Automated Classification of Sleep Stages Using Single-Channel EEG Signal: A Machine Learning-Based Method

Santosh Satapathy[1(✉)], Shrinibas Pattnaik[2], Badal Acharya[2], and Rama Krushna Rath[3]

[1] Department of Information and Communication Technology, Pandit Deendayal Energy University (PDEU), Gandhinagar, India
Santosh.Satapathy@sot.pdpu.ac.in
[2] Department of Electrical and Electronics Engineering, Gandhi Institute of Science and Technology, Rayagada, Odisha, India
[3] Department of Computer Science and Engineering, IIIT, Chittoor, Andhra Pradesh, India

Abstract. One of the major contributors to improper sleep patterns is the rapidly occurring changes in today's lifestyle. We aimed to develop an automated algorithm based on to classify the sleep stages during sleep hours. Maintaining such unhealthy sleep patterns for a longer period may lead to different neurological disorders. Delay in diagnosis further worsens the condition and leads to other serious health issues. The first step in analyzing any sleep-based abnormalities is the proper classification of the sleep stages. The proposed study obtains, a single-modal channel of electroencephalogram (EEG) signals as input to the model. The main objective is to screen the pertinent features which can assist in identifying the irregularities that occurred during sleep hours. The entire experiment was carried out on two different subgroups of the ISRUC-Sleep dataset and finally, we considered the support vector machine (SVM) for the classification of sleep stages. The proposed model yielded the best classification accuracy of 97.73%, and 96.51% with subgroup-I, and subgroup-III subjects, respectively. The proposed model is effective for automated multi-class sleep state classification method is developed for different medical-conditioned subjects. Compared to gold standard polysomnography, our algorithm doesn't require any additional electrodes and which are especially valuable in improving the sleep staging classification performance.

Keywords: EEG · Sleep staging · Feature selection · Machine learning

1 Introduction

The human body contains different components, which function with several physiological processes. It has been seen that most of these physiological processes represent

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themselves in the form of signals and these signals are of different types, viz. biochemical, biomedical, biomechanical, etc. Generally, biomedical signals hold a lot of information about the changes in the physiological activities of our bodies [1–3]. Disease and ailments may create a disturbance in the biological system of humans which causes disturbance in the smooth functioning of our daily activities. It has been observed that these diseases and ailments in the human biological system are counter-productive leading to several pathological conditions which affect the health and well-being of the system [4–6]. Analyzing these biomedical signals was quite difficult a few years ago since the obtained signals were contaminated with different types of irrelevant noise and powerline interferences. Sometimes it is also required to obtain their spectral properties to understand the characteristics of the signals' behavior in terms of the different frequency ranges, and modeling of the different feature representation and parameterization. The other major challenge concerning biomedical signal processing is the experience and expertise of the clinicians in analyzing and interpreting the signals in a proper way [7].

However, this entire process is subjective. In recent research developments, digital signal processing and pattern recognition have been the backbone of biomedical research applications [8, 9]. Another crucial aid to biomedical research is a computer-aided diagnostic system which assists the domain experts to make important decisions during the diagnostic process plus it also offers the possibility of online monitoring for critically ill patients. Thus, there is a huge demand for more reliable, effective, and affordable clinical and health services. Hence there are so many novel medical equipment, techniques being developed to support such diagnosis, monitoring, and treatment of irregularities, abnormalities, and ailments in the human body. In the present world, one of such major health issues has been sleeping deprivation and associated illnesses which adversely affect the quality of life across the global population irrespective of age group. Hence applications based on sleep studies and patterns become crucial to diagnosing and proposing solutions to such ailments. EEG signals are most appropriate to identify irregularities in the regular sleep pattern more effectively. Additionally, it also has some more advantages that are it is high speed, time-efficient, and also non-invasive. Therefore, the diagnosis with EEG signals is inexpensive and widely accepted in the diagnosis of different sleep-related diseases [10]. It has been seen from the recent research developments in the signal processing techniques, an improved approach for classification on the basis of PSG signals has been reported. These enhanced techniques can help to recognize the abnormal sleep patterns and irregularities in sleep leading to sleep-related diseases. An automatic sleep staging system is obtained in the diagnosis of several sleep disorders, which is considered one of the best tools apart from the visual inspection of the EEG signals by physicians [11].

1.1 Related Work

Some of the latest works on automated sleep stage classification making use of single-channel and multiple channels are presented in Table 1.

