an essential role in every individual's performance, learning capabilities and physical movement. Humans spend around one third of their life sleeping [1][2]. Sleep is separated into six different stages: Wakefulness, Rapid Eye Movement (REM) sleep and Non-REM (NREM). NREM sleep is further divided into four stages: 1, 2, 3 and 4 according to Rechtschaffen and Kales (R&K) sleep staging criteria [3]. It has been found that the EEG signals in REM and Stage 1 of NREM are similar in nature; this is why this paper merges both stages into one [4][5]. Sleep disorders are considered as one of the major public health issues in recent years. According to [6], more than 90% of depressive disorder patients suffer from sleep disorders. Liang *et al* [7] reported that sleep diseases such as insomnia and obstructive sleep apnea have a negative impact on the quality of human life. Sleep Apnea is estimated to be common in 2–4% of adults and in 1%–3% of children [8]. In addition, the occurrence of sleepiness is high and has serious effects on the physical health of people. Approximately 33% of the world's population suffers from insomnia symptoms [3]. According to [7], these sleep issues may cause sleepiness, depression or even death. According to National Highway Traffic Safety Administration in the United States, falling asleep while driving causes at least 100,000 automobile crashes annually; in Germany, one out of four traffic accidents; and in England 20% of traffic accidents [9]. Therefore, the need to distinguish human sleep stages is very important for diagnosis and treatment of sleep disorders such as sleep apnea, insomnia and narcolepsy [10].

Several biomedical signals such as Electroencephalogram (EEG) of the brain waves, Electrocardiography (ECG) of the heart rate, Electromyography (EMG) of muscle activity, and Electrooculography (EOG) of the eye movement provide valuable details for medical configurations that are used in the identification of sleep related disorders [4]. According to [4], the use of EEG signals is stated to be the gold standard for sleep stage recognition including Wakefulness, REM and NREM. Recently, many studies show that single channel EEG signal is an informative input for studying sleep stage recording and classification. According to the 10-20 system, EEG signals can be recorded by placing the electrodes either at C3-A2 or C4-A1 sites on the head of a subject [11]. Thus, the development of efficient sleep stage identification techniques using single channel EEG signal would be very beneficial to analysis, diagnosis and treatment of sleep disorders.

B. Related Work

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A number of techniques of sleep stage recognition have been presented in the past few years. According to [12], sleep stages classification was addressed based on graph domain features, single channel of EEG signal and multiclass Support Vector Machine (SVM) classifier. The accuracy results of six-state classification are able to attain rates 87.5%. Spectral analysis, Wavelet transform and Fuzzy clustering based on Fuzzy C-Means algorithm (FCM) were used by [13] for an automatic sleep stage detector, which can separate Awake stage, Stage1, Stage2, Stage3, Stage4 and REM stage using single channel EEG signals. The results showed that the algorithm could provide 92.27% success rate when using wavelet packets. Similarly, using single channel EEG signals, an in-flight automatic detection of low vigilance (wake/sleep) states was developed by [14]. The method was based on the comparison of mean values in α, β & θ, ratio [(α + θ)/β] or fuzzy logic fusion (α, β). The results confirm high efficiency of the designed technique during real flights. Another sleep stage classification study was done by Chen *et al* [15] to estimate sleep stages including Awake, Stage 1 and Stage 2, during daytime naps using four recorded EEGs signals. The proposed method achieved 80.6 accuracy rates based on the Hopfield Neural Network (HNN) classifier.

According to [16], a metric learning approach for automatic sleep stage classification based on single channel EEG data was introduced. K-Nearest Neighbor methods were used to classify Awake/Sleep and four sleep stages consisting of Awake, Stage1 + REM, Stage 2 and Slow Wave Stage (SWS). The achieved accuracies were 98.32% and 94.49% respectively. Another previous study was done by [17] that used an SVM based approach classifier to distinguish between awake and drowsy state using three channels of EEG waveforms. The drowsy state was defined as a combination of both sleep Stage1 and Stage2. The results of drowsiness detection approach indicate high accuracy and precision of 98.01% and 97.91% correspondingly. Moreover, Multi-class Support Vector Machine based on EEG and EOG signals was used for an automatic sleep stage detector, which can separate sleep stages in young healthy subjects and elderly patients automatically. The experimental results showed that the proposed algorithm could achive 91% success rate [18].

