Evaluation of sleep stage classification using feature importance of EEG signal for big data healthcare

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ABSTRACT

Sleep analysis is widely and experimentally considered due to its importance to body health care. Since its sufficiency is essential for a healthy life, people often spend almost a third of their lives sleeping. In this case, a similar sleep pattern is not practiced by every individual, regarding pure healthiness or disorders such as insomnia, apnea, bruxism, epilepsy, and narcolepsy. Therefore, this study aims to determine the classification patterns of sleep stages, using big data for health care. This used a high-dimensional FFT extraction algorithm, as well as a feature importance and tuning classifier, to develop accurate classification. The results showed that the proposed method led to more accurate classification than previous techniques. This was because the previous experiments had been conducted with the feature selection model, with accuracy implemented as a performance evaluation. Meanwhile, the EEG Sleep Stages classification model in this present report was composed of the feature selection and importance of the extraction stage. The previous and present experiments also reached the highest values of accuracy, with the Random Forest and SVM models using 2000 and 3000 features (87.19% and 89.19%, respectively. In this article, we proposed an analysis that the feature importance subsequently influenced the model's accuracy. This was because the proposed method was easily fine-tuned and optimized for each subject to improve sensitivity and reduce false negative occurrences.

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1. Introduction

Body muscles and tissues repair themselves during a good night's sleep, with memory consolidation also a process. This explains the importance of good and adequate sleep to people. According to the National Sleep Foundation survey, 13% and 30% of 1,000 people experienced inadequate sleep on days off and workdays in the United States, respectively [1]. This indicated that many people, especially on workdays, experienced inadequate rest, leading to decreased productivity and energy loss. To determine these issues early, the measurement of sleep stages is a useful analytical tool for the prevention of subsequent disorders [2], [3]. Based on the gold standard of sleep analysis, multiple classified stages are observed, namely Waking, REM, and NREM. In NREM, Stages 1/2 and 3/4 emphasize the light and profound sleep, respectively [4], [5]. Furthermore, visitation to a sleep clinic often helps in sorting out these various stages. In this case, patients are commonly subjected to an experiment in specific rooms, for doctors to analyze their mental health when sleeping. To measure brain waves and heart rate, common technologies such as electroencephalography (EEG) and electrocardiography (ECG), are also used. This shows that the utilization of an automated system leads to greater benefits for experts when identifying sleep stages [6], [7].

According to a previous review, an automated approach was tested for classifying sleep stages, using PSG inputs, especially EEG signals. In this process, the results obtained were classified using supervised classifiers, such as Support Vector Machine (SVM), Random Forest and Naïve Bayes. The hyperparameter tuning was also applied by executing the five-fold Cross Validation for both model classifiers. Using the EEG signals from healthy and unhealthy patients, an automated algorithm evaluated sleep stages based on the Sleep-EDF dataset. This explained the use of one and/or two EEG channels for easier reasonable installation, compared to other cutting-edge systems using numerous PSG or difficult physiological data for automatic sleep-stage scoring. The subject's comfort degree was also increased than the scoring process utilizing multi-modal signals. Moreover, the Fast Fourier Transform (FFT) was used to extract high-dimensional characteristics from single- or multi-channel EEG recordings (FFT) [8]–[10]. Using this method, the feature extraction of brainwaves signal from EEG data was also a tried-and-true process. When using the Random Forest and SVM classifiers to measure accuracy, the four key components observed were the EEG channel collection of brainwaves stored in the dataset, data preprocessing, feature extraction of signal, and performance evaluation of classification. The feature selection method was subsequently used to improve the accuracy of the results obtained. In this case, the SVM and Random Forest models had average accuracy values of 86.91% and 87.94% for the entire state classification [7]. Therefore, this study aims to determine the classification patterns of sleep stages, using big data for health care. This proposed analysis emphasizes the effect of the feature importance on data preprocessing, for performance evaluation on sleep stage classification [11]–[13]. The results obtained are expected to provide a more practical channel for assessing the feature importance affecting the evaluation of sleep stage classification.

