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A Comparative Analysis Of Multimodal Biomedical Signal-Based Techniques For Sleep Apnea Event Detection

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Abstract:
This paper presents a concise review of research on sleep apnea event detection using biomedical signals and machine learning techniques. The study explains the clinical importance of sleep apnea and the limitations of conventional polysomnography, which motivate the development of automated diagnostic solutions. The research paper reviews commonly used physiological signals, feature extraction methods, and machine learning and deep learning models applied for apnea detection and classification. In this paper, multimodal fusion and optimised learning frameworks are discussed, followed by the identification of key research gaps, including high system complexity, limited interpretability, and insufficient focus on multimodal approaches. This paper reviews 34 recent studies from 2020–2026 focusing on ECG-, EEG-, SpO_2-, and multimodal machine learning approaches.

Keywords: *Sleep apnea; Electrocardiogram (ECG); Electroencephalogram (EEG); Multimodal signal fusion; Machine learning; Deep learning; One-dimensional Convolutional Neural Network (1D-CNN)*

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I. Introduction

Sleep apnea is a common yet underdiagnosed sleep-related breathing disorder characterized by recurrent interruptions in respiration during sleep, leading to fragmented sleep and reduced oxygen saturation [1]. These repeated apnea and hypopnea events impose significant physiological stress on the body and are strongly associated with serious health complications such as cardiovascular diseases, hypertension, stroke, diabetes, cognitive impairment, and reduced quality of life [2]. Obstructive Sleep Apnea (OSA), the most prevalent form, occurs due to partial or complete airway obstruction, while Central Sleep Apnea (CSA) arises from impaired respiratory control by the central nervous system [10]. Early and accurate detection of sleep apnea events is therefore critical for effective clinical intervention and long-term health management [3]. The gold standard for diagnosing sleep apnea is overnight polysomnography (PSG), which simultaneously records multiple physiological signals including electroencephalogram (EEG), electrocardiogram (ECG), respiratory airflow, oxygen saturation, and muscle activity [6]. Although PSG provides comprehensive diagnostic information, it is costly, time-consuming, labor-intensive, and inconvenient for patients, as it requires specialized sleep laboratories and expert interpretation [11]. These limitations restrict its accessibility and scalability, motivating the need for automated, reliable, and less intrusive sleep apnea detection systems that can support or partially replace conventional diagnostic procedures [7]. This paper reviews recent multimodal sleep apnea detection methods.

In recent years, advances in biomedical signal processing and machine learning have enabled the development of intelligent systems for automated sleep apnea event detection [3]. Among various physiological signals, EEG and ECG have emerged as particularly informative due to their ability to capture neural activity related to sleep stages and autonomic cardiac responses associated with respiratory disturbances [5]. EEG signals provide insight into sleep architecture and arousal patterns, while ECG signals reflect heart rate variability and cardiovascular responses to apnea events [9]. Leveraging these signals allows the design of non-invasive and wearable-friendly diagnostic frameworks [11]. Machine learning and deep learning approaches have demonstrated strong potential in modeling the complex, nonlinear patterns present in biomedical signals [7]. Traditional machine learning methods rely on handcrafted features extracted from time, frequency, and nonlinear domains, whereas deep learning models automatically learn discriminative representations from raw or minimally processed signals [14]. Furthermore, multimodal learning, which integrates information from multiple physiological signals, has been shown to improve detection accuracy and robustness by exploiting complementary characteristics of different modalities [4].

Motivated by these developments, this paper focuses on the classification of sleep apnea event detection based on biomedical signals using a machine learning approach, with particular emphasis on ECG and EEG signals as a multimodal framework [10]. By combining effective signal preprocessing, feature learning, and optimized machine learning and heuristic deep learning techniques, the proposed approach aims to achieve accurate, reliable, and computationally efficient detection of sleep apnea events [15]. The work seeks to address existing limitations in single-signal systems and contribute toward the development of practical, automated sleep monitoring solutions suitable for real-world clinical and home-based applications [22].

II. Multimodal Sleep Apnea Event Detection Techniques

This section presents studies that utilize multimodal biomedical signals, where complementary physiological information from multiple sources, such as ECG, EEG, SpO_2, airflow, or respiratory effort, is fused to improve sleep apnea detection performance. Multimodal systems generally follow a structured pipeline involving synchronized data acquisition, preprocessing, feature extraction or deep feature learning, multimodal fusion, and classification. By combining cardiovascular and neurological responses to apnea events, these approaches enhance robustness and diagnostic accuracy compared to unimodal systems.