C. Contribution and Paper Organization

In the present work, the major contributions and main characteristics involved in proposing an efficient technique that could easily be implemented in hardware to differentiate between Wake, Sleep Stages1+REM, Stage2, Stage3 and Stage4 are discussed. The proposed approach will enable physicians to identify certain patterns in sleep such as fatigue, drowsiness, and/or various sleep disorders like apnea, insomnia and narcolepsy. The choice of filtering techniques with regards to decomposing the EEG signal into various sub-bands and the selection of features with less computational time for the purposes of classification is a key feature of this proposed methodology. It is based on several machine learning algorithms using a single channel of EEG signals for detection and classification procedure. Butterworth band-pass filters are designed to filter and decompose the EEG signal into five frequency sub-bands: delta wave (0-4Hz), theta wave (4-8Hz), alpha wave (8-12Hz), beta wave (12-30Hz) and gamma wave (>30 Hz). Then, discriminating features including energy, standard deviation and entropy are computed and extracted from each sub-band. Furthermore, the extracted features are then fed into the five classifiers for sleep stage recognition. In addition to the accuracy, the sensitivity and specificity were also considered to demonstrate the robustness of the proposed method. The experimental results on a number of subjects confirm high classification accuracy of the proposed work.

The subsequent structure of this paper is as follows: Section II describes the design principles, methodology and procedure including data acquisition process and data decomposition. Section III presents different statistical features extracted from EEG signals to validate the feasibility of the proposed scheme. Section IV briefly demonstrates the machine learning algorithms used in this work. Section V presents and discusses the experimental and comparison results of the proposed technique. Finally, concluding remarks are provided in Section VI.

II. METHODOLOGY AND PROCEDURE

A. Proposed Method

The overall objective of this work is on building a portable hardware device for sleep stage identification in an effort to assist physicians in the diagnosis and treatment of related sleep disorders. Thus, we focused on methodologies that can be easily implemented on any embedded system device. Figure 1 shows the flow chart of the proposed method including four parts: (1) Acquiring the Input EEG signal, (2) Filtering and Decomposition, (3) Features Extraction, and (4) Machine learning classification.

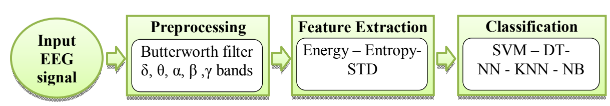


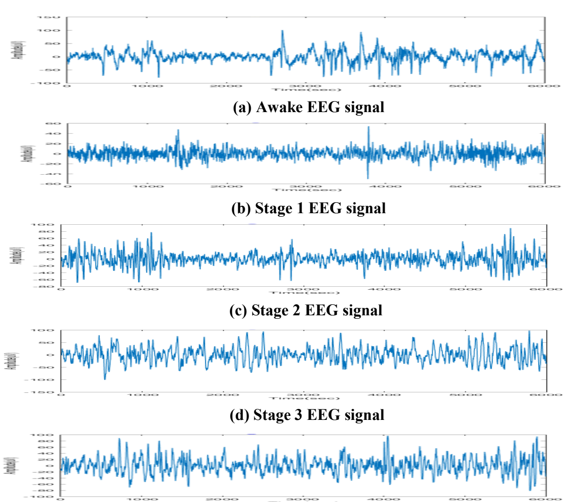
Figure 1. EEG sleep stages classification

B. EEG Dataset

The dataset used in this work is a publicly available dataset from PhysioNet website [19]. The EEG Sleep-EDF database is a collection of 61 polysomnograms (PSGs) that comes from two diffrent studies obtained in 1987-1991 and 1994, respectively. The first study utilized in this work consists of 20 healthy subjects; 10 males and 10 females, between the ages 25-34. Two PSGs of around 20 hours were recorded each day (including night time) for two days at the subjects' homes. The second night of subject 13, was not available due to a failure in recording cassette. The EEG signals were each sampled at 100 Hz. According to Van, sleep recording contains Fpz-Cz/Pz-Oz EEG signals instead of C4-A1/C3-A2 EEG signals [20]. The EEG Fpz-Cz channel is used in this work. Its associated hypnogram files contain sleep patterns corresponding to each subject. This pattern consists annotated sleep stages: W, 1, 2, 3, 4, R, M movement time and '?' as not scored. All hypnograms were manually scored by well-trained technicians according to Rechtschaffen and Kales manual. Each signal is processed in 60 second time-frames. For the purpose of illustration, Figure 2 shows samples of five different stages of EEG signals, which are used as inputs to the designed filter. Table I shows the number of Wake, Stage1, Stage2, Stage3, Stage4 and REM for each subject.

