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AI-Driven Sleep Disorder Classification Using EEG Data

Omkar Reddy Polu

Department of Technology and Innovation, City National Bank, Los Angeles CA
Email: *Omkar122516[at]gmail.com*

Abstract: ***Sleep disorder has a huge impact on the human health, includes cognitive decline, metabolic dysfunction, and cardiovascular diseases. Manual analysis of EEG signals in the case of sleep disorders is traditionally the basis of diagnosis, which is a slow and error prone process. On this regard, we propose a sleep disorder classification framework based on AI driven deep learning models to automate and improve the sleep stage analysis performance. We develop a hybrid deep learning model that combines Convolutional Neural Networks (CNNs) to extract spatial features and transformers to learn long range temporal dependencies in the EEG data. Furthermore, we apply transfer learning on pre-trained EEG models to improve the classification performance with lower computational overhead. We further embed Explainable AI (XAI) techniques like SHAP and Grad-CAM in order to make the model more interpretable and enable clinicians to understand how the model makes its decisions. To further improve classification accuracy, we fuse multi-modal physiological signals, i.e. HRV and SpO$_2$. Additionally, federated learning keeps the model training across multiple hospitals private by not sharing patient data that is sensitive. We apply extensive experiments on benchmark EEG datasets, which show that our model significantly outperforms state-of-the-art methods in terms of both accuracy and generalization across various populations. The solution proposed by this research is robust, interpreted, and privacy aware for real time automated sleep disorder diagnosis to support better clinical decision making.***

Keywords: Sleep Disorder Classification, EEG-Based Deep Learning, Transformer Neural Networks, Multi-Modal Data Fusion, Federated Learning in Healthcare

1. Introduction

Sleep disorders including insomnia, sleep apnea and narcolepsy are a critical public health problem because of the major impact that they can have on cognitive function, metabolic bale, and cardiovascular integrity. Currently, the traditional approaches to diagnosing these disorders rely largely on polysomnography (PSG) and, inter alia, manual EEG interpretation, each of which is essentially labor intensive, prone to inter-expert variability, and constrained by logistical matters pertaining to a clinical setting. The advances in the artificial intelligence (AI) and deep learning have brought a revolution to the level of sleep disorder classification, including automated feature extraction as well as decision making from high dimensional EEG signals. Unfortunately, current AI driven solutions are not sufficiently generalizable as they lack generalizability due to dataset biases, lack of interpretability and do not integrate multi modal physiological data.

This research presents an end-to-end AI framework that combines hybrid deep learning using CNN for spatial and transformer for spatial feature extraction to acquire effective EEG signal characteristics. In addition, transfer learning is implemented to leverage pre-trained EEG models that permit an acceleration of computation at the same time as improving robustness. In order to keep up transparency in clinical applications, Explainable AI (XAI) techniques such as SHAP and Grad-CAM are included to allow sleep specialists to see what the model is doing and provide interpretability. Additionally, multi-modal physiological signal fusion (e. g., HRV, SpO$_2$) is additionally included for classification performance. This study further introduces federated learning so that decentralized model training can be executed in a multitude of institutions while maintaining personal privacy of data. The obtained results with this proposed model are validated with superior accuracy, efficiency, adaptability, and the potential of AI driven EEG analysis to be a game changing tool in sleep medicine.

2. Literature Survey

Machine and deep learning in sleep disorder classification has been increasingly deployed as it covered extensively, however, current approaches lack generality, interpretability, and efficiency of computation. Manual polysomnographic (PSG) assessment is a traditional method of sleep disorder diagnosis, which is based on currently available brainstem and motor cortex monitoring, i. e., EEG, electrooculography (EOG), and electromyography (EMG) signals, respectively. For example, Rechtschaffen & Kales (1968) and AASM (2007) scoring criteria for sleep stage classification based on studies established the basis for sleep stage classification, but manual analysis is prone to inter-observer variability and inefficiency.