Recent advances in artificial intelligence, machine learning, and biomedical signal processing have significantly improved the automatic detection of sleep apnea events. Recent reviews have highlighted that multimodal physiological signal analysis provides better diagnostic performance than conventional single-signal approaches because it captures complementary physiological changes associated with sleep apnea [1], [2], [26]. Consequently, several researchers have focused on integrating ECG, EEG, SpO_2, respiratory airflow, and other physiological signals with advanced deep learning models to improve detection accuracy and clinical reliability.

P. Hemrajani, V. S. Dhaka, G. Rani, S. Verma, Kavita, M. Woźniak, J. Shafi, and M. F. Ijaz [3] introduced SleepNet, a multimodal deep learning framework that combines one-dimensional CNN and Bidirectional GRU networks for sleep apnea detection. Using single-lead ECG, the model achieved 95.08% accuracy, which increased to 95.19% after integrating additional physiological signals such as nasal airflow and abdominal respiratory effort. The proposed framework also achieved 96.12% sensitivity and 93.45% specificity, demonstrating the advantage of multimodal physiological fusion over unimodal systems. Y. Zhang, L. Zhou, S. Zhu, Y. Zhou, Z. Wang, L. Ma, Y. Yuan, Y. Xie, X. Niu, Y. Su, H. Liu, X. Hei, Z. Shi, X. Ren, and Y. Shi [4] proposed a multimodal multiscale Transformer framework that integrates ECG and SpO_2 signals for obstructive sleep apnea detection and severity assessment. Evaluated on 510 PSG recordings and validated using the Apnea-ECG and UCD Sleep Apnea datasets, the model achieved 96.08% detection accuracy and more than 88% accuracy for severity classification, demonstrating strong generalization and reliable estimation of the apnea–hypopnea index. A. Bhongade, T. K. Gandhi, and P. AP [5] developed an automated obstructive sleep apnea detection system using multimodal ECG features extracted from 95 recordings obtained from the PhysioNet and UCD Sleep Apnea datasets. After optimal feature selection using Sequential Forward Selection, the Random Forest classifier achieved 93.17% accuracy, confirming the effectiveness of handcrafted ECG features for apnea detection. N. La Porta, S. Scafa, M. Papandrea, F. Molinari, and A. Puiatti [6] proposed a large-scale multichannel machine learning framework using polysomnographic recordings from the Wisconsin Sleep Cohort. The method achieved 87.2 ± 1.8% event detection accuracy, while classification of different apnea types reached 62.9 ± 4.1% accuracy, highlighting the potential of interpretable machine learning for clinical sleep analysis.

A. F. Babaei, J. Tanha, M. A. Balafar, and S. Roshan [7] introduced a multimodal deep learning architecture integrating CNNs, GRUs, attention mechanisms, squeeze-and-excitation blocks, and a novel loss function to improve feature diversity. Using the Sleep Heart Health Study dataset, the model achieved an AUC of 91.94% and 83.87% accuracy, demonstrating good robustness and generalization for personalized sleep monitoring. J. Ramesh, Z. Solatidehkordi, A. Sagahyroon, and Fadi Aloul [8] investigated wearable-based obstructive sleep apnea screening using sleep-stage image representations together with demographic information instead of raw physiological signals. Evaluated on the Wisconsin Sleep Cohort dataset, the proposed neural network achieved an F1-score of 69.40, indicating the feasibility of large-scale screening despite limitations associated with single-night recordings. D. H. Zhang, J. Zhou, J. D. Wickens, and A. G. Veale [9] combined EEG, EMG, and sleep-stage labels for apnea and hypopnea event detection, demonstrating that integrating neurological and physiological information improves event recognition. Similarly, N. T. H. Trang, T. T. D. Linh, D. Q. Vu, B. T. H. Loan, N. N. Vinh, and T. N. Dang [10] developed an EEG–ECG multimodal framework using nonlinear wavelet features and ensemble machine learning classifiers. The proposed model achieved 98.8% accuracy, 99.1% sensitivity, and 98.5% specificity, outperforming standalone deep learning approaches and demonstrating the effectiveness of hybrid multimodal feature learning.

The studies discussed in literature are systematically summarized in Table 1, which presents an overview of multimodal and signal-based sleep apnea detection approaches.

