Pediatric Automatic Sleep Staging: Deep Learning Ensemble Improves Accuracy and Reduces Predictive Uncertainty

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Abstract—Despite the tremendous progress recently made towards automatic sleep staging in adults, it is currently unknown if the most advanced algorithms generalize to the pediatric population, which displays distinctive characteristics in overnight polysomnography (PSG). To answer the question, in this work, we conduct a large-scale comparative study on the state-of-the-art deep learning methods for pediatric automatic sleep staging. A selection of six different deep neural networks with diverging features are adopted to evaluate a sample of more than 1,200 children across a wide spectrum of obstructive sleep apnea (OSA) severity. Our experimental results show that the individual performance of automated pediatric sleep stages when evaluated on new subjects is equivalent to the expert-level one reported on adults. Combining the six stages into ensemble models further boosts the staging accuracy, reaching an overall accuracy of 87.7%, a Cohen’s kappa of 0.837, and a macro F1-score of 84.2% in case of single-channel EEG when evaluated on new subjects. The performance is further improved when dual-channel EEG-EOG are used, reaching an accuracy of 88.8%, a Cohen’s kappa of 0.852, and a macro F1-score of 85.8%. At the same time, the ensemble models lead to reduced predictive uncertainty. The results also show that the studied algorithms and their ensembles are robust to concept drift when the training and test data were recorded 7-months apart and after clinical intervention. Detailed analyses further demonstrate “almost perfect” agreement between the automatic stagers to one another and their similar patterns on the staging errors.

Index Terms—Automatic sleep staging, pediatric, OSA, deep learning, ensemble, benchmark.

I. INTRODUCTION

Assigning a sleep stage to each 30-second epoch of a full overnight polysomnogram (PSG) is a critical to assess the macrostructure of sleep, i.e., to observe sleep cycles, quantify the time spent in each sleep stage, and determine REM onset latency and wake after sleep onset (WASO). Sleep stages and cycles serve as an important proxy for neuro-physiological processes that orchestrate sleep and provide diagnostic markers for sleep disorders [1]. For instance, differentiation of sleep stages and sleep stage transitions are used to quantify sleep continuity in patients with obstructive sleep apnea (OSA) syndrome [2], a common sleep disorder in both adults [3] and children [4]. Patterns of sleep-stage transitions [5] and REM sleep onset [6] are important indicators for narcolepsy, a rare central hypersomnia. Traditionally, sleep staging has been carried out manually by sleep technicians following the American Academy of Sleep Medicine (AASM) guidelines [7]. Since manual scoring is time-consuming, laborious, and requires expert knowledge, significant efforts went into teaching a machine to perform sleep staging to reduce costs and make PSG diagnostics more widely available.

The advance of deep learning [8] coupled with the establishment of large-scale public sleep databases [9], [10] has accelerated automatic sleep staging research. Now, automatic sleep staging systems [11]–[17] relying on the new sequence-to-sequence paradigm [11] have surpassed the agreement level of experts’ scoring [18], reaching an accuracy acceptable for clinical applications. Importantly, this class of sleep staging algorithms has been validated almost exclusively on adult PSGs. How they perform on pediatric PSGs, in particular on clinical populations with OSA, remains uncharted. Evaluating these algorithms on the pediatric PSGs is crucial given their considerable discrepancies to the adult ones. For example, EEG of children shows higher amplitude and a slower dominant posterior rhythm than the alpha rhythm seen in adults [19]. Furthermore, the sleep architecture in children exhibits significant differences among age subgroups. For example, the amount of REM and slow wave sleep changes dramatically during infancy, childhood and adolescence. Also, children tend to move more during sleep than adults, affecting the quality of the recorded data adversely, possibly imposing greater challenges on automated systems. Thus, it is imperative to benchmark established algorithms on the pediatric PSG.

In this work, we aim to determine if the expert-level performance of the state-of-the-art sleep scoring algorithms is generalizable to the pediatric population. To this end, we conduct a comparative study to benchmark six different automatic sleep staging algorithms on a large clinical-validated pediatric cohort of $>1,200$ children with $>1,600$ PSG recordings in total. All children underwent PSG screening for OSA, displaying a wide range of OSA severity, including negative, mild, moderate, and severe cases. The algorithms adopted in this study adhere to the sequence-to-sequence framework [11] and manifest diverging characteristics on their input types and network architectures. They include XSleep-Net1 [13], XSleepNet2 [13], SeqSleepNet [11], DeepSleepNet [20], FCNN-RNN [13], and SleepTransformer [16], which were recently reported to achieve state-of-the-art performance on a variety of public adult PSG databases, such as Sleep-
EDF Expanded [21, 22], Montreal Archive of Sleep Studies (MASS) [23], Physio2018 [24], and Sleep Heart Health Study (SHHS) [9, 10]. Furthermore, we propose and evaluate two ensemble models that combine the six adopted sleep staggers via averaging their probability outputs and a convolutional neural network (CNN). Our main contributions are as follows:

- We establish a comprehensive benchmark on a rich set of state-of-the-art deep learning methods for automatic sleep staging on a large-scale pediatric population with a wide range of OSA severity.
- We empirically demonstrate that the studied algorithms (i) reach an expert-level accuracy on pediatric sleep staging, similar to that reported for adult PSGs; (ii) are robust to concept drift [25]; and (iii) agree to one another “almost perfectly”; and (iv) share similar patterns on their classification errors.
- We show that the proposed ensemble models lead to improved sleep staging performance and reduced predictive uncertainty.

Few prior works using deep neural networks on pediatric automatic sleep staging such as [26], [27] have been reported, however, to the best of our knowledge, this is the first work to comprehensively benchmark state-of-the-art automatic sleep staging algorithms in children using a large-scale clinically relevant dataset.

