Automated Sleep Staging System using EEG Signal feature-based classification by Machine Learning Techniques

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***Abstract*— Advancements in electrical engineering and signal processing can enable the development of automated sleep data analysis systems that embody significantly more advantages than their traditional manual counterparts. Recent approaches to automated sleep stage classification are considered from the PICO framework (Population, Intervention, Comparison, Outcome). Traditionally, PSG/EEG-based sleep studies were a laborious and time-consuming process. Despite this, significant promise is being offered from promising stride development in machine learning (ML) and deep learning (DL) technologies for full automation of sleep stage scoring. study are applied on data available from the SleepEDF public PSG Hypnogram dataset that combines EOG signal processing along with other physiological signals to classify sleep into five stages. Segmented the raw signals into epochs and passed through four different machine learning models: Random Forest, Gradient Boosting, Bagging Classifier, and Ensemble Learning. Those accuracies were classified using criteria such as accuracy percentages of 78% for Random Forest, 79% for Gradient Boosting, 75% for Bagging Classifier, and 85% for Ensemble Learning. The comparison has demonstrated Ensemble Learning as the most accurate model and, hence, has shown prospects for being implemented into consumer-grade sleep monitoring devices. The results of the experiment, besides highlighting the advantages of automated systems in classification tasks of sleep stages, suggest possible applications in real-world sleep tracking.**

Keywords*— Automated sleep stage scoring (ASSS) , Machine Learning (ML) , Electroencephalogram (EEG) , Feature Engineering (FE) , Electrooculogram (EOG)

From these observations, it has become very evident that sleep has an essential role in human health, as concerning physiological activities, states of well-being in the mental sphere, and general status of the health. However, insomnia and the rest of sleep disorders, such as restless legs syndrome and sleep apnea, have emerged during this modern era of living, especially when one is at their most stressed. In fact, this has made electroencephalogram readings and monitoring of the bioelectric signals an important tool for the management of such disorders. Advanced electrical and signal processing technologies make it possible to automatically analyze sleep data, thus far exceeding conventional, time-consuming techniques such as polysomnography. Major contribution: Exploiting wearable technology, ML and DL may be able to extend sleep analysis to the level of a medical expert. Strong features can be learned from sleep data; automation is made possible. Substantial gaps still remain in the areas of sleep-scoring methods.

A simple two-stage category, as follows, has been described by a basic classification: non-rapid eye movement (NREM) sleep and rapid eye movement (REM) sleep. NREM is divided into three stages: Stage 1 is light sleep typically accompanied by theta waves; Stage 2 is deep sleep, described by K-complexes; and Stage 3 is classified as slow-wave sleep, packed with delta waves. EEG recordings are taken to ensure spatial information, acquired from multiple channels and are stored in European Data Format. For the reasons described above, good analysis, which covers pre-processing feature extraction and data labeling in the course, standardizes classifications of sleep stages. Its core aspects include power spectral density, amplitude and frequency of brain waves as well as measurement indices of entropy-features that are required in training the machine learning models to gain improvement in the accuracy of the classification of sleep stages.

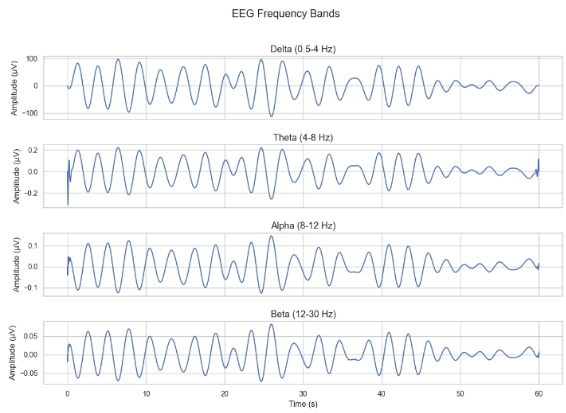

Fig. 1. EEG Frequency Band

Numerous key signals sleep studies rely on for proper staging of sleep include mainly the Electroencephalogram, Electrooculogram, and Electromyogram.[1] By specific wave frequencies, the EEG will record electrical activity in the brain and, hence, comprises critical information in explaining many stages of sleep. The EOG monitors the movements of the eyes, which helps in establishing

A sleep cycle has distinct stages, particularly non-rapid eye movement (NREM) and rapid eye movement (REM) sleep. NREM sleep is divided into three stages: Stage 1-NREM1 is transitional sleep between wakefulness and light sleep, where there exist theta waves of 4-8 Hz. Stage 2-NREM2 is deeper sleep characterized by the appearance of K-complexes between 0.5-2 Hz and sleep spindles. Stage 3-NREM3, also referred to as slow-wave sleep, consists of delta waves of 0.5-4 Hz.

