Development of Age-Specific Parametric Signal Models for Pediatric Sleep Apnea Integrating Respiratory Inductance Plethysmography with Deep Neural Networks

Authors

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Abstract

Pediatric sleep apnea remains significantly underdiagnosed due to the reliance on costly, labor-intensive polysomnography (PSG) and the absence of validated automated screening tools adapted to children's unique physiological characteristics. Current machine learning approaches for sleep apnea detection predominantly utilize adult-derived models that fail to account for age-dependent variations in respiratory mechanics and sleep architecture. This study addresses this critical gap by developing age-specific parametric signal models for pediatric sleep apnea detection, integrating respiratory inductance plethysmography (RIP) signals with deep neural network architectures. Using retrospective PSG data from 2,379 pediatric recordings sourced from the Nationwide Children's Hospital Sleep DataBank, we designed a hybrid CNN-LSTM framework incorporating an age-stratified parametric estimation module. The proposed model achieved a detection accuracy of 89.4% with a sensitivity of 91.2% and specificity of 87.6%, significantly outperforming conventional non-age-adjusted models (accuracy: 78.3%, $p<0.001$). Key findings demonstrate that age-specific parameterization of respiratory signal features critically enhances model performance, with the strongest improvements observed in children under 6 years and adolescents aged 12-17 years. This research provides a replicable, computationally efficient framework suitable for real-time screening applications, offering a

practical pathway toward accessible, non-invasive pediatric sleep apnea detection outside traditional sleep laboratory settings.

Keywords: Pediatric Sleep Apnea, Respiratory Inductance Plethysmography, Deep Neural Networks, Age-Specific Signal Modeling, LSTM, CNN, Polysomnography

1. Introduction

1.1 Background

Sleep apnea is a prevalent sleep disorder characterized by recurrent episodes of partial or complete upper airway obstruction during sleep, leading to intermittent hypoxemia, sleep fragmentation, and significant neurobehavioral and cardiovascular consequences [1]. In the pediatric population, the condition is particularly concerning, as it can disrupt critical developmental processes, affecting cognitive function, growth, and overall quality of life [2]. Despite affecting an estimated 1-5% of children, pediatric sleep apnea remains substantially underdiagnosed, partly due to the reliance on overnight polysomnography (PSG)—a resource-intensive, expensive, and often inaccessible procedure [3].

The clinical gold standard for sleep apnea diagnosis, PSG, involves comprehensive monitoring of multiple physiological signals including electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), electrocardiography (ECG), and respiratory signals. While accurate, PSG requires specialized facilities and trained personnel, creating significant barriers to widespread screening and early intervention [4]. This diagnostic bottleneck has motivated extensive research into automated screening methods utilizing reduced signal sets and machine learning approaches.

Recent advances in deep learning have demonstrated promising results in automated sleep apnea detection from respiratory signals [5]. Respiratory inductance plethysmography (RIP), which measures thoracic and abdominal movement to derive respiratory effort and airflow surrogate signals, has emerged as a particularly attractive modality for non-invasive screening applications [6]. RIP-based approaches offer the advantage of capturing respiratory mechanics without the complexity of oronasal thermistors or nasal pressure transducers, potentially enabling ambulatory monitoring.

1.2 Problem Statement

Despite the promise of machine learning-based approaches for automated sleep apnea detection, significant limitations persist. A critical yet frequently overlooked issue is the substantial physiological variation in respiratory signals across different age groups, particularly in children. Pediatric respiratory mechanics undergo marked developmental changes from infancy through adolescence, affecting breathing patterns, chest wall compliance, and the relationship between respiratory effort and airflow [7]. Existing deep learning models for sleep apnea detection are predominantly trained on adult populations and fail to account for these age-dependent characteristics .

Furthermore, studies have demonstrated that popular sleep stage classification models trained on adult data struggle to generalize to pediatric populations, particularly for children under 10 years of age . This finding underscores the fundamental physiological differences between pediatric and adult sleep and highlights the necessity for age-specific modeling approaches. The lack of validated automated screening tools that explicitly account for pediatric age-related variations represents a significant gap in current sleep medicine practice.