Table 1. A brief analysis of state-of-the-art works for the sleep staging

Study and year	Classifier	Signal	Number of channels	Results (%)
Oboyya et al. [12]	Fuzzy c-means algorithm	EEG	One channel	85%
Güneş, K. Polat et al. [13]	K-means clustering	EEG	One channel	83%
Aboalayon et al. [14]	SVM	EEG	One channel	90%
Hassan, A. R. et al. [15]	Bootstrap aggregating	EEG	One channel	92.43%
Diykh, M. et al. [16]	SVM	EEG	One channel	95.93%
Kristin M. Gunnarsdottir et al. [17]	Decision tree	EEG, EOG, and EMG	One channel	80.70%
Sriraam, N. et al. [18]	Feedforward neural network	EEG	One channel	92.29%
Memar, P. et al. [19]	Random forest	EEG	One channel	86.64%
Da Silveira et al. [20]		EEG	One channel	90%
Xiaojin Li et al. [21]		EEG	One channel	94.4%
Zhu, G et al. [22]	SVM	EEG	Two channels	87.50%
Satapathy, S. K. et al. [23]	Ensemble learning model	EEG	Two channels	91.10% 90.11%
Satapathy, S. K. et al. [24]	Stacking ensemble learning model	EEG	One channel	90.8%

From the state-of-the-art works, it can be seen that most of the studies have focused on single-channel and multiple-channel. Some of the studies were well performed with the input of single-channel, additionally, it gives well comfortable for the subject during sleep recordings. This advantage gives an improvement in sleep staging accuracy. But it has been also observed that major of the studies highly suffered from data imbalance problems, misclassification of the N1 sleep stage, and improper selection of features for the classifier.

Therefore our proposed work has different from other similar works in this context; we have obtained two different session recordings for the subject who was affected with a sleep disorder. This work aims to contribute to the comparative analysis of sleep staging methods by assessing the classification accuracy of statistical moments derived from single-channel EEG signals. With regards to classification techniques, we used SVM for testing them between participating subjects in the research work. We report all Cohen's kappa values for various sleep stages for the comparison of the classification algorithm. The proposed algorithm can be observed to present high values of accuracy and Cohen's kappa of the data of healthy subjects.

Further, our proposed research work is organized as follows: Sect. 2 presents the data used in the experimental work. In Sect. 3 we briefly present the proposed methodology. Section 4 briefly about the outcome of the experimental analysis. Section 5 remarks the concluding remarks.

2 Experimental Data

In this study, for experimental analysis, we have acquired two different categories of the patient's records, one from the subjects who were already suffered from mild sleep-related problems and the other category of the subjects, who were completely healthy controlled. The whole dataset is an accumulation of three types of sleep recordings belonging to different patients. The entire recordings were collected by a group of expert clinicians [25]. The whole recordings were obtained from different patients, who were already faced various kinds of sleep-related problems, and the other part of the recordings were obtained from healthy subjects.

In this work, for our experimental study, we used the C3-A2 channel for computing sleep stage classification. Table 2 presents a detailed account of the percentage of sleep epoch distribution in different sleep stages.

Table 2. Description of the percentage of epoch per individual sleep stages

Subject number	W%	N1%	N2%	N3%	REM%
Subject-1 Subgroup-I	22.00%	8.40%	23.07%	30.80%	15.73%
Subject-2 Subgroup-I	30.80%	9.60%	30.13%	19.60%	9.87%
Subject-3 Subgroup-I	15.87%	18.93%	25.87%	16.80%	22.53%
Subject-4 Subgroup-I	2.53%	5.87%	43.60%	28.53%	19.47%
Subject-5 Subgroup-I	32.67%	13.87%	26.53%	21.87%	5.07%
Subject-9 Subgroup-I	9.6%	19.06%	42%	18.13%	11.2%
Subject-16 Subgroup-I	17.07%	16.67%	37.33%	16.00%	12.93%
Subject-23 Subgroup-I	28.27%	13.20%	36.00%	8.67%	13.87%
Subject-1 Subgroup-III	19.87	12.13	35.60	21.07	11.33
Subject-5 Subgroup-III	67.00%	8.67%	38.27%	33.47%	10.67%
Subject-6 Subgroup-III	7.20%	14.80%	34.80%	32.93%	10.27%
Subject-7 Subgroup-III	27.47%	7.07%	20.53%	34.67%	10.27%
Subject-8 Subgroup-III	45.73%	9.73%	15.20%	15.47%	13.87%

(*continued*)

Table 2. (*continued*)

Subject number	W%	N1%	N2%	N3%	REM%
Subject-9 Subgroup-III	13.47%	19.33%	31.47%	30.00%	5.60%
Subject-10 Subgroup-III	16.80%	29.07%	23.07%	13.07%	18.00%

This study includes three categories of subjects. One is affected by sleep problems with one session recording sleep data. The second category of data was extracted from subjects with sleep disorders in two sessions of recording. Finally, the third category includes healthy subjects. The authors have obtained the EEG channel of C3-A2 signals of 6 subjects. The stage annotations are also provided in the data repository according to AASM rules. The unscored epochs are not considered for further analysis in the experimental work. Each epoch is considered a 30 s time length in this present work. For analysis, of the sleep behavior, we have presented the samples of all sleep stages of EEG signals extracted from different categories of subjects. The sleep EEG signals behavior changes according to the sleep cycle covered by the subject. Every stage of sleep is characterized by different behavior from sleeping brains such as low amplitude, mixed frequency, sawtooth waveforms, low amplitude in muscle movements, and rapid eye movements. However, the EEG signal behaviors are complex since they are not periodic and also because of the continuous changes of amplitude, frequency, and phase range according to the sleep stage. In the proposed method, the authors have applied the Butterworth bandpass filter to reduce the undesired segments from the input signal. The filter is a second-order Butterworth bandpass filter, and the frequency ranges applied range from 0.5 Hz to 35 Hz.