TABLE I. SUBJECTS INFORMATION

Subject	W	S1	S2	S3	S4	REM
Sub. 1	40	17	60	70	60	23
Sub. 2	50	42	40	55	5	20
Sub. 3	40	48	50	47	19	12
Sub. 4	50	36	84	35	32	23
Sub. 5	50	81	76	50	2	40
Sub. 6	40	49	56	83	8	10
Sub. 7	50	23	40	50	52	10
Sub. 8	75	48	50	43	77	20
Sub. 9	40	40	80	53	80	10
Sub. 10	40	24	70	60	39	18
Sub. 11	40	30	80	7	0	13
Sub. 12	40	10	80	44	27	18
Sub. 13	45	11	40	16	27	20
Sub. 14	40	52	50	29	43	17
Sub. 15	40	14	50	53	57	24
Sub. 16	40	29	79	70	54	10
Sub. 17	40	36	75	80	24	19
Sub. 18	50	20	69	70	33	18
Sub. 19	50	26	50	70	99	14
Sub. 20	52	25	50	57	11	15
Total epochs	912	661	1229	1042	749	354



(a) Awake EEG signal

(b) Stage 1 EEG signal

(c) Stage 2 EEG signal

(d) Stage 3 EEG signal

(e) Stage 4 EEG signal

Figure 2. Sample EEG Signal (a) Awake, (b) Stage 1, (c) Stage 2 (d) Stage 3 and (e) Stage 4.

C. Data Decomposition

The five frequency bands, namely: δ, θ, α, β and γ that are decomposed and filtered using Infinite Impulse Response (IIR) Butterworth band-pass filters for feature extraction process are derived as a result of the input EEG signal. The transfer function of IIR filters is not only simple but also easily realizable on digital signal processers or digital hardware engines, and/or embedded systems. The frequency response of Butterworth filters has no ripple in the passband and is extremely flat. Minimum order of filter is applied to yield precise and a significantly effective design [10]. The minimum order and cutoff frequencies are defined as $N=1/2 \times (\ln(\square_p/\square_s)/\ln(\omega_p/\omega_s))$ and $\omega_{c=}\ \omega_s/(\square_s)^{1/2N}$ respectively, whereas $\square_p$ is pass-band gain, $\square_s$ is stop-band gain, ω_p is corner pass-band frequency, and ω_s is corner stop-band frequency. The frequencies and amplitudes of δ, □, α, β and γ sub-bands during normal condition are shown in Table II [21].

TABLE II. AMPLITUDE AND FREQUENCY RANGE OF DECOMPOSED EEG SIGNAL

Rythm	Delta Δ	Theta θ	Alpha α	Beta β	Gamma γ
Frequency	0-4 Hz	4-8Hz	8-12Hz	12-22Hz	>30Hz
Amplitude	20-100μV	10μV	2-100μV	5-10μV	-

III. FEATURE EXTRACTION

According to the R&K rule, the parameter values corresponding to each EEG sleep stage is different [15]. In this paper, the characteristic parameters are measured based on three sample statistical features for each 60-s EEG data segment called epoch. For classification purposes, below are details about the extracted features at each five sub-bands frequency.

A. Energy

The power of the signal is represented by the energy at any period of time, which is given by:

$$E = \sum_{n=1}^{N} |\ x_i[n]\ | \qquad 1 \le n \le 6000, 1 \le i \le 5 \qquad (1)$$

B. Entropy

The entropy is a mathematical equation that measures uncertain outcomes of signals. It is given by:

$$EN = \sum_{j=1}^{N} (X_{ij}^2)\ \log(X_{ij}^2) \qquad 1 \le n \le 6000, 1 \le i\ 5 \qquad (2)$$

C. Standard Deviation

Standard deviation calculates the distribution of a set of data. The mathematical representation is expressed as:

$$STD = \sqrt{\frac{1}{N-1}\sum_{n=K+1}^{k+N}\left(y[n] - \frac{1}{N}\sum_{n=K+1}^{k+N} y[n]\right)^2} \qquad 1 \le n \le 6000 \qquad (3)$$

IV. MACHINE LEARNING ALGORITHMS

In this work, a combination of five classifiers have been used to improve the classification performance of sleep stages using MATLAB tool box.

The Support Vector Machine (SVM) is commonly used as a very powerful and flexible tool for the classification of real-world data. SVMs are binary classifiers, in which the objective is to locate a separating hyper-plane in the space between the two classes by mapping the data into a higher dimensional space [22]. For multi-class classification SVM, a "one-against-all" approach combined with linear kernel function was used in this work. It constructs k SVM models where k is the number of classes. Each classifier is trained to separate one class from the rest k-l classes [23].