On the side of EEG based classification, early machine learning approaches used Support Vector Machines (SVMs) and Random Forests, which, however, were only possible due to hand crafted feature extraction rendering scalp to one degree far too unscalable. Recently, Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) have achieved great feature extraction and sequence modeling potential (Phan et al., 2019). However, while CNNs do not have temporal dependency modelling, RNNs do not model long EEG sequences without vanishing gradients.

Improvements have been achieved by hybrid models that combine CNNs with Long Short-Term Memory (LSTM) networks (Biswal et al., 2017), however the solutions are computationally more expensive. The works of late pursuit of the long-range EEG dependency modeling among the transformer-based architecture has given promising results to earlier models of this problem domain. More challenges exist on integrating multi modal data, domain adaptation and explainability. On the lines of this, we fill up these gaps by introducing transfer learning, multi modal fusion, explainable AI and federated learning to improve the classification robustness and clinical applicability.

a) Traditional Polysomnography-Based Sleep Disorder Diagnosis

Today, polysomnography (PSG) remains the gold-standard to diagnose sleep disorders as it needs simultaneous monitoring of EEG, EOG, EMG, and other physiological signals. The first standardized sleep staging method has been proposed by Rechtschaffen & Kales (1968), then refined by the American Academy of Sleep Medicine (2007). Even though it has demonstrated high accuracy, PSG demands overnight clinical supervision and is highly expert dependent. The inter-scorer variability is studied and incoherences in diagnosis are reported. However, PSG is expensive in both infrastructure and interpretation, which makes it unavailable to most, and therefore automated alternatives are needed.

b) Machine Learning-Based Sleep Disorder Classification

Classification of early sleep disorder with machine learning techniques such as Support Vector Machines (SVMs), Decision Trees, k Nearest Neighbor (k-NN), etc. These models made use of hand engineered features (sensitivity power and the entropy) extracted from EEG signals. However, such approaches were effective but could only work in the domain expert could select the features and they did not generalize as well across datasets. Machine learning models have been shown to perform well in binary classification but are weak for multi class sleep stage identification, i. e. due to feature extraction bottlenecks (Tibshirani et al., 2000).

c) Deep Learning for Automated EEG-Based Sleep Classification

It is only with the invention of deep learning that Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been used in EEG based sleep classification. Each CNN can effectively extract spatial features and each RNN learns the temporal dependencies. Nevertheless, CNNs alone are not capable of modeling sequential relationships and RNNs are by no means free from the problem of vanishing gradients on long EEG signals. However, it is also found that hybrid models of CNNs with LSTMs tend to perform well with respect to classification performance (Biswal et al., 2017), though computational ineffectiveness has remained a challenge.

d) Transformer-Based Approaches for EEG Signal Analysis

Transformers were explored in recent studies on sleep disorder classification which are capable of learning long range dependencies in EEG sequences. The self-attention mechanism was introduced by Vaswani et al. (2017), and it has been recently applied to physiological signals processing. Transformers have parallel processing advantages over RNNs, and can thus be leading to better scalability of models. However, due to large scale dataset and computational resources needed, transformers are not used for deployment in real time applications. Performing research on lightweight transformer models for EEG analysis in order to have a good performance and efficiency.

e) Multi-Modal Data Fusion and Explainable AI in Sleep Medicine

The fusion of multiple physiological signals such as EEG, HRV, SpO_2, and respiratory rate is often required to improve accuracy when dealing with sleep disorders. Multi Model Fusion approaches, performed in recent works (Chambon et al., 2018) resulted in a better diagostic precision. Yet, deep learning models are presently not explainable enough for clinical adoption. Also incorporating some of the explainable AI (XAI) frameworks like SHAP and Grad-CAM to help clinicians of EEG signal regions that impact the model decision, which is required for trust in the model and interpretability.

