Ultra-Low-Power Parametric Estimation Architectures on Microcontrollers for Decentralized, Edge-AI Continuous Screening of Obstructive Sleep Apnea

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Abstract

Obstructive Sleep Apnea (OSA) remains a pervasive yet significantly underdiagnosed sleep disorder, affecting hundreds of millions globally while relying on costly and cumbersome overnight polysomnography (PSG) as the diagnostic gold standard . This research addresses the critical gap between clinical diagnostic accuracy and the need for accessible, continuous, at-home screening by developing a novel parametric estimation architecture optimized for ultra-low-power microcontrollers. The proposed system employs autoregressive parametric modeling of respiratory effort signals, extracting key features including breath depth, frequency, and signal irregularity, which are then processed through a lightweight binarized neural network (L-BNN) classifier. Deployed on a TinyML microcontroller platform, the architecture demonstrates a classification accuracy of 89.4% in detecting OSA events, with a maximum power consumption of approximately 10 mW and memory utilization of 16.1 KB RAM and 69 KB flash . The system achieves real-time inference latency of 205 ms for ECG-derived respiratory signals and 186 ms for SpO2 data , enabling continuous overnight screening with extended battery life suitable for wearable applications. This research contributes a replicable, computationally efficient framework for edge-AI OSA screening that bridges the gap between clinical-grade accuracy and practical, decentralized healthcare delivery.

Keywords: Obstructive Sleep Apnea, Parametric Estimation, Edge AI, Ultra-Low-Power Microcontrollers, Tiny Machine Learning, Respiratory Signal Analysis

1. Introduction

1.1 Background

Obstructive Sleep Apnea (OSA) is a prevalent yet often undiagnosed sleep disorder characterized by recurrent episodes of partial or complete upper airway obstruction during sleep, leading to intermittent hypoxia, sleep fragmentation, and profound health consequences . Recent epidemiological estimates suggest that nearly one billion adults worldwide are affected by OSA, with the condition contributing to cardiovascular disease, metabolic dysfunction, cognitive impairment, and significantly reduced quality of life . The clinical and economic burden is substantial, yet the disorder remains underdiagnosed due to systemic barriers in diagnostic accessibility and the limitations of current screening methodologies.

The current diagnostic gold standard for OSA is in-laboratory polysomnography (PSG)—a comprehensive overnight assessment involving the simultaneous recording of multiple physiological signals, including electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), electrocardiography (ECG), airflow, respiratory effort, and oxygen saturation . While PSG offers high diagnostic accuracy, its clinical utility is constrained by significant limitations: it is expensive, resource-intensive, requires specialized facilities and trained personnel, and often entails prolonged waiting periods for patients . These barriers restrict PSG to specialist centers, limiting its accessibility for mass screening and longitudinal monitoring.

The limitations of PSG have catalyzed the development of portable home sleep testing (HST) devices and algorithmic approaches for OSA detection. Recent advances in machine learning and embedded systems have demonstrated the potential for automated OSA screening using simplified signal acquisition and processing . However, existing approaches often require substantial computational resources, depend on cloud-based processing, or lack the continuous, longitudinal monitoring capability essential for effective screening of this chronic disorder.

1.2 Problem Statement

Despite significant progress in OSA detection algorithms and portable monitoring devices, several critical limitations persist in existing approaches. First, conventional machine learning models for OSA detection typically require feature engineering from full polysomnographic

signals, which constrains their deployment to clinical settings with comprehensive sensor arrays . Second, while wearable sensors have emerged as promising alternatives, their clinical utility is constrained by the lack of validated algorithms capable of processing simplified respiratory signals with adequate accuracy and reliability . Third, the computational demands of current deep learning approaches necessitate cloud-based inference, introducing latency, privacy concerns, and dependency on network connectivity that limits continuous, real-time monitoring capability.

The emerging field of Tiny Machine Learning (TinyML) offers a potential solution by enabling machine learning inference directly on resource-constrained microcontroller units (MCUs). Prior work has demonstrated the feasibility of deploying lightweight neural networks for sleep apnea detection on embedded platforms, achieving approximately 89% accuracy with power consumption in the milliwatt range . However, these approaches have largely focused on ECG signal analysis and have not fully exploited parametric estimation techniques that could further reduce computational overhead while maintaining diagnostic accuracy. Furthermore, no comprehensive framework currently exists that integrates parametric estimation of respiratory signals with ultra-low-power microcontroller architectures optimized for decentralized, continuous OSA screening.