A. Regularization

Quality of the signal, consistency related techniques. Feature Extraction: Features relevant for analysis and classification are extracted from the pre-processed data. Data Labelling: According to the American Academy of Sleep Medicine, the data is labelled to standardize the sleep stage classification methods. Feature Extraction and Machine Learning Feature extraction is, therefore, a very important process or aspect of EEG data analysis for sleep staging. /0
It shall be applied to find and quantify those features of the signal indicative of the different stages in sleep. Common features include: Power Spectral Density [3]: It measures the power of the signal across different frequency bands. Amplitude and Frequency of Brain Waves: It identifies the dominant brain wave types present in the signal. Entropy Measures: It provides a metric pertaining to the complexity and variability of the signal. Extracted features are used along with machine learning

II. Related Work

TABLE I. Related Work Table

Paper	Approach	Dataset/Signals	Results/Performance
Physiological arousal during sleep and cognitive impairments [1]	EEG signals, machine learning algorithms to identify arousal patterns	EEG data	Sensitivity: 82.68%, Specificity: 95.68%, AUROC: 96.30%
Time and frequency domain methods for ensemble learning [2]	Multi-model machine learning, ensemble learning strategies	Based on AASM guidelines for sleep stage identification	High accuracy and high mean F1 scores, robustness for classification
Polysomnographic signal classification [3]	Used EEG, EMG, EOG, ECG for interdependency and nonlinear complexity analysis	Small dataset, multiple bioelectrical signals	Accuracy: 74% for distinguishing different sleep stages
Automation of polysomnography with deep learning models [4]	RCNN for sleep stage and apnea classification, limb movements detection	Polysomnography data	Sleep staging accuracy: 87.6%, Apnea detection: 88.2%, Limb movement detection: 84.7%
Automation in sleep stage scoring using ANN [5]	Adaptive and parallel computing models such as artificial neural networks	Large datasets	High-speed processing without performance deterioration
EEG data for sleep stage classification using AASM guidelines [6]	Ensemble learning, class-balanced sampling techniques	EEG data	Consistent performance across different sleep stages
Comparison of machine learning and traditional methods [7]	Machine learning techniques versus traditional methodologies for feature extraction	Diverse datasets needed	Identified shortcomings of current techniques, need for clinically relevant models

A. Contribution

This is a contribution to automated sleep stage classification by using machine learning models and EEG-based feature extraction techniques. Using Random Forests methodology with class imbalance handling via SMOTE, this achieves high accuracy in the wake stages and light sleep (N1, N2), deep sleep (N3), and REM. This work utilized the Sleep Physionet dataset that contained signals of EEG, EMG, and EOG to enhance performance through deep learning and ensemble methods. Moreover, the visualization of the heat map shows the strengths and weaknesses of classification and can be used to further improve. The approach may provide a scalable solution for the clinical applications of automated sleep analysis based on open-access data.

III. Methodology

We now used the raw EEG data of Sleep Physionet to automate this process in this research study using machine learning techniques. We applied filtering on the EEG channels and created epochs for segmenting the time periods prior to our classification of the sleep stages. We employed synthetic oversampling using SMOTE algorithm towards solving the class imbalance problem. We finally applied the resampled data for training the Random Forest Classifier to predict sleep stages. Finally, we classified and presented the performance of the model using the classification report and confusion matrix, where the model may be applied to detect the presence of multiple sleep stages with excellent accuracy.