Recent research has confirmed strong age-related changes across numerous sleep metrics in children aged 4 to 17 years, with developmental trajectories observable in respiratory parameters, sleep architecture, and spectral power characteristics . These findings suggest that chronological age is a critical covariate that must be incorporated into computational models for pediatric sleep analysis. The absence of age-specific parametric signal models that capture developmental respiratory patterns impedes the development of accurate, generalizable automated detection systems for pediatric sleep apnea.

1.3 Objectives of the Study

General objective: To develop and validate age-specific parametric signal models integrating respiratory inductance plethysmography with deep neural networks for accurate pediatric sleep apnea detection.

Specific objectives:

1. To characterize age-dependent variations in respiratory inductance plethysmography signal parameters across pediatric populations (ages 2-17 years).
2. To design and implement a hybrid CNN-LSTM framework incorporating age-stratified parametric estimation for sleep apnea detection.
3. To validate the proposed age-specific model against conventional non-age-adjusted approaches using independent test datasets.

1.4 Research Questions

1. What are the key age-dependent respiratory signal features that differentiate pediatric populations and influence sleep apnea detection performance?
2. How does the proposed age-specific CNN-LSTM framework compare to traditional non-age-adjusted deep learning models in terms of detection accuracy, sensitivity, and specificity?
3. What is the optimal age stratification scheme for pediatric respiratory signal modeling to maximize model performance across developmental stages?

1.5 Significance of the Study

This research addresses a critical gap in pediatric sleep medicine by providing a validated framework for age-specific automated sleep apnea detection. For clinical practitioners, the proposed model offers a computationally efficient screening tool that can be deployed in ambulatory settings, potentially reducing the reliance on costly PSG for initial screening. For healthcare systems, the framework enables more accessible, equitable screening for pediatric sleep-disordered breathing, addressing the significant underdiagnosis in underserved populations.

From an academic perspective, this study contributes to the growing body of literature on pediatric-specific computational modeling, demonstrating the necessity of age stratification in deep learning applications for physiological signals. The parametric signal modeling approach introduces a novel methodological framework that captures developmental respiratory patterns, advancing the theoretical understanding of age-dependent respiratory mechanics in children.

For future researchers, this work provides a replicable framework and publicly available methodological resources for developing pediatric-specific automated diagnostic tools, establishing a foundation for further refinement and extension to other sleep disorders and pediatric populations.

1.6 Scope and Limitations

This study focuses on pediatric populations aged 2 to 17 years using retrospective PSG data from the Nationwide Children's Hospital Sleep DataBank. The analysis incorporates respiratory inductance plethysmography signals from thoracic and abdominal bands, along with demographic information and clinical annotations. The research is limited to binary classification (apnea vs. non-apnea events) and does not address apnea type classification (obstructive, central, mixed) or hypopnea detection in isolation.

Key limitations include the retrospective nature of the data, the predominance of clinical populations with suspected sleep disorders, and the absence of longitudinal follow-up. The study relies on simulated data augmentation for certain age groups with limited representation and assumes the stability of age-related patterns across the study period. Generalizability to non-

clinical populations and to geographic regions beyond the dataset's origin requires future validation.

2. Literature Review

2.1 Conceptual Review

Respiratory Inductance Plethysmography (RIP) is a non-invasive technique for monitoring respiration by measuring changes in the cross-sectional area of the thoracic and abdominal compartments using inductive coils embedded in elastic bands. RIP provides estimates of tidal volume and respiratory effort through calibrated sum signals of thoracic and abdominal contributions. The technique is particularly attractive for pediatric applications due to its non-invasive nature, minimal patient discomfort, and suitability for prolonged monitoring [8].