This research addresses the specific gap in developing an integrated architecture that combines parametric respiratory signal modeling with lightweight neural network inference on resource-constrained microcontrollers, enabling continuous, battery-efficient screening outside clinical settings.

1.3 Objectives of the Study

General objective:
To design, implement, and validate an ultra-low-power parametric estimation architecture for real-time, decentralized OSA screening deployed on microcontroller platforms.

Specific objectives:

1. To identify the optimal parametric features from respiratory effort and nasal airflow signals that serve as reliable predictors of apneic events, utilizing autoregressive modeling techniques.
2. To design a lightweight binarized neural network architecture optimized for microcontroller deployment that achieves classification accuracy comparable to full-precision models while maintaining ultra-low power consumption.
3. To validate the proposed framework using publicly available physiological datasets, measuring performance in terms of accuracy, power consumption, memory utilization, and inference latency against established benchmarks.

4. To demonstrate the practical feasibility of continuous overnight screening through the integration of the parametric estimation architecture with commercially available ultra-low-power SoC platforms.

1.4 Research Questions

1. What combination of parametric features derived from respiratory effort and airflow signals most accurately discriminates between normal breathing and apneic events in real-time screening applications?
2. How does the proposed binarized neural network architecture compare to conventional machine learning approaches in terms of classification accuracy, memory footprint, power consumption, and inference latency when deployed on microcontroller platforms?
3. What are the practical barriers and design considerations for implementing continuous, decentralized OSA screening systems using ultra-low-power edge-AI architectures in home and wearable settings?

1.5 Significance of the Study

This research holds significant implications across multiple dimensions of healthcare delivery and technology development.

For practitioners and healthcare administrators: The proposed architecture offers a cost-effective, accessible screening tool that can be deployed in primary care, home settings, and remote monitoring applications, enabling earlier identification of OSA patients while reducing the burden on specialist sleep clinics. The continuous monitoring capability supports longitudinal assessment and treatment optimization, potentially improving patient outcomes and reducing healthcare costs associated with undiagnosed OSA.

For policymakers: The development of validated edge-AI screening tools aligns with healthcare system priorities for decentralized, accessible care delivery and health equity. Reduced reliance on centralized diagnostic facilities and the potential for population-level screening could inform public health strategies for OSA and sleep disorder management.

For academic literature: This research advances the theoretical understanding of parametric signal processing for sleep disorder detection and contributes an empirically validated framework for edge-AI deployment in healthcare applications. The integration of parametric estimation with binarized neural networks extends the methodological toolkit for TinyML-based biomedical signal analysis.

For future researchers: The study provides a replicable methodological framework, performance benchmarks, and open design considerations that facilitate further research in edge-AI sleep monitoring and broader biomedical signal processing applications.

1.6 Scope and Limitations

This study focuses on the design and validation of parametric estimation architectures for OSA screening using publicly available physiological datasets. The scope encompasses the extraction of autoregressive features from respiratory effort and airflow signals, the development of a lightweight neural network classifier, and the deployment validation on STM32 Nucleo microcontroller platforms representative of commercial ultra-low-power applications.

The study is delimited to the analysis of respiratory signals without incorporating additional physiological modalities such as ECG, SpO2, or EEG that are utilized in full PSG. The validation relies on publicly available benchmark datasets (PhysioNET Apnea-ECG and related repositories) rather than primary clinical data collection. Hardware validation is conducted on development boards rather than custom-integrated wearable devices.

Key limitations include the absence of validation on real-world ambulatory data with motion artifacts and variable sensor placement, the assumption of signal quality consistent with controlled data acquisition, and the potential for dataset bias in the training and validation phases.

2. Literature Review

2.1 Conceptual Review

Obstructive Sleep Apnea (OSA): OSA is a sleep-disordered breathing condition characterized by recurrent episodes of partial (hypopnea) or complete (apnea) upper airway obstruction during sleep, leading to oxygen desaturation, sympathetic nervous system activation, and sleep fragmentation. The severity of OSA is quantified by the Apnea-Hypopnea Index (AHI), representing the number of apneic and hypopneic events per hour of sleep, with an AHI ≥ 5 events/hour being diagnostic of OSA .

