



Sleep-Wake Sleep Stages Classification using Machine Learning Techniques based on Single-channel of EEG Signal

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Abstract

Sleep-related disorders have one of the challenging health issues across the world. Identifying sleep irregularities will be one important primary step of treatment for any types of sleep diseases. To perform day-to-day activities, proper healthy sleep is required for an individual's life. This also plays one of the vital roles in human life to maintain the proper health both physically and mentally wise and which alternatively smoothly maintain our quality of life. The main objective of this research work is to propose a simple and efficient automated sleep stage classification methods based on a single channel of electroencephalogram (EEG) signal using machine learning techniques. Both time and frequency domain features are applied for that analysis of sleep quality and classifying the sleep stages for identification of sleep abnormality during sleep at night. Total 28 features are extracted from 750 epochs with 3000 sample points through the C3-A2 channel of EEG signal. We have considered two subjects of two different medical conditions, one subject with affected of mild sleep problem and another subject is healthy controlled. Both subject's information was collected from ISRUC-Sleep public sleep dataset, which is specifically designed for the sleep study. The present research work based on a two-state sleep stage classification model through two machine learning classifiers such as support vector machine (SVM) and decision tree (DT) and used 10-cross validation techniques and four evaluation parameters such as recall, specificity, precision, and F1-Score for measuring the performance of the proposed research work. The achieved results from evaluation matrices show an effective performance with the SVM classifier. The overall accuracy achieved for the two-state sleep classification problem is 95.60% through SVM and 91.20% through DT. Similarly, for subject-2 the results achieved for SVM and DT are 87.46% and 87.06% respectively. The proposed outcome shows that our two-state sleep classification system is similar and slightly better overall accuracy compared to earlier publish similar methods research work. The corresponding kappa coefficient scored for subject-16(0.92, 0.43) guarantees that excellent agreement, and for subject-02 (0.72, 0.12) indicates that substantial agreement of the classification.

Keywords: Electroencephalography (EEG), Sleep Stage Classification, Time-frequency domain features, Machine learning

1. Introduction

Healthy Sleep is the basic requirement for a human being and proper sleep habits affect our performance in both social and professional life and its direct link with our physiological activities. Proper sleep decides the quality of learning ability, physical activity, mental

ability, and performance of the overall activities [1]. In general complete sleep, the duration is covering through different stages of sleep which are interrelated with our biological system [2]. With the modern digital generation, the lifestyle of the human being is complicated and ultimately it has resulted that millions of people get a poor quality of sleep during night time.

This problem is seen across the world with all age groups of people and this is a global challenge in the health care sector because it has found from the different research that poor quality of sleep is the major responsibility of creating critical diseases such as bruxism [3], insomnia [4], narcolepsy [5], obstructive sleep apnea syndrome [6] and behavioral disorder [7]. Currently, there are two important sleep standards followed during sleep staging analysis. According to both standards, the whole sleep stages are divided into three basic categories: wakefulness, non-rapid eye movement (N-REM), rapid eye movement (REM). The first sleep handbook was edited by Rechtschaffen and kales (RK) in the year 1968. According to RK rules, the NREM sleep stage is further divided into four sub-sleep stages: N-REM1 stage, N-REM 2 stage, N-REM3 stage, and N-REM4 stage [8]. This sleep standard followed all clinicians during the analysis of sleep irregularities of the patients, but in the year 2008, another well-known institute named as American Academy of Sleep Medicine (AASM) determined new guidelines through small modifications on RK rules. As per AASM rules, the non-rapid eye movement is further segmented into three sub-sleep stages such as N-REM1, N-REM2, and N-REM3 [9]. The sleep cycle generally repeat-ed at regular interval of time between NREM stages to REM stages and each cycle of interval continued around 90 to 120 minutes [10].

Sleep staging is normally examined using polysomnographic (PSG) recordings from the admitted subject in the clinic. Basically during the PSG test, three different physiological recordings are collected from the subjects to measure the sleep quality during the night time such signals are electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), and electrocardiogram (ECG) [11]. Amongst these, major researchers the priority towards the analysis of sleep pattern abnormality through EEG signal because the EEG signal provides the information on brain activities and behavior of subjects during sleep. So most of the sleep studies are based on EEG signals. Currently, overnight sleep study through polysomnography is one of the standard procedures for

measuring sleep irregularities during sleep [12].

Recently, several works related to sleep stage scoring have been carried out by different researchers. The maximum work has been proposed in the literature and that work was implemented through the EEG signals, extracted the features from the representative input signals, next to that some of the authors have obtained different feature selection algorithms to select the most impact features for the classification model. Finally, different classification techniques were obtained to discriminate the EEG signals. In the literature, many of the research work already contributed with subject to automatic sleep stage classification based on a single channel of EEG signals. Oboyya et al. [13] proposed sleep stage scoring based on a single channel of EEG and selected subjects for this experiment work limited between 35 and 50. Features are extracted through wavelet transform techniques and selected features are fed into the fuzzy c-means algorithm for classification and the average accuracy resulted as 85%. Aboalayon [14] also developed EEG based sleep disorder analysis and obtained Butterworth bandpass filters that were used to reduce the irrelevant muscle movements and noise artifacts and extracted features fed into SVM classifiers to distinguish between different sleep stages. The research work reported 90% classification accuracy. Hassan, A. R [15] proposed a scheme using bootstrap aggregating for classification with help of two bench-mark sleep data resources called Sleep-EDF and DREAMS and their accuracy was 92.43%. In [16] the author proposed a sleep classification system with the concept of structural graph similarity. The experimental work is completely based on the input of EEG signals. Extracted time-domain features forwarded to the SVM classifier. The average classification accuracy was reported as 95.93%. Memar, P. et al. have designed a system for analysis of sleep irregularities in which the author has selected 25 sleep suspected subjects and 20 healthy subjects for experimental purposes. Here a total of 13 features are extracted from each eight (alpha, theta, sigma, beta1, beta2, gamma1, and gamma2) sub-band epochs. The extracted features are validated through the Kruskal-