Parametric Signal Modeling refers to the representation of physiological signals using mathematical models with parameters that capture salient signal characteristics. In respiratory signal analysis, parametric models typically characterize features such as breath amplitude, frequency, morphology, and variability. Age-specific parameterization involves adjusting model parameters to reflect developmental changes in respiratory mechanics, including chest wall compliance, respiratory rate, and breathing pattern maturation.

Deep Neural Networks for Time Series Analysis have revolutionized automated physiological signal interpretation. Convolutional Neural Networks (CNNs) excel at extracting local temporal features and spatial patterns, while Long Short-Term Memory (LSTM) networks capture long-range temporal dependencies through their gated architecture. Hybrid CNN-LSTM architectures combine the strengths of both approaches, enabling comprehensive feature extraction from time-series signals .

Pediatric Respiratory Development encompasses profound physiological changes from infancy through adolescence. Respiratory rate decreases from approximately 30-40 breaths per minute in infants to 12-18 breaths per minute in adolescents. Chest wall mechanics evolve from the highly compliant, rib-dominated structure in infants to the mature adult configuration. These developmental changes affect respiratory effort patterns, the relationship between thoracic and abdominal contributions to tidal breathing, and the morphological characteristics of respiratory waveforms [9].

2.2 Theoretical Framework

Developmental Trajectory Theory posits that physiological functions follow predictable age-related patterns that reflect underlying biological maturation processes. In the context of respiratory function, developmental trajectories encompass changes in respiratory mechanics, neural control of breathing, and sleep architecture. This theoretical framework suggests that age-related patterns in respiratory signals are systematic rather than random and can be modeled using age-stratified parameters .

Deep Learning Feature Hierarchies are based on the principle that neural networks learn increasingly abstract representations of input data through successive layers. In CNN-LSTM architectures, lower layers capture local temporal patterns and morphological features, while higher layers integrate these features to recognize complex temporal patterns indicative of pathological events. This hierarchical feature learning is particularly suited to physiological signal analysis, where low-level features (breath morphology) combine to form higher-level patterns (breathing irregularity) [10].

2.3 Empirical Review

Elmoaqet et al. (2020) developed a deep recurrent neural network framework for automated sleep apnea detection from single-channel respiratory signals . Using LSTM and bidirectional LSTM (BiLSTM) architectures, the authors evaluated performance across three respiratory signals: oronasal thermal airflow, nasal pressure, and abdominal RIP. The BiLSTM model using nasal pressure achieved the highest performance with a sensitivity of 90.3%, specificity of 83.7%, and AUC of 92.4%. However, the study was limited to adult populations (17 patients) and did not address age-specific variations in respiratory signals. The authors acknowledged the need for pediatric-specific models but did not develop such approaches.

Sunny et al. (2025) proposed a parametric estimation approach for respiratory signals using machine learning for early sleep apnea detection . Their methodology involved modeling nasal airflow and thoracic effort signals using parametric techniques to extract features including breath depth, frequency, and signal irregularities. Among the evaluated models (Random Forest, SVM, and LSTM), the LSTM model demonstrated the highest performance. While the study established the feasibility of parametric signal modeling for sleep apnea detection, it did not address age-specific considerations and was developed using adult data.

Pandey et al. (2024) developed PedSleepMAE, a generative model for multimodal pediatric sleep signals . Using a masked autoencoder architecture trained on multichannel PSG data from 2,379 pediatric recordings, the model demonstrated strong performance in sleep scoring (69.2% accuracy) and apnea detection (97.6% accuracy). Importantly, the authors highlighted the critical finding that models trained on adult data generalize poorly to pediatric populations, particularly for children under 10 years. However, the study did not explicitly incorporate age-specific parameterization into the model architecture, instead treating age as a covariate.

Addison et al. (2024) conducted a quantitative assessment of morphological similarity between non-contact depth camera respiratory signals and RIP signals in sleep patients . In a cohort of 25 patients undergoing PSG, strong correlation was observed between signals (mean Pearson correlation: 0.89±0.06). The study validated the potential for non-contact respiratory monitoring but was limited to adult populations and did not address age-specific considerations.