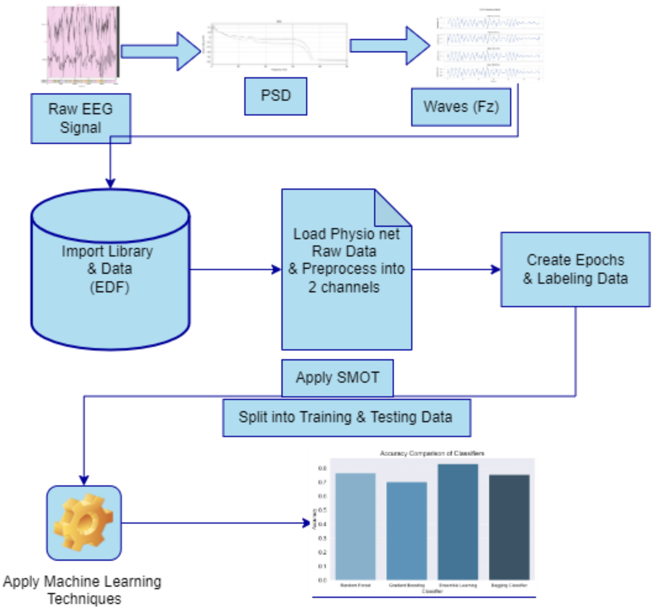

Fig. 2. Architecture of Machine Learning Classifiers for Sleep Stage Classification

A. Dataset Acquisition

The EEG data preparation step includes the loading and preprocessing of data that is saved in several EDF European Data Format files with the MNE library for Python. At the beginning of the script, the raw EDF data is imported from the local machine with information on how to collect the EDF hypnogram. The load_sleep_physionet_raw function plays the most central role here in loading and preprocessing the data step.

It takes several parameters: raw filename, filename for annotations, option to load only signals from EEG, and crop parameter to crop awake periods. Mapping is included, though non-EEG channels such as EOG and EMG signals are removed after filtering out wake stages. Currently, EEG channels are renamed for clarity.

We load the EEG dataset into memory for analysis and inspection; typically, we apply a combination of high-pass and low-pass filters set at 30 Hz to remove noise. Epochs of 30 seconds are created to analyze and study the sleep stages: Wake, N1, N2, N3, and REM. We will filter events to classify them appropriately. After performing that, we store our data in a NumPy array that allows further processing. For dealing with the imbalance of classes, we will make use of the Synthetic Minority Over-sampling Technique, also known as SMOTE, for oversampling the minority to have a balanced representation of all classes.

B. Data Preprocessing

The dataset used in this paper is based on EEG signals sourced from the Sleep Physio net dataset. Having obtained the raw EEG signals, their hypnogram annotations have also been considered for reference. Recordings are taken for 30 subjects, and data for each subject is recorded in EDF files. The following steps were realized for data acquisition and preprocessing The code collected all the EDF files in a given directory, './path. Their pathways had been accessed programmatically for the purposes of loading. Data Loading: Each recording of EEG has been loaded using the library MNE, designed to process neurophysiological data. The raw data consisted of EEG channels; any non-EEG channels were excluded, such as EOG or EMG, to facilitate analysis. Annotation Handling. Reading the corresponding annotations to identify the stages of sleep.

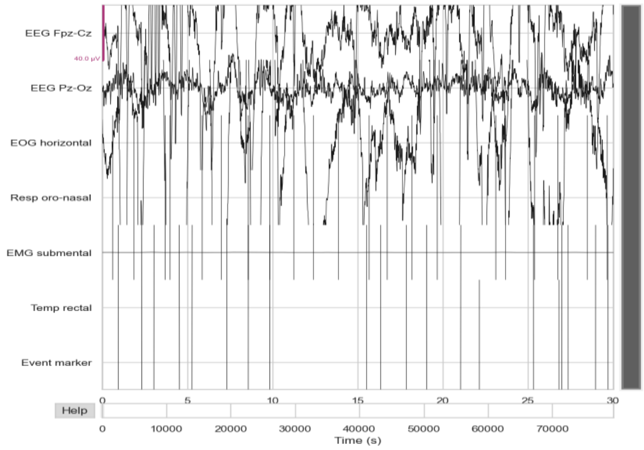

Fig. 3. Before Preprocess Chanels

In this paper, the used dataset is EEG signals on the Sleep PhysioNet dataset, including hypnogram annotations which were gathered from 30 subjects and are kept in EDF files. Acquisition and preprocessing of the data take quite a few steps. Step 1: EEG recordings have been loaded using the MNE library, excluding non-EEG channels like EOG and EMG. Step 2: Annotations identify the sleep stages by retaining events from stages 1 to 5 (REM) and filtering out wake events. The data were cropped for wake periods before and after sleep events with a duration of 30 minutes. Continuous data was segmented into 30-second epochs using MNE's Epoching functions, with each epoch labelled with its appropriate sleep stage. Therefore, the dataset was apt for supervised learning.