As non-linear classifier, a Decision Tree (DT) has been mainly used in solving problems related to machine learning and classifier systems. The learning and classification steps of such algorithm are simple, fast and it can handle multi-dimensional data. The concept of decision tree classifiers is a flowchart-like tree structure in which each decision discards a certain class until reaching the accepted class. It is consisted of nodes, branches, and leaves. Whereas, a node denotes a test on an attribute using transition rules, a branch represents the result of the test, and the leaf holds a class label [24][25].

A Neural Network (NN) is a learning algorithm built for information processing through mathematical or computational model [25]. Neural network typically is a number of interconnected neurons in which each connection has a weight associated with it. During the classification process, it can predict the correct class label of the input layer by modifying the weights. In general, neural network consists of an input layer, one or more hidden layers and an output layer. Selecting the number of hidden layers is different and depends on each application. In practice, one layer is usually used [25].

K-Nearest-Neighbor (KNN) classifier is a nonlinear classifier based on learning by analogy. KNN utilizes different distance metric such as Euclidean and Mahalanobis to achieve good performance. KNN algorithm compares a given unknown test sample with training samples that are stored in an *n*-dimensional pattern space in order to measure closeness. Nearest-Neighbor assigns the test sample to the most common class among its *k* closest neighbors [24][25].

Naive Bayes (NB) classifier is a statistical classifier based on Bayes theorem with robust probability and assumption. Naive Bayes classifier is known to be a simple Bayesian classifier which can predict class probabilities by a given tuple belonging to a specific class. The assumption of Bayesian classifier is called class conditional independence, which means that each attribute value of a specific class has independent effects from other attribute values. Theoretically, it is a superior classifier that can guarantee a high classification speed and accuracy when applied to large databases [25].

V. RESULTS AND DISCUSSION

To assess the performance of our proposed sleep staging method, features were extracted from 4947 60-second epochs from 20 subjects, which were used as our experimental dataset. The work has been implemented using MATLAB R2015a platform. As stated before, EEG signals in REM and Stage 1 of NREM are similar in nature and are merged into one. Hence, this study attempts to classify five sleep stages including Wake, Sleep Stages1+REM, Stage2, Stage3 and Stage4. For classification purposes, several machine learning algorithms were applied to train and test the datasets in different percentage levels: 50% and 50%, 70% and 30%, and 80% and 20%, respectively. The achievement of each classifier is described in the following tables: III, IV, V, VI, and VII. The performance of these classifiers can be determined by the computation of accuracy, sensitivity and specificity using TP, FP, FN, and TN values [5], where TP is true positives, TN is true negatives, FP is false positives, and FN is false negatives. The equations of accuracy, sensitivity and specificity are shown below:

$$Accuracy\ (A_{cc}) = (TP + TN)/(TP + FP + TN + FN) \quad (4)$$

$$Sensitivity\ (S_e) = TP/(TP + FN) \quad (5)$$

$$Specificity\ (S_p) = TN/(TN + FP) \quad (6)$$

I. Support Vector Machine (SVM)

The results of using Multi-class SVM by combining the one-against-all approach with the linear kernel function are described in Table III. The best performance is achieved by training 70% of the data set and testing the other 30%.

TABLE III. SVM PERFORMANCE RESULTS

Test percentage		Sleep EEG Classes					A_{cc}
		Stage1+REM	Stage2	Stage3	Stage4	Wake	
20	S_e	94.93	89.24	97.11	30.88	95.88	85.23
	S_p	97,40	98.64	86.46	99.88	99.01	
30	S_e	97.32	80.00	98.38	13.10	0.00	64.08
	S_p	94.59	99.46	60.59	99.84	NaN	
50	S_e	95.41	82.47	97.00	56.01	0.00	68.91
	S_p	95.33	98.92	67.22	99.51	0.00	

II. Decision Tree (DT)

From Table IV, it's clear that the tree structure can separate the sleep stage with large variations. The accuracy rate using 70% for training and 30% for testing of the dataset resulted in over 97%. However, other accuracies did not vary a lot between training and testing set.

