SLEEPING ABNORMALITIES DETECTION USING DEEP LEARING TECHNIQUE

Mr.K.SATHEESHKUMAR MCA, M.Phil,
SANTHOSH S, ANANTHANAYAKI S, SWATHIPRIYA K

Department of Computer Science and Engineering

University College of Engineering, Thirukkuvalai
(A constituent College Of Anna University::Chennai and Approved by AICTE, New Delhi)

ABSTRACT

Maintaining proper health and mental stability is critical for overall health and wellbeing. Despite a good deal of research investment, sleep quality continues to be a crucial public challenge. Nowadays, people of all age groups are affected by improper sleep quality. Poor sleep can lead to a variety of neurological disorders. Sleep disorders are common in all subsets of the population, independently of gender. This public health challenge greatly affects quality of life in terms of both physical and mental health. Insomnia, parasomnias, sleep-related breathing difficulties, hypersomnia, bruxism, narcolepsy, and circadian rhythm disorders are some common examples of sleep-related disorders. Some of these disorders can be treated with proper analysis of early symptoms; in such cases, adequate sleep quality is essential for the patient's recovery. Artificial intelligence has several applications in sleep medicine including sleep and respiratory event scoring in the sleep laboratory, diagnosing and managing sleep disorders, and population health. While still in its nascent stage, there are several challenges which preclude AI's generalizability and wide-reaching clinical applications. Artificial intelligence is a powerful tool in healthcare that may improve patient care, enhance diagnostic abilities, and augment the management of sleep disorders. However, there is a need to regulate and standardize existing machine learning algorithms and deep learning algorithm prior to its inclusion in the sleep clinic.

KEYWORDS: Artificial intelligence, Insomnia, Machine learning, Deep learning, Sleeping stage

1. INTRODUCTION

Sleep is the brain's primary function and plays a fundamental role in individual performance, learning ability, and physical movement. One of the essential physiological processes of humans is sleep vital for physical and cognitive well-being and resurgence. Sleep is a reversible state in which the eyes are closed, and several nerve centres are disabled. Sleep creates partial or unique or full anaesthesia for the individual, in which case the brain becomes a less complicated network.

The gold standard of sleep analysis, Polysomnography (PSG), includes measurements of several body functions, including brain activity and heart rhythm. The sleep stages are then manually classified. These factors cause the method to have high accuracy, but also makes it costly. The fact that the procedure is usually conducted in a sleep laboratory or hospital can have a negative impact on the sleep quality of the subject, in addition to the discomfort of wearing the equipment. This is a weakness because the goal is usually to analyse the normal sleep patterns of the subject. Another way to analyse sleep is actigraphy. An actigraphy is a body-worn sensor, consisting of a three-dimensional accelerometer and possibly other sensors.

The body movements data can be analysed in a variety of ways. Because of the inexpensive equipment and low intrusiveness of the method, it is preferable in some situations, for instance when the subjects are children, when data collection for several days is necessary, or when a large group of people is participating in a study. In this research work, an effective and robust method is applied to classify the sleep stages automatically based on the selected optimal set of features with an ensemble learning stacking model. The main purpose of this study is to analyse the effectiveness of selected features with a combination of ensemble learning for multi-class sleep stages classification problems. The proposed approach considers two different categories of sleep recordings which include subjects' effects with different types of sleep related disorders and the other category is subject having complete healthy control. The proposed work is divided into two phases, in the first phase identifying the suitable features from the extracted feature vector through obtaining different selection algorithms. In the second phase, an ensemble learning stacking model is considered for the classification of the sleep stages

Today, PSG is done to identify various disorders based on the analysis of sleep stages, the main component of which is the measurement of brain activity with EEG signal. Sleep disorders include several disorders associated with various symptoms such as insomnia, respiratory disorders, behavioural and motor-related sleep disorders that significantly affect EEG signals. By classifying the different stages of sleep, the correct diagnosis of sleep-related disorders can be achieved. After recording the EEG signal, feature extraction, and analysis of the signal recorded in a specified range, a classification algorithm to identify the sleep stage is used. However, improving the classification accuracy and reducing complexity are two main challenges in the classification of sleep stages. Fig 1 shows the different stages of sleeping cycles.