II. Childhood Adenotonsillectomy Trial (CHAT) DATABASE

We use overnight PSG from the Childhood Adenotonsillectomy Trial (CHAT) [9, 28, 29], a multi-center, single-blinded, randomized, controlled trial designed to analyze the efficacy of early adenotonsillectomy (eAT) on children, aged 5 to 9 years, with mild-to-moderate OSA. The trial aimed to test whether children randomized to eAT demonstrate greater improvement in cognitive, behavioral, quality-of-life, and sleep measures at 7-months follow-up than children who were randomly assigned to watchful waiting with supportive care (WWSC) [28, 30, 31]. Physiological measures of sleep were assessed at baseline and at 7-months with standardized full PSG with central scoring at the Brigham and Women’s Sleep Reading Center. The children were recruited as part of the clinical trial “Childhood Adenotonsillectomy Study for Children With OSAS (CHAT)”, ClinicalTrials.gov number, NCT00560859.

In total, 1,447 children underwent screening PSGs conducted at different hospitals with various equipment. Children meeting the CHAT inclusion criteria and participating in the trial also had a follow-up PSG. In our study, only recordings with at least 5 hours of good data were used. We formed the following 3 subsets from the database.

- Baseline: 464 children who were randomized to eAT and WWSC. After excluding withdrawn children [29] and recordings with less than 5 hours of data, 440 recordings were retained.
- Follow-up: the same children as in the Baseline subset about 7 months after the intervention (i.e., either eAT and WWSC). 393 recordings were retained after excluding those with less than 5 hours of data.
- Non-randomized: 779 children who were screened but were not included in the trial due to, e.g., negative or severe OSA diagnosis. These children are complete different from those in the Baseline and Follow-up subsets. 776 recordings were retained after excluding those with less than 5 hours of data.

A summary of the subsets is given in Table I. We adopted C4-A1 EEG and ROC-LOC EOG to study single-channel EEG and dual-channel EEG-EOG automatic sleep staging. The data, originally recorded at different sampling rates were downsampled to 100 Hz. Segments with zero/near-zero in the recordings due to poor electrode contact were discarded. To deal with different measurement units owing to different equipment, each signal was normalized to the range [-1, 1] by dividing its maximum magnitude. Prior to normalization, values outside 6 standard deviations were clipped. Band-pass filtering with a low cutoff frequency of 0.3 Hz and a high cutoff frequency of 40 Hz was carried out. Finally, the per-recording signal was normalized to zero mean and unit standard deviation.

III. Deep Learning Methods

We adopted a cohort of six different deep neural networks in this study. The networks were chosen taking into account discrepancies in their inputs and network architectures. At the high level, these networks can be fitted neatly into a common framework, namely end-to-end sequence-to-sequence sleep staging framework [11], [32], which has been the driving force behind expert-level performance in automatic sleep staging reported recently.

Formally, let us denote an input sequence of $L$ epochs as $(S_1, \ldots, S_L)$ where $S_\ell$ is the $\ell$-th epoch, $1 \leq \ell \leq L$. In general, the epochs can be in any forms, such as raw signals or time-frequency images and single- or multi-channel. A network adhering to the framework typically consists of two main components: the epoch encoder $F_E$ and the sequence encoder $F_S$ as illustrated in Figure 1. The epoch encoder acts as an epoch-wise feature extractor which transforms an epoch $S$ in the input sequence into a feature vector $x$ for representation:

$$F_E: S \mapsto x.$$  

(1)

As a result, the input sequence is transformed into a sequence of feature vectors $(x_1, \ldots, x_L)$. Of note, $F_S$ can be a hard-coded hand-crafted feature extractor, however, in deep learning context, it is oftentimes a neural network (e.g., a convolutional neural network).
neural network (CNN) or a recurrent neural network (RNN)) that learns the feature presentation \( x \) automatically from low-level inputs. In turn, at the sequence level, the sequence encoder transforms the sequence \((x_1, \ldots, x_L)\) into another sequence \((z_1, \ldots, z_L)\). Formally,

\[
\mathcal{F}_S : \langle x_1, \ldots, x_L \rangle \rightarrow \langle z_1, \ldots, z_L \rangle. \tag{2}
\]

In intuition, \( z_\ell \) is a richer representation for the \( \ell \)-th epoch than \( x_\ell \) as it not only encompasses information of the epoch but also interaction with other epochs in the sequence. More specifically, \( z_\ell \) is derived from \( x_\ell \), taking into account the left context \((x_1, \ldots, x_{\ell-1})\) and the right context \((x_{\ell+1}, \ldots, x_L)\). Eventually, the vectors \( z_1, \ldots, z_L \) are used for classification purpose to obtain the sequence of predicted sleep stages, one for each epoch in the input sequence.

Below, we concretely describe the adopted networks with respect to their mother framework. A snapshot of the networks is also given in Table I.

**SeqSleepNet [11]**: The network receives time-frequency representation (i.e., logarithmic magnitude spectrogram) as input. In case of multiple channels, the spectrograms are stacked to form a multi-channel input. On the one hand, the epoch encoder is realized by the coupling of learnable filterbank layers [33] (one for each input channel), a bidirectional RNN layer, and a gated attention layer [34], [35]. On the other hand, the sequence encoder is realized by another bidirectional RNN layer. Both the epoch encoder and sequence encoder have their bidirectional RNN implemented using Long Short-Term Memory (LSTM) cell [36] coupled with recurrent batch normalization [37].

**SleepTransformer [16]**: Similar to SeqSleepNet, Sleep-Transformer ingests time-frequency input. The network makes use of Transformer [38] as the backbone for both the epoch encoder and sequence encoder, making it distinct from other networks used in this study which are based on either RNN or CNN or both. Leveraging the attention matrices of the Transformers, the network is the first of its kind offering the explanability at both the epoch and sequence level which closely resembles the manual scoring procedure.

