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Heuristic Deep Learning Framework for EEG-based Sleep Apnea Event Classification

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Abstract

Sleep apnea is an increasingly prevalent and potentially serious sleep disorder marked by repeated interruptions in breathing during sleep. Polysomnography (PSG) serves as the clinical gold standard for diagnosis; however, its high cost, complexity, and limited accessibility hinder large-scale and home-based screening efforts. This study introduces a Heuristic Deep Learning (HeurDL) framework designed for the automated classification of sleep apnea events utilizing single-channel electroencephalogram (EEG) signals. The proposed framework combines wavelet-based EEG sub-band decomposition, heuristic domain-driven feature selection, and a lightweight one-dimensional convolutional neural network (1D-CNN) to enhance classification performance while minimizing computational complexity. EEG sub-bands of physiological significance are examined to identify distinguishing temporal, spectral, and nonlinear features linked to neural patterns associated with apnea. The proposed method differs from traditional end-to-end deep learning approaches by explicitly integrating heuristic knowledge from EEG physiology and empirical signal analysis, which improves interpretability and generalization. The framework has been implemented and assessed using publicly available benchmark EEG datasets, resulting in an overall classification accuracy of 91.2%, surpassing multiple existing EEG-based and wavelet–CNN hybrid methods. The findings indicate that heuristic-guided deep learning serves as an effective, scalable, and non-invasive approach for practical sleep apnea screening and decision-support applications.

Keywords: Convolutional Neural Network, Deep Learning, Electroencephalogram, Heuristic Learning, Sleep Apnea Detection.

Introduction

Periodic cessations of breathing while sleeping characterize sleep apnea. This condition can lead to reduced oxygen saturation, sleep fragmentation, and several adverse health outcomes, including cognitive decline, heart disease, daytime weariness, and metabolic abnormalities (1, 2). Obstructive Sleep Apnea (OSA) is the most common type of sleep apnea, impacting millions of people worldwide. Despite its widespread occurrence, the understanding, early diagnosis, and management of OSA remain limited, particularly in rural regions and areas with restricted healthcare resources. Currently, the most reliable method for diagnosing sleep apnea is overnight PSG, which is a comprehensive and multimodal recording procedure conducted in specialized sleep laboratories. It is a comprehensive and multi-modal recording methodology conducted in sleep laboratories. PSG is highly precise; yet, it is also prohibitively costly, labor-intensive, and impractical for continuous monitoring of large cohorts. These limitations have increased the demand for automated, user-friendly, and cost-effective diagnostic solutions (3, 4). EEG, an essential aspect of PSG, has become a vital signal modality because of its sensitivity to cortical arousals and changes in sleep stages associated with apneic events. Recent advances in signal processing and machine learning techniques enable the extraction of discriminative information from EEG signals, facilitating accurate classification of sleep disorders (5). Numerous research initiatives had explored the classification of sleep apnea using EEG signals in combination with various feature extraction techniques and Artificial Intelligence (AI)-based approaches. One study had utilized EEG-derived features, such as energy, entropy, and variance, to achieve optimal classification performance using a Support Vector Machine (SVM) classifier (6). Another approach had employed an Ensemble Bagged Tree model to analyze sleep-stage information derived from

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single-channel EEG signals, enabling differentiation of sleep phases and identification of salient features for apnea diagnosis (7). Empirical Mode Decomposition (EMD) had been applied to decompose EEG signals into Intrinsic Mode Functions (IMFs), which were subsequently used for OSA prediction through machine learning algorithms (8). Sleep apnea detection had been performed using nonlinear features extracted from combined ECG and EEG signals and integrated through a majority voting strategy, achieving an accuracy of 94.42% (9). A convolutional neural network (CNN) had been developed to detect apnea events in single-channel EEG data, reporting an accuracy of 69.9% (10). Frequency-domain and nonlinear EEG features had been exploited to design binary and multiclass classifiers for apnea classification using annotated EEG datasets (11). An expert system based on ensemble learning had been proposed for OSA identification by integrating discrete wavelet transform (DWT) using the db8 wavelet for EEG sub-band decomposition and statistical feature extraction from single-channel signals (12). Neural network-based approaches had analyzed physiological signals such as heart rate and respiratory effort to automatically identify apnea episodes during sleep (13). Subsequent studies had focused on EEG pattern classification to differentiate between CSA, OSA, and normal breathing events (14). The K-Nearest Neighbors (KNN) classifier had been employed to categorize subjects using inter-band energy ratio features derived from multi-band EEG signals (15).