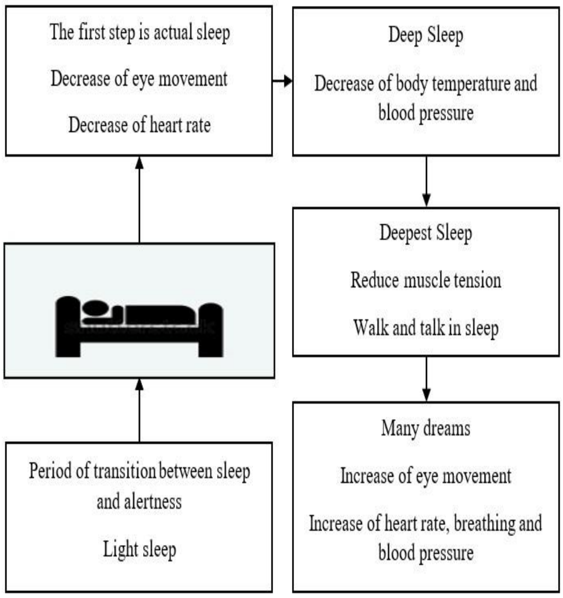

Figure 1: Different stages of Sleep

2. RELATED WORK

Malik, Asra, et al, … [1] have used both ECG and EMG signals for the detection of Insomnia. Our proposed model is based on rational classification and analysis of ECG and EMG signals acquired by non-invasive and minimal-cost sensors. The advanced method is accurate in the identification of Insomnia. In this method, integrating ECG and EMG signals with derived features and classifiers has provided 100% accuracy but the system needs to be realized on hardware which needs further investigation. The Cyclic Alternating Pattern (CAP) database from Physio net is used. Pre-processing by empirical mode decomposition (EMD) is carried out in this research. Features with high discriminative ability are extracted from signals to classify via logistic regression (LR), support vector machines (SVM), K-nearest neighbour (KNN), decision tree (DT), ensemble classifier (EC), and Naïve Bayes (NB) classification methods. we have achieved the highest accuracy of 100% on both ECG and EMG signals from our proposed methodology.

Yang, Bifan, et.al,…[2] proposed a 1DCNN model for automatic insomnia identification based on single-channel EEG labelled with sleep stage annotations, and further investigated the identification performance based on different sleep stages. Our experiments demonstrated that our 1D-CNN leveraging the 3 sub datasets composed of REM, LSS and SWS epochs, respectively, achieved higher average accuracy in comparison with baseline methods under both intra-patient and inter-patient paradigms. The experimental results also indicated that amongst all the sleep stages, 1D-CNN leveraging REM and SWS epochs exhibited the best insomnia identification performance in intra-patient paradigm, whereas no statistically significant difference was found in inter-patient paradigm. And conducted experiments under intra-patient and inter-patient paradigms, respectively. Our experiments demonstrated that our 1D-CNN leveraging 3 sub datasets composed of REM, LSS and SWS epochs, respectively, achieved higher average accuracies in comparison with baseline methods under both intra-patient and inter-patient paradigms.

Kuo, Chih-En, et.al,…[3] implemented a short-time insomnia detection system based on a single-channel sleep EOG with RCMSE analysis was proposed. First, a single-channel sleep EOG was filtered with a band pass filter to remove artifacts. Second, the RCMSE values with a scale factor of 1 to 8 were extracted from the all-night sleep EOG in 30-s epochs to compare the differences between the healthy and insomnia groups. Third, the RCMSE values from the first 27.5 min, with scale factor of 1 to 9 were used to compute its mean values as the input of classifier. Finally, the support vector machine (SVM) was used to detect insomnia. In addition, MSE and RCMSE were applied to analyse the sleep EOG signals from subjects belonged the different groups, and the MSE and RCMSE values with different sleep stages were also compared between the healthy and insomnia groups