Table 1: Literature Summary of Multimodal and Signal-Based Sleep Apnea Detection

Reference	Dataset	Methodology	Result Findings
P. Hemrajani, V. S. Dhaka et al. [3]	ECG, airflow, abdominal effort	CNN + BiGRU (SleepNet); unimodal & multimodal fusion	(i) Accuracy: 95.08% (ECG), 95.19% (multimodal); Sens. 96.12%, Spec. 93.45% (ii) Multimodal fusion improves robustness over single-signal models
Y. Zhang, L. Zhou et al. [4]	510 PSG + Apnea-ECG + UCD DB	Multimodal multiscale Transformer using ECG & SpO_2	(i) Detection accuracy: 96.08%; Severity accuracy > 88% (ii) Strong generalization with accurate AHI estimation
A. Bhongade, T. K. Gandhi et al. [5]	PhysioNet + UCD ECG (95 records)	Feature extraction + SFFS + Random Forest	(i) Accuracy: 93.17% (ii) Single-lead ECG sufficient for reliable OSA detection
N. La Porta, S. Scafa et al. [6]	Wisconsin Sleep Cohort	Interpretable ML for apnea event detection	(i) Event accuracy: 87.2 ± 1.8%; Type accuracy: 62.9 ± 4.1% (ii) Scalable and clinically interpretable framework
A. F. Babaei, J. Tanha et al. [7]	Sleep Heart Health Study	CNN + GRU + attention + SE blocks	(i) AUC: 91.94%; Accuracy: 83.87% (ii) Robust multimodal DL suitable for real-time monitoring
J. Ramesh, Z. Solatidehkordi et al. [8]	Wisconsin Sleep Cohort	Sleep-stage images + demographics + NN	(i) F1-score up to 69.40 (ii) Feasible for population-level OSA screening
D. H. Zhang, J. Zhou et al. [9]	EEG (6 ch) + EMG (2 ch), 26 pts	Explainable ML with sleep-stage rules	(i) MCC: 0.314 (LOPO) (ii) Sleep stages carry strong discriminative power
S. Yook, D. Kim et al. [11]	PSG (flow, SpO_2, ECG)	Xception-based DL + demographics	(i) Detection acc.: 94%; Screening acc.: 99% (AUC 0.99) (ii) Reduced sensors enable high-performance OSA screening
H. Fayyaz and R. Beheshti et al. [12]	Multimodal physiological signals	Modality-agnostic DL with missing-signal handling	(i) AUROC > 0.9 under noise/missing data (ii) Robust for real-world clinical deployment
E. S. Jeya Jothi, J. Anitha et al. [13]	ECG + PPG	Transfer learning (ResNet, VGG, AlexNet)	(i) Accuracy: 97.86%; F1: 98.90% (ii) Transfer learning effective for wearable-based OSA screening
J. E. Sturludóttir, S. Sigurðardóttir et al. [14]	Pediatric PSG (20 children)	CNN on nasal & mouth pressure	(i) Accuracy: 93.5%; Precision: 97.8% (ii) CNNs effective but limited by small datasets
A. K. Abasi, M. Aloqaily et al. [15]	PhysioNet Apnea-ECG (70 records)	Modified Honey Badger Optimization	(i) Accuracy: 91.3%; AUC: 97.5% (ii) Metaheuristic optimization improves ECG-based SA detection
A. R. Troncoso-García, M. Martínez-Ballesteros et al. [16]	PSG physiological signals	DL on airflow, EEG, ECG	(i) Airflow highest accuracy; EEG/ECG highest sensitivity (ii) Enables accessible PSG-free apnea diagnosis
S. Aswath, V. R. S. Sundaram et al. [17]	ECG signals	STFT + autoencoder + MCA-DLS	(i) Accuracy: 96.4% (optimized) (ii) Feature fusion + DL outperforms standard CNN/LSTM
V. Barroso-García, M. Fernández-Poyatos et al. [18]	Thoracic & abdominal signals	Joint 2D-CNN	(i) ICC: 0.75 (AHI), 0.83 (CAI) (ii) CNNs robust for central & obstructive apnea severity
A. Sheta, T. Thaher et al. [19]	Clinical & demographic data	Feature selection + ML ensembles	(i) Accuracy gain up to 10% (ii) Demographic-aware modeling improves diagnosis
C. Y. Tsai, W. T. Liu et al. [20]	PSG (3,529 patients)	Clinical features + Random Forest	(i) Accuracy: 79.32% (Mod-Sev), 74.37% (Sev) (ii) Effective for risk-based OSA screening
Y. Shang, B. Guo et al. [21]	Snoring sounds	MFCC + DS-MS DL model	(i) Accuracy: 94.17% (ii) Non-invasive audio-based apnea detection feasible
R. S. Arslan [22]	PSG (50 patients)	Two-layer DL + ML meta-learner	(i) Detection acc.: 95.74%; Type acc.: 99.4% (ii) Hybrid decision fusion improves reliability
X. Li, F. H. F. Leung et al. [23]	Sleep Heart Health Study	Two-stage feature selection + MER ensemble	(i) Accuracy: 94.66%; Sens. 96.37% (ii) Ensemble learning boosts classification robustness
D. Kim, J. Lee et al. [24]	Large-scale PSG EEG	CNN + Transformer for sleep staging	(i) Accuracy: 91.4% (ii) Comparable to expert scorers across OSA severities
X. Xin, Y. Zaru et al. [25]	EEG + ECG	Channel superposition + SVM	(i) Accuracy: 96.24% (ii) Multi-channel fusion enhances apnea detection
J. Saha, I. Dasgupta et al. [26]	Multiple physiological studies	Survey of AI-based OSA prediction	(i) Best accuracy: 97% (vibration/airflow) (ii) Confirms growing dominance of AI-driven methods
M. Sharma, D. Kumbhani et al. [27]	SpO_2 signals	Wavelet + entropy + RUSBoost	(i) Accuracy: 95.97%; AUC: 0.98 (ii) SpO_2 alone effective for home-based screening
H. Yue, Y. Lin et al. [28]	Nasal airflow (2 centers)	Mr-ResNet (OSASS)	(i) High acc., F1, κ agreement with experts (ii) Single-signal DL suitable for clinical OSA diagnosis
S. Saghafi, F. N. Rahatabad et al. [29]	EEG + ECG (25 patients)	Nonlinear features + PCA + classifier fusion	(i) Accuracy: 94.30% (binary); 88.35% (5-class) (ii) Majority voting improves reliability

