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Sleep Stage Classification on ECG Signal and HRV using Combination of Random Forest and SHAP Value

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Abstrak

Klasifikasi tahapan tidur adalah tugas penting dalam bidang pengobatan tidur, yang mempunyai implikasi signifikan dalam mendiagnosis dan mengobati gangguan tidur. Membuat anotasi tahapan tidur secara manual memiliki banyak kelemahan dan keterbatasan. Oleh karena itu, mekanisme otomatis yang menggunakan pembelajaran mesin diperlukan karena efektivitasnya yang diakui dalam klasifikasi tahapan tidur. Penelitian ini terutama berfokus pada membangun model klasifikasi tahapan tidur berdasarkan fitur Heart Rate Variability (HRV) yang berasal dari sinyal Elektrokardiogram (EKG). Makalah ini mengusulkan kombinasi model Random Forest sebagai pengklasifikasi dan nilai SHAP untuk pemilihan fitur guna mengklasifikasikan tahapan tidur. Dengan menggunakan kombinasi metode tersebut diperoleh hasil rata-rata akurasi 82,72%, 77,63%, 73,38%, dan 62,62% untuk kelas kasus 2, 3, 4, dan 6. Selain itu, makalah ini memberikan analisis perbandingan akurasi model terhadap model Random Forest tanpa pemilihan fitur. Hasil eksperimen menunjukkan bahwa metode nilai SHAP secara signifikan meningkatkan kinerja model klasifikasi sekaligus mengurangi kompleksitas fitur.

Kata Kunci: *tahapan tidur, Variabilitas Denyut Jantung, Elektrokardiogram, Random Forest, nilai SHAP*

Abstract

Sleep stage classification is a crucial task in the field of sleep medicine, with significant implications for diagnosing and treating sleep disorders. Manually annotating sleep stages has numerous weaknesses and limitations. Thus, an automatic mechanism employing machine learning is necessary due to its recognized effectiveness in sleep stages classification. This study primarily focuses on constructing a sleep stage classification model based on Heart Rate Variability (HRV) features derived from Electrocardiogram (ECG) signals. This paper proposed a combination of Random Forest model as classifier and SHAP value for feature selection to classify sleep stages. By using a combination of these methods, the results obtained mean accuracy 82.72%, 77.63%, 73.38%, and 62.62% for cases 2, 3, 4, and 6 classes. Additionally, this paper provides a comparative analysis of model accuracy against the Random Forest model without feature selection. The experimental results show that SHAP value methods significantly enhances the classification model's performance while reducing feature complexity.

Keywords: *sleep stages, Heart Rate Variability, Electrocardiogram, Random Forest, SHAP values*

INTRODUCTION

Sleep is a state of natural rest, characterized by unconsciousness, which is necessary for physical and physiological recovery in humans. A consistent sleep pattern is important for the well-being of humans. Inadequate sleep is associated with significant mortality and morbidity in older adults [1]. Among the pivotal factors influencing human health, sleep quality emerges as a critical determinant. The adverse consequences of poor sleep quality encompass feelings of fatigue, anxiety, diminished energy levels, weariness, depression, susceptibility to sleep disorders, and heightened mortality risk [2]. Understanding the various stages of sleep is essential for comprehending the intricacies of sleep patterns and their implications for health. The traditional sleep stage classification takes a lot of time and is very dependent on the experience of experts who assess the overall data. Therefore, an automatic scheme was developed to solve these problems by using the machine learning method based on the available data [3].

In previous research, [4] set a standard for assessing the stages of sleep (sleep stage) based on changes in physiological signals obtained at night. In this standard, Rechtschaffen and Kales categorizes the sleep stages into seven different stages, namely: the wakefulness stage, the four stages of non-rapid eye movement (NREM) sleep which are numbered from 1 to 4, the rapid eye movement stage (REM), and the body movement stage. In the context of sleep visual scoring, electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG) and electromyogram (EMG) were used. These signals are obtained by using a multiparametric testing system known as polysomnography (PSG) which is widely used in the hospital environment.

In recent years, several machine learning algorithms and model have been used to classify sleep stage. Reviewing the evaluation results of previous studies (especially in accuracy metrics), the sleep stage classification model can still be improved further to achieve better performance. In building a classification model, a feature extraction technique is needed that can represent the data well. In previous research, there is a feature extraction technique proposed in the study [5] by using HRV (Heart Rate Variability). There are some previous feature extraction techniques are time domain [6], Poincare [7], and frequency domain [5].