Andresini, Giuseppina, et.al,…[4] outlined a set of open challenges facing modern ML-based intrusion detectors relating to a lack of uniformity in the distribution of traffic data over time. To tackle them, we propose INSOMNIA, a semi-supervised approach that uses active learning to reduce latency in the model updates, label estimation to reduce labelling overhead, and applies explainable AI to describe how the model evolves to fit the shifting distribution. We extend the TESSERACT framework to perform a time aware evaluation of INSOMNIA on a recently published, revised version of CICIDS2017 and demonstrate that modern intrusion detection systems must address concept drift in order to be effective. We envision that future work may build on INSOMNIA in order to design robust intrusion detection models that can be sustained over time.
To evaluate INSOMNIA, we extend TESSERACT—a framework originally proposed for performing sound time-aware evaluations of ML-based malware detectors—to the network intrusion domain and show that accounting for drift is vital for effective detection. Sharma, Manish, et.al,[5] have used a small number of subjects to develop the model. This 321 is one of the limitations of this work. We intend to use more data with a greater number of subjects to validate our developed system in the future. We are also planning to explore the possibility of developing a deep learning model using huge database. Further, we also plan to extend this work using CAP database with other physiological signals such as multi-modal EEG and EOG. Some other disorders such as bruxism and narcolepsy, nocturnal frontal lobe epilepsy (NFLE), periodic leg movement (PLM), rapid-eye movement (REM) behavioural disorder and sleep disordered breathing can also be detected using such automated models. Sleep disorders such as sleep movement disorders, nocturnal front lobe epilepsy, insomnia, and narcolepsy are caused due to low sleep quality. Insomnia is one such sleep disorder where a person has difficulty in getting quality sleep. There is no definitive test to identify insomnia; hence it is essential to develop an automated system to identify it accurately. A few automated methods have been proposed to identify insomnia using either polysomnogram (PSG) or electroencephalogram (EEG) signals. To the best of our knowledge, we are the first to automatically detect insomnia using only electrocardiogram (ECG) signals without combining them with any other physiological signals.

Lee, Mi Hyun, et.al,…[6] investigated the differential spatial covariance pattern of blood oxygen level-dependent (BOLD) responses to single-task and multitask functional magnetic resonance imaging (fMRI) between patients with psychophysiological insomnia (PI) and healthy controls (HCs), and evaluated features generated by principal component analysis (PCA) for discrimination of PI from HC, compared to features generated from BOLD responses to single-task fMRI using machine learning methods. In 19 patients with PI and 21 HCs, the mean beta value for each region of interest (Rival) was calculated with three contrast images (i.e., sleep-related picture, sleep-related sound, and Stroop stimuli). We performed discrimination analysis and compared with features generated from BOLD responses to single-task fMRI. We applied support vector machine analysis with a least absolute shrinkage and selection operator to evaluate fve performance metrics: accuracy, recall, precision, specificity, and F2. Principal component features showed the best classification performance in all aspects of metrics compared to BOLD response to single-task fMRI. Bilateral inferior frontal gyrus (orbital), right calcarine cortex, right lingual gyrus, left inferior occipital gyrus, and left inferior temporal gyrus were identified as the most salient areas by feature selection.

Afshani, Mortaza, et.al,…[7] provides evidence that structural and functional brain measures can help to distinguish two common subtypes of ID from each other and from healthy subjects. Moreover, we observed that the multimodal brain measure is a bit better than the unimodal brain measure to separate ID subtypes. Insomnia disorder (ID) is a prevalent mental illness, which is associated with poor quality of life, an increased rate of motor vehicle accidents, depressive symptoms, emotion dysregulation, and memory impairment. Several behavioural and neuroimaging studies suggested that various subtypes of ID are existing. However, the neurobiological underpinnings of ID subtypes are poorly understood. Here, we aimed to assess whether unimodal and/or multimodal whole-brain neuroimaging measurements can discriminate between two of the commonly described ID subtypes (i.e., paradoxical and psychophysiological insomnia) and healthy subjects. We obtained T1-weighted images and resting-state fMRI from 34 patients with ID and 48 healthy controls. The outcome measures were voxel-wise values of grey matter volume, cortical thickness, amplitude of low-frequency fluctuation, degree centrality, and regional homogeneity. Subsequently, we applied support vector machines to classify subjects via unimodal and multimodal measures

Islam, Md Muhaiminul, et.al,…[8] shows that Logistic regression model performed best compared to other models. It will be very much handy in real-life prediction for its outstanding cross-validation score. But still, there have been some limitations in this study. For the lack of time, we were unable to gather massive data. Though the accuracy of our model is great but if we could gather more data, it could be greater. Again, this study is done basically done for predicting chronic insomnia in humans. So, feature was selected according to external symptoms only. If we had collected data on regular habits or lifestyle (smoking, drinking, level of using radio-wave devices) then it could be determined also that which factors cause insomnia and the work would be much beneficial. Our thoughts upon this work are not limited just in here. If we have enough scope in the future, we could complete this works also. But this kind of approach is not only expensive but also time-consuming. Expensive tests and equipment are also not available in many developing countries. To bridge this gap, we have decided to build an intelligent model based on a machine learning approach that is able to predict chronic insomnia. For acquiring best results 7 different machine learning classifiers were used where our Logistic regression model outperformed all of them.