NNs integrated with transformer architectures had been utilized to classify sleep stages using single-channel EEG data for clinical decision-support systems, achieving an accuracy of 91.4% (16). Random Forest classifiers had been applied to categorize sleep apnea using features extracted from individual EEG frequency bands (17). The neurophysiological effects of OSA had been examined through multi-channel EEG analysis using power spectral density, network-based metrics, and EEG microstate analysis (18). Convolutional recurrent neural networks (RNNs) had been employed to detect apnea events and estimate their duration using EEG data alone (19). A multi-instance learning framework had been proposed for automated OSA detection, incorporating a mapping module and a subframe-level multi-resolution convolutional feature extractor (20). A quasi-optimal approach had been developed to analyze single-channel EEG data from overnight sleep studies, improving the detection of apnea and hypopnea events and enabling differentiation between OSA and CSA (21).

A novel method has been introduced to detect sleep apnea by analyzing distinctive EEG features for classifying OSA, CSA, and normal breathing patterns (22). Sleep apnea identification had also been investigated through snoring sound analysis using a dual-structure multi-scale neural network with MFCC features, achieving an accuracy of 94.17% (23). A computer-aided diagnosis (CAD) system had been developed using EEG-derived complexity-based features, including Lempel–Ziv complexity, fractal dimensions, generalized Hurst exponents, and entropy measures, in conjunction with KNN and SVM classifiers (24). Another approach had involved the development of an automated deep learning framework in which CNNs extracted temporal features from variational mode decomposition outputs, followed by BiLSTM layers for apnea classification (25). A CAD system had also been proposed using time-domain, wavelet-domain, and frequency-domain EEG features combined with KNN and SVM classifiers (26). Furthermore, sleep apnea detection had been validated using a single EEG feature, namely Lempel–Ziv complexity, in combination with discriminant analysis, decision trees, and ensemble classifiers (27). Sleep stage classification had been achieved using an automated system based on photoplethysmography (PPG) signals obtained from a standard finger pulse oximeter, demonstrating the feasibility of non-EEG-based monitoring approaches (28).

Recent research on EEG-based detection of sleep apnea had faced several challenges. Many deep learning models had relied solely on raw EEG inputs, which had often led to overfitting and insufficient generalization, particularly when trained on limited or imbalanced datasets. These models had frequently lacked interpretability and had not incorporated physiological domain knowledge, thereby reducing their clinical reliability. Moreover, important frequency-specific EEG patterns had often been overlooked due to the absence of signal decomposition or sub-band analysis. Approaches that had depended exclusively on either handcrafted features or automatically learned representations had encountered difficulties in achieving an optimal balance between classification accuracy and robustness. These limitations had highlighted the need for hybrid, heuristic-based methodologies that integrate deep learning with expert-guided feature extraction.

This paper presents a Heuristic Deep Learning (HeurDL) framework for sleep apnea event classification using single-channel EEG signals. Unlike conventional end-to-end CNN or wavelet–CNN hybrid approaches, the proposed framework explicitly incorporates domain-driven heuristic knowledge into feature selection, model design, and learning strategy, achieving a balance between classification accuracy, interpretability, and computational efficiency. In this context, the term *heuristic* denotes the integration of physiological EEG insights, empirical design principles, and selective feature engineering, rather than reliance solely on raw signal learning. The framework combines wavelet-based EEG sub-band decomposition with handcrafted statistical, spectral, and nonlinear feature extraction to effectively capture apnea-specific EEG characteristics. These features are then processed using a lightweight and computationally efficient 1D-CNN architecture optimized through heuristic principles, enhancing model interpretability and robustness. The proposed approach is evaluated on publicly available benchmark EEG datasets and demonstrates competitive or superior performance compared to conventional CNN models and existing wavelet–CNN hybrid methods, while remaining suitable for practical and resource-constrained deployment.