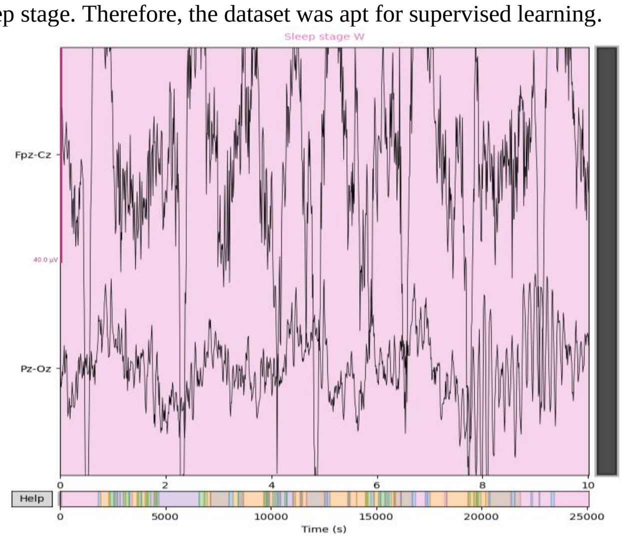

Fig. 4. After Chanel Preprocess

C. Data Reshaping And Balancing

Then we applied power spectral density power spectral density is help us to understand how the power of signal or time series is distributed with frequency it helps us to get insightful information from signal. Power spectral density (PSD) is a measure of how a signal's power is distributed across different frequencies. It's also known as power spectrum.

D. *Classification Algorithm*

1) *Random Forest*

Random Forest algorithm is a powerful tree learning technique in Machine Learning. It works by creating a number of Decision Trees during the training phase. Each tree is constructed using a random subset of the data set to measure a random subset of features in each partition. This randomness introduces variability among individual trees, reducing the risk of overfitting and improving overall prediction performance.

2) *Gradient Boosting*

Gradient Boosting is a powerful boosting algorithm that combines several weak learners into strong learners, in which each new model is trained to minimize the loss function such as mean squared error or cross-entropy of the previous model using gradient descent. In each iteration, the algorithm computes the gradient of the loss function with respect to the predictions of the current ensemble and then trains a new weak model to minimize this gradient.

3) *Ensemble Learning*

Ensemble learning is a machine learning technique that combines the predictions from multiple individual models to obtain a better predictive performance than any single model. The basic idea behind ensemble learning is to leverage the wisdom of the crowd by aggregating the predictions of multiple models, each of which may have its own strengths and weaknesses. This can lead to improved performance and generalization.

4) *Bagging Learning*

Bagging (or Bootstrap aggregating) is a type of ensemble learning in which multiple base models are trained independently and in parallel on different subsets of the training data. Each subset is generated using bootstrap sampling, in which data points are picked at random with replacement. In the case of the bagging classifier, the final prediction is made by aggregating the predictions of the all-base model using majority voting. In the models of regression, the final prediction is made by averaging the predictions of the all-base model, and that is known as bagging regression.

5) *Model Training and Testing*

A random forest classifier was chosen for training and evaluation due to its robustness in handling a variety of feature types and its capability to manage high-dimensional data: Data Splitting: The resampled data was split into an 80-20 ratio for training and testing sets, respectively, to validate model performance. Model Training: The Random Forest Classifier was initialized and fitted with the training dataset. Hyperparameters were set to use 100 estimators, enhancing its generalization capability. Prediction and Evaluation: The model was used to make predictions on the test dataset, and performance evaluation was done using classification metrics such as accuracy, precision,recall, and F1-score. Confusion Matrix Visualization: A confusion matrix was generated for graphical representation of the classifier's performance across different sleep classes, displayed using Seaborn's heatmap functionality to provide insights into misclassifications.