Ma, Xiaofen, et.al,…[9] present study demonstrated the nodal functional connectivity strength predicted unseen individuals' sleep quality in both short-term/acute and chronic insomnia. We further revealed changes in the functional connectivity pattern during the transition from the short-term/acute insomnia to chronic insomnia. The study may have clinical value by informing the diagnosis of sleep quality of insomniac patients, and may provide novel insights into the neural basis underlying the heterogeneity of insomnia. Using 29 short term/acute insomnia participants and 44 chronic insomnia participants, we used whole brain regional functional connectivity strength to predict unseen individuals' Pittsburgh sleep quality index (PSQI), applying the multivariate relevance vector regression method. Evaluated using both leave-one-out and 10-fold cross validation, the pattern of whole-brain regional functional connectivity strength significantly predicted an unseen individual's PSQI in both datasets.

Wen, Ze-Ying, et.al,…[10] highlights that HDWI patients had abnormal neural activities in the right MOG and right cerebellum, which might be potential neural markers for distinguishing HDWI patients from non-insomniacs, providing further support for the pathological mechanism of HDWI. Insomnia is one of the common problems encountered in the haemodialysis (HD) population, but the mechanisms remain unclear. we aimed to (1) detect the spontaneous brain activity pattern in HD patients with insomnia (HDWI) by using fractional amplitude of low frequency fluctuation (fALFF) method and (2) further identify brain regions showing altered fALFF as neural markers to discriminate HDWI patients from those on haemodialysis but without insomnia (Hoài) and healthy controls (HCs). Resting-state functional magnetic resonance imaging (rs-fMRI) is a non-invasive technique, which could detect the ongoing neuronal process at the "resting state" through measuring the spontaneous brain activity by low-frequency fluctuations in blood oxygen level-dependent (BOLD) signals, and consequently provide a new opportunity to investigate the functional abnormalities on several neurological disorders

3. MOTIVATION

The function of human body is frequently associated with signals of electrical, chemical, or acoustic origin. Such signals convey information that may not be immediately perceived because it is hidden in the signal's structure. However, signals' complexity is often considerable and therefore, the biomedical signal processing has become a vital tool for extracting clinically significant information hidden in signals. The artefacts such as body movements, sweating and sensor fault can reduce the accuracy in signal processing especially in sleep signal analysis. The conventional solution is to detect the artefacts and denoise the signal by removing corresponding epochs from the sleep signal. However, this way, the EEG signal will be manipulated and may lose important information. One of the motivations of this thesis is to develop and improve noise cancelation method that does not manipulate the signal and protect its originality. Deep learning is an emerging technique that can be applied to a broad field of science in order to improve learning and classification algorithms. Deep learning is rarely used to classify bio signals and still there is a lack of applying this technique to sleep staging problems. It is proven that shallow learning techniques are not adequate tools to discriminate among stages (e.g. still there is accuracy reduction in detecting S1).

4. PREPROCESSING

The presence of artefacts might lead to the misapprehension, low accuracy and distorted quantitative results. Therefore, a pre-processing step is necessary to cancel artefacts and remove cropped epochs to magnify informative components of raw EEG, EOG and EMG signals prior to any further analysis. Considering the fact that nowadays portable devices for patient monitoring and automatic sleep stage classification could be a helpful assistance for experts on the analysis of sleep signals, the main motivation for the current work is the lack of a systematic method for automatic artefact detection and cancellation which leads to an improvement in the automatic stage classification accuracy compared to the original acquired data

5. MULTIPLE CLASSIFIERS FOR SLEEPING STAGE CLASSIFICATION

Classification is the process of categorizing data into relevant groups. The first step in the classification process is the identification of features or characteristics that will enable the discrimination between the different groups of data. A classification model should be developed in a way that provides a structure for how the classification processes' actions will be realized. Ideally, this model should be chosen to optimize the system performance, although it may need to be revised as the classifier design progresses. A classifier is then implemented and "trained" to recognize the chosen features in the data, or to determine the best input-to-output mapping. Generally, there are two ways to train a classifier: supervised learning and unsupervised learning. A system is called supervised learning if it uses data labelled by the expert to create an optimal response for the system, which is used as feedback to the learning system to increase accuracy. In contrast, unsupervised learning occurs when the system does not use any labelled data to modify its output. Once the system has trained and learned, it is ready to recognize and classify specific inputs. It can be tested and evaluated with such metrics as speed of computation and accuracy of classification.

