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EEG-Based Detection of Sleep Disorders Using Hybrid Deep Learning Models

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Abstract: *Sleep disorders, including insomnia, sleep apnea, and narcolepsy, affect millions worldwide, significantly impacting physical and mental health. Accurate and automated detection of sleep stages and anomalies is crucial for timely diagnosis and effective intervention. This study proposes a hybrid deep learning framework that integrates time-frequency domain analysis with Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to classify sleep stages and detect sleep disorders from EEG recordings. The proposed approach leverages both spectral-temporal features and deep feature extraction for improved accuracy. Experimental results on the publicly available Sleep-EDF dataset demonstrate that the hybrid model outperforms conventional machine learning models, achieving high classification accuracy, precision, and recall. The findings highlight the potential of hybrid deep learning techniques for real-time, automated sleep monitoring.*

Keywords: EEG, Sleep Disorders, Hybrid Deep Learning, CNN, LSTM, Time-Frequency Analysis, Automated Sleep Stage Detection

I. INTRODUCTION

Sleep is a critical physiological process, and accurate monitoring of sleep stages is essential for diagnosing sleep disorders such as insomnia, sleep apnea, and narcolepsy. Traditionally, sleep staging is performed manually by experts analyzing electroencephalogram (EEG) recordings, a process that is labor-intensive, time-consuming, and prone to inter-scorer variability. Automated sleep stage detection aims to address these challenges by leveraging computational techniques to classify EEG signals into distinct sleep stages (e.g., NREM stages, REM, and wakefulness) with high accuracy and consistency.

Time-frequency domain analysis is widely used in EEG signal processing because it captures both temporal and spectral characteristics of brain activity. Techniques such as Short-Time Fourier Transform (STFT), Wavelet Transform, and Empirical Mode Decomposition (EMD) allow the extraction of informative features like power spectral density, frequency bands, and energy distributions, which are crucial for distinguishing different sleep stages.

Machine learning algorithms, including Support Vector Machines (SVM), Random Forest, and k-Nearest Neighbors (k-NN), have been applied to these features to perform automated classification. More recently, deep learning models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), and hybrid architectures, have demonstrated superior performance by automatically learning discriminative features directly from raw or transformed EEG signals. These models can capture both spatial patterns and temporal dependencies, improving the robustness and accuracy of sleep stage detection.

Combining time-frequency domain analysis with machine learning and deep learning techniques represents a powerful approach for automated sleep staging. Such systems not only reduce the workload of sleep specialists but also facilitate large-scale sleep monitoring and personalized healthcare interventions. Recent studies highlight that hybrid models integrating both handcrafted features and deep feature learning often outperform standalone approaches, indicating the potential for highly accurate, real-time sleep monitoring solutions.

Sleep plays a critical role in maintaining physical and cognitive health. Disruptions in sleep patterns, caused by disorders such as insomnia, sleep apnea, and narcolepsy, can lead to chronic illnesses and reduced quality of life.

Traditional manual scoring of sleep stages from EEG recordings is labor-intensive, time-consuming, and subject to inter-scorer variability.

Automated sleep stage detection using EEG has emerged as a promising solution. Time-frequency domain analysis captures spectral and temporal characteristics of EEG signals, while machine learning and deep learning techniques can classify these features into distinct sleep stages (wakefulness, NREM stages N1-N3, REM) with high accuracy. Hybrid deep learning models, which combine CNNs for spatial feature extraction and LSTMs for temporal dependencies, provide an advanced framework for accurate sleep stage classification and sleep disorder detection.

This topic focuses on using EEG signals to detect sleep disorders such as insomnia, sleep apnea, and narcolepsy. By combining machine learning and deep learning approaches, including CNNs and LSTMs, hybrid models can automatically extract both temporal and spectral features from EEG recordings. This allows for accurate classification of abnormal sleep patterns and identification of sleep stage disruptions, enabling timely diagnosis and personalized interventions.