Methodology

The proposed heuristic deep learning framework was designed for the classification of EEG-based sleep apnea events and is illustrated in Figure 1. The framework consisted of multiple stages, including EEG signal preprocessing, wavelet-based sub-band decomposition, handcrafted feature extraction, and classification using a heuristic deep learning model.

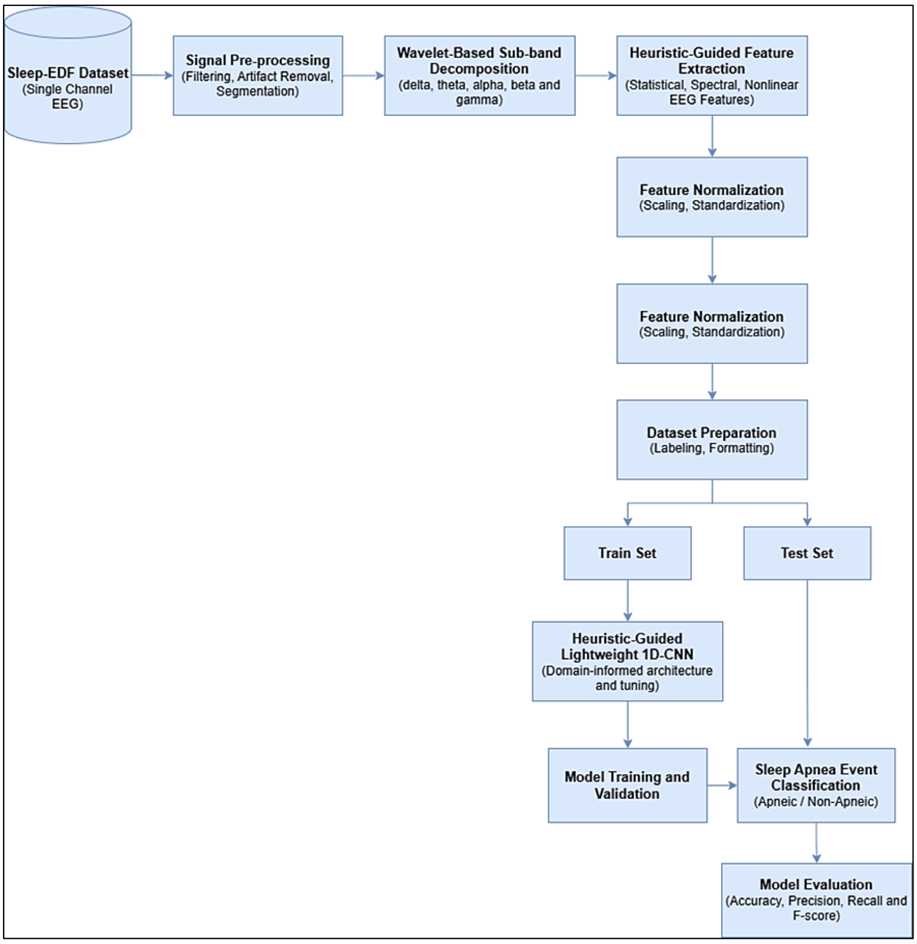

Figure 1: Heuristic Approach for Sleep Apnea Classification based on Deep Learning Framework

Sleep EDF Dataset

The proposed framework was assessed utilizing the Sleep-EDF Expanded dataset, which is publicly accessible from PhysioNet (29). This dataset comprises full-night polysomnographic recordings, featuring EEG signals sampled at 100 Hz. This study extracted single-channel EEG data (Fpz-Cz) to minimize complexity and concentrate on brain activity pertinent to sleep arousals and apneic events. The dataset's annotations were utilized to classify epochs as apneic or non-apneic, relying on airflow and respiratory signals.