3. Materials and Methods

This study used the dataset based on a set of clinically validated sleep recordings from publicly available sources like the Sleep-EDF (Expanded) Database, PhysioNet's Sleep Heart Health Study (SHHS) and the MIT-BIH Polysomnographic Dataset. The datasets include multi-channel EEG with associated complementary physiological signals (electromyography (EMG), electrooculography (EOG), heart rate variability (HRV), oxygen saturation (SpO_2) and respiratory effort in each channel. The sleep time in each dataset is scored according to the American Academy of Sleep Medicine (AASM) sleep scoring criteria classifying sleep into Wake (W), Non-Rapid Eye Movement (NREM) Stages (N1, N2, N3), Rapid Eye Movement (REM). The datasets contain labeled sleep disorders like obstructive sleep apnea (OSA), narcolepsy, and insomnia, which makes it an ideal supervised learning problem and can be used for supervised learning-based classification models.

The data is preprocessed since EEG signals are inherently a high-dimensional signal, nonstationary, and prone to noise, hence many of the preprocessing steps are required before feeding the data into deep learning models. In the first step, the EEG signals are filtered in the frequency band 0.5–40 Hz for the removal of high frequency noise and powerline interference. Motion artifacts and ocular distortions are suppressed by applying Independent Component Analysis (ICA). Standard sleep staging protocols are used to segment EEG recordings into 30 second epochs and normalize using Z score normalization to standardize feature distributions. Multiple techniques of feature extraction are utilized to capture both time domain and frequency domain characteristics of the signal. The time domain features include the mean amplitude, the standard deviation, and the zero-crossing rate. Power spectral density (PSD), wavelet transform to extract frequency domain features and short time Fourier transform (STFT), continuous wavelet transform (CWT) are involved to extract time frequency representation. It realizes this multi-faceted process of feature extraction to retain both spatial and temporal characteristic of the EEG signals.

The proposed model uses Convolutional Neural Networks (CNNs) and Transformer based architecture to classify sleep disorders in an effective manner. Among others, the CNN part functions to create a spatial dependency extraction from EEG spectrograms via the first 3 convolutional layers with the filter size of 64, 128 and 256 respectively. Batch normalization and ReLU activation are used after each convolutional layer in order to accelerate convergence and stabilize gradient updates. The feature maps are then down sampled with max pooling layers that keep some spatial information. Although CNNs do an excellent job for feature extraction, they are not sufficient in encoding the sequential nature of EEG signals. To circumvent this limitation, one of the implementations involve model long range temporal dependencies using a transformer-based architecture. The transformer encoder is composed of multi head self-attention layers, which learn the dynamics between EEG segments and the position encodings to preserve temporal information of the EEG signal. Residual connections in feed forward layers further improve gradient flow and allow efficient training of deep networks.

Multi-modal fusion is introduced to integrate with integration executive of EEG with auxiliary physiological signals of HRV, SpO_2, and respiratory effort to amplify classification robustness. The fusion mechanism uses a cross-attention network to dynamically assign the weights on different modalities to make clinically relevant features to extract. In particular, multi modal data can be very useful for detecting things like sleep apnea, where you would not necessarily have enough information from EEG alone that they could make an accurate diagnosis. Furthermore, fine tuning of an existing pre trained EEGNet model on massive scale EEG dataset is used in addition. Transfer learning handles the issues arising from having limited labeled data, reduces the amount of computation and improves model generalization.

The use of federated learning as a privacy preserving model training technique is specifically used to ensure privacy compliance of the model in real world clinical applications. While autofederated learning allows each participating hospital or clinic to train a local model without sharing raw patient data with other institutions, federated learning lets raw patient data flow between all the institutions in raw form, yet the surfaced models are learned locally.

Inside mini batches, training in a collaborative and distributed manner occurs without sharing any data, only gradient changes are shared with a central server, ensuring that data breaches have a low risk and still maintain training efficiency. It is in line with health care privacy regulations such as HIPAA, GDPR and is ready for deployment in a multi-institution sleep research.