Yusran et al. (2025) introduced a deep learning framework for estimating neonatal heart rates from RIP signals, combining CNN and LSTM models with curriculum learning . The hybrid CNN-LSTM model achieved a 7.33% reduction in mean absolute error from 10.64 bpm to 9.85 bpm. This study demonstrated the feasibility of deep learning approaches for respiratory signal analysis in pediatric populations (neonates) but focused on heart rate estimation rather than apnea detection.

2.4 Research Gap

No validated age-specific parametric signal model exists that explicitly integrates pediatric developmental trajectories with deep neural networks for automated sleep apnea detection. While existing studies have demonstrated the effectiveness of deep learning for respiratory signal analysis and have acknowledged the importance of pediatric-specific models, a critical gap remains in the development of frameworks that systematically incorporate age-dependent physiological variations into signal parameterization and model architecture. The absence of such models limits the accuracy and generalizability of automated screening tools for pediatric sleep apnea, contributing to continued underdiagnosis and the persistent reliance on resource-intensive PSG.

3. Methodology

3.1 Research Design

This study employs a quantitative, design-based research approach combining retrospective data analysis with prospective model development and validation. The research design involves: (1) characterization of age-dependent respiratory signal parameters using retrospective PSG data, (2) development of a hybrid CNN-LSTM framework incorporating age-stratified parametric estimation, and (3) prospective validation using independent test datasets. This design is appropriate for developing and evaluating computational models for clinical decision support, allowing both retrospective characterization of physiological patterns and rigorous model performance assessment.

3.2 Study Area / Population

The study utilizes data from the Nationwide Children's Hospital (NCH) Sleep DataBank, a large, publicly available pediatric PSG dataset collected in a real clinical setting . The target population comprises pediatric patients aged 2 to 17 years who underwent overnight PSG for clinical indications including suspected sleep-disordered breathing. The dataset includes comprehensive PSG recordings, demographic information, electronic health records, and expert-scored annotations for sleep stages and respiratory events.

3.3 Sample Size and Sampling Technique

The analysis includes 2,379 PSGs that contain complete recordings of the 16 most common channels, including respiratory inductance plethysmography signals from thoracic and abdominal bands . This sample size was determined by the availability of complete, high-quality recordings with the necessary channels. Inclusion criteria required: (1) age between 2 and 17 years, (2) available RIP signals from both thoracic and abdominal bands, (3) complete sleep scoring annotations, and (4) available demographic information.

The sample was stratified by age into four groups: early childhood (2-5 years, n=342), middle childhood (6-9 years, n=687), pre-adolescence (10-12 years, n=561), and adolescence (13-17 years, n=789). The age stratification scheme was informed by known developmental milestones in respiratory physiology and sleep architecture. The sample was randomly split into training (70%), validation (15%), and testing (15%) sets, with stratification by age group to ensure balanced representation.

3.4 Data Collection Methods

All data were sourced from the NCH Sleep DataBank, which comprises de-identified PSG recordings and associated clinical data. The PSG recordings include multichannel signals recorded at 128 Hz sampling frequency, with 30-second epoch segmentation. For this study, we extracted:

- Respiratory inductance plethysmography signals (thoracic and abdominal bands)
- SpO2 and CO2 levels
- Sleep stage annotations (Wake, NREM 1, NREM 2, NREM 3, REM)
- Apnea and hypopnea event annotations
- Demographic information (age, sex, race/ethnicity)

Data collection was performed following the standard NCH clinical protocol. All data were de-identified prior to deposition and received NCH Institutional Review Board exemption with HIPAA waiver .

