An Interpretable CNN-Transformer for Pediatric Sleep Apnea Diagnosis using ECG

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***Abstract*— Pediatric obstructive sleep apnea (OSA) is a common respiratory disorder that has been associated with increased cardiovascular risk. The standard diagnosis is polysomnography, but its complexity, cost, and inconvenience lead to underdiagnosis. To address this situation, we propose for the first time a simplified alternative using the overnight electrocardiogram (ECG) and a hybrid model based on a convolutional neural network and a transformer network to estimate the severity of pediatric OSA. In addition, the Gradient-weighted Class Activation Mapping (GradCAM) method is proposed to interpret the model results. For the development of the study, 2,591 recordings from the Childhood Adenotonsillectomy Trial (CHAT) and University of Chicago (UofC) databases were used. The model achieved a 4-class Cohen's Kappa of 0.392 in CHAT and 0.346 in UofC. GradCAM highlighted bradycardia-tachycardia patterns, and PQ and QT segments, as well as identified U waves. Therefore, this approach may improve the diagnosis of pediatric OSA and provide new related cardiac information, thus encouraging the adoption of automated systems in clinical settings.**

Keywords— Pediatric obstructive sleep apnea, Transformer, eXplainable Artificial Intelligence, electrocardiogram.

I. Introduction

Pediatric obstructive sleep apnea (OSA) is a common respiratory disorder that leads to changes in the cardiovascular (CV) system and increases CV risk [1]. The standard diagnostic method, polysomnography (PSG), is costly, complex, and uncomfortable, leading to under-diagnosis of children [1]. To address these complications, several studies have developed simplified strategies using a reduced number of PSG signals along with artificial intelligence techniques [1]. Focusing on pediatric OSA and cardiac signals, most studies have developed automated diagnostic alternatives using feature-engineering techniques [2]. Additionally, there is only one study that used a deep learning (DL) approach, which was based on a convolutional neural network (CNN) [3]. Despite the effectiveness shown in that study, CNNs are designed specifically to capture spatial features within the input data, disregarding the time dependencies present in sequences, such as those found in a nightly recording [4]. Another important limitation in all previous related literature is the lack of interpretability of the models used [5], thus hindering a higher acceptance of automatic models in clinical practice.

For these reasons, this study aims to assess the effectiveness of an interpretable hybrid DL network to identify spatial patterns through a CNN and temporal dependencies with a transformer (TF). Electrocardiogram (ECG) signals fed the CNN-TF model to establish OSA severity and uncover relevant ECG patterns associated with the disease.

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II. Methods

A. Subjects and signals preprocessing

Signals were acquired from the semipublic Childhood Adenotonsillectomy Trial (CHAT, *n*=1610) [6] and a private University of Chicago (UofC, *n*=981) databases [7]. CHAT was randomly partitioned into training (60%), validation (20%), and testing (20%) sets, while UofC was reserved for independent model evaluation (only test). The databases presented annotations according to OSA severity (no OSA: AHI<1 event/hour; mild OSA: AHI<5 e/h; moderate OSA: AHI<5 e/h; and severe OSA: AHI>10 e/h). Table 1 presents clinical and demographic data from children.

The ECG-II lead from both databases underwent uniform preprocessing procedures. The signals were resampled at 100 Hz and the continuous component was corrected by subtracting the signal mean within 30-second windows. Subsequently, a high-pass filter with a cut-off frequency of 0.5 Hz was applied to mitigate noise. Finally, the amplitude of the signal was standardized using z-score normalization.

B. Deep learning architecture

A hybrid CNN-TF architecture was developed to capture both spatial structure and long-range relationships. The model received overnight ECG signals as input. The convolutional part corresponded to the previously presented CNN model [3]. Subsequently, TF was implemented using attentional mechanisms to capture dependencies and contextual information throughout the night sequence [8]. The output of the model was the apnea-hypopnea index (AHI) per subject.

C. Model interpretability using GradCAM

Gradient-weighted Class Activation Mapping (GradCAM) method was used as an eXplainable Artificial Intelligence (XAI) technique. Its function was to comprehend the intrinsic mechanisms of the model concerning the identification of apneic events and discerning cardiac patterns linked with pediatric OSA [9]. The GradCAM computation entailed using gradients derived from individual convolutional layers to compute layer-specific heatmaps. The final heatmap was obtained by averaging all the generated heatmaps [10].

III. Results and Discussion

A. Diagnostic capability

Figure 1 shows the confusion matrices after the classification of the OSA severity. In the CHAT test set, the 4-class metrics obtained were Acc_4=61.2% and *kappa*=0.392, whereas, in the UofC test set, the model obtained Acc_4=55.1%

Table 1: Demographic and clinical data from CHAT and UofC datasets.

	CHAT			UofC
	Training	**Validation**	**Test**	**Test**
Subjects	988	323	299	981
Age (years)	7.00 [2.00]	7.00 [2.00]	6.90 [2.00]	6.0 [6.0]
Males (%)	51.72	49.23	46.15	61.37
BMI(kg/m^2)	17.31[5.92]	17.12[6.25]	17.43[6.04]	18.02[5.86]
AHI (e/h)	2.64[4.77]	2.45[4.77]	2.32 [5.11]	3.8[7.76]
AHI≥1(e/h)	488	167	144	401
AHI≥5(e/h)	159	44	49	178
AHI≥10(e/h)	129	45	41	229

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and *kappa*=0.346. In addition, Table 2 shows that the highest *Acc* is obtained for identifying the most severe children in both databases. Our approach demonstrated higher diagnostic performance in detecting pediatric OSA compared to prior studies, especially in severe children [7].