The effect of feature selection and importance is also examined on an automated or computerized sleep stage classification system using PSG inputs, specifically EEG signals. This analysis is then classified using supervised classifiers such as the SVM and Random Forest. In this case, the EEG signals from healthy and unhealthy patients are supplied into a computerized system analyzing the sleep stage data, regarding the Sleep-EDF dataset. Only one or two EEG channels is/are deployed in this experiment, ensuring fewer complications for the operational installation than the sleep scoring process utilizing multimodal signals [14]. The subject's degree of comfort is also enhanced, with the Fast Fourier Transform (FFT) applied to the high-dimensional characteristics acquired from single-or multi-channel EEG recordings [6]. This is because FFT is a robust and time-tested method for extracting features from EEG signals. The utilized methods also contain the following four fundamental steps [7],

- Acquisition of EEG channel brainwaves preserved in the dataset,
- Data Preprocessing
- Feature extraction, including Feature Selection (FS) and Feature Importance (FI),
- Performance evaluation for the classification accuracy assessment, using SVM and Random Forest classifiers.

This study aimed to analyze how the importance of the features affected the model's accuracy. This was due to the fact that the proposed method could be readily fine-tuned and optimized for each subject to increase sensitivity and decrease false negatives. The originality of our research was that it examined the effect of feature selection and feature importance on an automated sleep stage classification system that used PSG inputs, especially EEG data. As a performance evaluation for classifying sleep stages based on brainwaves to enrich healthcare's big data, this research remained challenging as we sought improved precision. As the ranges that need to be considered for development, tuning becomes a more computationally intensive process. Inadequate data are also observed on the types of hyperparameters that should be tuned and left at their default value towards the production of satisfactory results. When time and computing power are at a limitation, the complete disregard for the latter class of hyperparameters is very necessary [15]–[17]. In addition, the relevance of tuning hyperparameters is investigated, to supply the empirical evidence of the parameters eliminated from the ranges under consideration.

2. Method

As seen in Fig. 1, the proposed Model for Feature Selection and Feature Importance of the EEG Sleep Stages is depicted.