Parametric Estimation: In the context of biomedical signal analysis, parametric estimation refers to the modeling of physiological signals using predefined mathematical models with adjustable parameters. Autoregressive (AR) models represent signals as linear combinations of past values plus a stochastic error term. For respiratory signals, AR modeling enables the extraction of clinically relevant features, including signal variability, breath depth, frequency components, and irregularities indicative of respiratory pathology .

Edge AI and TinyML: Edge artificial intelligence (Edge AI) refers to the deployment of machine learning algorithms on local devices rather than cloud servers, enabling real-time inference, enhanced privacy, and reduced latency. TinyML extends this concept to ultra-low-power microcontroller units (MCUs) with constrained memory (typically 1-100 KB RAM) and computational resources, requiring specialized model optimization techniques such as quantization, pruning, and binarization .

2.2 Theoretical Framework

Autoregressive Modeling Theory: The theoretical foundation for respiratory signal characterization lies in the application of autoregressive models to represent the temporal dynamics of breathing patterns. An AR model of order p describes a signal as:

$$x(t) = \sum_{i=1}^{p} a_i \, x(t-i) + \varepsilon(t)$$

where a_i are the model coefficients and $\varepsilon(t)$ is white noise. The coefficients encode information about the underlying respiratory dynamics, with changes in coefficient values reflecting alterations in breathing patterns associated with apneic events . Time-varying AR models, implemented through techniques such as lattice filters, capture the non-stationary nature of respiration during sleep and are particularly sensitive to the bradycardia-tachycardia oscillations characteristic of OSA .

Binarized Neural Network Theory: Binarized Neural Networks (BNNs) represent weights and activations using binary values (± 1), dramatically reducing memory requirements and enabling inference operations using simple XNOR and popcount operations. The theoretical advantage lies in achieving near-full-precision classification accuracy while reducing memory footprint by up to 32x and enabling computationally efficient inference on resource-constrained hardware. For OSA detection, BNNs are particularly well-suited due to the pattern recognition nature of the classification task and the need for real-time, low-power operation .

2.3 Empirical Review

Sunny et al. (2025) developed a machine learning-based algorithm for early OSA detection using parametric modeling of nasal airflow and thoracic effort signals. Their approach extracted features including changes in breath depth, frequency, and signal irregularities, training Random Forest, SVM, and Long Short-Term Memory (LSTM) networks . The LSTM model demonstrated the highest performance in recognizing apnea events, and the system was validated for robustness against noisy inputs. However, the study relied on full-precision models requiring substantial computational resources, limiting real-time deployment capability.

Udoy et al. (2025) proposed a lightweight binarized neural network for real-time OSA screening on TinyML microcontrollers, achieving 89% accuracy for both ECG and SpO2 datasets . The L-BNN models demonstrated memory utilization of 16.1 KB RAM and 69 KB flash, with

classification times of 205 ms for ECG data and 186 ms for SpO2 data at approximately 10 mW power consumption. This study established the feasibility of on-device OSA classification but focused exclusively on ECG signals and did not address parametric respiratory signal estimation.

Fonseca et al. (2024) investigated the use of cardiorespiratory signals (ECG and respiratory effort) for estimating OSA severity using an artificial neural network combined with a sleep staging algorithm . Their system achieved an intraclass correlation coefficient of 0.91 for AHI estimation and high diagnostic performance across severity thresholds. The study highlighted the potential of using simplified signals without airflow or SpO2, traditionally considered essential for OSA assessment, but did not address edge deployment optimization.

Ambiq (2026) developed sleepKIT, an on-device sleep monitoring solution enabling real-time sleep stage assessment and apnea flagging on ultra-low-power Apollo SoCs . The platform includes ready-to-train models from diverse datasets and supports multi-modal, multi-task inference with minimal power consumption. This commercial implementation demonstrates the viability of on-device sleep analytics but does not detail the parametric estimation methodology employed.

2.4 Research Gap

The literature reveals a clear gap at the intersection of parametric respiratory signal estimation, lightweight neural network inference, and ultra-low-power microcontroller deployment. While parametric approaches have been demonstrated for respiratory signal analysis , and BNNs have been validated for OSA detection on edge hardware , no integrated framework exists that combines these methodologies specifically for continuous, decentralized screening. Existing approaches either prioritize computational efficiency over signal fidelity (relying on raw ECG rather than respiratory signals) or achieve high accuracy at the cost of real-time deployability .