Signal Pre-processing

The EEG signals were segmented into non-overlapping 30-second epochs, following standard sleep scoring guidelines. All segments underwent detrending and normalization to eliminate baseline drift and inter-subject variability. After eliminating power-line interference, a band-pass filter ranging from 0.5 to 45 Hz was applied to preserve the relevant physiological frequency components. The notch filters was set at 50 Hz. Segments containing substantial artifacts or absent labels were omitted from subsequent analysis.

Subband Decomposition

Each EEG segment was decomposed into five subbands to extract meaningful frequency-specific information, utilizing the Discrete Wavelet Transform (DWT) with the Daubechies-4 (db4) mother wavelet. The EEG subbands corresponded to standard frequency ranges: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–45 Hz). The subbands reflect cortical activity and autonomic responses that vary during sleep apnea events.

Feature Extraction

A comprehensive set of handcrafted features was extracted to capture the temporal, spectral, and nonlinear dynamics of the signals from each EEG subband. These features were categorized into three main types. Statistical features included the mean, standard deviation, skewness, variance, and kurtosis. Frequency-domain features consisted of band power, relative power, and spectral entropy. Nonlinear features comprised approximate entropy, sample entropy, and Higuchi’s fractal dimension. This heuristic feature selection was guided by prior knowledge of EEG signal behavior during sleep disturbances and empirical relevance across subjects.

Feature Normalization and Dataset Preparation

All extracted features were aggregated into a unified feature vector for each epoch. To maintain consistency across subjects and facilitate optimal convergence during model training, min-max normalization was applied, scaling all features to the [0, 1] range. The final feature vectors were normalized through min-max scaling, as represented by the equation [1].

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad [1]$$

To guarantee a subject-independent evaluation, the dataset was partitioned into training and testing sets, comprising 70% and 30% of the data, respectively.

Heuristic Deep Learning Model Architecture (1D-CNN)

A one-dimensional Convolutional Neural Network (1D-CNN) was developed to classify each EEG epoch as apneic or non-apneic using the extracted features. The network architecture was heuristically designed to optimize performance. It consisted of an input layer matching the length of the feature vector, followed by two convolutional layers with kernel sizes of 3 and 5, each paired with ReLU activation and max-pooling. Dropout layers with a rate of 0.3 were incorporated to reduce overfitting. Finally, a fully connected dense layer was included, leading to a softmax output layer for binary classification. The model architecture was chosen through iterative tuning to balance model complexity and performance and is defined in Table 1.

Table 1: 1D-CNN Configuration

Layer	Details
Input	1D feature vector (length = total features)
Conv1D_1	64 filters, kernel size = 3, ReLU activation
MaxPooling1D_1	Pool size = 2
BatchNorm_1	Normalization for training stability
Conv1D_2	128 filters, kernel size = 3, ReLU activation
MaxPooling1D_2	Pool size = 2
Dropout	Rate = 0.3 to reduce overfitting
Flatten	Flattens 3D output to 1D
Dense_1	64 units, ReLU
Dropout	Rate = 0.3
Dense_Output	2 units (Softmax for binary classification)

Model Training and Evaluation

In the proposed Heuristic Deep Learning Framework for EEG-Based Sleep Apnea Event Classification, the model was trained using the Adam optimizer with a learning rate of 0.001, with categorical cross-entropy as the loss function. To minimize overfitting, dropout layers and early stopping were incorporated. Model performance was evaluated using metrics derived from the confusion matrix, which provides a comprehensive summary of classification results.

In this context, the confusion matrix elements are defined as follows:

a) Correctly detected apnea events (True Positives, TP): instances where the model accurately identifies an apneic EEG epoch.
b) Correctly detected non-apnea events (True Negatives, TN): instances where the model correctly classifies an EEG epoch as non-apneic.
c) Incorrectly identified apnea events (False Positives, FP): cases where a non-apneic epoch is mistakenly classified as apneic.
d) Missed apnea events (False Negatives, FN): cases where an apneic epoch is incorrectly classified as non-apneic.