5.1 CONVENTIONAL CLASSIFIERS

Several papers provide evidence for the high performance of Support Vector Machine (SVM) specifically for high dimensional classification problems. In principle, SVMs are designed for binary classification problems (discrimination between two classes). However, as in many classification tasks, automatic sleep scoring requires discrimination between multiple classes (Awake, S1, S2, S3 and REM). Hence, for getting benefit from the assumed advantages of SVM classification, a multi class SVM framework needs to be implemented. Two of the most widely used approaches for multi-class SVM classification are the One-Against-All (OAA) and the One-Against-One (OAO) approaches. The OAA framework consists of using a binary SVM to distinguish each class from all other classes and the decisions obtained by applying a winner takes-all strategy. SVM techniques are often proposed for anomaly detection and decision-making tasks in healthcare services. However, SVM is not an appropriate method to integrate domain knowledge to use metadata or symbolic knowledge seamlessly with the measurements from the sensors. Moreover, like other classifiers, SVM cannot be applied to find the unexpected information from unlabelled data.

5.2 DEEP LEARNING APPROACHES

Unlike some of the machine learning areas such as natural language processing and object classification, the potential of deep learning techniques is not fully explored in automatic sleep stage classification. This fact is also noticeable when it comes to the feature transformation for sleep scoring. By the commonly adopted machine learning tradition naturally deep learning techniques classify into deep discriminative/supervised models 81 (e.g., deep neural networks (DNNs), RNNs, convolutional neural networks (CNNs), etc.) and generative/unsupervised models (e.g., restricted Boltzmann machine (RBMs), deep belief networks (DBNs), deep Boltzmann machines (DBMs), regularized autoencoders, etc.). The third category belongs to the class of hybrid deep network structures, which refers to the deep architecture that either comprises or makes use of both generative and discriminative model components. This two-way classification scheme, however, misses a key insight gained in deep learning research about how generative or unsupervised-learning models can greatly improve the training of DNNs and other deep discriminative or supervised-learning models via better regularization or optimization. deep learning has been proposed for unsupervised feature learning and has been applied to many domains, such as biomedical signals. One of the major advantages of deep learning compared to traditional approaches is that they can work directly on raw data and do not require any tuning or hand-crafted features. Instead, they can learn their own feature representations.

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5.3 CONVLUTIONAL NEURAL NETWORK

Convolutional Neural Network (CNN) A CNN is a multilayer perceptron designed specifically to recognize two dimensional shapes with a high degree of invariance to translation, scaling, skewing, and other forms of distortion. Learning section of this classifier is done in supervised method which includes the following structure:

- Feature extraction;
- Feature mapping;
- Subsampling;

The weights in all layers of a CNN are learned through training. Also, the network learns to extract its own features automatically

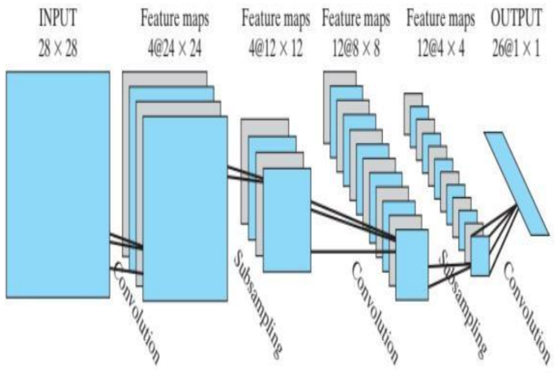

Fig 2: Convolutional neural network framework

This diagram shows the multiple layers such as input layer, four hidden layers, and an output layer. This network is designed to perform image processing. The input layer consists of 28×28 sensor neurones, receives the images of different characters that have been approximately centred and normalized in size. We can use the CNN algorithm framework to classify multiple sleeping stages.