Wallis test and selected features are classified through a random forest classifier. The overall classification accuracy achieved through fivefold and subject-wise cross-validation is 95.31% and 86.64% respectively [17]. Zhimin Zhang et al. proposed a novel, simple and efficient sleep disorder diagnosis system from EEG signal with 30s epochs length of input and obtained entropy features and the extracted features fed into SVM classification model and achieved an overall accuracy of 94.15% [18]. Zhu, G et al. proposed sleep stage classification methods based on time and frequency domain properties from a single channel of EEG signal and extracted features are represented into graph representation and selected features are forwarded into SVM classifiers for classifying multiple stages of sleep stages and their final accuracy was 87.50% for two-state sleep stage classification problems [19]. Eduardo T. Braun et al. proposed a portable and effective sleep staging classification system, in which he has experimented on the combination of features extracted from EEG signals and classifiers. He designed the system in such a manner that, the proposed research achieved the best classification accuracy by considering fewer frequency domain features, and the overall accuracy reported as 97.1 % for the two-state sleep stage classification problem [20].

The literature study presented in the above paragraph shows that the most of the contributions was based on the methodology with subject to five-class classification problem. But it has found that the other sleep-states classification problems like two-state, three-state and four-state have not been performed. Additinally it has also observed that the most of the sleep study was completely based on the one specific datasets subjects. Also it has been found that some of the existing contributions still there is some chances also there for improvements with regarding the classification accuracy with the cross-validation approaches.

The main objective of this proposed work is to propose an artificial intelligence based system to classify the sleep stages in different medical conditioned subjects

using machine learning model using the single-channel of EEG signals. The other objective for this work is to analysis the sleep behaviour of the subject through time and frequency domain features from the filtered signals, which directly helps for discriminating the sleep characteristics. The main steps involved for this proposed research work is explained in Figure 2.

Section 2 describes detailed on the experimental data preparation. In section 3, we describe the proposed methodology. In Section 4, we briefly discuss about the experiments and results of the proposed methodology and make result analysis with the state-of-the-art methods. In Section 5 ends with concluding remarks with future work description.

2. Experimental Data

In this study, we have used three different categories of subjects with different medical conditions. All related recorded data was collected from a comprehensive sleep repository, named as ISRUC-Sleep [28]. Specifically, this dataset has been designed for sleep disorders related to the study. This dataset contained the recorded subject details from different age groups, gender categories, and medical conditions. All recordings were recorded through the sleep experts in the sleep laboratory at the Hospital of Coimbra University (CHUC).

As per our proposed research objective, the first subject used for experimental work from Subgroup-I of ISRUC-sleep repository. In this section total, 100 subjects' record-ing details were collected. Out of those 100 subjects, the data from male subjects (55) and female subjects (45) between the ages of 20-85(mean age $\pm$ standard deviation, 51 ± 16 years).

The second category of a subject taken for our proposed experimental work from Subgroup-II of ISRUC-sleep database. These sections contained recordings of 8 sub-jects with suspicious sleep apnea symptoms. Among 8 subjects, 6 of them as male category and 2 of them as a female category. Here per subject, two-session recordings were collected with different dates. The considered subjects for this section between the ages of 26-79(mean age $\pm$ standard

deviation, 46.87 ± 18.7 years).

The third set of recordings obtained for the proposed research work from Subgroup-III of ISRUC-Sleep data resource. This section contained 10 subjects, among those 9 from the male sex and 1 from the female sex. All subjects are in healthy condition. Only one session recordings extracted from individual subjects. The ages of these subjects for this section in between 30-58(mean age $\pm$ standard deviation, 40 ± 10 years).

This dataset has been used by so many researchers for sleep stage classification problems. For the acquisition of signals, subjects attended an 8-9h full night PSG test