The key evaluation metrics, accuracy, precision, recall, and F1-score, were calculated based on these definitions and equations given below [2-5]:

$$Accuracy = \frac{Correctly\ detected\ apnea\ events + \ Correctly\ detected\ nonapnea\ events}{Total\ number\ of\ epochs} \quad [2]$$

$$Precision = \frac{Correctly\ detected\ apnea\ events}{All\ epochs\ classified\ as\ apnea} \quad [3]$$

$$Recall = \frac{Correctly\ detected\ apnea\ events}{All\ acutal\ apnea\ epochs} \quad [4]$$

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad [5]$$

These metrics provide a detailed evaluation of the model's ability to accurately detect sleep apnea events while minimizing errors, which is particularly important for imbalanced EEG datasets.

Results

The proposed experimentations were carried out on a Windows 11 workstation equipped with an Intel i5 processor and 16 GB of RAM, using the PyCharm IDE in combination with the Anaconda distribution. EEG recordings from the PhysioNet sleep apnea dataset served as the input for training and evaluating the model. The performance of the proposed heuristic deep learning framework was measured using standard key metrics, computed from the confusion matrix for both the training and testing datasets. To ensure a comprehensive assessment, the dataset was partitioned into 70% for training and 30% for testing. The proposed heuristic 1D-CNN model underwent evaluation using a subject-independent test set. The results were averaged over a 10-fold cross-validation process. Ten-fold cross-validation was employed to ensure robustness. Figure 2 displays a representative EEG signal obtained from the dataset, demonstrating the characteristic waveform patterns identified in sleep recordings. The raw signal functions as the main input for pre-processing, sub-band decomposition, and the subsequent feature extraction within the proposed classification framework.

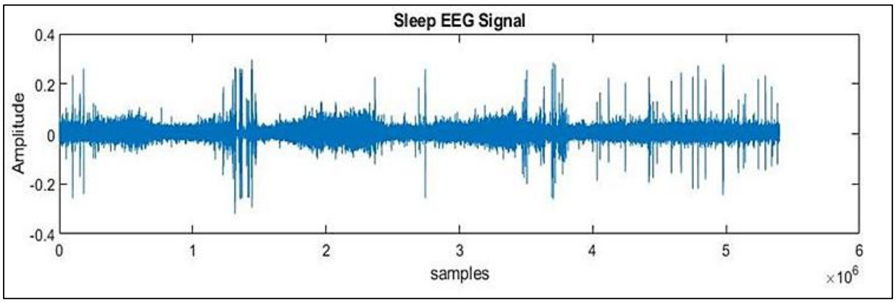

Figure 2: Test Sample of Normal and Apnea Sleep Event

Figure 3 presents the results of the EEG signal sub-band decomposition, effectively showcasing the separate frequency components obtained via wavelet transform. This decomposition highlights the importance of each EEG sub-band, delta, theta, alpha, beta, and gamma, in the extraction of features for the proposed classification framework. The application of sub-band decomposition effectively captures frequency-specific changes induced by apneic events, thereby enhancing model sensitivity. The proposed framework decreases computational demands relative to end-to-end deep models, rendering it appropriate for real-time or embedded applications in portable sleep monitoring devices.