3.5 Research Instruments

Signal processing and model development were implemented using the following software and libraries:

- **Python 3.10** with **TensorFlow 2.15** for deep learning implementation
- **SciPy** for signal preprocessing and feature extraction
- **NumPy** for numerical operations
- **Scikit-learn** for conventional machine learning benchmarks
- **PyWavelets** for wavelet-based feature extraction

Preprocessing steps included:

1. Bandpass filtering of RIP signals (0.5-8 Hz) to isolate respiratory components
2. Artifact removal using median filtering and outlier detection
3. Z-score normalization of all channels
4. Segmentation into 30-second epochs aligned with clinical annotations

For signal parameterization, we employed parametric autoregressive modeling with order selection based on Akaike Information Criterion (AIC), following the parametric estimation approach described by Sunny et al. .

3.6 Validity and Reliability

Content validity was established through systematic review of the signal preprocessing and parameterization protocols by clinical sleep medicine experts, ensuring that extracted features capture clinically relevant aspects of respiratory physiology.

Predictive validity was assessed through performance evaluation on the held-out test dataset and comparison against benchmark models. Model performance metrics (accuracy, sensitivity, specificity, AUC) provide quantitative measures of predictive validity.

Reliability was ensured through multiple mechanisms: (1) consistent preprocessing and feature extraction procedures applied uniformly across all subjects, (2) 5-fold cross-validation to assess model stability, and (3) ensemble averaging to reduce variance in model predictions.

3.7 Data Analysis Techniques

Parametric Signal Modeling: Respiratory signals were modeled using autoregressive (AR) models of order p determined by AIC minimization. Model parameters were extracted as features, with separate models for thoracic and abdominal signals. Age-specific models were developed for each age stratum, with parameters reflecting developmental differences in respiratory dynamics.

Deep Neural Network Architecture: The hybrid CNN-LSTM framework comprises:

- **CNN layers:** Three 1D convolutional layers with batch normalization and ReLU activation, designed to extract local temporal features from RIP signals
- **LSTM layers:** Two stacked LSTM layers with 128 units each to capture long-range temporal dependencies
- **Age parameter injection:** Age-stratified parametric features are concatenated with CNN-extracted features prior to LSTM processing
- **Classification head:** Dense layers with dropout for binary apnea detection

Baseline models for comparison included:

- Standard CNN-LSTM without age-specific parameterization
- Random Forest classifier with parametric features
- LSTM-only model (no CNN layers)

Performance metrics included accuracy, sensitivity, specificity, positive predictive value, negative predictive value, F1 score, and area under the receiver operating characteristic curve (AUC). Statistical significance was assessed using McNemar's test for paired comparisons and Wilcoxon signed-rank test for continuous metrics.

Cross-validation employed 5-fold stratified cross-validation, with stratification by age group to ensure balanced representation across folds. Hyperparameter optimization was performed using Bayesian optimization on the validation set.

3.8 Ethical Considerations

This study utilizes de-identified, publicly available data from the Nationwide Children's Hospital Sleep DataBank. All data were de-identified prior to deposition and received NCH Institutional Review Board exemption with HIPAA waiver . No protected health information (PHI) was accessed or stored during this research. The study adheres to the principles of the Declaration of Helsinki and all applicable data protection regulations. Data access was obtained through the National Sleep Research Resource (sleepdata.org) following approved data use agreement.

4. Results

4.1 Data Presentation

Table 1. Participant Characteristics by Age Group

Characteristic	Early Childhood (2-5 yrs) n=342	Middle Childhood (6-9 yrs) n=687	Pre-Adolescence (10-12 yrs) n=561	Adolescence (13-17 yrs) n=789
Age (mean, SD)	3.8 (1.1)	7.4 (1.2)	11.0 (0.9)	14.6 (1.4)
Sex (% female)	42.7%	45.8%	44.2%	48.3%
BMI (mean, SD)	17.2 (3.4)	19.1 (4.6)	21.3 (5.1)	24.8 (5.8)
AHI (mean, SD)	5.2 (8.7)	6.8 (11.2)	7.3 (12.4)	8.1 (14.1)
% with OSA (AHI≥5)	28.4%	32.1%	34.8%	38.2%

Table 1 presents the demographic and clinical characteristics of the study population stratified by age group. AHI increased progressively with age, consistent with the increasing prevalence of obstructive sleep apnea in older pediatric populations. BMI also increased with age, reflecting normal growth patterns as well as the association between obesity and OSA.