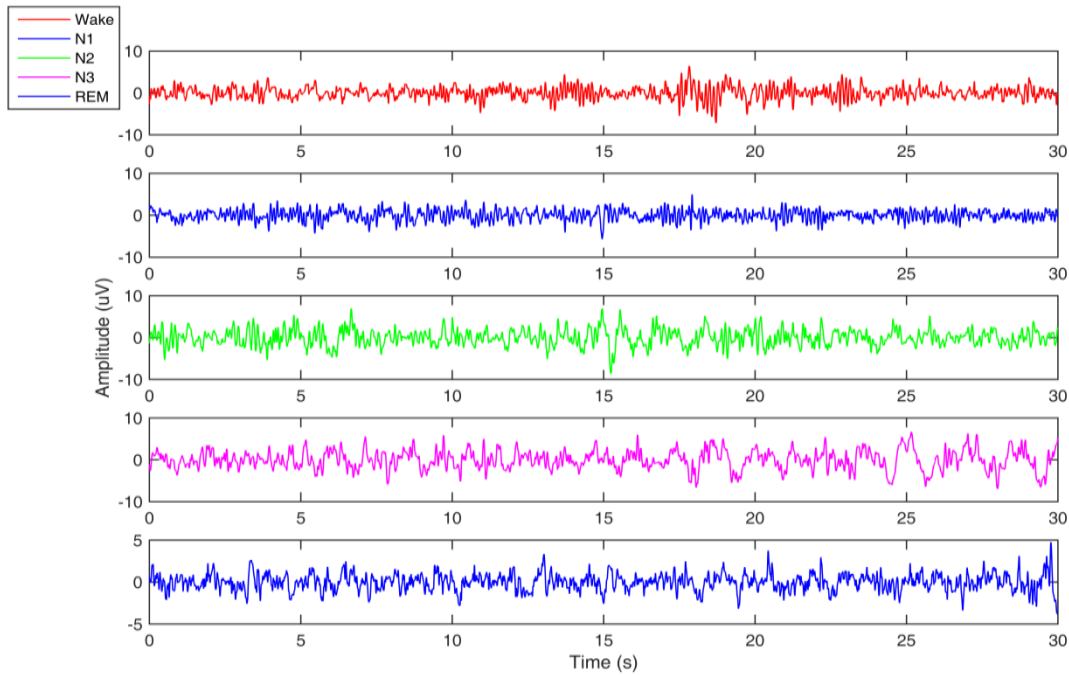
at a sleep laboratory. These three sections' signals were sampled at 200MHz and each epoch length was considered a timeframe of 30s according to AASM standard. As per AASM, the pattern of sleep stages is labeled as awake (W), NREM (N1, N2, and N3), and REM(R). All three subgroups contained bio-signals recordings of EEG, EOG, and EMG signals through 11 electrodes. In this study, we used the C3-A2 channel for computing sleep stage classification. The ISRUC-sleep dataset description briefly mentioned in Table 1 and Table 2 shows the detailed information of sleep records of enrolled subjects in this experimental study.

Table 1. ISRUC-Sleep Subgroup-I/II/III Dataset Structure

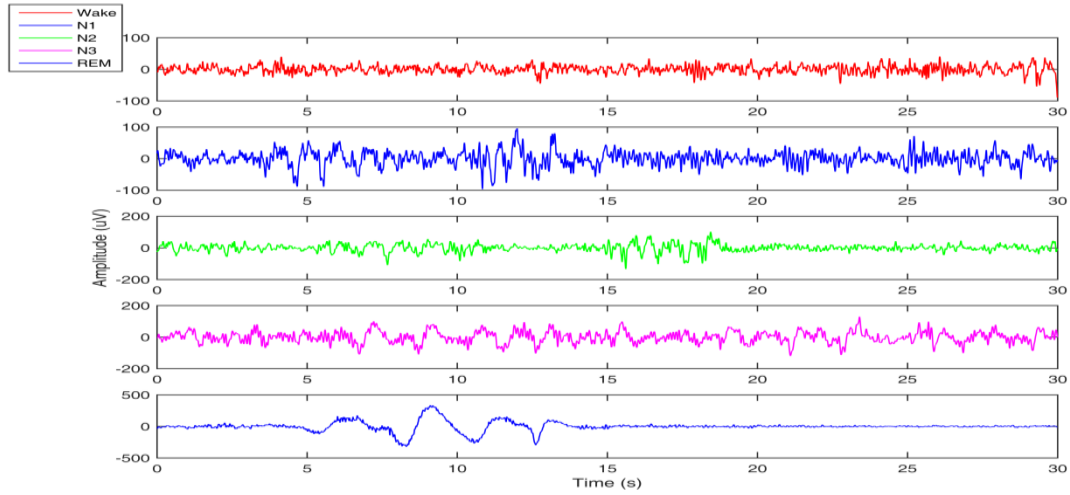
Acquired Bio-signals	Channels
Electroencephalogram	EEG _{C3-A2} , EEG _{C4-A1} , EEG _{F3-A2} , EEG _{F4-A1} , EEG _{O1-A2} , EEG _{O2-A1}
Electrooculogram	EOG _{LOC-A2} , EOG _{ROC-A1}
Electromyogram	EMG _{Chin-EMG} , EMG _{Leftleg-EMG} , EMG _{RightLeg-EMG}

Table 2. Detailed information of each subjects sleep dataset records used in this study

Database Used-ISRUC-Sleep						
Subject Number/Subgroup(I/II/III)	W	N1	N2	N3	R	TotalEpochs
Subject-16 /Subgroup-I/ One Session	128	125	280	120	97	750
Subject-2 /Subgroup-III/ One Session	89	120	274	149	118	750



(a)



(b)

Figure 1. An example of 30s epochs sleep behaviors from different sleep stages (a) subject-16, (b) subject-02

3. Methodology

In this work, we have obtained subjects with different medical conditions. Here we also considered different session recordings of subjects during computation of sleep stage scoring. Figure 1 describes the current

research study on identifying sleep disorders. All the steps mentioned in the block diagram are used during the treatment of sleep-related disorders and each step description mentioned below:

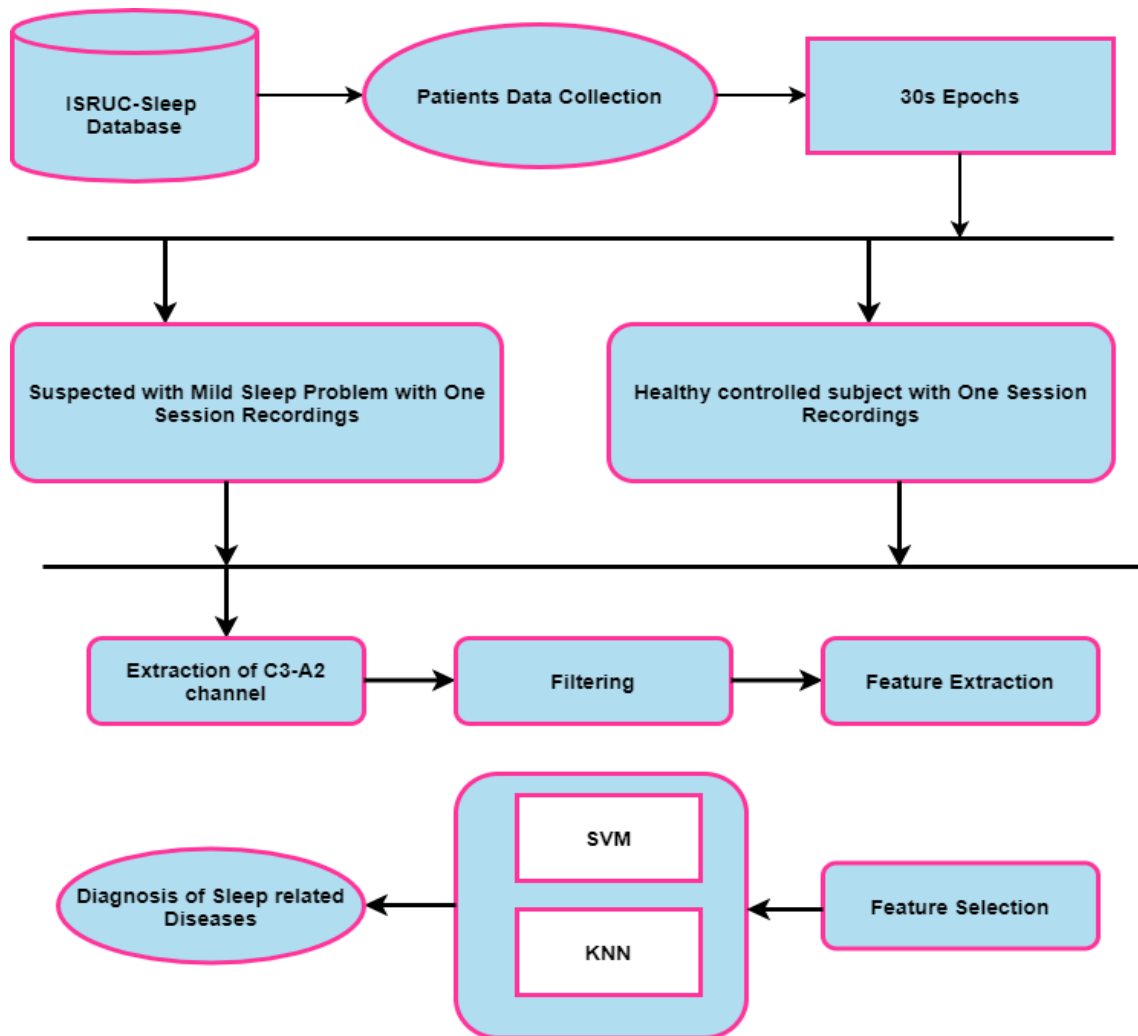


Figure 2. Block diagram of the proposed research work

3.1 Feature Extraction

Feature extraction is one of the most important parts of the classification because it directly links with the performance of a classification; if the features are not chosen well then the performance of classification will be degraded. In this study, the EEG signals are segmented

into smaller segments called epochs. The interval of each segment is 30 seconds (6000 sample data points) in this sleep analysis study according to AASM manuals. In this sleep study, we extracted 28 features including both time and frequency domain features. Out of the total extracted features, 13 features are from the time domain and 15 features are from frequency domain-oriented.

Table 3. Short explanation of the extracted features for this proposed study

Extracted Time Domain Features			
Extracted Feature Set	Feature No	Extracted Feature Set	Feature No
Mean Value	FE1	Maximum value	FE2
Minimum Value	FE3	Standard Deviation Value	FE4
Median	FE5	Variance	FE6
Zero Crossing Rate	FE7	75percentile	FE8
Signal Skewness	FE9	Signal Kurtosis	FE10
Signal Activity	FE11	Signal Mobility	FE12
Signal Complexity	FE13		
Extracted Frequency Domain Features			
Extracted Feature Set	Feature No	Extracted Feature Set	Feature No
Relative Spectral Power in $\delta, \beta, \alpha, \theta$ bands	FE14, FE15, FE16, FE17	Power Ratios $\delta/\beta, \delta/\theta, (\theta+\alpha)/(\alpha+\beta), \theta/\alpha, \theta/\beta, \alpha/\beta, \alpha/\delta$	FE18, FE19, FE20, FE21, FE22, FE23, FE24
Band power in $\delta, \theta, \alpha, \beta$ bands-F25, F26, F27, F28			

3.2 Feature Selection

To get the most appropriate features and reach the best optimize classification result, it is important to remove the irrelevant features in the extracted feature set. In our proposed sleep study, we have obtained the machine learning techniques for classification purposes and it requires proper input features to predict the

correct outputs most efficiently. With consideration of more number of input, features may be hampering to reach best classification accuracy and degraded the classification performances in many cases. In this study, we have considered the Online Streaming Feature Selection (OSFS) techniques for selecting suitable features for the classification tasks [22].