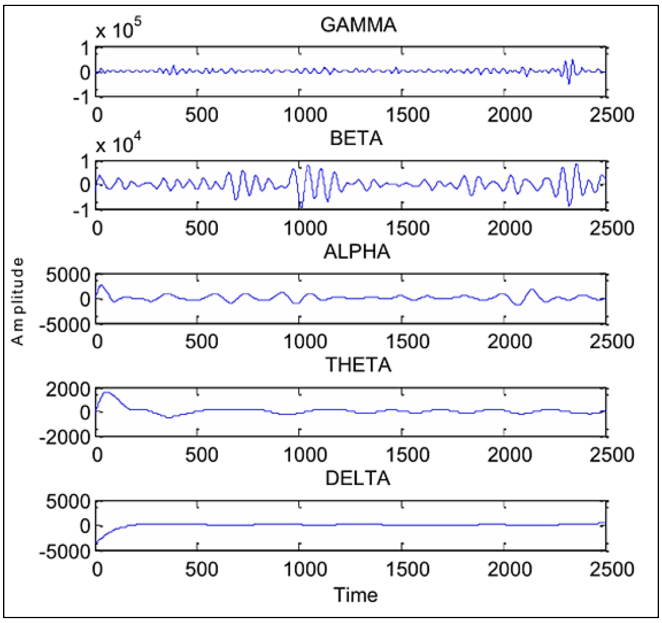

Figure 3: EEG Signal Sub-Band Decomposition

Table 2 presents the confusion matrix corresponding to the classification results of the proposed model, illustrating the counts of correctly and incorrectly classified apnea and non-apnea events. This matrix provides a detailed evaluation of the model's ability to distinguish between sleep apnea and normal epochs. The findings demonstrate that the model successfully detects both apneic and non-apneic events, achieving high precision and recall rates.

Table 2: Confusion Matrix Classification

	Labels	Predicted Labels	
		Apnea	Non-apnea
Actual Labels	Apnea	185	15
	Non-apnea	28	172

Table 3 presents the classification report, offering a detailed evaluation of the proposed model's performance. The results indicate a balanced performance across both apnea and non-apnea classes. A precision of 89.3% for the apnea class reflects a low rate of false positives, while a recall of 93.0% highlights the model's capability to accurately identify true apnea events. The F1-score is 91.1% for both classes, demonstrating consistent classification performance. With an overall accuracy of 91.2%, the model exhibits a high level of predictive correctness. Additionally, the macro and weighted averages further confirm the model's robustness and generalization ability on the test dataset.

Table 3: Classification Report Performance

Class	Precision (%)	Recall (%)	F-score (%)
Apnea	89.3	93.0	91.1
Non-apnea	93.1	89.2	91.1
Overall Accuracy			91.2

Table 4: State-of-art Comparison of Existing Models

Reference	Models	Approach	Accuracy (%)
(10)	Explainable CNN	Deep Learning	69.90
(11)	SVM	Traditional ML	75.90
(12)	Ensemble Learning	ML Ensemble	86.00
(14)	SVM	Traditional ML	90.00
(23)	Random Forest	Ensemble Tree-Based	88.99
(27)	KNN	Distance-Based ML	82.69
Proposed Model	Heuristic 1-D DeepCNN	Hybrid Deep Learning	91.2

Table 4 compares the proposed heuristic 1D-CNN framework with various existing machine learning and deep learning methods utilized for EEG-based sleep apnea event classification.

The proposed heuristic deep learning framework attains a peak accuracy of 91.2%, surpassing both traditional AI models, as illustrated in the comparison table. The Explainable CNN emphasizes model interpretability; however, lower performance is observed, which is likely attributed to limited feature representation or insufficient diversity in the training data (10). Moderate to high classification accuracy is achieved using SVM-based approaches; however, strong dependence on handcrafted features is observed, which may limit adaptability across different subjects (11, 14). Improved generalization over single-classifier models is achieved through an ensemble-based approach; nevertheless, the performance remains inferior to that of the proposed model (12). An accuracy of 88.99% is achieved using the Random Forest classifier due to its ability to model nonlinear relationships; however, limitations may arise in capturing temporal dependencies inherent in EEG signals (23). An accuracy of 82.69% is achieved using the KNN classifier, indicating reduced effectiveness when handling high-dimensional or noisy EEG feature spaces (27).

Discussion

The enhanced performance of the proposed heuristic 1D-CNN was attributed to its effective sub-band decomposition, which facilitated frequency-specific analysis. Handcrafted features were extracted to capture statistical, spectral, and nonlinear EEG characteristics. A deep learning classifier based on a 1D-CNN was employed, capable of modeling complex patterns using a compact and carefully optimized architecture. These results demonstrated that the integration of domain-specific signal processing with deep learning substantially improved the classification of sleep apnea events from EEG signals, thereby providing a reliable and precise diagnostic support mechanism.