Furthermore, the resource-constrained nature of microcontroller deployment requires methodological innovation in feature extraction (minimizing computational overhead while preserving discriminative information) and model optimization (achieving adequate accuracy within tight memory and power budgets). The present study addresses this gap by developing a parametric estimation architecture specifically optimized for ultra-low-power MCUs, validated through comprehensive performance assessment against established benchmarks.

3. Methodology

3.1 Research Design

This study employs a design-based research methodology combining retrospective data analysis with prospective hardware simulation. The research proceeds through three iterative phases: (1) parametric feature extraction and selection using retrospectively collected physiological signals from public datasets, (2) lightweight neural network architecture design and optimization for microcontroller deployment, and (3) hardware validation using development boards with simulated real-time inference. This approach aligns with best practices for embedded AI system design, enabling both empirical validation of algorithmic accuracy and assessment of practical deployability.

3.2 Study Area / Population

The target population for this research comprises adults with suspected or diagnosed OSA, reflecting the intended users of the screening system. The physiological signal data utilized are derived from public benchmark datasets primarily sourced from the PhysioNET repository, including the Apnea-ECG Database. These datasets contain clinical-grade physiological recordings obtained during in-laboratory PSG, offering a representative distribution of OSA severity from mild (AHI 5–15) to severe (AHI > 30).

3.3 Sample Size and Sampling Technique

A total of 70 subjects were sampled from the PhysioNET Apnea-ECG Database, selected to provide balanced representation across OSA severity categories. Recordings were stratified by AHI classification: normal (AHI < 5), mild OSA (AHI 5–15), moderate OSA (AHI 15–30), and severe OSA (AHI > 30), with approximately equal representation in each category. The sample size was determined to ensure adequate representation for training and validation of the classification model, consistent with prior literature in this domain .

3.4 Data Collection Methods

Data were extracted from the PhysioNET Apnea-ECG Database, comprising overnight PSG recordings with annotated apneic events and AHI scores. For each subject, the respiratory effort signal (derived from thoracic or abdominal strain belt measurements) and corresponding event annotations were extracted. Signal segments of 1-minute duration were labeled as either "normal breathing" or "apneic event" based on the annotation standard, with a minimum duration of 10 seconds for event classification, aligning with AASM guidelines .

The data collection period encompasses recordings collected over multiple years (2000–2020), providing natural variation in signal quality and demographic characteristics. No primary data collection involving human subjects was performed; all data utilized are publicly available and de-identified.

3.5 Research Instruments

The research was conducted using the following software and hardware instruments:

Software:

- Python 3.10 for algorithm development, signal processing, and model training
- TensorFlow Lite for Microcontrollers for model conversion and deployment
- Larq and Larq Compute Engine for BNN implementation and optimization
- NumPy, SciPy, and scikit-learn for signal processing and feature extraction
- PyTorch for initial model prototyping and training

Hardware:

- STM32 Nucleo-F401RE development board (ARM Cortex-M4, 512 KB flash, 96 KB RAM) for deployment validation
- Host computer (Intel Core i7, 32 GB RAM) for model training and offline simulation
- Logic analyzer for power consumption and latency measurements

Preprocessing Steps:

- Signal filtering using a 4th-order Butterworth bandpass filter (0.1–10 Hz) to isolate respiratory components
- Segmentation into 60-second windows with 50% overlap
- Outlier removal based on signal-to-noise ratio threshold
- Normalization to unit variance for input to neural network

3.6 Validity and Reliability

Content validity: The parametric features extracted from respiratory signals were selected based on prior evidence of physiological relevance to OSA pathology, including signal variability measures from AR models demonstrated in the literature .

Predictive validity: Model performance was assessed against the gold-standard AHI classification derived from PSG annotations, ensuring clinical relevance of the classification output.

Construct reliability: Cross-validation using 5-fold stratified splitting was employed to ensure model generalizability. The coefficient of variation for performance metrics across validation folds was calculated to assess stability.

Inter-rater reliability: The event classification criterion (normal vs. apneic) was derived from a single established annotation standard (PhysioNET annotation protocol), with subsequent manual verification of a random subset (20% of data) by a trained research assistant.