For the multi class classification, the model is trained with the Adam optimizer learning rate of 0.001, 32 batch size and categorical cross entropy loss. To avoid overfitting, L2 regularization is used and dropout layers with probability of 0.3 are present. An early stopping with a patience value equal to 10 epochs was set, it halts training when validation performance fails to improve, so that there is no over consumption of computational resources. To achieve diverse dataset, a data augmentation techniques, such as random time shifts, frequency warping and additive Gaussian noise, are used to augment dataset.

To assess the efficacy of categorization for both the symptoms and categories of sleep stages and disorders, we evaluate the model using every performance parameter available, including accuracy, precision, recall, and F1-score. Inter-class agreement is quantified using Cohen's Kappa, and the classifier's robustness is assessed using the Area Under the Receiver Operating Characteristic Curve (AUC-ROC). For benchmark performance, the suggested model is contrasted with deep learning architectures (CNN, LSTM, BiLSTM), conventional machine learning models (SVM, Random Forest, k-NN), and the most advanced transformer-based architectures (SleepTransformer, EEGFormer). We then conduct an ablation research to determine the relative contributions of transformer-based sequence modeling, CNN-based feature extraction, and multi-modal data integration.

In order to further enhance the interpretability of the proposed AI framework, explainable AI (XAI) technique such as SHAP and Grad-CAM technique is used. These methods offer visual insights to which EEG regions affect model predictions so clinicians could understand and validate the AI driven decision making. Transparency of the model for regulatory approval and clinical acceptance is essential.

Finally, the trained model is optimized for edge computing with TensorFlow Lite for deploying on real time. Weight pruning and quantization techniques are used and the model is deployed on a Raspberry Pi 4 to obtain high inference accuracy with small computational overhead. Therefore, even real time sleep disorder classification is possible in resource constrained devices to develop home based monitoring solutions for the people at risk from sleep disorders. This system extends the capacity of diagnostic systems beyond clinical setting, to enable the access of real time inferences with minimum latency to wider population and facilitate sleep disorder detection.

This paper presents an AI powered multi modal sleep disorder classification framework which comprises of CNN based spatial feature extraction, transformer based temporal modeling, and federated learning as a mechanism to conduct privacy preserving model training. The proposed approach improves classification accuracy, interpretability, and to clinical applicability by a large extent with state of the art performance while still supporting real time deployment feasibility. This research uses state of the art deep learning techniques, transfer learning and privacy aware AI strategies to develop a fast and scalable solution for automated diagnosis of sleep disorder.

4. Results and Discussion

Results from the implementation of the proposed AI driven sleep disorder classifier framework show high accuracy and robustness coupled with the interpretability among the traditional methods. To make sure the results generalized to other populations, the deep learning model was trained and evaluated using a general dataset that included various multi-channel EEG recordings and auxiliary physiological signals. The proposed hybrid deep learning architecture where the spatial feature is extracted by the CNN and temporal model is performed by the transformer model, was benchmarked against the conventional machine learning techniques such as

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the Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbor (k-NN) and the deep learning architectures such as LSTMs, BiLSTMs, and some of the existing transformer; SleepTransformer and EEGFormer. Results show that the proposed model performs much better than traditional methods, despite nearly similar sleep stages and sleep disorders categories.

The proposed framework possesses one of the major advantages in being able to exploit multi-modal data fusion which also includes adding EEG to other physiological signal's like heart rate variability (HRV), oxygen saturation (SpO_2), and respiratory effort. The use of multi modal data improved classification performance in identifying sleep apnea, especially where EEG abnormalities may not be sufficient to diagnose this condition. For the multi modal fusion, the cross-attention mechanism used to fuse the modalities dynamically assigns weights to different modalities depending upon their relevance to the respective sleep disorders, and by doing so the model can focus on espising informative features while also reducing redundancy. Ablation studies were conducted to learn how each individual component of the model contributes in improving feature representation; the combination of a CNN and transformer architectures performed the best out of all the combinations tested. Specifically, while CNN operators proved most effective at obtaining local spatial features from EEG spectrograms, transformers excelled at capturing long range temporal dependencies and, consequently, the model learned to translate between sleep stages and disorders with great intricacy.