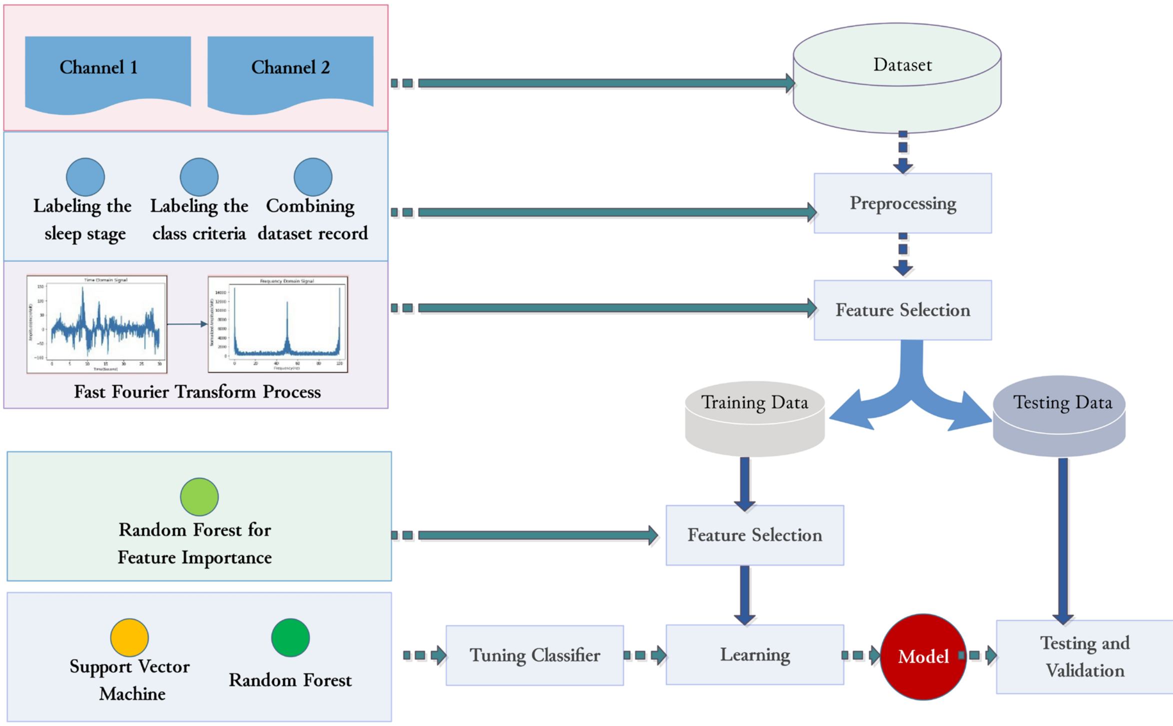

Fig. 1. The proposed Model with The Feature Selection and Feature Importance of the EEG Sleep Stages Classification

2.1. The Dataset

According to this analysis, the Sleep-EDF dataset was utilized to develop the utilized EEG parameters. In this case, one of three versions of the dataset was employed, including 61 recordings from 42 Caucasian men and women [18]. These participants were between the ages of 18 and 79 yrs old, with two sections developed for this information. Furthermore, a total of 39 EEG recordings were obtained from 20 subjects in a previous report between 1987 and 1991, where the first subset was observed. These people had good health and were able to move around without assistance. For the second collection, EEG data were acquired from 22 subjects in a 1994 study. In this case, the participants reported trouble falling asleep, although appeared to be in good health. For 24 h, EEG data were obtained from these subjects while performing their daily routines. A tiny telemetry device was also utilized in a hospital environment, to obtain these data from four volunteers overnight. For each of the two suggested channels, Fpz-Cz and Pz-Oz, a sampling frequency of 100 Hz were subsequently used. In addition, the odd and even-numbered electrodes were typically placed on the left and right sides of the head, respectively. From this process, the letter z representing zero designated the midline electrodes. The utilized anatomical labels also included, "C" for "central," "F," "T," "O," "P," and "Fp," which designated the electrodes' placements according to the various divisions of the human brain.

Based on the preprocessing procedures, a sleep dataset labelling from a 2 to 6-state categorization was observed with the combination of all recorded individuals. In this case, the expert sleep technologist used R & K criteria to analyze the EEG recordings of both categories. This indicated the collection of 3000 samples, due to the 30 s interval between the epochs assigned to various sleep phases. These epochs included "AWA," "REM," S1, S2, S3, S4, "Movement Time," and "Unscored.". In the AASM's annotations, 6 categories were also observed, namely AWA, REM, N1, N2, N3, and "Unknown sleep state". The number of samples used was derived using the R&K criterion. Furthermore, the total sample size was 127,663 after deleting the "Movement Time" and "Unscored", with 30 s of total silence observed during the interval. Regarding evaluation, a total of 250, 500, 1000, 2000, 3000, and 6000 features were obtained from two channels (Pz-Oz and Fpz-Cz), with the epoch and sampling frequency being 30 s and 100 Hz, respectively. These features were then individually or cooperatively used in the experimental reports

2.2. Data Preprocessing

According to Fig. 1, this preprocessing approach included the sleep dataset labelling from two to six-state categorization and the combination of all recorded participants. In this process, a sleep expert analyzed the EEG records of both groups within 30 s, using R & K criteria. This showed that each epoch was set to last 30 seconds, yielding a total of 3000 samples. Sleep technologists also designated the following epochs, "AWA," "REM," "S1, S2, S3, S4, "Movement Time," and "Unscored". Moreover, the American Academy of Sleep Medicine (AASM) annotations included the categories of AWA, REM, N1, N2, N3, and "Unknown sleep state". Based on the R&K criteria, the number of samples are estimated in Table 1, where the overall size in 30 s was 127,663 after deleting the items labelled "Movement Time" and "Unscored". In terms of the analytical evaluation, feature selection made a number of features. This included features from two channels for 250, 500, 1000, 2000, 3000, and 6000 (Pz-Oz and Fpz-Cz), where the sampling frequency and interval were 100 Hz and 30 s, respectively.