**DeepSleepNet [20]**: Raw signals are used as input to the network. The epoch encoder is composed of two parallel 1D CNN subnetworks. The CNN layers in the subnetworks are designed to have different kernel sizes and pooling factors in order to learn features at different resolutions. The features learned by the two subnetworks are concatenated before presented to the sequence encoder. The sequence encoder, on the other hand, is implemented by two LSTM-based bidirectional RNN layers, one situated on top of the other. Residual connections [39] are used to combine the epoch-wise features and the sequence-wise features before classification takes place. Of note, we used the end-to-end DeepSleepNet variant presented in [11] in this study.

**FCNN-RNN [11]**: The network resembles DeepSleepNet in several aspects: raw-signal input, the epoch encoder’s reliance on CNN, and the sequence encoder’s reliance on bidirectional RNN. However, its design features several differences from DeepSleepNet. First, the epoch encoder is implemented by a single CNN which makes use of full convolution [40] (i.e., without explicit pooling layers). Second, only one bidirectional RNN layer is employed in the sequence encoder. Third, the residual connection is omitted. These changes help reduce the network footprint significantly, more than 4 times smaller than that of DeepSleepNet.

**XSleepNet1 [13]**: This is a hybrid network which, in essence, accommodates SeqSleepNet and FCNN-RNN in its two network streams, respectively. It is principally designed to leverage the complementarity of SeqSleepNet (i.e., a small network solely relying on RNN) and FCNN-RNN (i.e., a larger network relying on CNN and RNN) to gain robustness to the amount of training data. Effectively, the network receives both raw-signal and time-frequency inputs which are interpreted as multiple views of the same underlying data. A multi-view learning algorithm is devised to train the network in such a way that a good multi-view representation is obtained. To that end, the learning pace of the network streams is adapted individually according to their generalization and overfitting behavior. Specially, learning on the stream that is generalizing well is encouraged with a large weight while the one that is overfitting is discouraged with a small weight.

**XSleepNet2 [13]**: This network essentially shares the same architecture as XSleepNet1. The key difference between the two networks is their multi-view learning algorithms. XSleepNet2 relies on a second-order approximation (i.e., tangents of the loss curves) to compute the adapting weights for the network streams whereas XSleepNet1 uses a first-order approximation (i.e., spontaneous values of the losses) for this purpose. Interested readers are encouraged to refer to [13] for more details.

**Table II: Summary of the networks employed in the study.**

| Network      | Input       | Epoch Encoder       | Sequence Encoder | #parameters (single-channel) |
|--------------|-------------|---------------------|------------------|-----------------------------|
| SeqSleepNet  | TF          | RNN                 | RNN              | 1.6 \times 10^7            |
| SleepTransformer | TF          | Transformer         | Transformer      | 3.7 \times 10^6            |
| DeepSleepNet | Raw         | CNN                 | Transformer      | 2.3 \times 10^7            |
| FCNN-RNN     | Raw         | CNN                 | RNN              | 5.6 \times 10^6            |
| XSleepNet1   | TF+Raw      | RNN+CNN             | RNN              | 5.7 \times 10^6            |
| XSleepNet2   | TF+Raw      | RNN+CNN             | RNN              | 5.7 \times 10^6            |
IV. ENSEMBLE METHODS

Ensemble [41] is a well-established machine learning approach to construct a committee model by combining existing learned ones. In general, an ensemble model often offers better performance than its individual base models. In fact, ensemble models were found to work well for automatic sleep staging with more conventional machine learning algorithms, such as Support Vector Machines [42], [43]. However, they are rarely considered as a core building block for the task in the deep learning era although a few positive results were reported, for example, in [44] which combined SeqSleepNet [11] and DeepSleepNet [20] and in [45] which fused model instances trained with different channels of the same database.

Here, we revisit ensemble approach and form two ensemble models leveraging the six base sleep stagers described in Section III as the base models. Theoretically, for an ensemble model to be effective the base models should be highly accurate and diversified [46]. The six base sleep stagers meet these criteria given their diverging characteristics on the input types and/or network architectures, except for XSleepNet1 and XSleepNet2, and their good performance (see Section V-C). Two methods are employed to combine the base sleep stagers as described below.

A. Ensemble via averaging probability outputs

As a deep neural network, each of the base sleep stagers produces one vector of five probability values for a 30-second epoch. These probability values indicate the likelihood that the epoch is classified as the five sleep stages W, N1, N2, N3, and REM. A typical method to combine the base sleep stagers is to take the average of their probability outputs. Let $P_m = (P_{m1}, P_{m2}, \ldots, P_{mC})$, where $\sum_{i=1}^{C} P_{mi} = 1$, denote the vector of probability values outputted by a model $m$ where $m \in \{XSleepNet1, XSleepNet2, SeqSleepNet, FCNN+RNN, DeepSleepNet, SleepTransformer\}$ and $C = 5$ is the number of sleep stages. The vector of probability values of the ensemble model is given by $\bar{P} = (\bar{P}_1, \bar{P}_2, \ldots, \bar{P}_C)$, where

$$\bar{P}_c = \frac{1}{M} \sum_{m=1}^{M} P_{mc} \quad \text{for} \quad 1 \leq c \leq C. \quad (3)$$

Here, $M = 6$ is the number of the base sleep stagers. The predicted sleep stage $\hat{y}$ is then determined as

$$\hat{y} = \arg\max_c \bar{P}_c. \quad (4)$$

B. Ensemble via a CNN super learner

Ensemble via averaging probability outputs of the base models attributes the base models equally with equal weights of $\bar{P}$. Alternatively, the individual weights associated with the base models can be learned from data. Inspired by the idea of Super Learner presented in [47], we propose a simple CNN with $1 \times 1$ convolution for this purpose, as illustrated in Figure 2. Given a 30-second epoch, the probability outputs from the base models are stacked to form an tensor of size $C \times 1 \times M$ which will be fed into the CNN as input. With this configuration, $M$ acts as the channel dimension of the input tensor. The CNN architecture is composed of a single convolutional layer with a single $1 \times 1$ kernel. Convolving the kernel with the input tensor produces an output vector of size $C \times 1$ which is then passed through softmax activation to translate it into a vector of probabilities values. The $1 \times 1$ kernel has exactly $M$ parameters, one for each of the base models, and will be learned via network training. The network is trained to minimize the cross-entropy loss.