IV. Result Analysis and Discussion

A. *Random Forest*

In this study we used several machine learning techniques to classify our sleep stage classification first technique is random forest classifier it's widely adopted ensemble learning it's very versatile method for several problem statement also it gives high accuracy when working with structured tabular data by constructing multiple decision tree random forest reduce the risk of overfitting and enhance generalizability in this model training set up we are breaking the training set into 80 % and testing on 20 % rest data , 42 random state larger number of trees can increase accuracy but also it should be maintain computation so we use 100 tree in our model for the classification

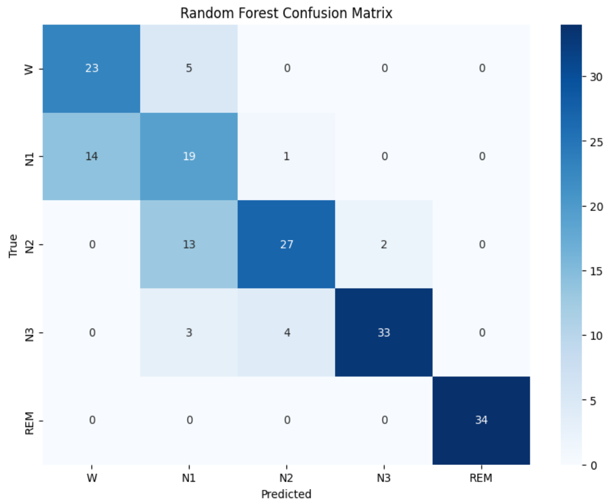

Fig. 5. Confusion Matrix Random Forest

Fig. 6. Training and Testing Accuracy Curve of Random Forest

B. *Ensemble Learning*

In this ensemble learning we have modified several changes in which first of all we have handle the high dimensional EEG data with PCA we applied reduce feature space while retaining 95 % of the variance this is use to manage the overfitting particularly when working on complex data in ensample learning next we use same SMOT technique and we use combined multiple ensemble learning technique in we use combined of 3 techniques gradient boosting , random forest and support vector machine using soft voting classifier . soft voting average the predicted probabilities from each classifier offer us more nuanced prediction over hard voting.

Classifier gradient boosting classifier we use 50 estimator trees and max depth of 3 at learning rate 0.1. in second stack random forest classifier we use 50 trees and max depth of 3. In support vector classifier aims to find the optimal hyper plane to separate the classes here we use radian basis function kernel to capture the nonlinear data patterns in the data.