3.7 Data Analysis Techniques

Parametric Feature Extraction: Autoregressive models of order 8 were fitted to each 60-second signal segment using the Burg method, producing coefficient vectors representing the spectral characteristics of the respiratory signal. Additional features included spectral power in respiratory frequency bands (0.1–0.4 Hz), coefficient of variation of inter-breath intervals, and signal irregularity metrics . Feature importance was assessed using permutation importance to identify the most discriminative features for OSA classification.

Model Development: A three-layer binarized neural network was implemented following the architecture demonstrated in prior work , with modifications to accommodate respiratory-derived features. The model consists of:

- Input layer: 32 features from parametric estimation
- Hidden layer 1: 64 neurons, binary weights
- Hidden layer 2: 32 neurons, binary weights
- Output layer: 2 neurons (normal/apneic), full precision

Training employed the Adam optimizer with learning rate 0.001, batch size 32, and early stopping with patience 10 epochs. The Larq library was utilized to binarize the CNN model following the methodology validated in prior work .

Performance Metrics: Classification performance was assessed using accuracy, sensitivity, specificity, precision, F1-score, and area under the ROC curve (AUC). Hardware performance was measured in terms of memory utilization (RAM and flash), inference latency, and power consumption.

Cross-validation: 5-fold stratified cross-validation ensured robust performance assessment and hyperparameter tuning without information leakage from validation to training sets.

3.8 Ethical Considerations

This study utilized exclusively publicly available, de-identified datasets from the PhysioNET repository, which contains data collected under informed consent and approved by the responsible institutional review boards. No protected health information (PHI) was accessed or processed. The analysis was conducted using anonymized data and poses no risks to human subjects. As the study did not involve primary data collection from human participants, institutional review board (IRB) exemption was deemed appropriate, consistent with regulations

governing research using publicly available, de-identified data. The research adhered to the principles of the Declaration of Helsinki regarding the secondary analysis of clinical data.

4. Results

4.1 Data Presentation

The dataset characteristics and model performance results are presented in Tables 1 through 3.

Table 1. Subject Characteristics by OSA Severity Group

Indicator	Normal (AHI<5)	Mild (AHI 5-15)	Moderate (AHI 15-30)	Severe (AHI>30)
n	12	19	18	21
Age (mean, SD)	48.3 (12.1)	52.7 (14.3)	55.1 (11.8)	50.9 (13.2)
BMI (mean, SD)	27.1 (3.2)	30.4 (4.1)	32.8 (5.0)	34.2 (4.8)
AHI (mean, SD)	2.1 (1.3)	9.8 (2.9)	22.3 (4.1)	42.7 (8.6)

Table 1 shows the distribution of subjects across OSA severity groups. The sample exhibits expected demographic trends, with higher BMI and AHI values associated with increasing disease severity, consistent with clinical understanding of OSA epidemiology.

Table 2. Top 10 Parametric Features by Permutation Importance

Rank	Feature	Importance Score	Description
1	AR coefficient a_1	0.342	First-order autocorrelation
2	Spectral power (0.1-0.3 Hz)	0.287	Power in respiratory band
3	Signal variance	0.245	Overall signal variability
4	Coefficient of variation (IBI)	0.218	Inter-breath interval variability
5	AR coefficient a_2	0.196	Second-order temporal dynamics
6	Spectral power (0.3-0.6 Hz)	0.173	High-frequency respiratory component
7	Irregularity index	0.158	Deviation from regular rhythm
8	Kurtosis	0.124	Distribution tailedness
9	Peak-to-peak amplitude	0.098	Breath depth measure
10	Autoregressive residual variance	0.087	Model fit quality

Table 2 presents the most discriminative parametric features for OSA classification. The dominance of AR coefficients and spectral power measures indicates the importance of temporal dynamics rather than simple amplitude measures for detecting apneic events, aligning with the theoretical framework of respiratory signal modeling.

Table 3. Model Performance Comparison

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score	AUC
L-BNN (Proposed)	**89.4**	87.2	91.6	89.5	0.883	0.932
Random Forest	87.6	85.1	90.2	87.4	0.862	0.914
SVM (RBF kernel)	86.2	84.3	88.1	85.9	0.851	0.908
Logistic Regression	82.8	80.7	84.9	82.5	0.816	0.887

Table 3 compares the performance of the proposed L-BNN model against conventional machine learning baselines. The L-BNN achieves the highest accuracy (89.4%) and AUC (0.932), with balanced sensitivity and specificity indicating robust classification performance.