TABLE IV. DT PERFORMANCE RESULTS

Test percentage		Sleep EEG Classes					A_{cc}
		Stage1+REM	Stage2	Stage3	Stage4	Wake	
20	S_e	98.61	98.80	95.67	93.38	97.17	**97.06**
	S_p	99.74	99.59	98.59	98.82	99.63	
30	S_e	99.70	99.17	95.14	92.71	97.75	**97.30**
	S_p	99.73	99.55	98,55	99.21	99.75	
50	S_e	98.80	98.87	94.80	90.90	98.41	**96.64**
	S_p	99.69	99.35	81.10	78.76	99.65	

III. Nerul Network (NN)

The designed networks were trained and tested with 100 hidden neurons. From Table V, the training neural network, which was used to classify sleep stages of the different testing sets, achieved the best average accuracy of 91.7% when 20% samples were used for testing.

TABLE V. NN PERFORMANCE RESULTS

Test percentage		Sleep EEG Classes					A_{cc}
		Stage1+REM	Stage2	Stage3	Stage4	Wake	
20	S_e	96.8	96.3	88.6	76.0	95.6	**91.7**
	S_p	96.4	96.0	81.2	87.0	96.7	
30	S_e	98.6	95.3	88.2	69.5	94.5	**90.2**
	S_p	95.2	97.8	76.1	85.6	96.7	
50	S_e	97.1	93.2	83.0	78.3	95.8	**90.1**
	S_p	94.5	95.8	80.4	80.0	97.0	

IV. K-Nearest Neighbors (KNN)

Table VI illustrates the classifier output results using default distance metric Euclidean with *k* neighbors equal to

K-Nearest Neighbors reached best accuracy when 30% of the data set was used for testing.

TABLE VI. KNN PERFORMANCE RESULTS

Test percentage		Sleep EEG Classes					A_{cc}
		Stage1+REM	Stage2	Stage3	Stage4	Wake	
20	S_e	88.94	95.21	93.75	66.17	83.05	**87.36**
	S_p	97,21	96.47	90.52	98.00	99.50	
30	S_e	91.09	95.61	91.90	66.01	83.89	**88.10**
	S_p	99.47	96.60	91.06	97.74	99.42	
50	S_e	86.85	96.46	93.40	62.16	86.45	**86.45**
	S_p	99.55	95.78	89.85	98.20	99.45	

V. *Naive Bayes (NB)*

As can be seen from Table VII, the result of the statistical classifier produces an accuracy of 84% for all training and testing sets.

TABLE VII. NB PERFORMANCE RESULTS

Test percentage		Sleep EEG Classes					A_{cc}
		Stage1+REM	Stage2	Stage3	Stage4	Wake	
20	S_e	92.16	90.03	68.26	78.67	93.22	**84.5**
	S_p	97.92	97.42	86.17	93.08	98.52	
30	S_e	94.36	85.20	70.55	80.09	91,01	**84.1**
	S_p	96.33	98.03	95.06	93.34	98.27	
50	S_e	92.03	85.85	71.20	76.90	93.45	**84.03**
	S_p	96.65	97.67	93.76	94.04	98.26	

The tables above show a detailed comparison of sensitivity and specificity of each sleep stage and overall accuracy for the five analyzed classifiers: SVM, DT, NN, KNN and NB in three different training and testing datasets. It is observed that there is improved performance for DT and KNN classifiers when 70% of the dataset is used for training while 30% is applied for testing; whereas, SVM, NN and NB achieved best accuracy when 20% is used for testing and 80% for training. Also, it's clear that the DT classifier achieved high performance in separate sleep stages; where the sensitivity and specificity in all stages were better than other classifiers. Overall, DT, NN and KNN achieve best accuracies 97.30, 91.2 and 88.10 in percentages, respectively. The performance result of using multiple classifiers is illustrated in Figure 3.

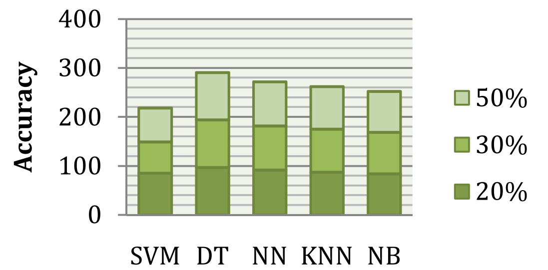


Figure 3. Overall results for each Classifier

Table VIII displays the comparison of our proposed approach with some recent related works on the same EEG EDF Sleep Dataset. In comparison with some of prior work, our approach is higher in terms of classification accuracy.