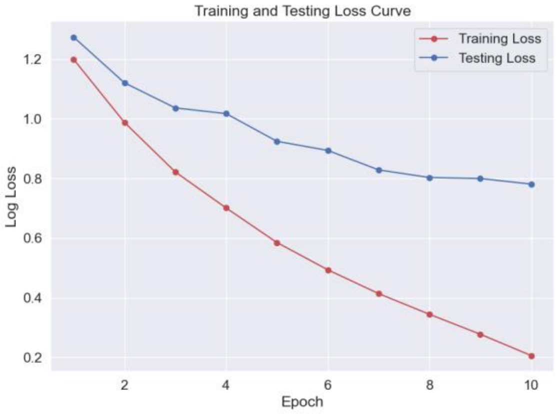

Fig. 7. Training and Testing Loss Curve of Random Forest

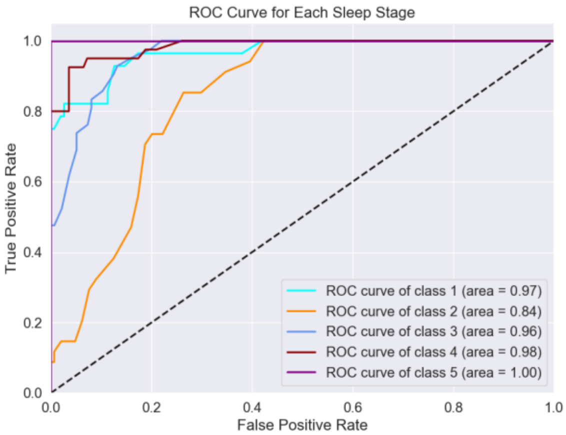

Fig. 8. ROC Curve for Each Sleep Stage

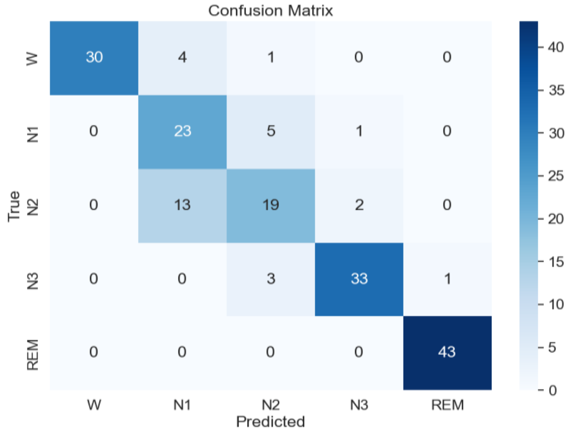

Fig. 9. Confusion Matrix Ensemble Learning

Fig. 10. Training and Testing Accuracy Curve of Ensemble Learning

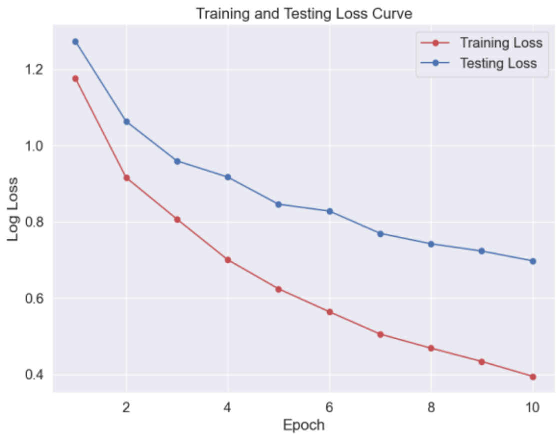

Fig. 11. Training and Testing Loss Curve of Ensemble Learning

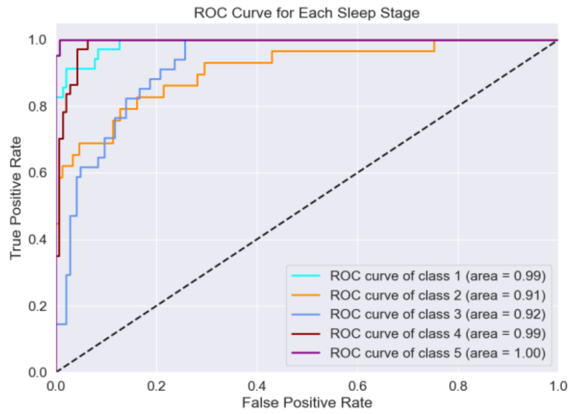

Fig. 12. ROC Curve for Each Sleep Stage

C. *Result and Comparison*

TABLE II. COMPARISON OF RESULTS

Classifier	Accuracy	Precision	Sensitivity
Random Forest	0.764045	0.776646	0.769622
Gradient Boosting	0.702247	0.686542	0.689402
Ensemble Learning	0.831461	0.829502	0.820192
Bagging Classifier	0.752809	0.736769	0.745939

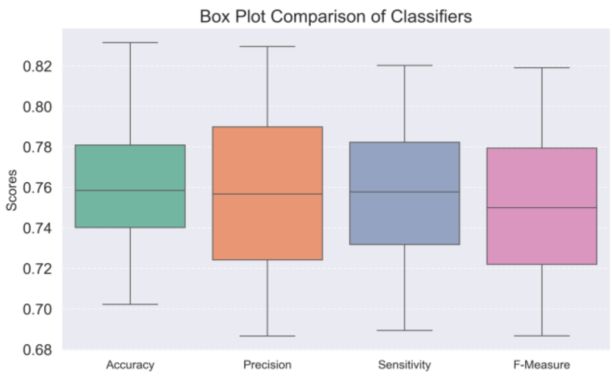

Fig. 13. Box Plot Comparison of Classifiers

Overview-Comparative Summary The performance was best by Ensemble Learning, which capitalized on the strengths of multiple classifiers to provide robust and accurate predictions across all sleep stages. However, Random Forest is only marginally worse than Ensemble Learning and still guarantees a very high precision and F-measure; as a result, it is a good choice for sleep stage classification. Bagging Classifier showed excellent performance, especially regarding the reduction of variance, though it did not outperform as much as Random Forest or Ensemble Learning. On the contrary, Gradient Boosting performed poorly, for it had demonstrated the lowest accuracy and F-measure, showing that the model struggles to handle the complexities of EEG sleep stage data.