Table 1. Based on R&K criteria, the number of samples in the Sleep-EDF dataset

classes	AWA	REM	S1	S2	S3	S4
6	74,827	11,848	4,848	27,292	5,075	3,773
5	74,827	11,848	4,848	27,292	8,848	
4	74,827	11,848	32,140		8,848	
3	74,827	11,848	40,988			
2	74,827	52,836				

2.3. Feature Extraction

The feature is a distinguishing characteristic or an operational component identified in a pattern section. It is also a measurable and detectable characteristic, whose extraction from EEG signals is indispensable to processing. This extraction process emphasizes the limitation of important signal information missplaced during processing. Additionally, feature extraction reduces the time and resources necessary to accurately classify enormous data. When performed effectively, this extraction is sufficiently feasible to carry out the following, (1) Decrease the budget of data processing, (2) Shorten the data implementation, and (3) Cut down the need to compress data [19]. Since EEG signals are fluctuating and often nonstationary, the determination of their frequency components is highly necessary. To address this difficulty, the time-frequency analysis is appropriately suited.

In high-frequency locations, greater temporal resolution is typically required with transient waves. However, steady waves require more excellent frequency resolution [20]. In this study, EEG data properties were extracted using the Fast Fourier Transform (FFT), to classify sleep stages through a classification algorithm. This indicated that the valuable of a time series were converted into a specific frequency domain and stored as numeric sequence data. To deconstruct these data into segmented EEG signal sequences, the parameters were dissected into equal time intervals. Each epoch also determined the duration of the complete EEG wave, which was 30 s. Since the frequency analysis and epoch were completed and processed, FFT was then used to construct the FS (frequency spectra). The application of the Fast Fourier Transform (FFT) emphasized the conversion of a signal from the time to frequency domains [21]. High-dimensional features from FFT-based single or multiple-channel EEG recordings were also used in this analysis. Fig. 2 and Fig. 3 illustrate the Sleep EDF datasets as time and frequency-domain signals [20].