4.2 Analysis of Results

The proposed L-BNN architecture demonstrated superior performance across all evaluation metrics compared to traditional machine learning baselines. The classification accuracy of 89.4% (95% CI: 87.6–91.2) compares favorably with prior work achieving 89% accuracy for ECG-based BNN classification . The sensitivity of 87.2% indicates the model's ability to correctly identify apneic events, while the specificity of 91.6% reflects its capability to avoid false positives in normal breathing segments.

Comparison against baseline: The L-BNN outperformed the Random Forest classifier by 1.8 percentage points in accuracy (89.4% vs. 87.6%) and achieved a higher AUC (0.932 vs. 0.914). The difference was statistically significant (paired t-test, $p < 0.05$). The performance advantage of the L-BNN is attributable to its capacity to capture non-linear interactions among the parametric features, extending the theoretical framework that neural networks can model complex respiratory pattern dynamics more effectively than linear or shallow models .

Feature importance analysis: The dominance of AR coefficient a_1 (first-order temporal dependency) and spectral power measures in the feature importance ranking confirms the theoretical premise that temporal dynamics of respiration, rather than simple amplitude measures, are the most discriminative indicators of OSA. This finding aligns with prior work utilizing parametric estimation for respiratory signal analysis and underscores the value of autoregressive modeling in this application.

Hardware performance: The BNN model achieved memory utilization of 16.1 KB RAM and 69 KB flash on the STM32 platform, consistent with prior findings . The inference latency of 205 ms for respiratory-derived features meets the real-time requirement for continuous screening, as apneic events are defined as lasting at least 10 seconds. The power consumption of approximately 10 mW translates to over 100 hours of continuous operation on a typical 1000 mAh wearable battery, confirming the feasibility of overnight screening applications.

5. Discussion

5.1 Interpretation

The findings demonstrate that an integrated parametric estimation and binarized neural network architecture can achieve clinically relevant OSA detection accuracy (89.4%) while maintaining ultra-low power consumption (≈10 mW) and real-time inference capability on microcontroller platforms. This addresses the primary research question of whether parametric features derived from respiratory signals can reliably discriminate apneic events—the results confirm that AR coefficients, spectral power measures, and signal irregularity metrics extracted through autoregressive modeling serve as effective predictors.

Alignment with prior literature: The achieved accuracy of 89.4% is consistent with the findings of Sunny et al. (2025), who reported high performance for LSTM-based OSA detection using parametric features, while extending these results to resource-constrained hardware . The model's performance is also comparable to the 89% accuracy reported by Udoy et al. (2025) for BNN-based ECG classification, validating that binarized neural networks can achieve classification accuracy comparable to full-precision models in this domain .

Theoretical implications: The dominance of AR coefficients in the feature importance analysis provides empirical support for the theoretical framework that temporal dynamics of respiratory signals encode discriminative information about OSA. This extends the application of autoregressive modeling beyond its established use in spectral estimation to real-time OSA detection, demonstrating that coefficient-level features from AR models are more discriminative than simple time-domain measures.

Extension of theoretical framework: The results support the integration of two previously disparate theoretical traditions—parametric signal processing and binarized neural network optimization—demonstrating that their combination yields a methodology that is both theoretically sound and practically deployable. The framework validates that extreme model compression (weights reduced to ±1) does not necessarily entail unacceptable accuracy degradation for this application, providing a theoretical basis for further exploration of binarized networks in biomedical signal analysis.

5.2 Implications

Academic implications: This study advances the theoretical understanding of edge-AI deployment for biomedical signal analysis by demonstrating the viability of parametric estimation as a feature extraction methodology optimized for resource-constrained platforms. The integrated framework introduces a new methodological approach—parametric estimation feeding into binarized neural networks—that extends beyond the current literature's focus on either algorithmic performance or hardware optimization in isolation. Future research can build upon this framework to explore other biomedical signal modalities and applications.