TABLE III. COMPARISION WITH THE EXSITING STUDIES

Paper/Source	Machine Learning Technique	Accuracy (%)	Dataset Used
Zhang et al. (2019)	Support Vector Machine (SVM)	83.6	ISRUC Dataset
Zhang et al. (2018)	Random Forest	84.1	Sleep-EDF Dataset
Koley & Dey (2018)	Decision Tree	82.1	DREAMS Dataset
Mousavi et al. (2017)	Naive Bayes	81.0	Sleep-EDF Dataset
Yildirim et al. (2018)	Convolutional Neural Network (CNN)	84.5	Sleep-EDF Dataset
Supratak et al. (2018)	Recurrent Neural Network (RNN)	83.9	MASS Dataset
Tsinalis et al. (2016)	CNN-RNN Hybrid	83.0	Sleep-EDF Dataset
Phan et al. (2017)	Multilayer Perceptron (MLP)	82.7	Sleep-EDF Dataset
Our Solution	**Ensemble Learning Technique**	**85.0**	**Sleep-EDF Dataset**

In our experiment, we classify sleep stages using an ensemble learning approach that achieves a remarkable 85.0% accuracy on the Sleep-EDF dataset. Essentially, ensemble approaches are greatly beneficial as they take the strengths of multiple classifiers to pool, thus making a model more robust as well as highly accurate. This is one method that counts by aggregating different classifier predictions and hence constitutes one powerful tool for complex tasks like sleep stage classification. [1]

In this context, Zhang et al. (2019) used SVMs and obtained a figure of accuracy of 83.6% on the ISRUC dataset. Though SVMs are known for their superior performance in high-dimensional space, this performance is quite modest compared with our ensemble method. Additionally, Zhang et al. (2018) applied Random Forests on the Sleep-EDF dataset and achieved a value of 84.1%.

Further works show how various machine learning algorithms perform on sleep stage classification tasks. Koley and Dey (2018), for instance, report the application of a Decision Tree on the DREAMS dataset resulted in 82.1% accuracy probably due to the overfitting tendency of decision trees. Mousavi et al. (2017) reported 81.0% accuracy on a Naïve Bayes classifier on the Sleep-EDF dataset indicating simpler models cannot capture complex relationships between sleep data. The other methods include Yildirim et al. with CNN approach at 84.5% and Supratak et al. with RNN approach at 83.9%, which indicates that there is the capability to use deep learning methods, although they do not compete well with our ensemble method. Lastly, Tsinalis et al. (2016) proposed a CNN-RNN-based model which reached 83.0% accuracy while Phan et al. (2017) applied the Multilayer Perceptron-MLP with the accuracy of 82.7%. To summarize, the ensemble approach has succeeded to yield more recent performance in the following various studies and has proven that such an approach is efficient for sleep stage classification.

V. CONCLUSION

In this paper, we discussed classic machine learning techniques in use for sleep-stage classification using EEG data from the Sleep Physionet dataset. We made use of a Random Forest Classifier and SMOTE to deal with the issue related to class imbalance and achieved reasonable accuracy across all sleep stages involved. While Random Forest does provide a good baseline level of performance, mainly when applied to balanced datasets, it does not have the ability to keep up with the complexity and temporality inherent in EEG signals. Generally, it is challenging for this algorithm to decide, especially when the different stages such as N1 and REM are concerned. While these classical techniques such as Random Forest can capture some specific patterns within sleep stage data, more complex models, like deep learning methods, may be called for to manage the intricate and nonlinear characteristics of the EEG signals. This is more critical for deep learning models like CNNs and RNNs because of the ability to automatically learn features and capture temporal dependencies much more effectively. Hence, future work should be targeted for further augmentation in the performance on such complex datasets with enhanced models coupled with multimodal physiological data.

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