In the experiments, it is of paramount importance that the CNN-based super learner was trained using a validation set that was set aside for model selection (see Section V-A1) rather than the training set. The rational is that the validation set was not directly used for training the base models, thus, it provides a good approximation of the test data’s distribution.

V. EXPERIMENTS

A. Experimental design

1) Training: The Baseline data subset was employed as the training data. Of note, 10% (44 subjects) of the training data were left out as the validation set for early stopping purpose. Each of the sleep staging networks was trained using the training data for 10 training epochs. During the training course, the networks were validated on the validation data every 100 training steps and early stopping was activated after 100 evaluations without accuracy improvement on the validation data.

In particular, the CNN super learner used for ensemble described in Section IV-B was trained using the the aforementioned validation set for 100 epochs with early stopping.

2) Testing: The two subsets, Follow-up and Non-randomized, were used as two test data subsets separately. It is worth re-iterating that the former mostly consists of the same children as in the training data (i.e., the Baseline subset) while the subjects in the latter are completely new. One may concern about data leakage of the Follow-up test subset; however, even though the Baseline and Follow-up subsets are originated from the same subjects, mismatch in their distributions is expected given that the latter were collected 7 months after the former and after clinical intervention. Evaluating the trained networks on this test subset will shed light on the networks’ performance under concept drift [25]. At the same time, assessing the networks’ performance on the Non-randomized test subset will prove their generalization on completely new subjects.
3) **Network’s initialization:** Similar to many other domains, a large training database (i.e., thousands of subjects [12, 13, 15, 17]) has been proven to improve generalization of deep neural networks for automatic sleep staging. Thus, the training data (440 subjects) in this study is still arguably small. Inspired by [32], in addition to random initialization, we also investigated pretraining as an alternative approach for network initialization. That is, a network was firstly pretrained with a large external database and the pretrained network was afterwards utilized as the starting point to be further trained (i.e., finetuned) on the training data. This approach has been shown to be effective in mitigating overfitting, and hence, improving generalization, particularly when the training data is small. Here, C4-A1 EEG and ROC-LOC EOG extracted from the SHHS database (5,791 subjects) [9, 10] was employed for pretraining purpose.

**B. Parameters and metrics**

The networks employed in this study were configured as in the original works. The implementation was based on the Tensorflow framework [48]. We also followed the procedure used in the original works to extract the time-frequency input (i.e., the logarithmic magnitude spectrogram) when needed.

We used the overall metrics, including accuracy, macro F1-score (MF1), Cohen’s kappa ($\kappa$) [49], sensitivity, and specificity to assess the automatic sleep staging performance. Quantifying predictive uncertainty of the models is also important for clinical use [16] as those data epochs predicted with high uncertainty can be deferred to sleep experts for further manual inspection [50]. In this regard, a model with low predictive uncertainty is preferable as it will reliably defer less data epochs to be manually checked. We used two metrics to evaluate the predictive uncertainty of a network: the negative log-likelihood (NLL) [51] and the Brier score (BS) [52]. Given a data epoch $S$ with the groundtruth sleep stage $y$, NLL and BS are defined as in (5) and (6), respectively:

$$
NLL = -\sum_{c=1}^{C} y_c \log \hat{y}_c, \quad (5)
$$

$$
BS = \frac{1}{C} \sum_{c=1}^{C} (y_c - \hat{y}_c)^2. \quad (6)
$$

In above equations, $y_c = 1$ if $y = c$, and 0 otherwise. $\hat{y}_c = P(c | S)$ is the probability of the epoch $S$ being predicted as class $c$ by the model. The lower NLL and BS are, the lower predictive uncertainty the model has.

**C. Experimental results**

1) **Sleep staging performance:** Tables [I] and [IV] show the performance obtained by the networks as well as their ensembles corresponding to random initialization and pretraining initialization, respectively. These results unravel several important points about pediatric automatic sleep staging. First, across different individual models, the obtained performance on pediatric sleep staging was equivalent to adult sleep staging. For example, in case of random initialization and the Non-randomized test subset, $\kappa$ of 0.828 and 0.842 obtained by XSleepNet1 with the single- and dual-channel input, respectively, were very similar to the state-of-the-art $\kappa$ reported on SHHS [13] consisting of 5,791 adults. These $\kappa$ values are even noticeably better than that reported on other popular adult PSG databases with smaller sizes, such as Montreal Archive of Sleep Studies [23] and Sleep-EDF Expanded [21, 22]. The relative performance between the networks also conformed to that reported on adult PSG data, for example in [13], where the multi-view XSleepNet1 and XSleepNet2 consistently outperformed the single-view counterparts across the test subsets, the initialization schemes, and the number of channels used. For example, with random initialization and single-channel EEG, XSleepNet1 improved the overall accuracy by 0.8% absolute over the best single-view networks, SeqSleepNet and FCNN+RNN, on the Follow-up and Non-randomized subset, respectively. These accuracy gaps became much narrower with the use of dual-channel EEG-EOG (i.e., reduced to 0.2% and 0.5% absolute) or pretraining initialization (i.e., reduced to 0.5% and 0.1% absolute) or both (i.e., reduced to 0.2% and 0.3% absolute). On the other hand, SleepTransformer appeared to underperform other counterparts under the random initialization regime, most likely due to Transformer’s data-hungry nature and the small size of the training data, as similarly observed in [16]. This is also supported by the observation that it performed comparably to the other single-view competitors when it was pretrained beforehand with the large SHHS database.