Table 4. Final Feature Selection List

Participants Name/ Gender	Best Feature combination(30s Epochs)
Subject-16 MALE	FE1 ₁₆ , FE2 ₁₆ , FE3 ₁₆ , FE4 ₁₆ , FE5 ₁₆ , FE7 ₁₆ , FE9 ₁₆ , FE10 ₁₆ , FE11 ₁₆ , FE13 ₁₆ , FE14 ₁₆ , FE15 ₁₆ , FE22 ₁₆ , FE25 ₁₆ , FE27 ₁₆ , FE31 ₁₆ (16 Features)
Subject-02 MALE	FE1 ₀₂ , FE2 ₀₂ , FE3 ₀₂ , FE4 ₀₂ , FE5 ₀₂ , FE7 ₀₂ , FE8 ₀₂ , FE9 ₀₂ , FE11 ₀₂ , FE12 ₀₂ , FE13 ₀₂ , FE14 ₀₂ , FE21 ₀₂ , FE22 ₀₂ , FE25 ₀₂ (15 Features)

3.3 Classification

Support Vector Machine (SVM): It is a more popular classification approach among machine learning techniques and its concept is based on statistical learning

theory [30]. It supports both classification and regression methods which easily handle the classification with a huge amount of records. This classification technique dealt with both the linear and non-linear classification problems. SVM is strongly mathematically approached and it is

closely associated with some well-established theories in statistics concepts, for that reason SVM is capable to manage non-linear separation problems by introducing the hyper-plane idea and kernel function. In our experimental part, the radial basis function (RBF) was used as a kernel function [23].

Decision Tree Classifier (DT): It is one of the structured and comprehends classification techniques incomparable to another classification algorithm. Majorly DT used by different type's classification tasks [24] and the major cause behind this is its simplicity and ease of understanding the rules regarding tree structures. A decision tree is constructed from a considered training dataset and each sample of the dataset is contained feature values and its class labels. Generally, DT is working like inductive inference. The major advantage of DT is, it can deal with noisy data and missing data in the dataset. It is also used for multiple stages and consecutive approach during the classification procedure. During the first step of classification, the tree is generated, after that one by one data is applied to the classification process. Each node in the decision tree is represented as testing features belong to the training set and the generated branch from this node is the proper value of the feature. There are so many algorithms are designed in connection to DT, but some algorithms are more accepted with subject to different types of classification applications. Some of the most used algorithms in the literature are C4.5, ID3, and C5.

3.4 Model Performance Evaluation

To validate the proposed model performance with subject to sleep stage classification system, we obtained five evaluation metrics these are classification accuracy [23], sensitivity [24], specificity [25], precision [26], and F1 Score [26]. The mathematical expression of these statistical indices is defined in Eqs. (1)- (5)

$$Sensitivity = \frac{TP}{TP + FN} \times 100\% \quad (1)$$

$$Specificity = \frac{TN}{TN + FP} \times 100\% \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \times 100\% \quad (3)$$

$$Accuracy = \frac{Sensitivity + Specificity}{2} \times 100\% \quad (4)$$

$$F1Score = \frac{2 \times TP}{(2TP + FP + FN)} \quad (5)$$

Where TP, TN, FP, and FN are true positive, true negative, false positive, and false negative, respectively. Apart from above all evaluation metrics, additionally, we also include the k-cross-validation techniques in our experiment. It is one of the popular measurements in the problem type of pattern recognition. It is used most of the time in the classification method by dividing the correctly identified classification results by the total number of cases. In this procedure the whole dataset is divided into k subsets, out of that one subset is considered for the testing portion, while others are considered as training subsets. In this work, we have used the 10-fold cross-validation techniques upon the considered dataset.

4 Experimental Results and Discussion

To diagnose sleep-related irregularities, first of all, analysis of the different sleep-related disorders must detect and classified. To resolve these issues classification on different sleep stages analysis is needed. In this paper, we have approached the two-state sleep stage classifications to monitor the abnormality in sleep patterns. The working model for this proposed scheme is illustrated in Figure 1. To evaluate the performance of the proposed research work, the different categories of medical conditions of subjects with their different session recordings are described in Section 3. As described before; in this experiment only one channel was used as data acquisition from the brain. Next to that we have filtered out the muscle artifacts and removing noisy portions from recorded signals through the Butterworth bandpass filter. The length of each epoch is a 30s time framework. Thus, EEG epochs of 6000 data points were used for each hypnogram representation. The set of experiments is conducted to extract the features from the respective acquired channel in both the time and frequency domain. Hence there exist a total of 28 features from both domains. The extracted feature names are mentioned in Table 4. We obtained the feature selection technique as OSFS to find out the suitable

properties for the classification task.