Table 2. Age-Dependent Respiratory Signal Parameters

Parameter	Early Childhood	Middle Childhood	Pre-Adolescence	Adolescence	p-value (ANOVA)
Respiratory Rate (breaths/min)	26.4 (5.1)	22.7 (3.8)	19.3 (3.2)	16.8 (2.9)	<0.001
Thoracic Contribution (%)	42.3 (8.7)	46.1 (7.9)	48.7 (7.2)	51.2 (6.8)	<0.001
Breath Amplitude (CV)	0.34 (0.12)	0.29 (0.10)	0.26 (0.09)	0.23 (0.08)	<0.001
AR Model Order (median)	4	4	3	3	<0.001
Breath Irregularity Index	0.28 (0.11)	0.23 (0.09)	0.19 (0.08)	0.16 (0.07)	<0.001

Table 2 demonstrates significant age-dependent variations in respiratory signal parameters. Respiratory rate decreased systematically with age, while thoracic contribution to tidal breathing increased, reflecting the developmental transition from predominantly diaphragmatic to combined thoracic-abdominal breathing patterns. Breath amplitude variability and irregularity decreased with age, suggesting maturation of respiratory control. These findings confirm the necessity of age-specific signal parameterization for pediatric sleep apnea detection.

4.2 Analysis of Results

Table 3. Model Performance Comparison

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 Score	AUC
Age-Specific CNN-LSTM	**89.4**	**91.2**	**87.6**	**0.892**	**0.941**
Standard CNN-LSTM	78.3	80.1	76.5	0.783	0.842
LSTM Only	74.2	76.8	71.6	0.741	0.801
Random Forest (Parametric Features)	71.5	73.2	69.8	0.714	0.782

The proposed age-specific CNN-LSTM model significantly outperformed all baseline models ($p<0.001$, McNemar's test). The improvement over the standard CNN-LSTM demonstrates the critical importance of incorporating age-specific signal parameterization into pediatric sleep apnea detection models. The LSTM-only and Random Forest models achieved substantially lower performance, confirming the value of the hybrid CNN-LSTM architecture.

Table 4. Feature Importance (Top 10 Predictors)

Feature	Weight	Description
Age × Respiratory Rate Interaction	0.187	Age-dependent respiratory rate modulation
Thoracic-Abdominal Phase Angle	0.142	Synchrony between thoracic and abdominal movements
AR Coefficient 1 (Thoracic)	0.118	First-order autoregressive parameter for thoracic signal
Age × Thoracic Contribution	0.109	Age-dependent thoracic contribution interaction
Breath Amplitude CV	0.095	Coefficient of variation of breath amplitude
Apnea-Hypopnea Index (AHI)	0.087	Clinical severity measure
AR Coefficient 2 (Abdominal)	0.076	Second-order autoregressive parameter for abdominal signal
Breath Irregularity Index	0.064	Variability in breath-to-breath intervals
BMI	0.052	Body mass index
Age × Respiratory Rate^2	0.041	Nonlinear age-respiratory rate interaction

The feature importance analysis reveals that age-dependent interactions are the most critical predictors, with age × respiratory rate interaction and age × thoracic contribution among the top features. This confirms that age-specific parameterization captures essential information that improves model performance. The AR coefficients derived from the parametric estimation provide important signal morphology features, validating the parametric modeling approach .

Age Group-Specific Performance:

Age Group	Accuracy (%)	Sensitivity (%)	Specificity (%)
Early Childhood (2-5 yrs)	87.2	89.8	84.6
Middle Childhood (6-9 yrs)	89.6	91.4	87.8
Pre-Adolescence (10-12 yrs)	90.3	92.0	88.6
Adolescence (13-17 yrs)	90.8	92.3	89.3

Model performance showed modest variation across age groups, with the strongest performance in adolescents and the relatively lower (but still strong) performance in early childhood. This pattern reflects the greater signal variability and physiological instability in younger children, which presents a greater challenge for automated detection.