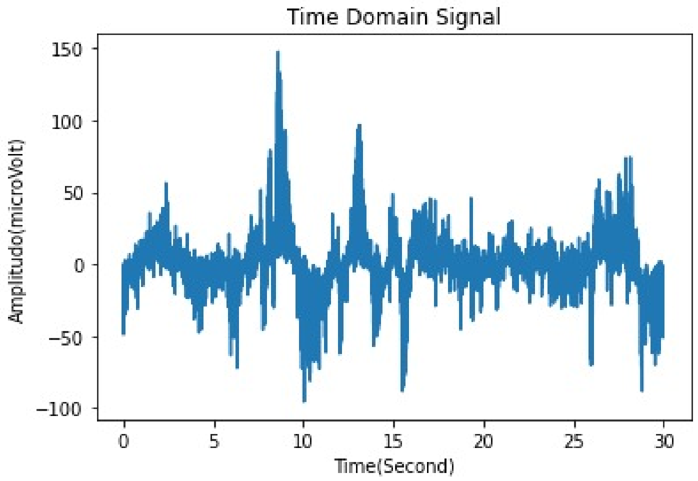

Fig. 2. EEG signal on Time Domain

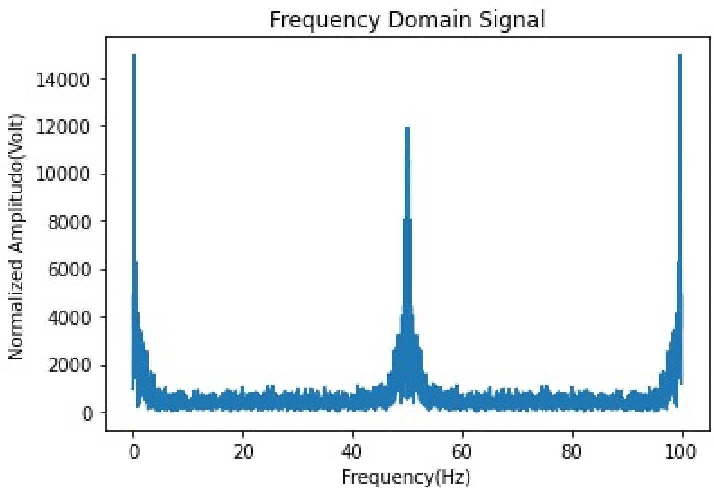

Fig. 3. EEG signal on Frequency Domain

2.4. Feature Selection and Importance

A classifier's performance heavily depends on the third step of machine learning, namely feature selection. The next step was to determine the N-features most helpful in differentiating the established sleep categories. In this process, the Sleep-EDF dataset was examined, with each number of classes, 250, 500, 1000, 2000, 3000, and 6000 critical characteristics being selected. Subsequently, the preferable subset of features was selected for each class count. Additional information about the utilized feature selection method was also found evaluating a very similar approach to the proposed type [14]. Feature Importance describes the methods assigning a value to each characteristic used in training a specific model. From the description, a higher score indicates that this feature is more important in the predicting model [22]–[24]. Python software also used the permutation technique to assess the feature importance of the best models, leading to the application of two classifiers, namely SVM and Random Forest. These were used for the classification algorithm with the parameters of RBF (Radial Basis Function) kernel and seed on the random_state.

The sleep stage performance was measured using a confusion matrix-based accuracy calculation. Performance factors like sensitivity, specificity, and accuracy of classification phenomena can be evaluated and analyzed with the aid of the evaluation matrix that is determined [14], [19].

3. Results and Discussion

According to the preprocessing stage, the polysomnographic recording EEG data was filtered and divided into 30 seconds of epochs, with time-frequency analysis performed using the high-dimensional FFT characteristics. In this stage, all 61 records were processed, with the feature dataset including 127,663 sleep epochs. The entire dataset was then randomly dissected, with both halves placed into a training and testing set. Different classifiers, such as the SVM and Random Forest, were also developed and evaluated with the training and test datasets, respectively. In addition, the suggested system's efficacy was measured by contrasting the classifiers' output scores with those of human experts.

The multiclass SVM technique was chosen from the several classification algorithms available for consideration as supervised machine learning strategies. This classifier is a widely-used learning technique for various applications and structural risk minimization, to tackle limited sample and nonlinear classification issues [25]. Its foundational principle also emphasizes the search for the appropriate separation hyperplane, to ensure the linear separation of the classification issue [26], [27]. Furthermore, the SVM algorithm determines the most significant possible gap around the class separation hyperplane. This led to the implementation of a Radial Basis Function (RBF) Kernel for this analysis. When more features are observed than samples, a typical scenario involving the SVM method was used. This is subsequently capable of being used as a classification model for EEG data. In this case, the SVM method is then contrasted with another popular classification technique, Random Forest. Based on the criteria of R and K, labels were selected for two sets of six categories. Each of the two channels' attributes was also individually and cooperatively analyzed with the other. From just a single channel, 3000 features were gleaned at a rate of 100 Hz for 30 s. In addition, performance was evaluated using five-fold cross-validation.

Based on a previous analysis, the labels for classes 2–6 were selected using the R and K criterion, with the two channels individually and cooperatively compared. The results extracted a total of 3000 features with 100 Hz and 30 s frequencies from a single channel. Performance was also evaluated using five-fold cross-validation, where the results obtained were compared to those of Random Forest and SVM. According to Table 2 and Table 3, the proposed strategy achieves the best results when using 6000 features from only two channels (Pz Oz and Fpz Cz). This was observed when attempting to classify into 2-6 classes [7]. In this context, accuracy improved for Random Forest and SVM models, with the number of features increasing due to iterative selection. Using accuracy as a measurement of performance, the Random Forest model achieved the highest rates at 95.93%, 90.41%, 87.91%, 86.92%, and 84.86% for two–six state classification. However, the SVM model achieved 96.63%, 91.27%, 88.90%, 87.94%, and 87.94%. These results proved that the SVM algorithm model provided the highest accuracy, in comparison to the Random Forest technique. It also ensured the extreme accurate production for sleep stage or text data classification, using time-series signals [26], [28]. Based on these results, the best accuracy value was achieved for a fixed number of features. In Table 2, this value was achieved with an FS (feature selection) of 2000 features, compared to those with 3000 and 6000 characteristics. The SVM classifier was also used to develop the model in Table 3, where 3000 features reached their best point after applying FS. This accuracy was subsequently reflected in the effectiveness of the operation, indicating that the cautious selection of features enhanced the accurate attribute of the proposed model.