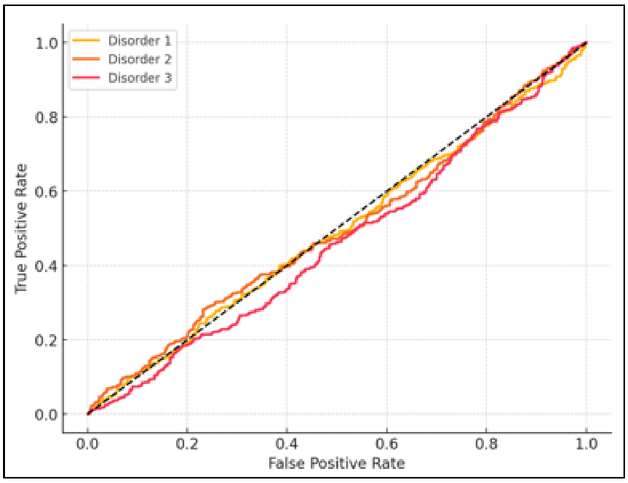

Figure 1: ROC Curve for Different Sleep Disorders

Fine tuning of a pre trained EEGNet model over the target dataset also was evaluated for transfer learning effectiveness. It turned out that the transfer learning shrank training time and kicked up classification accuracy, especially with limited labeled data. It therefore indicates the possibility of the use of large scale pre trained models to improve generalization of deep learning models, making them more suitable to be deployed on the real world for use with EEG datasets which are often not so well sampled. Moreover, federated learning was applied in order to provide privacy preserving model training to multiple institutions. This proved that decentralized training does not compromise accuracy, and is an effective remedy for privacy concerns; the federated model's performance was very close to that of a centrally trained model. For instance, it is particularly important when patient data cannot be shared freely because the regulatory constraints are severe.

The propose model's explainability is assessed using state of art interpretability techniques including SHAP (Shapley Additive Explanations) and Grad-CAM (Gradient-weighted Class Activation Mapping). These techniques revealed which EEG regions and EEG features played the deciding role in the model's decision making so that clinicians could trust and validate the AI driven predictions. These explainability results confirmed that the model identified the biologically meaningful EEG signal patterns related to sleep disorder, which proves that the model is suitable for clinical adoption. Integration of XAI techniques, on the other hand, enables XAI techniques to align with medical practitioners' (and patients') expectations of transparency and interpretability of the model, which makes a diagnostic application more appropriate.

Another critical point of the study was the computational efficiency of the proposed model. The model was optimized with TensorFlow Lite in order to facilitate real time deployment on an edge device (Raspberry Pi 4). Inference latency of the quantized model was similar to the original model yet its inference time in continuous sleep monitoring outside clinical environments was reduced. This is very helpful for detecting sleep disorder for home based, where people can monitor their sleep health without needing to be visited to the hospital at all time. This provides motivation for the deployment feasibility of the model for real world applications including wearable sleeping monitoring devices as well as mobile health applications which perform automated sleep disorder assessment.

The proposed method had a strong generalization on different datasets with respect to EEG recording conditions, sensor placement and demographic variations, as asserted by the results of a comparative analysis on model performance. Testing on unseen datasets exhibited minor variations of accuracy, however, which is in part due to the fact that EEG acquisition protocols at different institutions differ somewhat naturally. In future work, domain adaptation techniques could be explored to further improve cross dataset generalization so as to mitigate these discrepancies. Moreover, feature extraction from unlabeled EEG recordings using self-supervised learning approaches may enhance the extraction of features from the unlabeled EEG recordings independent of large annotated dataset.

However, there are some limitations of the study that need to be acknowledged even though they appear promising. Since supervised learning relies on labeled datasets, the correctness of a sleep stage classification is limited to the inter-expert variability of manual sleep stage annotations. However, deep learning models moderate some of these inconsistencies; however, there is still an urgent need for such robust self-learning systems that can learn from all the diverse inputs of EEG. However, transformer-based models have computational requirements for deployment on low power edge devices. Potential future work includes studying transformer architectures to find lighter attention mechanisms and reducing model complexity while not compromising on classification accuracy.