The HRV technique generates numerous features, but not all are effective representative of the data. Excessive unrepresentative features can lead to model overfitting or bad of performance result. Hence, a feature selection mechanism is essential to identify high-predictive-power features. In this research, a combination of SHAP (SHapley Additive exPlanations) values and Random Forest is proposed. SHAP value selected as feature selection method to selecting optimal features and improve model evaluation results (especially in accuracy score). The SHAP framework identifies the class of additive feature importance methods and shows there is a unique solution in this class that adheres to desirable properties [8]. In this study, Random Forest model used for classification case due to its capacity to address overfitting, handle large datasets, and provide interpretability of relevant features. The mean classification testing accuracy will be used to measure the proposed model's performance.

RELATED WORKS

There are some studies that have been done on the sleep stage classification using various methods and techniques. Adnane et al. classified sleep and wake stage using support vector machine (SVM) in 2009. The experiment used MIT-BIH dataset and got 78.05% accuracy score with 7 features [9]. This research was continue in 2012 by adding more features for classification. Accuracy score reported 79.31% and 79.99% accuracy, using 12 and 10 features respectively [10].

In 2012, Xiao et al. classified sleep stages to 3 classes: wake, rapid eye movement (REM) sleep and non-REM (NREM) sleep using 41 features. This experiment achieved 88,67% accuracy score [11]. Lesmana et al. achieved accuracy score 82.1%, 76.77%, 71.52%, and 62.66% for 2, 3, 4, and 6 classes respectively using ELM-PSO algorithm. Originally, there are 18 features extracted from the MIT-BIH ECG recording. PSO algorithm was selected for feature selection and number of hidden node determination [12]. Sleep stage classification using Deep Neural Network obtained 77% accuracy score with 11 features in Wei et al. research [13].

In several research about sleep stage classification using MIT-BIH Polysomnographic Database (slpdb), the features used are not only obtained from the ECG signal, but also from the EEG signal. In 2011, Rossow et al. achieved 60,14% accuracy score for 3 class classification using EEG signal [14]. Hidden Markov method was selected as classifier in this research. In 2014, 7 features were extracted from EEG signal in [15] research and obtained 83,6% accuracy score for 2 class classification of sleep stages. In 2019, research [16] achieved 94,31% accuracy score using LSTM and CNN model.

Combination of EEG and ECG signal were used by [17] research to classified 2 and 4 classes. DNN model was selected in this research and achieved 95,71% and 73,70% accuracy score. Zhao et al. also used EEG and ECG signal in 2021, obtained 97.97%, 98.84%, 88.80%, and 80.40% for classified 'deep sleep vs. light sleep', 'rapid eye movement stage (REM) vs. non-rapid eye movement stage (NREM)', 'sleep vs. wake', and 'wake, deep sleep, light sleep, and REM'[18].

RESEARCH METHODOLOGY

3.1 Research Stages

The stages of this research can be described through the flowchart in Figure 1.