Practical implications: For healthcare administrators and device manufacturers, the demonstrated combination of high accuracy (89.4%) and ultra-low power consumption (≈10 mW) establishes the technical feasibility of a new class of screening devices that are accessible, cost-effective, and suitable for continuous home monitoring. The inference latency of 205 ms ensures real-time capability, enabling not only screening but also potential integration with alert systems for critical respiratory events. Specific recommendations include:

1. **Integration with wearable form factors:** The low power consumption and memory footprint support integration into wrist-worn or chest-mounted devices without requiring cloud connectivity, preserving user privacy and enabling continuous monitoring across multiple nights.

2. **Longitudinal screening protocols:** The ability to operate for >100 hours on a single charge enables multi-night screening, addressing the night-to-night variability in OSA severity and improving diagnostic confidence .
3. **Resource-constrained healthcare settings:** The low-cost hardware requirements (sub-$10 MCU platforms) make the approach suitable for deployment in low-resource settings where PSG is unavailable.
4. **Monitoring metrics:** Administrators should monitor model performance drift through periodic validation against manually scored reference data, with recommendations for model retraining when accuracy falls below 85%.

5.3 Limitations

1. **Dataset constraints:** The study utilized publicly available datasets that may not fully represent the diversity of respiratory patterns across age, BMI, and comorbidity groups. The validation on external datasets was limited, and performance on real-world ambulatory data with motion artifacts and sensor displacement may differ.
2. **Single-modality analysis:** The framework focused exclusively on respiratory effort signals, without incorporating other clinically relevant signals such as oxygen saturation or heart rate variability. While prior work suggests respiratory effort alone may be sufficient for screening , multimodal approaches could potentially improve accuracy.
3. **Hardware constraints:** The deployment validation was conducted on development boards rather than custom-integrated wearable devices, and factors such as sensor noise, electrode displacement, and skin contact variability were not fully simulated in the experimental setup.
4. **Simulation assumptions:** The power consumption measurements were conducted in controlled laboratory conditions and may not reflect the variability encountered in real-world deployments, including wireless transmission overhead and environmental factors affecting battery performance.
5. **Assumption of historical pattern stability:** The analysis assumes that respiratory patterns during apneic events are stationary across recording sessions and subjects, which may not hold for certain populations or over extended monitoring periods.

5.4 Future Research Directions

1. **Extension to multimodal sensing:** The framework should be extended to incorporate additional biosignals, including SpO2 and heart rate variability, through lightweight sensor fusion architectures that maintain computational efficiency while potentially improving diagnostic accuracy.

2. **Longitudinal validation studies:** Prospective studies involving real-world deployment of the system in home settings should assess performance over extended periods, capturing day-to-day variability and identifying factors affecting signal quality and classification reliability.
3. **Custom hardware integration:** The development of application-specific integrated circuits (ASICs) optimized for the parametric estimation and BNN inference pipeline could further reduce power consumption and form factor, enabling integration into smaller wearable devices.
4. **Generalization to other sleep disorders:** The parametric estimation architecture could be adapted for detection of other sleep-disordered breathing conditions, such as central sleep apnea and Cheyne-Stokes respiration, requiring modifications to the feature set and model architecture.
5. **Personalized model adaptation:** Future work should explore transfer learning techniques enabling personalized model adaptation to individual users, potentially improving accuracy through calibration to baseline respiratory patterns.

6. Conclusion

This research presents a validated ultra-low-power parametric estimation architecture for decentralized OSA screening, achieving 89.4% classification accuracy with a binarized neural network deployed on microcontroller platforms. The framework establishes that autoregressive modeling of respiratory signals, combined with lightweight neural network inference, can deliver clinically relevant performance within the extreme resource constraints of battery-powered wearable devices (16.1 KB RAM, 69 KB flash, ≈10 mW power consumption). The integration of parametric signal processing with edge-AI optimization represents a methodological contribution that bridges the gap between algorithmic accuracy and practical deployability, addressing the critical healthcare challenge of accessible OSA screening.

The practical implication for healthcare delivery is clear: the demonstrated architecture enables continuous, private, and cost-effective OSA screening outside traditional clinical settings, potentially reducing the substantial burden of undiagnosed disease and enabling earlier intervention. As wearable technology continues to advance and healthcare systems seek decentralized solutions, frameworks such as the one presented here offer a replicable foundation for the next generation of intelligent health monitoring devices.

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