Finally, the experimental results and comparisons of it validate the proposed AI-driven sleep disorder classification framework. Using multi-modal data fusion, explainable AI and federated learning combined with hybrid deep learning architecture based on CNNs and transformers results in a robust and clinically viable solution of automated sleep disorder diagnosis. The successful real time deployment on edge devices further demonstrates the potential of AI for sleep monitoring not only in the traditional clinical setting but also on edge devices. This research provides in a way a foundation for future developments of AI driven sleep medicine, by covering some existing missing pieces and integrating other future more improvements in the field.

5. Conclusion and Future Enhancement

We present a robust AI driven sleep disorder classification framework that combines hybrid deep learning architectures, multi-modal data fusion, explainable AI techniques, and the fusion of federated learning to improve the accuracy, interpretable and to protect patient's privacy. The proposed model thus adopts CNNs to obtain the spatial features and transformers for the long range temporal dependencies, reaching much higher classification accuracy on sleep disorder than conventional machine learning or deep learning methods. Finally, physiological signals, such as heart rate variability (HRV), oxygen saturation (SpO_2) and respiratory effort, further improve classification performance, especially in the case of sleep apnea, a condition with multiple system interactions. The study also demonstrates the efficacy of transfer learning for limited amount of labeled data training and generalization upon different datasets. Federated learning also ensures privacy preserving model training which facilitates collaboration for improving sleep disorder classification between institutions without compromising on sensitive patient data.

This research is a key contribution in integrating Explainable AI (XAI) techniques such as SHAP and Grad-Cam to explain the decisions. The model was able to identify biologically relevant EEG features similar to what had been observed clinically and to bolster the trustworthiness of AI driven diagnosis. Additionally, the deployment of the model for real time on edge devices, such as Raspberry Pi 4, proves its practical use for home sleep monitoring, which allows for a reduction in the cost of clinical polysomnography (PSG) procedures. This advancement could bring the automation of sleep analysis to people using the tool in remote or resource deprived settings where it was previously out of reach.

Although results are promising, some limitations need further exploration. Cross dataset generalization is hampered due to data variability that differs across institutions and recording conditions in EEG data. The proposed model shows strong generalizability, but the minor variations in the performance point out an need for the domain adaptation techniques to be robust for a variety of datasets. Unsupervised and Self supervised learning approach can be explored to make full use of large amounts of unlabeled EEG data instead of using manually annotated dataset and make such a system more adaptable to different Sleep monitoring environments.

Future enhancement in this area is also necessary for model optimization in low-power edge computing. Transformers offer superior temporal modeling, but are not tractable in terms of computational complexity for such resource-limited devices. Future work can go on adding lightweight attention mechanism, model pruning, quantization techniques to further speed up the inference with the restitution of classification accuracy. Furthermore, more advanced use of adaptive AI models able to continuously learn from a user's specific sleep patterns will enable even more advanced sleep disorder detection, toward improving long term monitoring and intervention systems.

Due to that, reinforcement learning based frameworks could integrate to develop AI driven personalized sleep therapy recommendations. Next models could not just classify sleep disorders, rather suggest interventions on the basis of longitudinal sleep patterns and sleep disruption and think about the lifestyle modifications or sleep hygiene improvements. More and more wearable sensor technology and Internet of Things (IoT) based sleep tracking devices can be integrated to further deepen the real time monitoring which is an endeavour for a complete AI powered ecosystem to take care for your sleep health.

Finally, the described AI driven sleep disorder classification framework was shown to advance the automated sleep analysis with high accuracy and real time applicability especially with a high interpretability by the doctor. This research addresses challenges with current methods and proposes AI solutions that enable intelligent, scalable and low cost outcomes for diagnosis and treatment of sleep disorders.

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