Here we have conducted the test separately for the subject with suspected sleep disorder with one-time session recordings and the healthy subject with one session recordings. In this proposed study, we have evaluated the classification accuracy from both subjects and conduct a comparative analysis based on achieved results from evaluation metrics. In this proposed study we have considered some evaluation parameters such as recall specificity, precision, and F1-Score for measuring the performance of the proposed sleep analysis study.

From the experimental results, we notice that the SVM depicts an overall classification accuracy of 95.6% and 91.20% achieved through DT classifiers for subject-16. For subject-02 the same classifiers SVM and DT reached overall accuracy of 87.46% and 87.06% respectively.

Table 5 shows the confusion matrix for both the enrolled subjects in this proposed sleep EEG study. To measure the impact of classification techniques with subject to sleep stage scoring, we compute Cohen's kappa coefficient for our proposed two-state sleep stage classification case. It is one of the robust approaches for evaluation of how best the classification algorithm performed with the proposed system as compared to how well it performed by agreement. The computation of kappa coefficient is of six levels of agreements: 1) excellent agreement ranging from 0.80 to 1, 0.60 to 0.80 considered as substantial agreement, 0.40 to 0.60 represents as moderate agreement, 0.20 to 0.4 basically interpreted as fair agreement, 0 to 0.20 mentioned as slight agreement, less than zero considered as poor interpretation [27].

Table 5. Confusion matrix obtained for Subject-16 and Subject-02(30s Epochs Length)

Subject-16(ISRUC-Sleep) Subgroup I/Session1_Recording				Subject-02(ISRUC-Sleep) Subgroup I/Session1_Recording			
C3-A2		Wake	Sleep	C3-A2		Wake	Sleep
SVM	Wake	133	30	SVM	Wake	20	69
	Sleep	3	584		Sleep	25	636
C3-A2		Wake	Sleep	C3-A2		Wake	Sleep
DT	Wake	134	29	DT	Wake	3	86
	Sleep	37	550		Sleep	11	650

Table 6. Overall Performance of C3-A2 channel of SleepEEG study for Subject-16 and Subject-02

	Subject Enrolled Epochs Length-30s			
Channel	SVM Classifier		DT Classifier	
C3-A2	16	02	16	02
Accuracy	95.60%	87.46%	91.20%	87.06%
Precision	95.11%	90.21%	94.99%	88.32%
Recall	99.49%	96.22%	93.70%	98.34%
Specificity	81.60%	22.47%	82.21%	3.37%
F1-Score	97.25%	93.12%	94.34%	93.06%

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evaluation of how best the classification algorithm performed with the proposed system as compared to how well it performed by agreement. The computation of kappa coefficient is of six levels of agreements: 1) excellent

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fair agreement, 0 to 0.20 mentioned as slight agreement, less than zero considered as poor interpretation [27].

Table 9. Performance of Classification accuracies and Kappa statistic for subject with Mild sleep problem and healthy control subject of 30s epochs length

Subject with Mild Sleep Problem (One Session) Recording	Subject-16 (30s Epochs Length)		Subject-2 (30s Epochs Length)		
	Classifiers	Accuracy Rate	Kappa Coefficient	Accuracy Rate	Kappa Coefficient
	SVM	95.60%	0.92	87.46%	0.72
	DT	91.20%	0.43	87.06%	0.19

The results achieved in the current research work are compared in between different contributed state-of-art literature, in which the obtained input channel is EEG, two stages classification, statistical features, datasets are addressed. Table 10 presents the performance comparison results of the proposed research methods and five similar existing reported contributions [87-92], that work also, used EEG recordings from the same datasets using a single channel of EEG.

Khalighi et al. [28] used the maximum overlap discrete wavelet transform and obtained both linear and non-linear properties and obtained mRMR feature selection algorithm for screening the suitable features. The system reported an overall accuracy of 95% for the classification of the wake-sleep stages using SVM classification techniques.

Hugo Simoes et al. [29] used the R-square Pearson correlation coefficient and selected relevant features were applied into the Bayesian classifier and achieved overall classification accuracy as 83%.

Khalighi, S. et al. [30] used three categories of subjects records from ISRUC-Sleep repository and extracted both temporal and spectral features extracted from the obtained input channel and applied SSM4S classification method, achieved overall classification accuracy with consideration of ISRUC-Sleep Subgroup-I, Subgroup-II, and Subgroup-III as 94.10%, 92.40%, and 95.39%, respectively.

Sousa et al. [31] proposed a two-step classifier based on EEG signal, obtained SVM classifier for distinguishing epochs suspected misclassification and obtained both times, and frequency domain features and classified features were forwarded into SVM classifier and reported classification accuracy as 86.75%.

Khalighi et al. [32] designed subject-independent improved automated sleep stage classification with application wake-sleep classification and classified through the SVM classifier and achieved 81.74% overall classification accuracy.

K D Tzimourta et al. [33] proposed a methodology for human sleep stage classification by considering brain EEG signals and extracted energy features, forwarded into random forest classifier, results with subject to classification accuracy reached 75.29%.

Najdi et al. [34] proposed a sleep study based on the two-layer stacked sparse auto-encoder and obtained frequency, time-frequency, time-domain features were extracted from EEG signals. The resulted classification accuracy reported as 82.2%.