3 Methodology

This study demonstrates a unique method of two-stage sleep scoring using a single EEG channel. Figure 1 represents the workflow of the proposed sleep stage classification system.

3.1 Proposed Automatic Sleep Stage Detection Method

The sleeping study can be divided into four layers. These are the subject layer, classification layer, section layer, and instance layer. The subject layer is divided into two sections. One section contains information about EEG, and another section represents sleep information. These two sections are the main domains of this study and compose the classification layer. The section layer represents the associated concepts related to the EEG signals and sleep sections. While the EEG section defines the used electrode name, obtained features, and participants enrolled for this experimental work, the sleep section addresses the obtained sleep stage rules for sleep quality analysis. Finally, the instance layer considered the specific settings associated used the experiments conducted in the research and is defined according to the other layers. In this proposed study, two different medical condition subjects' details from the ISRUC-Sleep dataset from the University Hospital of Coimbra, Portugal are evaluated. We have made use of the OSFS systems for feature selection [26, 27]. The final feature selection output is presented in Table 3.

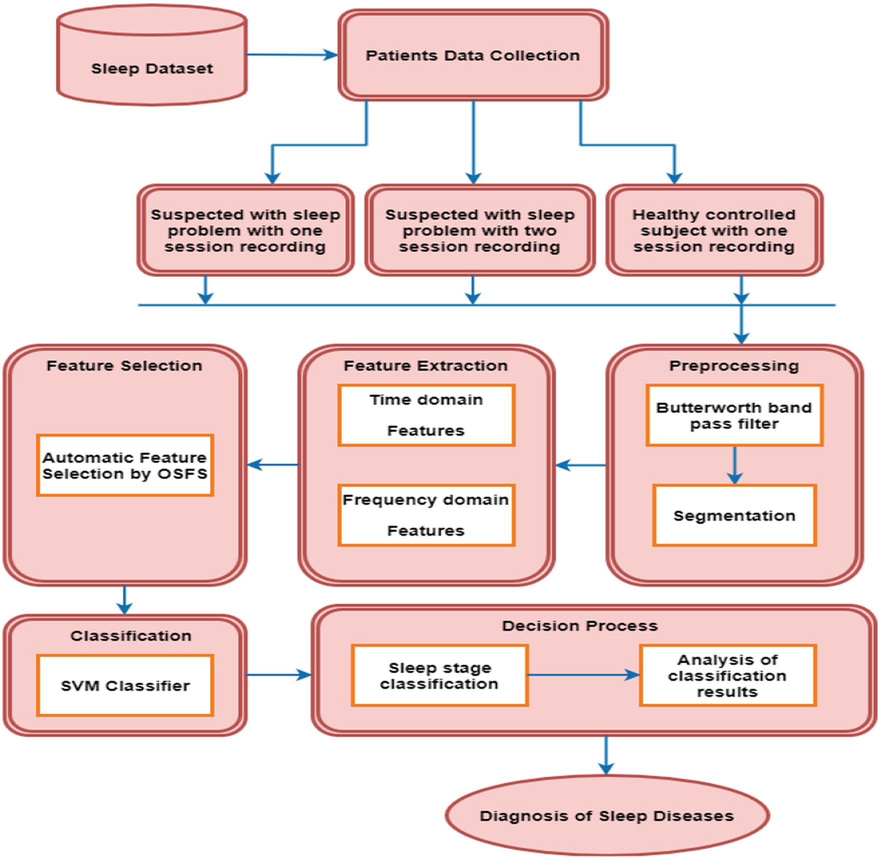

Fig. 1. Workflow of the proposed method

Algorithm 1
Automated SleepEEG Classification Test.
Procedure: *Sleepstage_Scoring = SleepStage_Classify (Feature List, Labels).*
Input: *Patient Records* [Extracted from Sleep_Dataset]

$$P_V = \{P_1, P_2, \cdots \cdots \cdots \cdots, P_N\}$$

$$P_{SI} = \{S_1, S_2, \cdots \cdots \cdots \cdots \cdots, S_M\}$$

$$P_{SE} = \{S_{I1}, S_{I2}, \cdots \cdots \cdots \cdots \cdots, S_{IZ}\}$$

%N = Number of Patients enrolled for SleepEEG test.