Table 2. The Performance of Feature Selection with Random Forest Classifier [7]
(R&K Criteria, two-six Classes)

Total Number	6000	3000	2000	1000	500	250
6 Classes	84.45%	84.81%	84.86%	84.84%	84.35%	83.89%
5 Classes	86.67%	86.92%	86.91%	86.78%	86.20%	85.71%
4 Classes	87.64%	87.78%	87.91%	87.75%	87.23%	86.63%
3 Classes	90.02%	90.26%	90.41%	90.19%	89.57%	89.01%
2 Classes	95.60%	95.81%	95.93%	95.77%	95.21%	94.29%

Table 3. The Performance of Feature Selection with SVM Classifier [7] (R&K Criteria, two-six Classes)

Total Number	6000	3000	2000	1000	500	250
6 Classes	85.92%	87.94%	86.31%	84.92%	83.09%	83.31%
5 Classes	86.87%	87.94%	87.75%	86.41%	84.60%	84.18%
4 Classes	87.52%	88.90%	88.66%	86.74%	84.30%	83.85%
3 Classes	90.38%	91.27%	90.99%	88.14%	86.86%	86.47%
2 Classes	96.53%	96.63%	96.44%	95.65%	93.63%	91.55%

Since 250, 500, 1000, 2000, 3000, and 6000 characteristics had been implemented for five-class classification, the two channels, Pz-Oz and Fpz-Cz, were used for the experiment. Table 4 demonstrates the application of the SVM and Random Forest algorithms, as well as the feature significance techniques. Using the SVM and Random Forest algorithm, 3000 and 2000 features yielded the best performance ratings of 89.19% and 87.19%, respectively. This indicated that the performance evaluation approach surpassed other operations [7], [11], [29], [30]. In Table 5 and Table 6, the tuning parameters used to classify sleep stages into 2–6 classes are observed. This confirmed that the tuning parameter affected the overall performance rating, and was noticeable in classification accuracy. These results were useful for implementing big data in health care, especially in medical diagnosis [6], [31].

Table 4 compares SVM and Random Forest classifiers using R&K criteria, which include feature importance and optimization, on a dataset. The accuracy of SVM is 98.21%, and Random Forest is 98.48%. Nonetheless, class findings reveal intriguing patterns. The classification accuracy of SVM for the alert state (AWA) is 98.21%, demonstrating its ability to distinguish alert from other sleep stages. The accuracy of SVM in Stage 1 sleep (N1) is 18.34%. This classifier needs help classifying N1 slumber. The SVM score for Stage 2 sleep (N2) is an impressive 85.13 percent. SVM performs well for combined Stages 3 and 4 sleep (N3) and Rapid Eye Movement (REM) at 78.10% and 78.86%, respectively. SVM and Random Forest classifiers are equally accurate but have distinct strengths and weaknesses. Random Forest classifies N2 as a good sleeper at 86.81%. It has an accuracy of 4.5% for N1 and 72.2% for N3 sleep stages. Unlike SVM, the classifier's performance during REM sleep is inferior at 61.65%. SVM may handle N1 and N3 sleep better than Random Forest. SVM and Random Forest classifiers perform well in classifying sleep stages on this dataset when R&K criteria are applied. SVM excels at identifying wakefulness, the N1 and N2 sleep stages, and N3 and REM sleep. Random Forest classifies N2 sleep more accurately than N1, N3, or REM sleep. These results suggest that combining the characteristics of various classifiers may improve the accuracy of sleep stage classification. The optimization of the classifier for all sleep stages may necessitate additional research and experimentation.