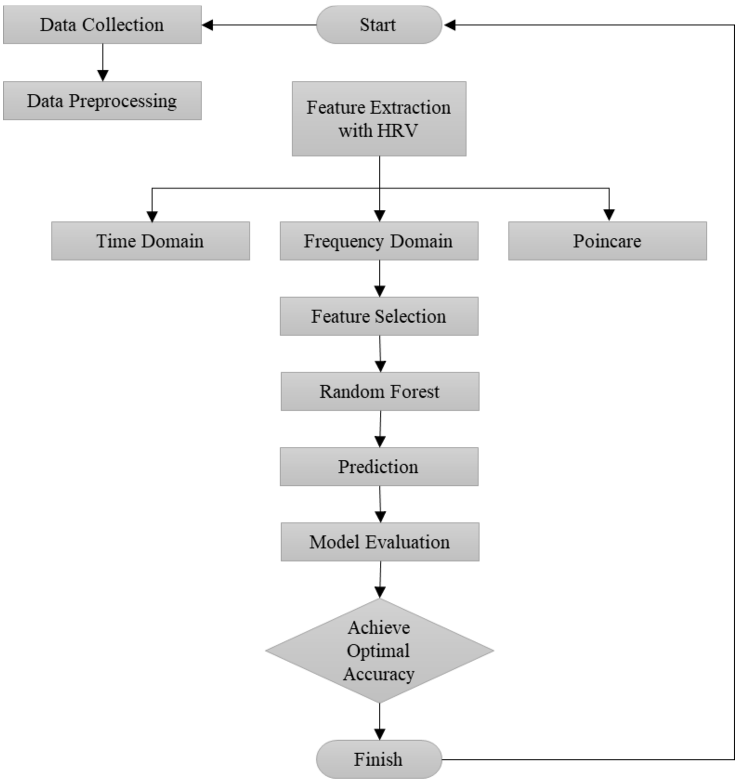


Figure 1. Research Stages Flowchart

Dataset

The dataset that used in this research is MIT-BIH Polysomnographic Database (slpdb) [19]. This dataset is a public dataset that can be accessed via https://physionet.org/. This dataset contains columns: time, ECG, EEG, blood pressure, and respiration. This research uses time and ECG signal columns. The ECG signal in dataset has a sampling frequency of 250 Hz and 12 bits/sample. This dataset consists of 18 records and have a different duration in each record. The recordings were taken from 16 different people. In each recording, every 30 seconds the data is made into 1 sample, which is called 1 epoch. The total number of epochs in this dataset is 10274.

Heart rate variability (HRV)

Heart rate variability (HRV) is the temporal variation that occurs between successive heartbeat sequences [20]. The amount of fluctuation in heart rate occurs due to continuous changes in the balance of the parasympathetic and sympathetic nerves. Based on the results of the ECG waveform, the QRS complex must be detected in order to obtain the R impulse value. HRV measures the impulse variability from the next R to R point, also known as the RR interval. The RR interval is the difference between the impulses in one R and the next R. Many features can be generated from this RR interval. These features can later be used to build a classification model. HRV features can be obtained by taking several approaches, namely Time Domain, Poincare, and Frequency Domain. The features used in this research are:

Table 1. Feature List

No	Feature	Method	Description
1	AVNN	Time Domain	The average of all RR interval. $$AVNN = \frac{1}{N}\sum_{j=1}^{N} RR_j$$
2	SDNN	Time Domain	Standard deviation of all RR interval. $$SDNN = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}\left(RR_j - \overline{RR}\right)^2}$$
3	RMSSD	Time Domain	The square root of the average of the sum of the squares of differences between adjacent RR intervals $$RMSSD = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N-1}\left(RR_{j+1} - RR_j\right)^2}$$
4	SDSD	Time Domain	Standard deviation of differences between adjacent RR intervals

5	NN50	Time Domain	The count of adjacent RR intervals differences that are more than 50 ms $$Number\ of\ (RR_{j+1} - RR_j) > 50$$
6	pNN50	Time Domain	The division of NN50 by total of all RR intervals minus one times 100. $$pNN50 = \frac{NN50}{N-1} \times 100$$
7	TP	Frequency Domain	Total power
8	LFnorm	Frequency Domain	$$LFnorm = \frac{LF}{TP - VLF}$$
9	HFnorm	Frequency Domain	$$LFnorm = \frac{HF}{TP - VLF}$$
10	LFHF Ratio	Frequency Domain	Ratio of LF and HF
11	VLF	Frequency Domain	Total power of 0 to 0.04 Hz
12	LF	Frequency Domain	Total power of 0.04 to 0.15 Hz
13	HF	Frequency Domain	Total power of 0.15 to 0.4 Hz
14	SD1	Poincare	Standard deviation of the point perpendicular to the line of identity. $$SD1^2 = \frac{1}{2} SDSD^2$$
15	SD2	Poincare	Standard deviation of the point along the line of identity. $$SD2^2 = 2SDNN^2 - \frac{1}{2} SDSD^2$$
16	SD1SD2 Ratio	Poincare	Ratio between SD1 and SD2. $$SD1\ SD2\ Ratio = \frac{SD1}{SD2}$$
17	S	Poincare	Area of ellipse $$S = \pi \times SD1 \times SD2$$

Random Forest

Random Forest is a supervised learning algorithm developed from the Decision Tree algorithm. The Random Forest concept is to form a combination of several trees as predictors where each predictor depends on the value of a random vector that is sampled independently and with the same distribution for each tree in the forest [21]. Let $\{h(x, \Theta_k), k = 1, \ldots\}$ where $\{\Theta_k\}$ is a vector that is iid (independent identically distributed) and each tree will select the class with the most number of data (majority vote). Prediction results from Random Forest are obtained through the most results from each individual tree (in the form of voting for classification cases and the average for regression cases).