VI. CONCLUSION

In this work, the sleep stages identification for a single channel EEG signal based on a novel filtering and classification technique is presented. The experiment is conducted in this work by using a set of machine learning algorithms. The proposed methodology achieves the average classification sensitivity, specificity and accuracy of 96.89%, 99.35% and 97.30% respectively, when the

TABLE VIII. COMPARISON TABLE

No	Author name	Technique employed	Number of stages classified	Signal , Size & Test set	Accuracy	Year
1	Agustina *et al*	NN	Drowsiness/Alertness = 2	EEG 10 Subjects MIT-BIH database	86.5%-81.7%	2010
2	Eka *et al*	FNGL-VQ-GLVQ	3-NREM/Wake/REM = 5	ECG 10 Subjects Mitra -MIT-BIH database	68%-70%	2012
3	Estrada *et al*	Feature Extraction	Stage1/Wake/ REM = 3	EEG-EOG 10 Subjects NPSG dataset	100%	2006
4	Sheng *et al*	SVM-AASM-Feature selection	2-NREM/ Wake/REM = 4	EEG 12 Subjects	77%	2013
5	Chen *et al*	HNN	3-NREM = 3	EEG 10 Subjects	80.6%	2013
6	Adnane & Jiang	SVM	Sleep/wake = 2	ECG 16 Subjects MIT-BIH database	78.05%	2009
7	Estrada *et al*	AR-Feature Extraction	4-NREM/Wake/ REM = 6	EEG 1 Subjects	NAN	2004
8	Obayya & Abou-Chadi	Fuzzy Clustering	4-NREM/ Wake/ REM = 6	EEG 12 Subjects Cairo sleep database	92.27%	2014
9	Zhu *et al*	SVM	4-NREM/ Wake/ REM = 6	EEG 8 Subjects Sleep EDF database	87.5%	2014
10	Ebrahimi *et al*	NN-Packet coefficient	3-NREM/ Wake/ REM = 5	EEG 7 Subjects Sleep EDF database	93.0%	2008
11	Herrera *et al*	SVM	2-NREM/ Wake/ REM = 4	EEG 10 Subjects	70%	2011
12	Yuan *et al*	NN	Drowsiness/Alertness = 2	EEG 10 Subjects	79.1%-90.9%	2009
13	Li *et al*	KNN	2-NREM/ Wake/ REM = 4	EEG 8 Subjects Sleep EDF database	81.7%	2009
14	Vatankhah *et al*	SVM	NREM/ REM = 2	EEG Sleep EDF database	98%	2010
15	Zhovna & Shallom	Kullback-Leibler	3-NREM/ Stage5 = 4	EEG 25 Subjects	93.2%	2008
16	Estrada *et al*	Itakura Distance	4-NREM/ Wake/ REM = 4,2	EEG- EOG 10 Subjects	NAN	2005
17	Phan *et al*	KNN	Awake/Sleep & 3-NREM/ Wake = 2,4	EEG 4 Subjects Sleep EDF database	98.3%-94.4%	2013
18	Raymond & Liang	SVM	2-NREM/Wake/ REM = 4	EEG- MIT-BIH database	96.2%	2011
19	Yu *et al*	SVM	Wake/Drowsy = 2	EEG 16 Subjects CAP Sleep database	97.64%	2013
20	Liu *et al*	NN	2-NREM/Wake/ REM = 4	EEG 7 Subjects Sleep EDF database	NAN	2010
21	Mora *et al*	KNN-SVM-GPROP-KANTS	3-NREM/ Wake/ REM = 5	EOG-EEG-EMG 9 Subjects	70%	2010
22	Sirvan *et al*	SVM	(Awake/Sleep) 3-NREM/ Wake/REM =2,5	EEG-EOG Laboratory dataset Coimbra	95%-93.0%	2011
23	Liang *et al*	DT	3-NREM/ Wake/ REM = 5	EOG-EEG-EMG4,20 Subjects	86.5%	2011
24	**Proposed Method**	**DT-SVM-NN-NB-KNN**	**3-NREM/ Wake/ REM = 5**	**EEG 20 Subjects Sleep EDF database**	**97.30%**	**2015**

Decision Tree based-rule is applied. The filters employed to extract the sub-bands are less complicated; rendering our design easy, rapid and more feasible; hence, making our work not only appealing but also easy to implement in any embedded system/hardware engine as a personalized stand-alone device for identifying certain patterns such as fatigue, drowsiness, and/or various sleep disorders like sleep apnea. In comparison with certain recently available work on classification of sleep stages, the performance of this proposed work has certain advantages in terms of accuracy and feasibility.

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