Finally, Hashem Kalbkhani [35] introduced stockwell transform for signal decomposition and the decomposed features processed through SVM and KNN classifier. The average accuracy reported for SVM as 82.33% and for KNN as 81.00%.

Table 10. Performance Comparisons of proposed study with existing similar contributed works

Study	Year	Dataset/Input Signal	Classifier Used	Accuracy
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Ref [28]	2011	ISRUC-SLEEPDataset/ EEGSignal	SVM	95%
Ref [29]	2010		Bayesian Classifier	83%
Ref [30]	2016		SVM	93.37%
Ref [31]	2015		SVM	86.75%
Ref [32]	2013		SVM	81.74%
Ref [33]	2018		Random Forest	75.29%
Ref [34]	2017		Stacked Sparse Auto-Encoders (SSAE)	82.2%
Ref[35]	2018		SVM	83.33%
Ref[18]	2018		SVM	94.15%
Proposed Study	Present		SleepEEG study +SVM and DT classifier	95.60% (SVM)
		91.73% (DT)		

5. Conclusion

This research article presents an efficient, automated two-state sleep stage classification from EEG signal through machine learning techniques. Both time and frequency domain features are extracted, which becomes more effective for distinguishing the sleep stages. The positive aspect of this application is to analyze the irregularities that occurred during sleep hours from single channel of EEG with 28 features for scoring two-state (Wake versus Sleep) sleep stage classification according to the AASM standards and additionally this application also successfully deals with the different medical conditions of the subjects. The OSFS algorithm was used for selecting the suitable features based on strong relevance. Classification based on SVM and DT.

In the present research work, there were certain benefits as follows. First thing is only single channel is only used for sleep analysis; second advantage is with related to More than 1500 epochs of 30s from public sleep dataset are analyzed highlighting the effectiveness of proposed system. The introduced method achieves best performance for distinguishing the sleep stages between wake versus sleep with related to other existing similar contributions. Our future research implementation will focus the effects of class imbalance problem and also including the multiple

PSG signal such as EOG, EMG and ECG. **Conclusion and future work**

also consider more number of clinical sleep data, especially include the different sleep problem patients to measure the performance of the proposed research work for a higher accuracy.

References

- [1] Aboalayon KAI, Faezipour M, Almuhammadi WS, et al. "Sleep stage classification using EEG signal analysis: A Comprehensive Survey and New Investigation". Entropy 18: 272, 2016.
- [2] Chung MH, Kuo TB, Hsu N, Chu H, Chou KR, Yang CC. Sleep and autonomic nervous system changes - enhanced cardiac sympathetic modulations during sleep in permanent night shift nurses. ScandJ Work Environ Health, 5(3):180-7, 2009.
- [3] M. B. B. Heyat, F. Akhtar, and S. Azad, "Comparative analysis of original wave & filtered wave of EEG signal used in the detection of bruxism medical sleep syndrome," Int. J. Trend Sci. Res. Develop., vol. 1, no. 1, pp. 7–9, 2016.
- [4] M. B. B. Heyat, S. F. Akhtar, and S. Azad, "Power spectral density are used in the investigation of insomnia neurological disorder," in Proc. Pre Congr. Symp., Organized Indian Acad. Social Sci. (ISSA)