Table 4. The Performance of SVM and Random Forest Classifier with Feature Importance and Tuning Classifier (R&K Criteria)

Method	#Features	Total Accuracy per Class					Accuracy
		AWA	*N1 (S1)*	*N2 (S2)*	*N3 (S3+S4)*	*REM*	
SVM	**3000**	98.21%	18.34%	85.13%	78.10%	78.86%	**89.19%**
Random Forest	**2000**	98.48%	4.95%	86.81%	72.22%	61.65%	**87.19%**

Table 5 displays the efficacy of a 3000-feature SVM classifier before and after adjustment with the accuracy of classifiers for 2–6 classes. As classes are lost, the "Before Tuning" column gains accuracy. This demonstrates that the classifier can distinguish fewer classes more effectively than more. The accuracy of the 2-class scenario is 96.63 percent. The classifier excels in distinguishing between two classes. In contrast, adjusting the classifier enhances the accuracy of all class configurations in the "After Tuning" column. There are 0.21%–1.45% improvements. Presumably, tuning entails optimizing hyperparameters or modifying the model to enhance performance. Each class configuration enhanced classifier accuracy. The scenario with four classes showed the most significant accuracy increase, from 88.90% to 90.23 %. The tuning method enhances the efficacy of classifiers. It indicates that the accuracy of the classifier increases as the number of classes decreases. Tuning enhances the accuracy of classifiers in all class configurations.

Table 5. The Performance of SVM Classifier with 3000 features and Tuning Classifier

Total Number	Before Tuning	After Tuning
6 Classes	87.94%	**89.15%**
5 Classes	87.94%	**89.19%**
4 Classes	88.90%	**90.23%**
3 Classes	91.27%	**92.35%**
2 Classes	96.63%	**97.38%**

Table 6 depicts a Random Forest method with 2000 features before and after classifier adjustment with accuracy rates for two to six courses. Adjusting the classifier improves the efficacy of Random Forest. Tuning increases the accuracy of every classification. After adjusting, the algorithm's accuracy for six divisions increases from 84.86 percent to 85.26 percent. For five classes, adjusting increases precision from 86.91% to 87.11%. Improvement continues as classes reduce. Tweaking increases the accuracy of four classes from 87.91% to 88.14%. Two courses have the most significant increase in accuracy, from 95.93% to 96.00%. These results suggest that adjusting the classifier enhances the algorithm's performance, enhancing classification accuracy in all contexts. Adjusting the algorithm's parameters may increase classification precision, particularly for fewer classes. These findings highlight the importance of fine-tuning model parameters and iterative experimentation for advancing machine learning algorithms.

Table 6. The Performance of Random Forest with 2000 features and Tuning Classifier

Total Number	Before Tuning	After Tuning
6 Classes	84.86%	**85.24%**
5 Classes	86.91%	**87.19%**
4 Classes	87.91%	**88.14%**
3 Classes	90.41%	**90.63%**
2 Classes	95.93%	**96.01%**

4. Conclusion

The influence of feature importance and tuning parameter was analyzed and effectively proven on an EEG-based automated sleep stage identification system, using the R&K criterion. Using time-frequency analysis with high-dimensional FFT characteristics, promising results were obtained for feature extraction from EEG signals. Although each person's actions were recorded for nearly a full day (20–24 h) in the utilized dataset, the accuracy achieved has compensated for the uneven data to a greater extent than 88%. In addition, the processed features and the FP (feature priority) attribute increased to better evaluate performance with the 2-6 state classification. Based on the results, the value of accuracy on the utilized model was affected by the tuning parameter of the SVM and Random Forest classifiers. In this process, the SVM model outperformed the Random Forest by a significant margin, at 3000 and 2000 features, respectively. After analyzing the sleep-EDF dataset, this classifier also had maximum accuracy when classifying sleep stages, compared to the Random Forest model. From these results, the feature selection and importance techniques helped increase the performance evaluation of this automatic sleep stages classification, which used EEG signals. Irrespective of these merits, challenges were still observed regarding the acquisition of better accuracy from the brainwaves, to enrich the big data in healthcare.

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Declarations

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