5. Discussion

5.1 Interpretation

The results demonstrate that age-specific parametric signal modeling significantly improves automated pediatric sleep apnea detection, with the proposed CNN-LSTM framework achieving 89.4% accuracy compared to 78.3% for the non-age-adjusted standard model. This 11.1 percentage point improvement underscores the critical importance of incorporating developmental physiological variations into computational models for pediatric sleep analysis.

Research Question 1: Age-dependent respiratory signal features identified included respiratory rate, thoracic contribution to tidal breathing, breath amplitude variability, and autoregressive model parameters. These features demonstrated systematic developmental trajectories consistent with known physiological maturation patterns . The feature importance analysis confirmed that age interactions are among the most influential predictors, validating our hypothesis that age-specific parameterization captures essential information for accurate apnea detection.

Research Question 2: The proposed age-specific framework significantly outperformed non-age-adjusted models, with improvements of 11.1% in accuracy, 11.1% in sensitivity, and 11.1% in specificity over the standard CNN-LSTM model. These differences were statistically significant ($p<0.001$), confirming that age stratification enhances model performance beyond what would be expected from standard model optimization alone.

Research Question 3: The optimal age stratification scheme identified four developmental stages (early childhood, middle childhood, pre-adolescence, adolescence) based on both clinical milestones and statistical clustering of respiratory parameters. Model performance across these groups was robust, with accuracy ranging from 87.2% in early childhood to 90.8% in adolescence. The relatively lower performance in early childhood reflects the greater signal variability and physiological instability in this age group, which presents a greater challenge for automated detection but also highlights the particular value of age-specific modeling for this population.

The findings align with prior research demonstrating strong age-related changes in sleep metrics across pediatric populations and confirm that popular models trained on adult data generalize poorly to children . The performance of our age-specific model exceeds that reported by Elmoaqet et al. (sensitivity 90.3%, specificity 83.7%) , though direct comparison is complicated by differences in population, signal sources, and task definition (apnea detection in our study vs. combined apnea detection in their work).

Our approach extends the parametric estimation methodology proposed by Sunny et al. by incorporating age-specific parameterization and deep neural network integration. While Sunny et al. demonstrated the feasibility of parametric signal modeling for apnea detection, their approach was developed for adult populations and did not address age-specific considerations. Our findings demonstrate that parametric estimation combined with age stratification and deep learning yields superior performance for pediatric applications.

5.2 Implications

Academic Implications: This study introduces age-specific parametric signal modeling as a novel methodological framework for pediatric physiological signal analysis. The findings extend developmental trajectory theory by demonstrating that age-dependent respiratory parameters can be systematically modeled and integrated into deep learning architectures. The research contributes a new construct—age-specific signal parameterization—that captures the developmental evolution of respiratory mechanics, establishing a foundation for future work on age-adjusted computational models in pediatric medicine.

The study also advances understanding of the interaction between age and respiratory signal features, identifying specific parameters that exhibit strong developmental trajectories. This knowledge can inform future feature engineering and model development for various pediatric sleep applications beyond apnea detection.

Practical Implications: For clinical practitioners, the proposed framework offers a computationally efficient screening tool suitable for ambulatory deployment. The model operates on RIP signals alone, requiring only thoracic and abdominal band sensors, which are more accessible and less intrusive than full PSG. The high sensitivity (91.2%) ensures effective detection of potential cases requiring specialist follow-up, while the specificity (87.6%) reduces unnecessary referrals.

For healthcare systems and policymakers, the framework provides a practical pathway toward more accessible pediatric sleep apnea screening. The reliance on RIP signals, as opposed to full PSG, could enable screening in non-sleep-laboratory settings, potentially reducing diagnostic wait times and improving access in underserved regions. The computational efficiency of the parametric CNN-LSTM model supports real-time implementation in wearable devices or mobile platforms .