%M = Number of Session recordings considered per individual enrolled subjects.
%Z = Number of Sleep stages epochs.
Pre_Predict_Label = *pre-predicted annotations of sleep stages.*
Output: Sleepstage_Scoring = *Correct predicted sleep stage sequences.*
Step-1: Let P be the enrolled patient's records from different health conditions.
Step-2: Let K be the total sleep recordings of enrolled subjects from a single channel of EEG signal.
Step-3: For each EEG recording from individual enrolled patients in the SleepEEG study do.
Step-4: P = P + 1.
Step-5: Divide the whole K segments of sleep recordings into 30s epochs-wise.
Step-6: Extracting both time and frequency domain features from each epoch and stored into specific feature vectors per individual enrolled patients.

Feature Extraction (Extracted Feature Set)

$$FV_{P1} = \{P1_{F1}, P1_{F2}, \ldots\ldots\ldots, P1_{FE}\}$$
$$FV_{P2} = \{P2_{F1}, P2_{F2}, \ldots\ldots\ldots, P2_{FE}\}$$
$$\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots$$
$$FV_{PN} = \{PN_{F1}, PN_{F2}, \ldots\ldots\ldots, PN_{FE}\}$$
$$F_j = \{y_1, y_2, y_3, \ldots\ldots\ldots\ldots, y_T\}$$

%N=Patients number, %E=number of feature types, %T=number of feature elements

Step-7: Forwarded the extracted features to the proposed feature selection techniques and select the suitable features and store them into the selected feature vector patients-wise.

Feature Selection (Selected Feature Set)

$$FS_{P1} = \{P1_{y1}, P1_{y2}, P1_{y3}, \ldots\ldots\ldots\ldots, P1_{yT}\}$$
$$FS_{P2} = \{P2_{y1}, P2_{y2}, P2_{y3}, \ldots\ldots\ldots\ldots, P2_{yT}\}$$
$$\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots$$
$$FS_{PN} = \{PN_{y1}, PN_{y2}, PN_{y3}, \ldots\ldots\ldots\ldots, PN_{yT}\}$$

%Piyj: an element of feature selection set

Step-8: Forwarded selected feature vector list and predicted sleep stage segments into the proposed classification model.
Sleepstage_Scoring = SleepStage_Classify (Feature_Selection_PN, Pre_Predict_Label).
Step-9: if the Sleep stage classification accuracy is suitable then recommend the sleep stage scoring approach in the diagnosis of sleep-related problems, go to step 11.
Step-10: else go to step 6 [For new feature extraction from sleep recordings of the enrolled subjects].
Step-11: end if.
Output: *Automated Corrected Sleep Stage Sequences of the Subjects.*

