Using Novel EEG Phenotypes and Artificial Intelligence to Estimate OSA Severity

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Introduction & Motivation

- 10-25 million EEG studies are performed annually to monitor and diagnose neurological conditions including epilepsy, seizure disorders, TBI, stroke, and others.
- Ambulatory EEG, EEG-video monitoring, continuous EEG, and long-term EEG monitoring typically result in one or more full nights of EEG data during sleep.
- The severity of disordered breathing is understood to correlate with the degree of sleep fragmentation and disruption of normative sleep architecture.
- We leverage artificial intelligence methods that have achieved breakthrough performance in related domains with a large clinical EEG dataset to explore our hypothesis that neurological phenotypes that highly correlate with sleep disordered breathing can be extracted from overnight EEG recordings.
- We further hypothesize that these EEG phenotypes can be used to accurately estimate a patients OSA severity, without accompanying cardiopulmonary data.

Methods & Study Sample

- We used cross-sectional analyses of adult patients (N = 4,650) who completed an overnight PSG study.
- All signals were excluded from analysis except the 10/20 EEG sensor array, to simulate an ambulatory or video-EEG acquisition for the present study.
- Global phenotypic features were derived from EEG study sleep architecture and fragmentation profiles.
- Local phenotypic features were derived by analyzing biomarker patterns and respiratory cycle-related EEG changes exhibited in the EEG signals directly.
- AI methods including Bidirectional-LSTM, Deep-CNN, and a combination of both were trained, optimized, and evaluated to model the relationship between global and local EEG phenotypes and OSA severity.
- Performance for predicting moderate and severe OSA (AHI ≥ 15) was evaluated using randomized 10-fold cross-validation.

Extensions to In-patient Sleep Monitoring

- Increasing awareness and clinical evidence have demonstrated sleep deprivation and fragmentation in the ICU and in-patient care settings contribute to increased risk for delirium and length-of-stay.
- Enables opportunity to introduce in-patient sleep monitoring into ICU research and clinical practice.

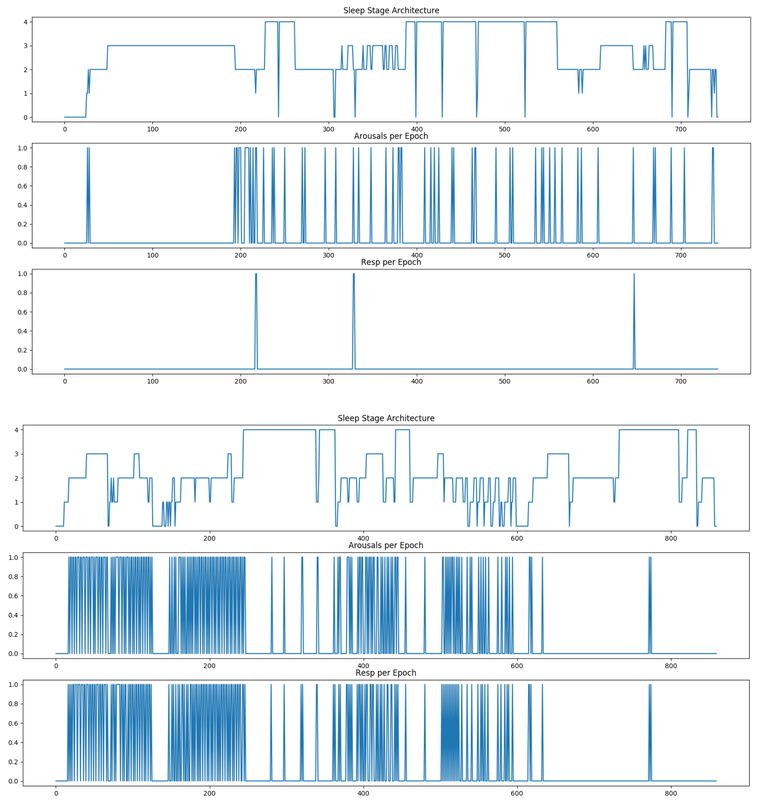
OSA Severity Estimation Results and Statistical Analysis