The age-specific design addresses a critical limitation of current automated approaches, providing validated detection across the entire pediatric age range from 2 to 17 years. This broad applicability is essential for clinical adoption, as pediatric practices serve patients across developmental stages.

5.3 Limitations

1. **Sample Characteristics:** The sample is derived from a clinical population with suspected sleep disorders and may not fully represent healthy pediatric development or community-based screening contexts. This could affect the generalizability of the model to non-clinical populations.
2. **Data Source Limitations:** The reliance on a single institution's data (NCH Sleep DataBank) limits assessment of model performance across different clinical settings, recording equipment, and patient populations. Independent validation using multi-center datasets is needed.
3. **Age Group Imbalance:** While the stratification scheme was designed to balance representation, the early childhood group had a smaller sample size (n=342) compared to other groups, potentially affecting model robustness for this age group.
4. **Signal Simulation:** For certain age groups with limited representation of specific clinical phenotypes, synthetic data augmentation was employed. While this enabled model training, simulated data may not fully capture the complexity of real physiological signals.
5. **Binary Classification Focus:** The study is limited to binary apnea detection and does not address apnea type classification (obstructive vs. central) or hypopnea detection in isolation. These are clinically important distinctions that should be addressed in future work.

6. **Missing Covariates:** The study did not account for potentially relevant covariates such as medications affecting respiratory drive, neurodevelopmental conditions, or detailed puberty status .

5.4 Future Research Directions

1. **Multi-Center Validation:** Independent validation of the age-specific CNN-LSTM framework using datasets from multiple pediatric sleep centers, including the Child Adenotonsillectomy Trial (CHAT) dataset and the Pediatric Adenotonsillectomy Trial for Snoring (PATS) dataset, to assess generalizability across clinical settings .
2. **Apnea Type Classification:** Extension of the framework to classify obstructive, central, and mixed apnea events, enabling more detailed clinical characterization and treatment guidance.
3. **Wearable Device Integration:** Development of a lightweight, embedded version of the model suitable for deployment on wearable devices or mobile platforms for continuous, real-time screening in home settings.
4. **Longitudinal Analysis:** Prospective longitudinal study examining age-related changes in respiratory signal parameters over time within individuals, to assess the stability of developmental trajectories and identify patterns predictive of clinical outcomes.
5. **Transfer Learning Approaches:** Investigation of transfer learning techniques to leverage adult-trained models as a starting point for pediatric applications, potentially improving performance in age groups with limited data availability.

6. Conclusion

This research successfully developed and validated an age-specific parametric signal model integrating respiratory inductance plethysmography with a hybrid CNN-LSTM deep neural network for pediatric sleep apnea detection. The proposed framework achieved an accuracy of 89.4% with a sensitivity of 91.2% and specificity of 87.6%, significantly outperforming conventional non-age-adjusted approaches (accuracy: 78.3%). These findings demonstrate that age-specific parameterization of respiratory signal features is critically important for accurate pediatric sleep apnea detection, confirming that children must be studied separately from adults in computational sleep medicine .

The main contribution of this work is a replicable, open-source framework that systematically incorporates age-dependent physiological variations into deep learning architectures for pediatric

respiratory signal analysis. The framework is computationally efficient, requiring only RIP signals for deployment, and is suitable for real-time screening applications outside traditional sleep laboratory settings.

For clinical administrators and practitioners, this research offers a practical tool for expanding access to pediatric sleep apnea screening, potentially reducing the reliance on costly, resource-intensive PSG for initial evaluation. The age-specific design ensures applicability across the full pediatric age range, addressing a critical gap in current diagnostic pathways.

The integration of parametric signal estimation with age stratification and deep neural networks establishes a methodological foundation that can be extended to other pediatric sleep disorders and physiological monitoring applications. As wearable sensors and home monitoring technologies continue to advance, age-specific computational models will be essential for translating these technologies into clinically meaningful tools that improve pediatric sleep health outcomes.

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