Table 3. Final feature selection list

Subject	Selected features	Total
Subject1	$F1_1$, $F2_1$, $F3_1$, $F4_1$, $F5_1$, $F7_1$, $F9_1$, $F10_1$, $F11_1$, $F13_1$, $F14_1$, $F15_1$, $F22_1$, $F25_1$, $F27_1$	15
Subject2	$F1_2$, $F5_2$, $F6_2$, $F7_2$, $F8_2$, $F9_2$, $F10_2$, $F11_2$, $F12_2$, $F13_2$, $F14_2$, $F16_2$, $F18_2$, $F20_2$, $F27_2$	15
Subject3	$F1_3$, $F5_3$, $F6_3$, $F7_3$, $F8_3$, $F10_3$, $F12_3$, $F13_3$, $F17_3$, $F18_3$	10
Subject4	$F1_4$, $F2_4$, $F3_4$, $F4_4$, $F10_4$, $F12_4$, $F14_4$, $F15_4$, $F16_4$, $F17_4$, $F18_4$, $F22_4$, $F24_4$, $F28_4$	14
Subject5	$F1_5$, $F5_5$, $F6_5$, $F7_5$, $F8_5$, $F9_5$, $F10_5$, $F12_5$, $F13_5$, $F14_5$, $F15_5$, $F17_5$, $F18_5$, $F23_5$, $F28_5$	15
Subject9	$F1_9$, $F5_9$, $F6_9$, $F7_9$, $F8_9$, $F9_9$, $F10_9$, $F12_9$, $F13_9$, $F14_9$, $F18_9$, $F28_9$	12
Subject16	$F1_{16}$, $F2_{16}$, $F3_{16}$, $F4_{16}$, $F5_{16}$, $F7_{16}$, $F9_{16}$, $F10_{16}$, $F11_{16}$, $F13_{16}$, $F14_{16}$, $F15_{16}$, $F22_{16}$, $F25_{16}$, $F27_{16}$	15
Subject23	$F1_{23}$, $F2_{23}$, $F3_{23}$, $F4_{23}$, $F5_{23}$, $F7_{23}$, $F11_{23}$, $F12_{23}$, $F15_{23}$, $F16_{23}$, $F17_{23}$, $F20_{23}$, $F24_{23}$, $F26_{23}$	14
SubjectH1	$F1_{H\_01}$, $F5_{H\_01}$, $F6_{H\_01}$, $F8_{H\_01}$, $F10_{H\_01}$, $F16_{H\_01}$, $F17_{H\_01}$, $F18_{H\_01}$, $F22_{H\_01}$	9
SubjectH2	$F1_{02}$, $F2_{02}$, $F3_{02}$, $F4_{02}$, $F5_{02}$, $F7_{02}$, $F8_{02}$, $F9_{02}$, $F11_{02}$, $F12_{02}$, $F13_{02}$, $F14_{02}$, $F21_{02}$, $F22_{02}$, $F25_{02}$	15
SubjectH5	$F1_{05}$, $F2_{05}$, $F3_{05}$, $F4_{05}$, $F5_{05}$, $F7_{05}$, $F8_{05}$, $F9_{05}$, $F11_{05}$, $F12_{05}$, $F13_{05}$, $F14_{05}$, $F21_{05}$, $F22_{05}$, $F25_{05}$	15
SubjectH6	$F1_{H\_06}$, $F3_{H\_06}$, $F4_{H\_06}$, $F5_{H\_06}$, $F8_{H\_06}$, $F9_{H\_06}$, $F13_{H\_06}$, $F14_{H\_06}$, $F15_{H\_06}$, $F16_{H\_06}$, $F17_{H\_06}$, $F18_{H\_06}$, $F22_{H\_06}$	13
SubjectH7	$F1_{H\_07}$, $F5_{H\_07}$, $F6_{H\_07}$, $F7_{H\_07}$, $F8_{H\_07}$, $F10_{H\_07}$, $F16_{H\_07}$ $F18_{H\_07}$, $F28_{H\_07}$	9
SubjectH8	$F1_{H\_08}$, $F10_{H\_08}$, $F11_{H\_08}$, $F12_{H\_08}$, $F13_{H\_08}$, $F14_{H\_08}$, $F15_{H\_08}$, $F17_{H\_08}$, $F18_{H\_08}$, $F19_{H\_08}$	10
SubjectH9	$F1_{H\_09}$, $F4_{H\_09}$, $F5_{H\_09}$, $F6_{H\_09}$, $F7_{H\_09}$, $F8_{H\_09}$, $F10_{H\_09}$, $F12_{H\_09}$, $F13_{H\_09}$, $F16_{H\_09}$, $F17_{H\_09}$	11
SubjectH10	$F1_{H\_10}$, $F5_{H\_10}$, $F6_{H\_10}$, $F8_{H\_10}$, $F10_{H\_10}$, $F13_{H\_10}$, $F15_{H\_10}$, $F17_{H\_10}$, $F18_{H\_10}$, $F22_{H\_10}$	10

4 Experimental Results and Discussion

This complete methodology procedure of this proposed work is explained in pseudo-code format, which is described in Algorithm 1. The complete illustrations of the experimental steps of this proposed work are shown in Fig. 1. For each sampled patient, the experimental results were concluded separately. Multiple evaluation metrics such as accuracy (Acc) [28], recall (Rec) [29], specificity (Spe) [30], precision (Pre) [31], F1score (F1sc)

[32], and Cohen's Kappa Score [33, 34] to analyze the performance of the proposed sleep studies.

4.1 Classification Accuracy of Category-I Subjects ISRUC-Sleep Database

Table 4. Performance evaluation results for ISRUC-Sleep subgroup-I

C3-A2/SVM	Pre	Rec	Spe	F1Sc	Acc	Kappa score
Subject-1	92.3%	96.72%	71.51%	94.48%	91.2%	0.71
Subject-2	94.72%	96.71%	87.87%	97.7%	94%	0.84
Subject-3	94.4%	96.66%	69.74%	95.51%	92.4%	0.70
Subject-4	98.62%	99.04%	47.36%	98.81%	97.73%	0.5
Subject-5	96.16%	94.64%	92.24%	95.4%	93.85%	0.84
Subject-6	96.17%	96.60%	63.88%	96.37%	93.45%	0.60
Subject-16	95.1%	99.48%	81.60%	97.22%	95.60%	0.84
Subject-23	93.09%	95.1%	82.08%	94.10%	91.47%	0.77

The results for subject-1, subject-2, subject-3, subject-4, subject-5, subject-6, and subject-16 show an overall classification accuracy of 91.2%, 94%, 92.4%, 97.73%, 93.86%, 93.46%, 95.60% and 91.46% using SVM classifier. The higher precision value is presented for subject-4 using the SVM method of 98.63%. The highest specificity and F1-score performance results are 92.24% (Subject-5) and 98.83% (Subject-4) using the SVM method. The Kappa scores for subjects-2, 5, and 16 are found in excellent agreement with the subject to the best accuracy for investigation of sleep irregularities. The reported evaluation metrics performances for all subjects for both the session recordings are described in Table 4.