- King George Med. Univ. State Takmeelut-Tib College Hospital, Lucknow, Uttar Pradesh, pp. 45–50, 2016.
- [5] Rahman, Farook, Heyat, Siddiqui, "An Overview of Narcolepsy", IARJSET, vol. 3, pp. 85-87, 2016.
- [6] Kim, T., Kim, J. & Lee, K. Detection of sleep disordered breathing severity using acoustic biomarker and machine learning techniques. *BioMed Eng OnLine* 17, 16, 2018
- [7] M. Siddiqui, G. Srivastava and S. Saeed, "Diagnosis of insomnia sleep disorder using short time frequency analysis of PSD approach applied on EEG signal using channel ROC-LOC", *Sleep Science*, vol. 9, no. 3, pp. 186-191, 2016.
- [8] A. Rechtschaffen, "A manual for standardized terminology techniques and scoring system for sleep stages in human subjects", *Brain Inf. Serv*, 1968.
- [9] C. Iber, "The AASM manual for the scoring of sleep and associated events: rules, terminology and technical specifications: American Academy of Sleep Medicine", 2007.
- [10] M. A. Carskadon and W. C. Dement, "Normal human sleep: An overview," in *Principles and Practice of Sleep Medicine*, M. Kryger, T. Roth, and W. C. Dement, Eds., 6th ed. Amsterdam, The Netherlands: Elsevier, pp. 15–24, 2017.
- [11] J. V. Holland, W. C. Dement, and D. M. Raynal, "Polysomnography: A response to a need for improved communication," presented at the 14th Annu. Meeting Assoc. Psychophysiology. Study Sleep, 1974.
- [12] U. R. Acharya et al., "Nonlinear dynamics measures for automated EEG-based sleep stage detection," *Eur. Neurol.*, vol. 74, nos. 5–6, pp. 268–287, 2015.
- [13] M. Obayya and F. Abou-Chadi, "Automatic classification of sleep stages using EEG records based on Fuzzy c-means (FCM) algorithm," in *Radio Science Conference (NRSC)*, 31st National, 2014, pp. 265-272, 2014.
- [14] K. Aboalayon, H. T. Ocbagabir, and M. Faezipour, "Efficient sleep stage classification based on EEG signals," in *Systems, Applications and Technology Conference (LISAT)*, 2014 IEEE Long Island, pp. 1-6, 2014.
- [15] A. R Hassan, A. Subasi, "A decision support system for automated identification of sleep stages from single-channel EEG signals". *Knowledge-Based Systems*, 128, 115–124, 2017.
- [16] M. Diyk, Y. Li, P. Wen, "EEG Sleep Stages Classification Based on Time Domain Features and Structural Graph Similarity". *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 24(11), 1159–1168.
- [17] P. Memar, F. Faradji, "A Novel Multi-Class EEG-Based Sleep Stage Classification System". *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 26(1), 84–95, 2018.
- [18] F. Pernkopf, P. O'Leary "Feature Selection for Classification Using Genetic Algorithms with a Novel Encoding". In: Skarbek W. (eds) *Computer Analysis of Images and Patterns*. CAIP 2001. *Lecture Notes in Computer Science*, vol 2124. Springer, Berlin, Heidelberg
- [19] G. Zhu, Y. Li, P. P. Wen "Analysis and Classification of Sleep Stages Based on Difference Visibility Graphs From a Single-Channel EEG Signal" *IEEE Journal of Bio-medical and Health Informatics*, 18(6), 1813–1821, 2014.
- [20] E. T. Braun, A. D. J. Kozakevicius, T. L. T. Da Silveira, C. R., Rodrigues, G. Baratto "Sleep Stages Classification Using Spectral Based Statistical Moments as Features". *Revista de Informática Teórica e Aplicada*, 25(1), 11, 2018.
- [21] S. Khalighi, T. Sousa, J. M. Santos, U. Nunes, ISRUC-Sleep: A comprehensive public dataset for sleep researchers. *Computer Methods and Programs in Biomedicine*, 124, 180–192, 2016.
- [22] Masaaki, Hanaoka., Masaki, Kobay, ashi., Haruaki, Yamazaki.: Automated Sleep Stage Scoring by Decision Tree Learning. *Proceedings of the 23rd Annual EMBS International Conference*, October 25-28, Istanbul, Turkey, 2001.
- [23] T. H. Sanders, M. McCurry, and M. A. Clements, "Sleep stage classification with cross frequency coupling," in *Proc. 36th Annu. Int. Conf. IEEE Eng. Med. Biol. (EMBC)*, pp. 4579–4582, 2014.
- [24] V. Bajaj, R. B. Pachori, "Automatic classification of

- sleep stages based on the time-frequency image of EEG signals,” *Comput. Methods Programs Biomed.*, vol. 112, no. 3, pp. 320–328, 2013.
- [25] Y.-L. Hsu, Y.-T. Yang, S. Wang and C.-Y. Hsu, “Automatic sleep stage recurrent neural classifier using energy features of EEG signals,” *Neurocomputing*, vol. 104, pp. 105–114, Mar. 2013.
- [26] D. M. Powers, “Evaluation: from precision, recall and f-measure to roc, informedness, markedness and correlation,” 2011
- [27] S.-F. Liang, C.-E. Kuo, Y.-H. Hu, and Y.-S. Cheng, “A rule-based automatic sleep staging method,” *Journal of neuroscience methods*, vol. 205, no. 1, pp. 169–176, 2012.
- [28] S. Khalighi, T. Sousa, D. Oliveira, G. Pires, U. Nunes, “Efficient feature selection for sleep staging based on maximal overlap discrete wavelet transform and SVM”. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society* 2011.
- [29] H. Simões, G. Pires, U. Nunes, V. Silva “Feature Extraction and Selection for Automatic Sleep Staging using EEG”. In *Proceedings of the 7th International Conference on Informatics in Control, Automation and Robotics*, 3, 128-133.
- [30] S. Khalighi, T. Sousa, J. M. Santos, U. Nunes “ISRUC-Sleep: A comprehensive public dataset for sleep researchers”. *Computer Methods and Programs in Biomedicine* 2016, 124, 180–192.
- [31] T. Sousa, A. Cruz, S. Khalighi, G. Pires, U. Nunes, “A two-step automatic sleep stage classification method with dubious range detection”. *Computers in Biology and Medicine* 2015, 59, 42–53.
- [32] S. Khalighi, T. Sousa, G. Pires, U. Nunes, “Automatic sleep staging: A computer assisted approach for optimal combination of features and polysomnographic channels”. *Expert Systems with Applications* 2013, 40(17), 7046–7059.
- [33] K. D. Tzimourta, A. K. Tsilimbaris, A. T.; Tzioukalia, M. G. Tzallas, L. G. Tsipouras, “EEG-Based Automatic Sleep Stage Classification”. *Biomed J Sci & Tech Res* 2018, 7(4).
- [34] S. Najdi, A. A., Gharbali, J. M. Fonseca, “Feature Transformation Based on Stacked Sparse Auto encoders for Sleep Stage Classification”, *Technological Innovation for Smart Systems* 2017, 191–200.
- [35] H. Kalbkhani, P.G. Ghasemzadeh, M. Shayesteh, “Sleep Stages Classification from EEG Signal based on Stockwell Transform”. *IET Signal Processing* 2018.