Random forests are usually used to solve problems related to classification, regression, and so on. The following is a Random Forest algorithm [22]:

1) Create a bootstrap sample or Z sampling with the replacement of a size N of the data set.
2) Choose m variables at random from p variables, where $m \leq p$. Usually the best size m is chosen by approximating the square root of the total number of p variables, namely $\lfloor \sqrt{p} \rfloor$.
3) After selecting m randomly, the tree is executed without pruning. The best node split in a tree is done using the Gini index.
4) Steps 1-3 are carried out n times to form a forest of n trees.
5) After the forest is formed, then look for the misclassification error value (Out of Bag Error) to estimate the error and determine the variable importance.

Prediction results of a class will be determined by majority vote.

SHAP Values

SHAP values (SHapley Additive exPlanations) is a method based on cooperative game theory and used to increase transparency and interpretability of machine learning models. This algorithm was first published in 2017 by Lundberg and Lee to reverse-engineer the output of any predictive algorithm [8]. The objective of SHAP is to provide a transparent and interpretable understanding of machine learning models.

At a high level, the Shapley value approach attempts to explain why an machine learning model reports the outputs that it does on an input. This type of technique has been widely used in complex non-linear models to explain the impact of variables on the Y dependent variable, or y-hat [24], [25].

a) SHAP Feature Importance

SHAP feature importance is a method for quantifying the impact of individual features on the predictions made by a machine learning model. The idea behind SHAP feature importance is simple. Global importance can be obtained by calculate average of absolute Shapley value per feature across the data.

b) SHAP Summary Plot

A SHAP summary plot is a graphical representation that provides a comprehensive view of feature importance for a machine learning model. It typically displays a summary of the Shapley values for each feature across a dataset. The summary plot combines information about feature importance and feature effects. The y-axis is determined by the feature and the x-axis by the Shapley value. The color represents the value of the features from low to high. The features are ordered according to their importance.

c) SHAP Interaction Values

SHAP interaction values, also known as SHAP interaction effects, extend the SHAP framework to capture interactions between features. While SHAP feature importance focuses on individual feature contributions, SHAP interaction values aim to uncover how pairs or groups of features interact to influence predictions. These values provide insights into not only the importance of individual features but also the combined effects of feature interactions. They are valuable for understanding the complex relationships between features in your model.

RESULTS AND DISCUSSION

Classification is divided into 4 scenarios, where each scenario contains 2, 3, 4, and 6 classes. The scenarios are: (1) awake and sleep, (2) awake, NREM, and REM, (3) awake, deep sleep, light sleep, and REM, (4) awake, stage 1, stage 2, stage 3, stage 4, and REM. Each scenario uses 70% training data and 30% for testing.

Preprocessing Result

In preprocessing step, some data that have no annotation, incomplete RR interval, or non-relevant annotation were removed. There are 120 or about 1.17% instances removed. From those remaining data, the next step is synchronizing RR interval and annotation data, feature extraction, and data normalization.

Random Forest Result

A single Random Forest developed with full features that extracted from HRV. This experiment does not use any feature selection method. Figure 1 shows the result of this experiment. The highest mean of testing accuracy occurred in 2-classes data, followed by 3-classes data, 4-classes data, and 6-classes data.