4.2 Classification Accuracy of Category-III Subjects ISRUC-Sleep Database

Finally, the final experimental results for the proposed SleepEEG method are done through the analysis of signals taken from healthy subjects, who haven't been on medication of any sort prior to the experiment. The one-session recording was taken into consideration for monitoring the sleep irregularities and the performances achieved for all the healthy controlled subjects are presented in Table 5.

It can thus be observed that the model achieves an overall accuracy of 92.5%, 92.26%, 91.73%, 91.6%, 96.53%, 66.13%, 95.06% and 93.06% through SVM classifier with ISRUC-Sleep subgroup-III data for subject-1, 2, 5, 6,7,8,9 and 10 respectively. The highest precision was reported from subject-07 (97.26%). The specificity performance was achieved as the highest form subject-07 (92.71%). Furthermore, the F1-Score performance reports the highest value of 97.75% from subject-02. The kappa score for subject-02 and subject-07 is well suitable with SVM classification models. A comparative system performance with respect to other sleep studies has also been performed by the authors and is presented in Table 6.

Table 5. Performance evaluation with ISRUC-Sleep subgroup-III data

C3-A2/SVM	Pre	Rec	Spe	F1sc	Acc	Kappa coefficient
SubjectH-1	93.32%	97.67%	71.81%	95.44%	92.53%	0.74
SubjectH-2	96.82%	98.70%	84.84%	97.75%	92.26%	0.86
SubjectH-5	93.61%	97.28%	49.42%	95.41%	91.73%	0.53
SubjectH-6	92.82%	98.56%	1%	95.60%	91.6%	0.007
SubjectH-7	97.26%	97.97%	92.71%	97.61%	96.53%	0.91
SubjectH-8	70.73%	64.12%	68.51%	67.26%	66.13%	0.32
SubjectH-9	96.08%	98.30%	74.25%	97.18%	95.06%	0.77
SubjectH-10	95.85%	96.47%	79.36%	96.16%	93.6%	0.76

Table 6. Result analysis in between the proposed method with previously contributed research works

<table>
<tr><th>Studies</th><th colspan="2">Models</th><th>Accuracy</th></tr>
<tr><td>Ref. [35]</td><td colspan="2">SVM</td><td>95%</td></tr>
<tr><td>Ref. [36]</td><td colspan="2">Bayesian classifier</td><td>83%</td></tr>
<tr><td>Ref. [37]</td><td colspan="2" rowspan="3">SVM</td><td>93.97%</td></tr>
<tr><td>Ref. [38]</td><td>86.75%</td></tr>
<tr><td>Ref. [39]</td><td>81.74%</td></tr>
<tr><td>Ref. [40]</td><td colspan="2">Random forest</td><td>75.29%</td></tr>
<tr><td>Ref. [41]</td><td colspan="2">Stacked Sparse Auto-Encoders (SSAE)</td><td>82.03%</td></tr>
<tr><td>Ref. [42]</td><td colspan="2">SVM</td><td>83.33%</td></tr>
<tr><td rowspan="2">Proposed</td><td rowspan="2">SVM</td><td>ISRUC-Sleep (Subgroup-I)</td><td>97.73%</td></tr>
<tr><td>ISRUC-Sleep (Subgroup-III)</td><td>96.53%</td></tr>
</table>

5 Conclusion and Future Directions

Maintaining proper sleep quality is crucial for both physical and mental health. The best way of measuring sleep quality is to classify the sleep stages using the single-modal signal. However manual inspection of sleep stages classification is quite difficult, consumes more time, and is highly subject-oriented. To overcome these difficulties, an automated sleep staging system was proposed which considers the basic steps such as pre-processing of signals, feature extraction, feature selection, and classification. Proper feature extraction and selecting the most suitable features play an important role during the automated sleep staging process and it ultimately affects the classification process. Besides a good amount of work has already been contributed in this field, but still, some gaps need to be dealt with. In this work, an attempt was made to address a few of these issues by presenting appropriate solutions for feature combinations, feature screening, and generalized classification models. Additionally, we also analyzed the effectiveness of the proposed methodology via various evaluation metrics. The following points are summarized from the proposed sleep staging classification results. The most significant features are chosen to improve the sleep staging classification performance compared to existing contributions and other methods considered in this research study.