B. *Identification of ECG patterns*

In Figure 2, GradCAM reveals heart rate alterations in the form of bradycardia-tachycardia patterns. In addition, heatmaps highlight U waves and PQ and QT segments. The CNN model utilizes information from bradycardia-tachycardia patterns, consistent with the physiological response of the heart to apneic events [11]. The inclusion of P, Q, and T-wave data also aligns with the observed dispersion of the P-wave and QT interval in severe pediatric OSA patients, indicating potential consequences for the onset of atrial fibrillation and elevated risk of sudden death [12]. The U-wave presence may be associated with long QT syndrome and bradycardia, both clinical factors linked to pediatric OSA [11]. Thus, heatmaps revealed ECG patterns related to OSA and potential indicators of CV risk.

IV. Conclusions

The integration of an ECG-interpretable CNN-TF model enables reliable diagnosis of pediatric OSA. In addition, GradCAM facilitates the identification of disease-related cardiac patterns. This approach may be a useful starting point when assessing the risk of CV comorbidities, a clinically relevant issue in pediatric OSA. In conclusion, this approach is an attractive alternative for PSG, as it offers a faster, more objective, and cost-effective method to diagnose OSA.

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Table 2: Diagnostic performance in the test sets.

AHI cutoff	Test set	*Se* (%)	*Sp* (%)	*PPV* (%)	*NPV* (%)	LR^+	LR^-	*Acc* (%)
1 e/h	CHAT	94.9	29.2	82.8	61.3	1.3	0.2	80.6
	UofC	95.7	14.5	83.9	41.7	1.1	0.3	81.4
5 e/h	CHAT	75.6	92.3	81.0	89.8	9.9	0.3	87.3
	UofC	73.5	84.7	77.3	81.8	4.8	0.3	80.0
10 e/h	CHAT	61.0	96.1	71.4	93.9	15.7	0.4	91.3
	UofC	59.4	97.3	87.2	88.7	22.3	0.4	88.5

LR^+ and LR^- (positive and negative likelihood ratio).

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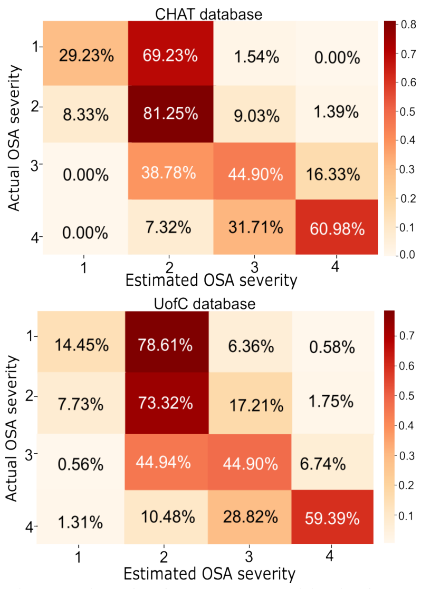

Figure 1: Confusion matrices for the 4 OSA severities in the test sets. 1: No OSA (AHI<1 e/h); 2: mild OSA (1≤AHI<5 e/h); 3: moderate OSA (5≤AHI<10 e/h); 4: severe OSA (AHI≥10 e/h).

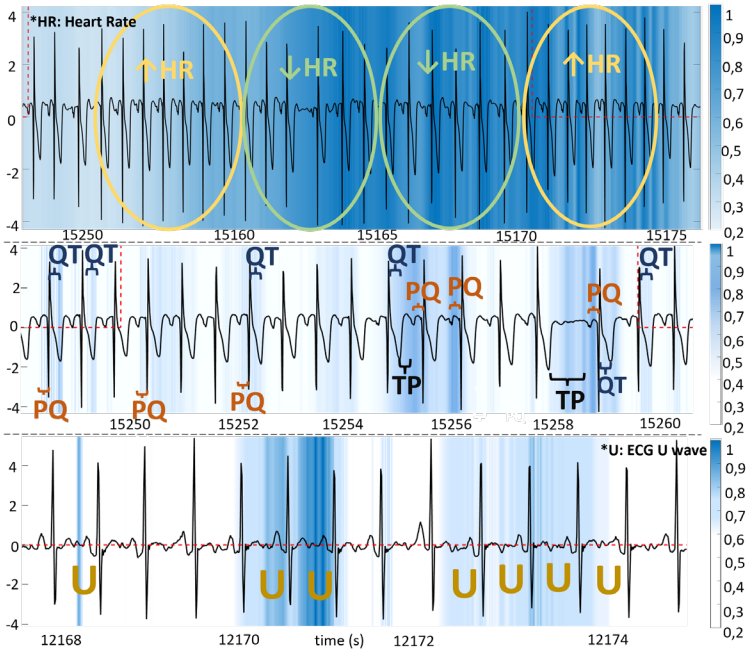

Figure 2: GradCAM visualization of relevant ECG regions from nocturnal recordings. ↑ HR and ↓ HR: increase and decrease in heart rate.