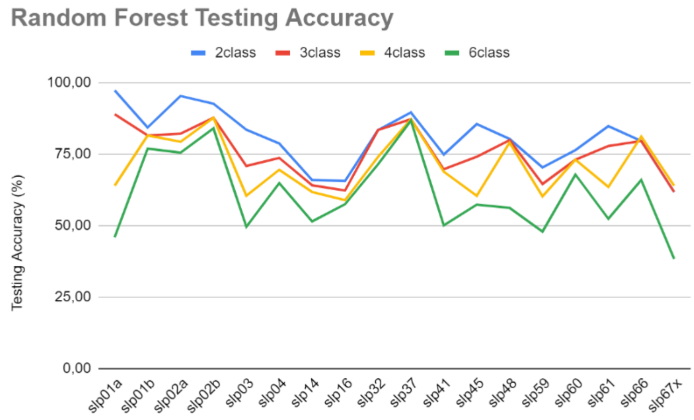


Figure 2. Random Forest testing accuracy result

SHAP Value Result

SHAP value selected as method for feature selection. In each experiment (2, 3, 4, and 6 classes), we calculate the SHAP value and sort it by the highest value. This SHAP value shows the predictive power of a feature against its target. We can see the features rmssd, sd1, and nni_mean always appear in every Top 5 features in each SHAP value result on figure 2,3,4, and 5. If we expand to Top 10 features, we get the features rmssd, sd1, nni_mean, pnn50, vlf, sdsd, hf, and ellipse_area. For Top 15 features, there are rmssd, sd1, nni_mean, pnn50, vlf, sdsd, hf, ellipse_area, lf, tp, sd_ratio, sd2, and hf_norm. These results show various important features based on the SHAP value in each classification experiment (2, 3, 4, and 6 classes).

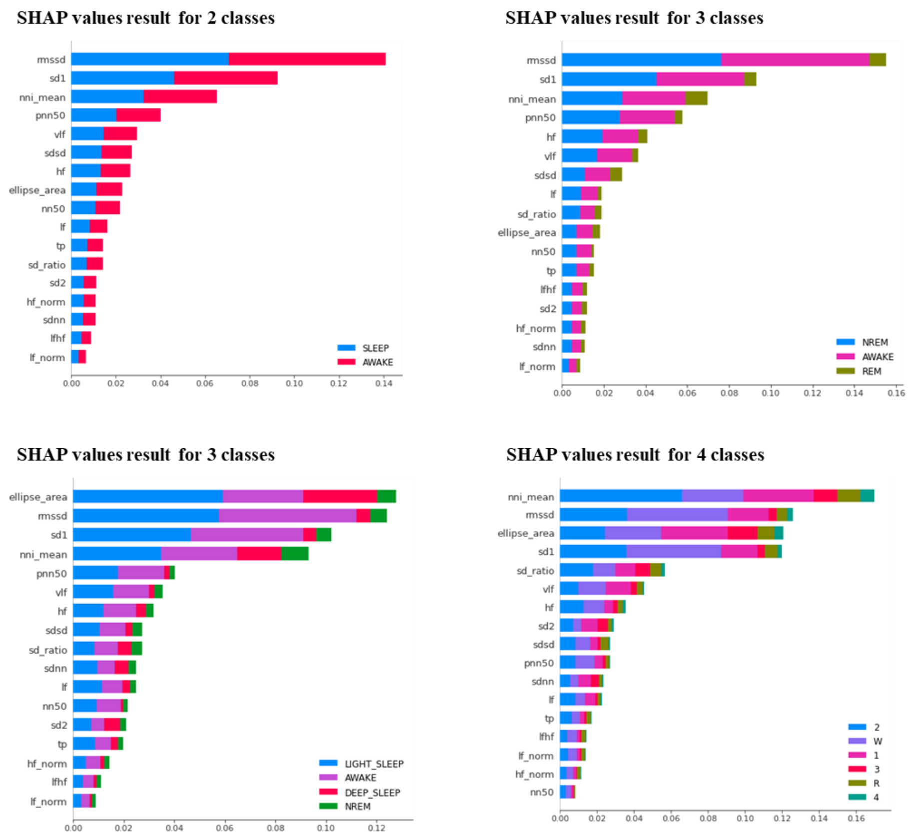


Figure 3. SHAP value result on 2, 3, 4, and 6 classes

The Combination of Random Forest and SHAP Value Result

Based on previous result, combination of Random Forest and SHAP Value is proposed to improve previous result. In this experiment, modeling is done by selecting the top 5, 10, and 15 features based on the SHAP value. After that, evaluate the mean of training and testing accuracy for 2, 3, 4, and 6 classes.

Table 2. Top 5 feature list based on SHAP value

Classes	Features	Testing Accuracy
2	rmssd, sd1, nni_mean, pnn50, vlf	81.81%
3	rmssd, sd1, nni_mean, pnn50, hf	76.39%
4	ellipse_area, rmssd, sd1, nni_mean, pnn50	72.15%
6	nni_mean, rmssd, ellipse_area, sd1, sd_ratio	62.13%