References

1. Panossian, L.A., Avidan, A.Y.: Review of sleep disorders. Med. Clin. N. Am. **93**, 407–425 (2009). https://doi.org/10.1016/j.mcna.2008.09.001
2. Smaldone, A., Honig, J.C., Byrne, M.W.: Sleepless in America: inadequate sleep and relationships to health and well-being of our nation's children. Pediatrics **119**, 29–37 (2007)
3. Hassan, A.R., Bhuiyan, M.I.H.: Automatic sleep scoring using statistical features in the EMD domain and ensemble methods. Biocybern. Biomed. Eng. (2016). https://doi.org/10.1016/j.bbe.2015.11.001
4. Aboalayon, K., Ocbagabir, H., Faezipour, T.: Efficient sleep stage classification based on EEG signals. In: Systems Applications and Technology Conference (LISAT), pp. 1–6 (2014)
5. Obayya, M., Abou Chadi, F.: Automatic classification of sleep stages using EEG records based on Fuzzy C-means (FCM) algorithm. In: Radio Science Conference (NRSC), pp. 265–272 (2014)
6. Alickovic, E., Subasi, A.: Ensemble SVM method for automatic sleep stage classification. IEEE Trans. Instrum. Measur. (2018). https://doi.org/10.1109/TIM.2018.2799059
7. Abeyratne, U.R., Swarnkar, V., Rathnayake, S.I., Hukins, C.: Sleep-stage and event dependency of brain asynchrony as manifested through surface EEG. In: Proceedings of the 29th IEEE Annual International Conference of the Engineering in Medicine and Biology Society, pp. 709–712 (2007)
8. Rechtschaffen, A., Kales A.: A Manual of Standardized Terminology, Techniques and Scoring Systems for Sleep Stages of Human Subjects. U.G.P. Office, Public Health Service; Washington, DC, USA (1968)
9. Iber, C., Ancoli-Israel, S., Chesson, A.L., Quan, S.F.: The AASM manual for the scoring of sleep and associated events: rules, terminology and technical specification. In: American Academy of Sleep Medicine (2007)
10. Satapathy, S.K., Loganathan, D.: Machine learning approaches with heterogeneous ensemble learning stacking model for automated sleep staging. Int. J. Comput. Digit. Syst. Univ. Bahrain J. https://doi.org/10.12785/ijcds/100109
11. Cogan, D., Birjandtalab, J., Nourani, M., Harvey, J., Nagaraddi, V.: Multi-biosignal analysis for epileptic seizure monitoring. Int. J. Neural Syst. (2017). https://doi.org/10.1142/S0129065716500313
12. Obayya, M., Abou-Chadi, F.: Automatic classification of sleep stages using EEG records based on Fuzzy C-means (FCM) algorithm. In: Radio Science Conference (NRSC), pp. 265–272 (2014)
13. Güneş, S., Polat, K., Yosunkaya, Ş: Efficient sleep stage recognition system based on EEG signal using k-means clustering based feature weighting. Expert Syst. Appl. **37**, 7922–7928 (2010)
14. Aboalayon, K., Ocbagabir, H.T., Faezipour, M.: Efficient sleep stage classification based on EEG signals. In: Systems, Applications and Technology Conference (LISAT), pp. 1–6 (2014)
15. Hassan, A.R., Subasi, A.: A decision support system for automated identification of sleep stages from single-channel EEG signals. Knowl.-Based Syst. **128**, 115–124 (2017)