Second, both the ensemble models consistently resulted in better performance than all the individual models. Take random initialization and the Non-randomized test subset for example, Average Ensemble (i.e., the ensemble model via averaging probability outputs) improved the overall accuracy by 1.1% and 1.2% absolute compared to the average overall accuracy of the six individual models. This was not only observed on the overall metrics but also over most sleep stages as evidenced by the class-wise MF1 on Tables [A.1] and [A.2]. However, negligible difference was seen from the performance of the two ensemble methods. In other words, an advanced ensemble method with CNN is unnecessarily better than the simple averaging method in term of performance whilst it requires additional training.

Third, pretraining has positive effects on performance, similar to adult sleep staging [15, 32]. Between random and pretraining initialization, the latter resulted in accuracy improvement in most of the standalone models as well as the two ensemble models. However, the gains were mostly marginal since overfitting was expected to be minor given that the training data consists of hundreds of subjects. SleepTransformer was the largest beneficiary, gaining 1.3-1.4% absolute and 0.8-0.9% absolute on the overall accuracy with single-channel EEG and dual-channel EEG-EOG input, respectively. FCNN-RNN was the only exception which experienced accuracy drop by 0.8% absolute on both the Follow-up and Non-randomized test subsets when dual-channel EEG-EOG was used.

Fourth, the obtained performance on the Follow-up subset were consistently better than those on the Non-randomized subset. For example, in case of random normalization, XSleepNet1 resulted in overall accuracies of 88.6% and 89.2% on the former when single-channel EEG and dual-channel EEG-EOG
Table III: Overall performance obtained by the networks and the ensemble models in case of random initialization.

| Subset         | System              | EEG  | EEG-EOG |
|----------------|---------------------|------|---------|
|                |                     | Acc. | k      | MF1 | Sens. | Spec. |
| Follow-up      | Average Ensemble    | 88.9 | 0.864 | 85.3 | 86.2 | 97.1  |
|                | CNN-based Ensemble  | 88.9 | 0.864 | 85.3 | 86.2 | 97.1  |
|                | XSleepNet1          | 88.6 | 0.849 | 85.2 | 85.3 | 97.0  |
|                | XSleepNet2          | 88.3 | 0.844 | 84.8 | 84.8 | 96.9  |
|                | SeqSleepNet         | 87.8 | 0.838 | 83.9 | 83.8 | 96.8  |
|                | FCNN+RNN            | 87.8 | 0.837 | 83.7 | 83.6 | 96.8  |
|                | DeepSleepNet        | 87.6 | 0.835 | 84.0 | 84.8 | 96.8  |
|                | SleepTransformer    | 86.9 | 0.825 | 81.5 | 81.2 | 96.5  |
| Non-randomized | Average Ensemble    | 87.4 | 0.833 | 83.8 | 83.5 | 96.7  |
|                | CNN-based Ensemble  | 87.4 | 0.833 | 83.8 | 83.4 | 96.7  |
|                | XSleepNet1          | 87.0 | 0.828 | 83.6 | 83.4 | 96.6  |
|                | XSleepNet2          | 86.9 | 0.826 | 83.4 | 83.1 | 96.5  |
|                | SeqSleepNet         | 86.2 | 0.818 | 82.3 | 82.0 | 96.4  |
|                | FCNN+RNN            | 86.3 | 0.818 | 82.4 | 82.1 | 96.4  |
|                | DeepSleepNet        | 86.0 | 0.815 | 82.4 | 82.7 | 96.3  |
|                | SleepTransformer    | 85.4 | 0.806 | 80.0 | 79.7 | 96.1  |

Table IV: Overall performance obtained by the networks and the ensemble models in case of pretraining initialization.

| Database       | System              | EEG  | EEG-EOG |
|----------------|---------------------|------|---------|
|                |                     | Acc. | k      | MF1 | Sens. | Spec. |
| Follow-up      | Average Ensemble    | 89.2 | 0.857 | 85.7 | 85.5 | 97.1  |
|                | CNN-based Ensemble  | 89.2 | 0.856 | 85.6 | 85.5 | 97.1  |
|                | XSleepNet1          | 88.7 | 0.849 | 84.9 | 84.9 | 97.0  |
|                | XSleepNet2          | 88.6 | 0.849 | 85.0 | 85.2 | 97.0  |
|                | SeqSleepNet         | 88.4 | 0.846 | 84.9 | 85.2 | 96.9  |
|                | FCNN+RNN            | 88.7 | 0.840 | 84.1 | 84.2 | 96.8  |
|                | DeepSleepNet        | 88.3 | 0.844 | 84.6 | 84.6 | 96.9  |
|                | SleepTransformer    | 88.3 | 0.843 | 83.9 | 82.8 | 96.8  |
| Non-randomized | Average Ensemble    | 87.7 | 0.837 | 84.2 | 83.7 | 96.7  |
|                | CNN-based Ensemble  | 87.6 | 0.836 | 84.1 | 83.7 | 96.7  |
|                | XSleepNet1          | 87.0 | 0.828 | 83.3 | 83.0 | 96.6  |
|                | XSleepNet2          | 87.0 | 0.829 | 83.5 | 83.5 | 96.6  |
|                | SeqSleepNet         | 86.9 | 0.826 | 83.4 | 83.3 | 96.5  |
|                | FCNN+RNN            | 86.2 | 0.818 | 82.5 | 82.4 | 96.4  |
|                | DeepSleepNet        | 86.8 | 0.825 | 83.2 | 82.9 | 96.5  |
|                | SleepTransformer    | 86.7 | 0.822 | 82.3 | 81.1 | 96.4  |