Performance and Statistical Significance of EEG based OSA Severity Estimation

A randomized 10-fold cross-validation was applied to an EEG dataset extracted from N = 4,650 in-lab sleep studies to predict moderate to severe OSA (AHI >= 15) using Deep Convolutional Neural Networks (DCNN), Bi-directional Long-Short Term Memory Networks (B-LSTM), and a combined DCNN-BLSTM network learning architectures:

- The best performance was obtained by a combination of the B-LSTM and DCNN architectures (DCNN-BLSTM), with an average accuracy, sensitivity, and specificity of 91%, 86%, and 99% respectively for predicting moderate to severe OSA.
- The runner-up best performance was observed from the DCNN model, with an average accuracy, sensitivity, and specificity of 84%, 88%, and 87% respectively.
- Based on statistical analysis of two-sided 95% bootstrap percentile confidence intervals, statistically significant differences were observed in the level of performance of the top DCNN-BLSTM model relative to DCNN and BLSTM models respectively.

Machine Learning Model	Sensitivity	Specificity	Accuracy
DCNN-BLSTM	86.9%	99.5%	91.1%
Deep Convolutional Neural Network	84.2%	87.9%	86.8%
Bi-directional LSTM Network	70.6%	98.3%	87.6%



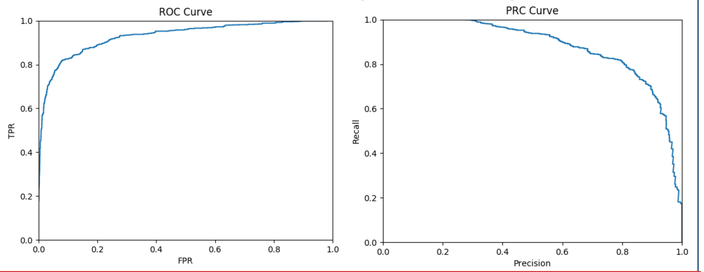
Top: Ex. Sleep-Arousal Architecture estimated low-risk for OSA by AI model (AHI <= 15)
Bottom: Ex. Sleep-Arousal Architecture estimated high-risk OSA by AI model (AHI >= 15)

Flexibility of Predictive Performance Characteristics

Analysis of Variation of AI Model Discrimination Threshold

We analyzed the statistical characteristics of the machine learning models using a Receiver Operating Characteristic Curve (ROC) and Precision-Recall Curve (PRC) to elucidate architecture-specific performance advantages and flexibility:

- Bi-directional LSTM model learns temporal relationships over multiple timescales that contribute to model performance.
- Deep CNN model learns multi-scale feature representations of local and global input data that contribute to performance.
- Combined DCNN-BLSTM model learns multi-scale temporal relationships between multi-scale feature representations, enabling architectural benefits from both learning paradigms.
- Observed ROC-AUC and PRC-AUC values confirm tunability of statistical performance characteristics based on use-case.
- Existing, validated methods are used today for screening and referring high-risk OSA candidates for diagnostic evaluation: STOP-BANG (SB), Epworth Sleepiness Scale (ESS), 4-Variable screening tool (4-V), and others.
- Given the complimentary nature to these existing screening methods and the prevalence of OSA in EEG study indicated populations, we hypothesize a high-specificity configuration may optimize for clinical utility and patient outcome benefits to enable “passive” OSA screening for all overnight EEG studies.



Discussion & Conclusions

- This and prior work have demonstrated a promising opportunity to estimate OSA severity with a host of EEG study types using applied artificial intelligence.
- Future research involving a cohort of ambulatory EEG subjects, controlled for OSA severity, can validate the efficacy of this approach in the clinical setting.
- With further validation, AI based risk estimates could be incorporated into diagnostic EEG reports, providing clinicians with an additional means for identifying patients with moderate and severe OSA that may benefit from follow-up diagnosis and treatment.
- Future work will also focus on practical considerations to operationalize sleep referrals that originate from an EEG study in terms of prior-authorization and related issues.