16. Diykh, M., Li, Y., Wen, P.: EEG sleep stages classification based on time domain features and structural graph similarity. IEEE Trans. Neural Syst. Rehabil. Eng. **24**(11), 1159–1168 (2016)
17. Gunnarsdottir, K.M., Gamaldo, C.E., Salas, R.M.E., Ewen, J.B., Allen, R.P., Sarma, S.V.: A novel sleep stage scoring system: combining expert-based rules with a decision tree classifier. In: 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (2018)
18. Sriraam, N., Padma Shri, T.K., Maheshwari, U.: Recognition of wake-sleep stage 1 multichannel EEG patterns using spectral entropy features for drowsiness detection. Australas. Phys. Eng. Sci. Med. **39**(3), 797–806 (2018). https://doi.org/10.1007/s13246-016-0472-8
19. Memar, P., Faradji, F.: A novel multi-class EEG-based sleep stage classification system. IEEE Trans. Neural Syst. Rehabil. Eng. **26**(1), 84–95 (2018)
20. Da Silveira, T.L.T., Kozakevicius, A.J., Rodrigues, C.R.: Single-channel EEG sleep stage classification based on a streamlined set of statistical features in wavelet domain. Med. Biol. Eng. Comput. **55**(2), 343–352 (2016). https://doi.org/10.1007/s11517-016-1519-4
21. Wutzl, B., Leibnitz, K., Rattay, F., Kronbichler, M., Murata, M.: Genetic algorithms for feature selection when classifying severe chronic disorders of consciousness. PLoS ONE **14**(7), e0219683 (2019)
22. Zhu, G., Li, Y., Wen, P.P.: Analysis and classification of sleep stages based on difference visibility graphs from a single-channel EEG signal. IEEE J. Biomed. Health Inform. **18**(6), 1813–1821 (2014)
23. Satapathy, S.K., Bhoi, A.K., Loganathan, D., Khandelwal, B., Barsocchi, P.: Machine learning with ensemble stacking model for automated sleep staging using dual-channel EEG signal. Biomed. Signal Process. Control **69**, 102898 (2021). https://doi.org/10.1016/j.bspc.2021.102898
24. Satapathy, S.K., Loganathan, D.: Prognosis of automated sleep staging based on two-layer ensemble learning stacking model using single-channel EEG signal. Soft. Comput. **25**(24), 15445–15462 (2021). https://doi.org/10.1007/s00500-021-06218-x
25. Khalighi, S., Sousa, T., Santos, J.M., Nunes, U.: ISRUC-Sleep: a comprehensive public dataset for sleep researchers. Comput. Methods Programs Biomed. **124**, 180–192 (2016)
26. Eskandari, S., Javidi, M.M.: Online streaming feature selection using rough sets. Int. J. Approximate Reasoning **69**, 35–57 (2016)
27. İlhan, H.O., Bilgin, G.: Sleep stage classification via ensemble and conventional machine learning methods using single channel EEG signals. Int. J. Intell. Syst. Appl. Eng. **5**(4), 174–184 (2017)
28. Sanders, T.H., McCurry, M., Clements, M.A.: Sleep stage classification with cross frequency coupling. In: 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 4579–4582 (2014)
29. Bajaj, V., Pachori, R.: Automatic classification of sleep stages based on the time-frequency image of EEG signals. Comput. Methods Programs Biomed. **112**(3), 320–328 (2013)
30. Hsu, Y.-L., Yang, Y.-T., Wang, J.-S., Hsu, C.-Y.: Automatic sleep stage recurrent neural classifier using energy features of EEG signals. Neurocomputing **104**, 105–114 (2013)
31. Zibrandtsen, I., Kidmose, P., Otto, M., Ibsen, J., Kjaer, T.W.: Case comparison of sleep features from ear-EEG and scalp-EEG. Sleep Sci. **9**(2), 69–72 (2016)
32. Berry, R.B., et al.: The AASM manual for the scoring of sleep and associated events: rules, terminology and technical specifications. In: American Academy of Sleep Medicine (2014)
33. Sim, J., Wright, C.C.: The kappa statistic in reliability studies: use, interpretation, and sample size requirements. Phys. Ther. **85**(3), 257–268 (2005)
34. Liang, S.-F., Kuo, C.-E., Kuo, Y., Cheng, Y.-S.: A rule-based automatic sleep staging method. J. Neurosci. Methods **205**(1), 169–176 (2012)

35. Khalighi, S., Sousa, T., Oliveira, D., Pires, G., Nunes, U.: Efficient feature selection for sleep staging based on maximal overlap discrete wavelet transform and SVM. In: Annual International Conference of the IEEE Engineering in Medicine and Biology Society (2011)
36. Simões, H., Pires G., Nunes U., Silva V.: Feature extraction and selection for automatic sleep staging using EEG. In: Proceedings of the 7th International Conference on Informatics in Control, Automation and Robotics, vol. 3, pp. 128–133 (2010)
37. Khalighi, S., Sousa, T., Santos, J.M., Nunes, U.: ISRUC-sleep: a comprehensive public dataset for sleep researchers. Comput. Methods Programs Biomed. **124**, 180–192 (2016)
38. Sousa, T., Cruz, A., Khalighi, S., Pires, G., Nunes, U.: A two-step automatic sleep stage classification method with dubious range detection. Comput. Biol. Med. **59**, 42–53 (2015)
39. Khalighi, S., Sousa, T., Pires, G., Nunes, U.: Automatic sleep staging: a computer assisted approach for optimal combination of features and polysomnographic channels. Expert Syst. Appl. **40**(17), 7046–7059 (2013)
40. Tzimourta, K.D., Tsilimbaris, A.K., Tzioukalia, A.T., Tzallas, M.G., Tsipouras, L.G.: EEG-based automatic sleep stage classification. Biomed. J. Sci. Tech. Res. **7**(4), 6032–6037 (2018)
41. Najdi, S., Gharbali, A.A., Fonseca, J.M.: Feature transformation based on stacked sparse autoencoders for sleep stage classification. In: Camarinha-Matos, L.M., Parreira-Rocha, M., Ramezani, J. (eds.) DoCEIS. IAICT, vol. 499, pp. 191–200. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-56077-9_18
42. Kalbkhani, H., Ghasemzadeh, P.G., Shayesteh, M.: Sleep stages classification from EEG signal based on Stockwell transform. IET Signal Process. **13**(2), 242–252 (2018)