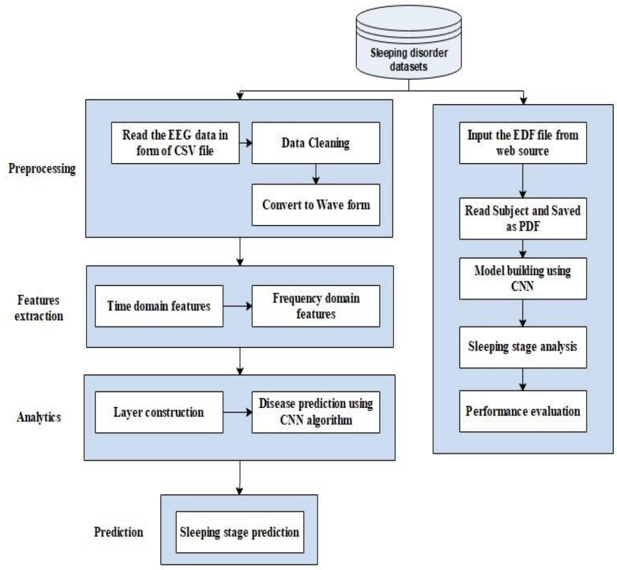

Fig 3: Proposed Work

The proposed work shown in fig 3 to analyse two types of datasets such as CSV file and EDF datasets. Then perform CNN algorithm to classify the sleeping stage with improved accuracy rate.

6.EXPERIMENTAL RESULTS

In this study we can input the EEG datasets related to sleeping stages and developed in Python framework. Accuracy as main criterion is considered for evaluating and comparing the different classification methods. The performance of the sleep stage classification is evaluated using repeated random sub-sampling validation. To measure the classification accuracy, the overall accuracy value is calculated as follows

$$\text{ACCURACY} = \frac{\text{Number of true detections}}{\text{Total number of epochs}}$$

ALGORITHMS	ACCURACY (%)
SUPPORT VECTOR MACHINE	60
DEEP NEURAL NETWORK	65
CONVOLUTIONAL NEURAL NETWORK	70

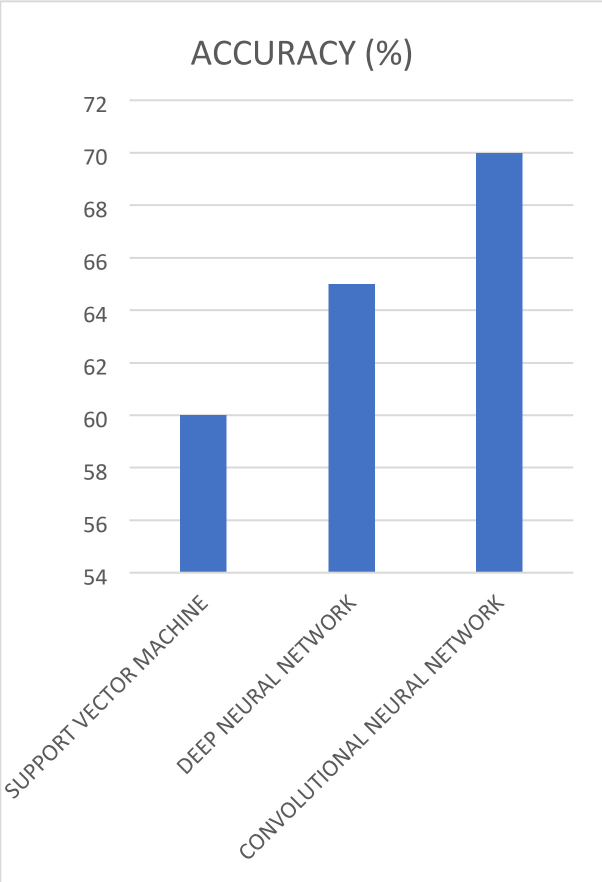

Fig 3: Accuracy

From the diagram, convolutional neural network provides the improved accuracy than the existing frameworks

7. CONCLUSION

In this work, we presented an automatic sleep stage classification model that could achieve good performance on the public dataset and accurately predict the sleep stage on our own laboratory dataset. There are many solutions for classification of sleep signals. In this paper, we proposed two methods and explored their utility and benefits in the study of sleep. Convolutional neural network provides improved performance than the existing machine learning and deep learning.

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