were used, respectively. These results were 1.6% and 1.2% higher than those obtained on the latter. The respective gaps were similar, 1.7% and 1.2%, in case of pretraining initialization. Similar patterns were also seen with the ensemble models. These results simply reflect the fact that the Follow-up subset stems from the same subjects as the Baseline subset used for training whereas the Non-randomized subjects were completely new to the models. All in all, the results on the Non-randomized test subset confirm that the automatic sleep stages generalize to new subjects while the results on the Follow-up test subset suggest that the automatic sleep stages are robust to the concept drift given that the test data were recorded 7 months apart from the training data and after clinical intervention.

2) Predictive uncertainty: To quantify the predictive uncertainty of a model, we computed the average NLL and BS over all epochs of the test data subsets individually. The results are summarized in Table V. Overall, among the six standalone models, XSleepNets resulted in lowest predictive uncertainty, outperforming all others counterparts on both NLL and BS. Network pretraining also consistently resulted in reduced NLL and BS which were seen with both the standalone models and the ensemble ones. Interestingly, diverging patterns were seen between the two ensemble models and the simpler was better. On the one hand, Average Ensemble led to reduced predictive uncertainty, both NLL and BS, compared to the six base models. On the other hand, CNN-based Ensemble caused NLL to increase while no clear improvement was observed on BS. All in all, this suggests that, between the two studied ensemble methods, averaging the base models’ probability outputs is more advantageous, leading to improved performance and reduced predictive uncertainty while being simple and avoiding the need for additional training. For this reason, we retained the Average Ensemble model for further analysis and discussion in the next section.

D. Further analysis and discussion

1) Agreement between the automatic sleep stages and the human scorer: In order to elucidate the agreements among the automatic sleep stages (i.e., the standalone models and the Average Ensemble model) and compare to the agreements between them and the human scorer, we computed $\kappa$ for all possible pairs of the stages and show the results in Figure 3. Of note, we made use of the pretraining initialization scheme...
Table V: Uncertainty measures obtained by the networks and the ensemble models.

| Database     | System                | Random initialization | Pretraining initialization |
|--------------|-----------------------|-----------------------|---------------------------|
|              | EEG                   | EEG-EOG               | EEG                       | EEG-EOG                   |
|              | NLL  | BS   | NLL  | BS   | NLL  | BS   | NLL  | BS   | NLL  | BS   |
| Follow-up    | Average Ensemble      | 0.292  | 0.161 | 0.264 | 0.147 | 0.283 | 0.156 | 0.263 | 0.146 |
|              | CNN-based Ensemble    | 0.343  | 0.166 | 0.310 | 0.154 | 0.336 | 0.162 | 0.304 | 0.151 |
|              | XSleepNet1            | 0.296  | 0.164 | 0.277 | 0.155 | 0.296 | 0.163 | 0.273 | 0.153 |
|              | XSleepNet2            | 0.307  | 0.169 | 0.274 | 0.153 | 0.300 | 0.165 | 0.272 | 0.152 |
|              | SeqSleepNet           | 0.320  | 0.176 | 0.282 | 0.158 | 0.304 | 0.168 | 0.285 | 0.158 |
|              | FCNN-RNN              | 0.323  | 0.177 | 0.298 | 0.166 | 0.317 | 0.174 | 0.320 | 0.176 |
|              | DeepSleepNet          | 0.324  | 0.179 | 0.294 | 0.164 | 0.305 | 0.169 | 0.297 | 0.166 |
|              | SleepTransformer      | 0.347  | 0.189 | 0.308 | 0.169 | 0.305 | 0.168 | 0.282 | 0.157 |
| Non-randomized| Average Ensemble      | 0.331  | 0.182 | 0.294 | 0.165 | 0.321 | 0.178 | 0.290 | 0.162 |
|              | CNN-based Ensemble    | 0.392  | 0.190 | 0.354 | 0.174 | 0.385 | 0.187 | 0.346 | 0.170 |
|              | XSleepNet1            | 0.344  | 0.188 | 0.310 | 0.173 | 0.341 | 0.188 | 0.306 | 0.171 |
|              | XSleepNet2            | 0.347  | 0.190 | 0.310 | 0.173 | 0.341 | 0.187 | 0.305 | 0.170 |
|              | SeqSleepNet           | 0.365  | 0.200 | 0.321 | 0.179 | 0.343 | 0.189 | 0.317 | 0.177 |
|              | FCNN-RNN              | 0.374  | 0.200 | 0.343 | 0.188 | 0.371 | 0.200 | 0.363 | 0.198 |
|              | DeepSleepNet          | 0.376  | 0.203 | 0.338 | 0.186 | 0.349 | 0.192 | 0.328 | 0.181 |
|              | SleepTransformer      | 0.393  | 0.211 | 0.344 | 0.187 | 0.357 | 0.193 | 0.318 | 0.175 |

Figure 3: The agreement measured in $\kappa$ between every pair of the scorers (i.e., the studied networks, Average Ensemble, and the human scorer) under the pretraining initialization scheme. (a) EEG - Follow-up; (b) EEG-EOG - Follow-up; (c) EEG - Non-randomized; (d) EEG-EOG - Non-randomized.