Table 3. Top 10 feature list based on SHAP value

Classes	Features	Testing Accuracy
2	rmssd, sd1, nni_mean, pnn50, vlf , sdsd, hf, ellipse_area, nn50, lf	82.72%
3	rmssd, sd1, nni_mean, pnn50, hf, vlf, sdsd, lf, sd_ratio, ellipse_area	77.22%
4	ellipse_area, rmssd, sd1, nni_mean, pnn50, vlf, hf, sdsd, sd_ratio, sdnn	73.38%
6	nni_mean, rmssd, ellipse_area, sd1, sd_ratio, vlf, hf, sd2, sdsd, pnn50	62.62%

Table 4. Top 15 feature list based on SHAP value

Classes	Features	Testing Accuracy
2	rmssd, sd1, nni_mean, pnn50, vlf , sdsd, hf, ellipse_area, nn50, lf, tp, sd_ratio, sd2, hf_norm, sdnn	82.26%
3	rmssd, sd1, nni_mean, pnn50, hf, vlf, sdsd, lf, sd_ratio, ellipse_area, nn50, tp, lfhf, sd2, hf_norm	77.63%

4	ellipse_area, rmssd, sd1, nni_mean, pnn50, vlf, hf, sdsd, sd_ratio, sdnn, lf, nn50, sd2, tp, hf_norm	73.08%
6	nni_mean, rmssd, ellipse_area, sd1, sd_ratio, vlf, hf, sd2, sdsd, pnn50, sdnn, lf, tp, lfhf, lf_norm	62.15%

The Combination of Random Forest and SHAP Value Result

By comparing Random Forest result and combination of Random Forest and SHAP value result, we can see combination of Random Forest and SHAP value result got higher accuracy in data with any number of classes. Comparison of these two methods shows an improvement in accuracy of Random Forest up to 2.64%.

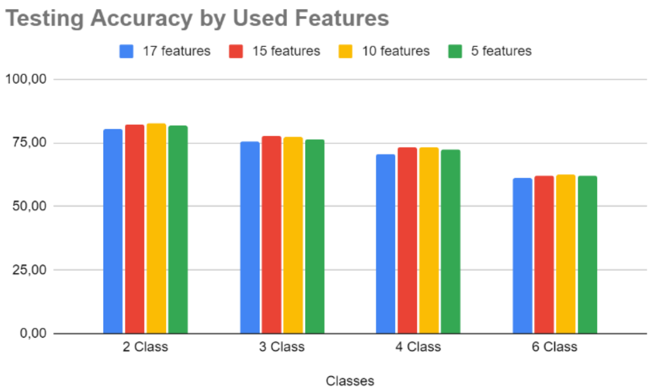
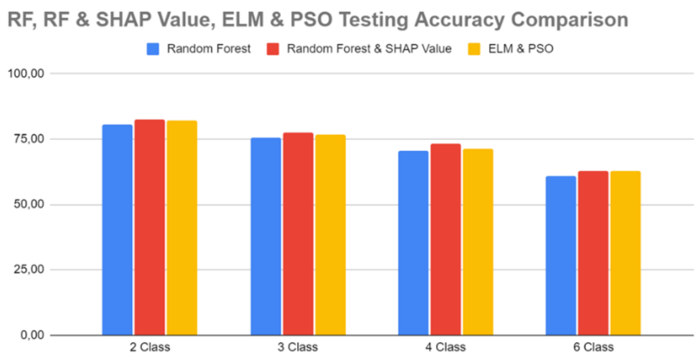


Figure 7. Methods comparison results

By selecting best result of the combination of Random Forest and SHAP value, the results of the comparison of methods are obtained based on the value of testing accuracy. This result also compared with previous study by Lesmana et.al. [12], presented in Fig.7.



Method	2 Class	3 Class	4 Class	6 Class
Random Forest	80,50	75,62	70,74	61,05
Random Forest & SHAP Value	82,72	77,63	73,38	62,62
ELM & PSO	82,10	76,77	71,52	62,66

Figure 8. Performance of combination RF and SHAP value compared to the other works

CONCLUSION

In this paper, our proposed method (combination of Random Forest and SHAP value) obtain accuracy values of 82.72%, 77.63%, 73.38%, and 62.62% for 2, 3, 4, and 6 number of classes. The results show that the combination of Random Forest and SHAP value obtain better accuracy than single Random Forest method in each experimental scenario (2, 3, 4, and 6 classes). Our proposed method also obtain better accuracy in scenarios of 2, 3, and 4 classes compared to previous study with ELM & PSO methods. This result also shows that combination Random Forest and SHAP value as feature selection can give improvement in accuracy score with fewer features for sleep stages classification.

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