Reference	Dataset	Methodology	Result Findings
J. Zhang, Z. Tang et al. [30]	Apnea-ECG DB	CNN + LSTM on single-lead ECG	(i) Accuracy: 96.1%; κ = 0.92 (ii) Effective ECG-only OSA monitoring
H. Korkalainen, J. Aakko et al. [31]	PPG (894 patients)	CNN-RNN for sleep staging	(i) 3-stage acc.: 80.1%; κ = 0.65 (ii) PPG enables EEG-free sleep analysis
D. Jarchi, J. Andreu-Perez et al. [32]	ECG + EMG	DL-based multi-disorder classification	(i) Accuracy: 72%; F1 = 0.57 (ii) Differentiates OSA and movement disorders
D. Álvarez, A. Cerezo-Hernández et al. [33]	At-home oximetry + airflow (239 pts)	Feature fusion + SVR	(i) ICC: 0.93; 4-class acc.: 81.3% (ii) Dual-signal ML improves home OSA screening
C. Mencar, C. Gallo et al. [34]	Clinical + questionnaire (313 pts)	PCA + ML regression & classification	(i) Moderate acc.; RMSE = 22.17 (ii) Useful for prioritizing PSG testing

III. Research Gap And Challenges

Sleep apnea detection has come a way with machine learning and deep learning. However there are still some challenges to overcome [1]. Although substantial progress has been made in sleep apnea detection using machine learning and deep learning techniques, many existing approaches continue to rely on either single-modality physiological signals or complex multimodal sensing systems. Several studies have achieved high diagnostic performance using respiratory airflow, pulse oximetry, or polysomnographic signals; however, these approaches require multiple sensors, specialized equipment, and controlled clinical environments, limiting their suitability for continuous or home-based monitoring [5], [33]. ECG-based methods provide a convenient and non-invasive alternative for sleep apnea detection but primarily capture cardiac autonomic responses and may not adequately reflect neurophysiological alterations associated with sleep-disordered breathing [15], [19]. In contrast, EEG-based approaches offer valuable information regarding brain activity during sleep but increase acquisition complexity and computational burden [2], [9]. Therefore, a compact multimodal framework integrating ECG and EEG signals has the potential to provide complementary physiological information while reducing the limitations associated with conventional multimodal systems.

Another important limitation identified in the literature is the dependence of many multimodal frameworks on conventional deep learning architectures employing fixed feature fusion strategies. Although recent multimodal deep learning models have demonstrated improved detection performance through feature fusion and attention mechanisms, these methods generally utilize static fusion schemes that may not effectively adapt to inter-subject variability or complex nonlinear relationships among physiological signals [4], [7]. Heuristic optimization techniques have been explored to improve deep learning performance, particularly through optimization of convolutional neural networks and feature selection [15], [17]. Nevertheless, the integration of heuristic optimization with deep multimodal learning for joint EEG–ECG analysis remains largely unexplored. Consequently, there is a need for adaptive heuristic-driven frameworks capable of optimizing feature selection, fusion strategies, and classification parameters to enhance sleep apnea event detection.