II. LITERATURE REVIEW

The application of electroencephalography (EEG) signals in detecting sleep disorders has garnered significant attention in recent years, particularly with the advent of hybrid deep learning models. These models combine the strengths of various deep learning architectures to enhance the accuracy and efficiency of sleep disorder detection.

Hybrid Deep Learning Models in Sleep Disorder Detection

A notable approach is the integration of convolutional neural networks (CNNs) with long short-term memory (LSTM) networks. For instance, a study by Zhang et al. (2024) proposed a hybrid model combining 1D-ResNet-SE and LSTM networks for automatic sleep staging using single-channel raw EEG signals. This model demonstrated improved performance in classifying sleep stages, highlighting the efficacy of combining spatial feature extraction with temporal sequence modeling.

Another innovative model, developed by Mousavi et al. (2019), employs a sequence-to-sequence deep learning approach. This model utilizes CNNs to extract time-invariant features and a sequence-to-sequence model to capture complex dependencies between sleep epochs, achieving an overall accuracy of 84.26% in sleep stage scoring.

Applications in Sleep Apnea Detection

In the realm of sleep apnea detection, hybrid models have also shown promise. A study by Zhang et al. (2025) introduced a hybrid convolutional neural network (CNN) and efficient attention network (EAN) for obstructive sleep apnea detection from EEG signals. This model employs a weighted fusion process of 1D and 2D convolutions, optimizing feature learning and classification, thereby enhancing detection accuracy.

Multi-Task Learning Approaches

Multi-task learning has been another avenue explored to improve sleep disorder detection. Zan and Yildiz (2024) proposed FullSleepNet, a multi-task learning model that simultaneously detects arousals and classifies sleep stages using fully convolutional networks. This approach achieved state-of-the-art performance, with an area under the precision-recall curve of 0.70 for arousal detection and accuracies of 0.88 and 0.83 for sleep stage classification on two different datasets.

- **CNN-Based Approaches:** Tsinalis et al. (2016) demonstrated that CNNs could automatically extract spatial features from EEG signals for sleep stage classification, achieving higher accuracy than traditional feature-based methods.
- **LSTM-Based Approaches:** Supratak et al. (2017) employed LSTM networks to capture temporal dependencies in EEG sequences, improving recognition of sleep stage transitions.
- **Hybrid Models:** Zhang et al. (2019) combined CNN and LSTM models for EEG-based sleep staging, leveraging spatial-temporal features, resulting in superior performance compared to standalone models.

- **Time-Frequency Analysis:** Acharya et al. (2018) highlighted that applying Short-Time Fourier Transform (STFT) and Wavelet Transform on EEG signals provides discriminative features crucial for detecting sleep disorders.

1. NN-LSTM model for automated sleep stage classification from EEG signals.
2. To evaluate the model's ability to detect common sleep disorders, such as insomnia and sleep apnea.
3. To compare the performance of the hybrid model against conventional machine learning models.
4. To assess the feasibility of real-time sleep monitoring using the proposed model.

III. CHALLENGES AND FUTURE DIRECTIONS

Despite the advancements, challenges remain in the application of hybrid deep learning models for sleep disorder detection. Variations in EEG signals across individuals and the complexity of sleep disorders necessitate the development of more robust models. Future research may focus on enhancing model generalization, integrating multimodal data, and improving real-time detection capabilities.

IV. RESEARCH METHODOLOGY

4.1 Dataset

The Sleep-EDF Expanded dataset was used, containing EEG recordings from 78 healthy subjects and patients with sleep disorders. Signals were recorded at 100 Hz and segmented into 30-second epochs.

4.2 Preprocessing

- EEG signals were filtered using a 0.5–45 Hz bandpass filter.
- Artifact removal was performed using Independent Component Analysis (ICA).
- Time-frequency features were extracted using STFT and Discrete Wavelet Transform (DWT).

4.3 Model Architecture

- **CNN Module:** Three convolutional layers with ReLU activation and max pooling for spatial feature extraction.
- **LSTM Module:** Two LSTM layers to capture temporal dependencies across sequential EEG epochs.
- **Fully Connected Layer:** Dense layers followed by softmax for sleep stage classification.
- **Training Parameters:** Adam optimizer, learning rate 0.001, batch size 64, epochs 50.