The findings of the proposed study indicated significant potential for practical sleep apnea screening and preliminary diagnostic assistance through automated EEG-based detection, eliminating the need for full polysomnography and thereby reducing associated costs, setup complexity, and clinician workload. The Heuristic Deep Learning (HeurDL) framework was found to be well suited for large-scale screening and home-based monitoring, requiring rapid and non-invasive assessments. However, its clinical deployment necessitated addressing regulatory and technological challenges, including validation on large, multi-center datasets, compliance with medical device regulations, data privacy and security standards, and interoperability with existing hospital systems and wearable health technologies. Additionally, variations in EEG acquisition protocols, device calibration, and signal quality across platforms were expected to influence performance, emphasizing the need for standardized procedures and clinical certification before its adoption as a diagnostic system rather than solely a decision-support tool.

The proposed framework was specifically designed for EEG signals, offering a simplified, non-invasive, and scalable approach for sleep apnea screening, particularly in home-based environments. EEG was shown to capture sleep-stage dynamics and neurophysiological disturbances associated with apneic events, enabling accurate event differentiation without reliance on multiple biosignals. Although multimodal polysomnography incorporating ECG, airflow, and oxygen saturation remained the clinical gold standard for definitive diagnosis, exclusive reliance on EEG was recognized to potentially reduce sensitivity to certain respiratory events. Consequently, the proposed framework served as an effective screening and decision-support system, complementing rather than replacing comprehensive clinical diagnosis, with multimodal integration identified as a potential direction for future enhancement.

The Heuristic Deep Learning (HeurDL) framework was designed to exhibit robustness and generalizability under real-world conditions. The model adapted to inter-subject variability by leveraging physiologically relevant EEG sub-band features obtained through wavelet decomposition, accounting for differences in age, gender, and individual neurophysiology. The reliance on normalized spectral and temporal features instead of raw signal amplitudes facilitated compatibility with diverse EEG acquisition systems, including clinical PSG setups and low-cost wearable devices. The heuristic feature selection strategy focused on apnea-specific EEG patterns, thereby reducing interference from coexisting sleep disorders such as insomnia or periodic limb movement disorder. Future extensions involving multi-label classification were anticipated to further enhance discrimination performance. The integration of comprehensive preprocessing with CNN-based learning enabled effective operation under real-world conditions; including noise, motion artifacts, and home sleep environments, supporting scalable and non-invasive sleep apnea detection.

Conclusion

This paper presented a heuristic deep learning framework that integrated EEG sub-band decomposition, domain-driven feature extraction, and a 1D-CNN for the classification of sleep apnea events. The application of DWT facilitated the separation of physiologically significant frequency bands, while the incorporation of statistical, spectral, and nonlinear features provided a comprehensive representation of EEG dynamics. The experimental results demonstrated that the proposed classification framework achieved an accuracy of 91.2%, outperforming state-of-the-art models. This hybrid approach successfully addressed several limitations identified in prior studies, including overfitting on raw EEG data, limited interpretability, and suboptimal utilization of frequency-specific EEG information. Furthermore, the model's low computational complexity and high classification performance rendered it suitable for real-time and home-based sleep monitoring applications.

Future models may incorporate additional physiological data, such as SpO_2, airflow, and ECG, to enhance classification accuracy and identify various forms of apnea, including obstructive and central types. Employing pre-trained models alongside domain adaptation techniques enhances performance across diverse datasets and facilitates user personalization without necessitating model retraining.

Abbreviations

DS-MS: Dual-Structure Multi-Scale, DWT: Discrete Wavelet Transform, EMD: Empirical Mode Decomposition, IMF: Intrinsic Mode Functions, KNN: K-Nearest Neighbors, PSG: polysomnography, OSA: Obstructive Sleep Apnea.

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Author Contributions

All authors contributed equally to this work and participated in every stage of the research. All authors have read and approved the final version of the manuscript.

Conflict of Interest

The authors declare no conflicts of interest.

Declaration of Artificial Intelligence (AI) Assistance

The authors confirm that generative AI tools were used only for language refinement and grammatical correction. No AI-generated content, analysis, or interpretation contributed to the work. All research design, data processing, and manuscript preparation were carried out independently by the authors without AI involvement.

Ethics Approval

This study used EEG recordings from the publicly available Sleep-EDF Expanded dataset, which was previously collected with ethical approval and fully anonymized before release. Since no new data were collected and no identifiable information was accessed, additional ethics approval was not required for this research.

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