Furthermore, many existing studies primarily focus on obstructive sleep apnea screening, severity estimation, or Apnea–Hypopnea Index (AHI) prediction rather than detailed event-level classification. Although these approaches provide valuable clinical information, they do not explicitly classify individual apnea events occurring during sleep, which is essential for accurate diagnosis and treatment planning [18], [20]. Moreover, several models are developed using specific datasets or population groups, thereby limiting their generalizability across diverse clinical settings [8], [31]. This highlights the need for a generalized event-level classification framework capable of maintaining high sensitivity and specificity across different patient populations while utilizing physiologically meaningful biomedical signals.

Finally, despite the promising performance reported by recent deep learning models, many existing approaches remain computationally intensive and require large volumes of annotated training data, restricting their deployment in practical clinical environments [4], [11]. Conversely, conventional machine learning models offer lower computational complexity but often fail to capture the complex temporal and spectral characteristics of biomedical signals required for accurate sleep apnea detection [23], [32]. Therefore, there remains a significant need for a balanced framework that combines heuristic optimization, deep feature learning, and multimodal ECG–EEG analysis to achieve accurate, computationally efficient, and clinically applicable sleep apnea event detection.

In summary, the existing literature has not adequately explored the integration of ECG and EEG signals within a compact multimodal framework enhanced by heuristic-optimized deep learning for event-level sleep apnea classification. Addressing this gap forms the primary motivation of the proposed research, which aims to exploit the complementary physiological information provided by ECG and EEG signals while incorporating heuristic optimization to improve feature fusion, model adaptability, and classification performance.

IV. Conclusion

Sleep apnea remains a major sleep-related breathing disorder that requires timely and accurate diagnosis to reduce the risk of serious cardiovascular, neurological, and metabolic complications. This paper examined recent trends in machine learning and deep learning techniques for sleep apnea event detection using biomedical signals published between 2020 and 2026. The reviewed papers demonstrate that artificial intelligence has significantly improved the automatic detection and classification of sleep apnea events through the use of ECG, EEG, SpO_2, respiratory airflow, polysomnography, and other physiological signals.

Deep learning architectures, including CNNs, recurrent neural networks, Transformers, attention mechanisms, and ensemble learning techniques, consistently achieve superior performance compared with conventional machine learning approaches by automatically learning discriminative features from biomedical signals. Multimodal learning has shown greater robustness and diagnostic accuracy than unimodal approaches by exploiting complementary physiological information from multiple signal sources. Recent studies have reported promising detection performance, with many multimodal frameworks achieving accuracy exceeding 90%, demonstrating the potential of artificial intelligence for reliable sleep apnea diagnosis. In spite of these advances, several important challenges remain. Many existing methods rely on complex multimodal sensing systems, large polysomnography setups, or computationally intensive deep learning models, which limit their applicability in real-world clinical and home-based environments. In addition, most studies focus on sleep apnea screening or severity estimation rather than event-level classification, while adaptive feature fusion and heuristic optimization have received comparatively limited attention. The integration of ECG and EEG signals within a compact multimodal framework has also been insufficiently investigated despite their complementary representation of cardiac autonomic and neurophysiological responses during sleep apnea events.

So, the literature suggests that future research should focus on developing lightweight, interpretable, and computationally efficient multimodal frameworks capable of accurate event-level classification. Some heuristic-optimised deep learning models that integrate ECG and EEG signals offer a promising direction for improving feature learning, adaptive fusion, and classification performance while supporting practical deployment in both clinical and home-based sleep monitoring systems. Such approaches have the potential to enhance the reliability, accessibility, and clinical applicability of automated sleep apnea diagnosis.

V. Future Scope

The reviewed literature in this study indicates that significant opportunities remain for improving automated sleep apnea detection systems. Future research should focus on developing compact multimodal frameworks that effectively integrate ECG and EEG signals to exploit both cardiovascular and neurophysiological information for more accurate event-level classification. The incorporation of heuristic optimisation techniques with deep learning models can additionally enhance feature selection, feature fusion, and model optimisation while reducing computational complexity. Future studies should emphasise the development of lightweight and interpretable artificial intelligence models that can be easily deployed in real-world clinical and home-based environments. Validation using larger and more diverse datasets from different populations is also essential to improve the generalizability and reliability of proposed models. In future, integrating wearable sensing technologies, Internet of Medical Things (IoMT) devices, and edge computing can enable continuous, non-invasive, and real-time sleep monitoring, making automated sleep apnea diagnosis more accessible and practical. These research directions have the potential to improve diagnostic accuracy, support clinical decision-making, and facilitate the development of intelligent healthcare systems for effective sleep apnea management.

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