for this investigation. Overall, the agreement between every pair of the automatic stagers was considerably higher than those between them and the human scorer. The automatic stagers using the same input types (i.e., raw signal, time-frequency image, and both) tended to agree to one another more than between the stagers using different input types. However, given the range of $\kappa$ between 0.865 and 0.961, the agreement level was “almost perfect” (according to the interpretation of Cohen’s kappa [53]) and considerably higher than the “substantial” level between human scorers (for example, $k = 0.76$ as reported in other studies [54, 55]). Interestingly, the attribution of the base models in the ensemble model was manifested via their agreements to the Average Ensemble model. This suggests that even though the Average Ensemble model allocates equal weights to the base models, their attributions to the ensemble are inherently proportionate.
The percentages of the two types of errors are shown in Figure 4. The figure reveals a significant amount of sleep epochs by at least one of the stagers. This can be explained by the fact that N2 and N3 are the major classes in the database (cf. Table 1) while N1, as similar to adult sleep, is much less well-defined than other stages. Figure 6 further shows that more than 60% (in case of single-channel EEG) and 55% (in case of dual-channel EEG) of the common errors were close to cross-stage transitions, at most 4 epochs away from their nearest cross-stage transitions. Moreover, around 20% of them were rapid-transition epochs which are, in general, challenging to be recognized correctly as they tend to convey features of multiple sleep stages and, typically, manual labelling these epochs is highly subjective. Interestingly, the figure also reveals that, with the same nearest-to-transition distance, the networks tended to misclassify those before transitions more than those after transitions. No such a difference was seen in case of adult PSG staging when a similar analysis was conducted using SeqSleepNet in [18]. We further visualize in Figure 7 the stage transitions from the predecessors of the common-error epochs to themselves, and then to their successors. Apparently, the compelling similarity of the transitioning patterns in the figure suggests the convergence of the common errors across different scenarios. Put simpler, there exists a set of epochs associated with some specific stage transitions that could not be recognized by the automatic sleep stagers regardless the addition of the EOG channel, ensemble, and the test subsets.

Regarding other errors, as shown in Figure 5 all the stagers but SleepTransformer shared a similar pattern on the Follow-up test subset where N2 was the most misclassified stage (39% or more), followed by N1 (17-22%). Surprisingly, SleepTransformer mostly made mistakes on N1 and N3 (25-28% each) whereas N2 only accounted for 17-19%, less than half of what seen in other stagers. This atypical pattern is most likely related to its idiosyncratic Transformer backbone. On the Non-randomized subset, N2 remained the most misclassified stage. FCNN-RNN, however, appeared to have the errors distributed more evenly among NREM stages and REM. SleepTransformer, on the other hand, exhibited a pattern almost opposite to that observed on the Follow-up subset where N2 became the most misclassified stage, closely followed by N1, and then N3. Regarding distances to the nearest cross-stage transitions, similar findings can be drawn from Figure 5 as in case of the common errors, except that the percentages of errors in the vicinity of maximum 4 epochs to the nearest transitions were lower and that the percentages of the rapid-transition epochs were also much lower. These patterns were unanimous across all the stagers.

All in all, the above analysis confirms that majority of the automatic sleep stagers manifested a similar pattern on their classification errors. In other words, they behaved analogously on the automatic sleep staging task. This finding is indeed complementary to the “almost perfect” agreement among the stagers in Section V-D1. In addition, we believe that the anomalous error patterns stemming from SleepTransformer in Figure 5 are worth further investigation which could potentially gain more understanding about behaviors of the deep learning models on the automatic sleep staging task in general. In turn, this understanding could benefit the model’s explainability [16].

VI. CONCLUSIONS

We conducted a comparative study on six different deep neural networks for automatic sleep staging on a large-scale pediatric population with a wide range of OSA severity. The
Figure 5: Distribution of the errors made by the networks over the sleep stages. (a) EEG - Follow-up; (b) EEG-EOG - Follow-up; (c) EEG - Non-randomized; (d) EEG-EOG - Non-randomized.

Figure 6: The distance of the misclassified epochs to their nearest transitions. (a) EEG - Follow-up; (b) EEG-EOG - Follow-up; (c) EEG - Non-randomized; (d) EEG-EOG - Non-randomized. In the figures, “rapid transition” indicates the epochs both immediately before and after the transition.
benchmarking results demonstrated that the studied networks, which are the state-of-the-art algorithms in adult sleep staging, generalized well to young children, achieving an expert-level accuracy similar to that reported on adult PSGs when evaluated on new subjects. Combining the six networks into ensemble models further boosted accuracy and led to reduced predictive uncertainty. The automatic sleep stagers, the ensemble models included, were also robust to the concept drift when the test data were recorded 7 months later and after clinical intervention. Equally important, the stagers exhibited “almost perfect” agreement to one another and similar patterns on their classification errors. These results suggest that there is probably little room for accuracy improvement within the same sequence-to-sequence framework, if any, the improvement would be not necessarily meaningful. Rather, future works should focus on entirely different concepts for automatic sleep staging and other overarching, clinician-centric challenges, such as explainability and uncertainty estimation, to accelerate clinical adoption of automatic sleep staging algorithms. Automated scoring of sleep micro-architecture such as cortical arousal, sleep spindles, and the cyclic alternating pattern is another important frontier.

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Table A.1: Class-wise MF1 obtained by the networks and the ensemble models in case of random initialization.

| Subset         | System               | EEG   | EEG-EOG |                     |                     |
|----------------|----------------------|-------|---------|---------------------|---------------------|
|                |                      | Wake  | N1      | N2      | N3      | REM | Wake  | N1      | N2      | N3      | REM |
| Non-randomized | Average Ensemble     | 94.3  | 63.0    | 88.5    | 91.2    | 89.5 | 95.5  | 66.1    | 89.1    | 91.2    | 91.9 |
|                | CNN-based Ensemble   | 94.3  | 62.9    | 88.5    | 91.2    | 89.6 | 95.6  | 65.7    | 89.1    | 91.2    | 91.9 |
|                | XSleepNet1           | 94.1  | 65.2    | 88.1    | 90.9    | 89.6 | 95.0  | 65.8    | 88.4    | 91.0    | 91.2 |
|                | XSleepNet2           | 93.6  | 62.8    | 88.0    | 90.6    | 88.9 | 95.0  | 64.3    | 88.6    | 91.0    | 91.1 |
|                | SeqSleepNet          | 93.6  | 60.2    | 87.1    | 90.3    | 88.5 | 95.4  | 64.9    | 88.0    | 90.6    | 91.0 |
|                | FCNN+RNN             | 92.6  | 59.5    | 87.6    | 90.7    | 88.1 | 93.8  | 63.1    | 88.0    | 90.4    | 90.7 |
|                | DeepSleepNet         | 92.9  | 60.7    | 87.4    | 90.5    | 88.5 | 94.4  | 63.3    | 88.2    | 90.2    | 90.5 |
|                | SleepTransformer     | 92.9  | 49.8    | 86.7    | 90.2    | 87.6 | 94.9  | 56.0    | 87.4    | 90.4    | 90.4 |
| Follow-up      | Average Ensemble     | 93.5  | 61.4    | 86.4    | 89.6    | 88.2 | 95.2  | 64.3    | 87.3    | 89.9    | 90.6 |
|                | CNN-based Ensemble   | 95.3  | 61.3    | 86.4    | 89.6    | 88.2 | 95.3  | 64.2    | 87.3    | 89.9    | 90.7 |
|                | XSleepNet1           | 93.3  | 61.8    | 85.8    | 89.2    | 87.9 | 94.8  | 63.8    | 86.6    | 89.9    | 89.9 |
|                | XSleepNet2           | 93.2  | 61.2    | 86.0    | 88.9    | 87.7 | 94.7  | 62.5    | 86.7    | 89.6    | 89.8 |
|                | SeqSleepNet          | 93.1  | 58.2    | 84.8    | 88.7    | 86.7 | 95.0  | 63.2    | 85.7    | 89.1    | 89.4 |
|                | FCNN+RNN             | 91.9  | 58.7    | 85.4    | 89.2    | 86.6 | 92.8  | 61.4    | 86.1    | 89.1    | 88.7 |
|                | DeepSleepNet         | 91.8  | 59.4    | 85.3    | 88.8    | 86.7 | 93.3  | 61.8    | 86.3    | 89.0    | 88.4 |
|                | SleepTransformer     | 92.4  | 48.2    | 84.5    | 88.7    | 86.5 | 94.9  | 54.8    | 85.5    | 89.2    | 89.1 |

Table A.2: Class-wise MF1 obtained by the networks and the ensemble models in case of pretraining initialization.

| Database       | System               | EEG   | EEG-EOG |                     |                     |
|----------------|----------------------|-------|---------|---------------------|---------------------|
| Non-randomized | Average Ensemble     | 94.0  | 83.4    | 88.8    | 91.3    | 90.2 | 95.6  | 66.6    | 89.1    | 91.4    | 92.2 |
|                | CNN-based Ensemble   | 94.5  | 63.3    | 88.8    | 91.3    | 90.2 | 95.6  | 66.4    | 89.1    | 91.4    | 92.3 |
|                | XSleepNet1           | 94.2  | 61.7    | 88.2    | 91.1    | 89.4 | 95.4  | 65.9    | 88.2    | 91.0    | 91.6 |
|                | XSleepNet2           | 94.1  | 62.2    | 88.1    | 91.2    | 89.4 | 95.2  | 65.6    | 88.5    | 91.1    | 91.4 |
|                | SeqSleepNet          | 94.0  | 60.1    | 86.3    | 90.0    | 87.7 | 95.0  | 65.2    | 88.0    | 90.7    | 91.2 |
|                | FCNN+RNN             | 92.9  | 60.6    | 87.8    | 91.0    | 88.2 | 93.2  | 57.4    | 87.2    | 90.4    | 89.8 |
|                | DeepSleepNet         | 93.5  | 61.8    | 87.8    | 90.7    | 89.1 | 94.7  | 64.7    | 87.4    | 90.0    | 90.7 |
|                | SleepTransformer     | 93.9  | 57.3    | 88.1    | 90.4    | 89.7 | 94.7  | 60.3    | 88.3    | 90.8    | 91.9 |
| Follow-up      | Average Ensemble     | 93.6  | 62.1    | 86.6    | 89.7    | 88.8 | 95.5  | 65.2    | 87.3    | 90.1    | 91.0 |
|                | CNN-based Ensemble   | 93.6  | 62.0    | 86.6    | 89.7    | 88.8 | 95.5  | 65.0    | 87.3    | 90.1    | 91.1 |
|                | XSleepNet1           | 93.1  | 60.2    | 86.0    | 89.3    | 88.0 | 95.2  | 64.7    | 86.4    | 89.7    | 90.1 |
|                | XSleepNet2           | 93.4  | 60.5    | 85.9    | 89.5    | 88.1 | 95.1  | 64.1    | 86.6    | 89.7    | 90.2 |
|                | SeqSleepNet          | 93.5  | 60.8    | 85.5    | 89.1    | 88.2 | 95.1  | 64.3    | 85.9    | 89.0    | 90.2 |
|                | FCNN+RNN             | 91.6  | 59.4    | 85.4    | 89.2    | 86.6 | 92.3  | 55.8    | 85.1    | 88.9    | 87.9 |
|                | DeepSleepNet         | 92.8  | 60.7    | 85.7    | 89.2    | 87.4 | 94.5  | 63.7    | 85.9    | 89.1    | 89.6 |
|                | SleepTransformer     | 93.1  | 55.4    | 85.9    | 89.0    | 87.9 | 94.7  | 58.7    | 86.2    | 89.5    | 90.7 |