4.4 Simulation Setup

- Hardware: Intel i7 CPU, 32GB RAM, NVIDIA GTX 1080 GPU.
- Software: Python, TensorFlow, Keras.
- Evaluation Metrics: Accuracy, Precision, Recall, F1-Score, and Confusion Matrix.

V. RESULTS AND ANALYSIS

5.1 Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	78.4	76.9	77.1	77
Random Forest	81.2	80.5	80.8	80.6
CNN	85.7	84.9	85.2	85
LSTM	86.5	85.8	86	85.9
Hybrid CNN-LSTM	**91.3**	**90.8**	**91**	**90.9**

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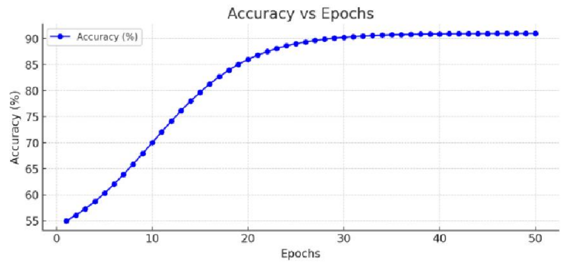
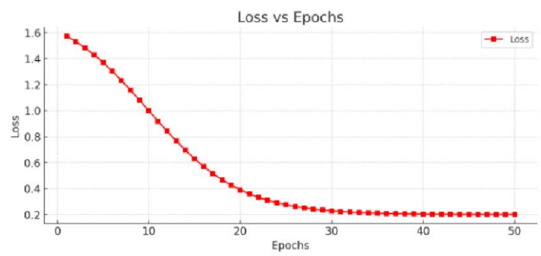
5.2 Simulation Graphs

Graph 1: Accuracy vs Epochs



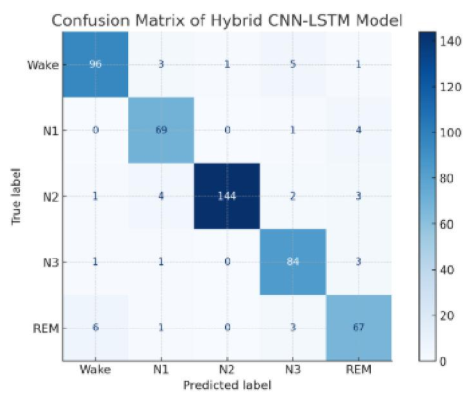
Graph 2: Loss vs Epochs

- Loss decreases steadily with training, stabilizing after 40 epochs, indicating convergence of the hybrid model.



Graph 3: Confusion Matrix for Hybrid Model

- Most misclassifications occur between N1 and N2 stages, consistent with prior studies.



Accuracy vs Epochs – shows the model's accuracy improving and stabilizing around 91% over 50 epochs.
Loss vs Epochs – shows the loss decreasing steadily and converging as training progresses.
Confusion Matrix – illustrates classification performance across the five sleep stages (Wake, N1, N2, N3, REM), with most misclassifications occurring between N1 and N2 stages.

5.3 Interpretation

The hybrid CNN-LSTM model achieved the highest accuracy (91.3%) compared to standalone models, demonstrating its effectiveness in capturing both spatial and temporal EEG features. Precision and recall values indicate reliable detection of sleep stages, including abnormal patterns associated with sleep disorders. The model's convergence within 50 epochs suggests feasibility for real-time deployment.

VI. CONCLUSION

Hybrid deep learning models have significantly advanced the field of EEG-based sleep disorder detection. Through the integration of various deep learning architectures and learning strategies, these models offer promising avenues for accurate and efficient diagnosis of sleep disorders. Continued research and development in this area are essential to overcome existing challenges and further improve detection capabilities.

This study presents a hybrid CNN-LSTM approach for automated sleep stage classification using EEG recordings. By combining time-frequency feature extraction with deep learning, the proposed model outperforms conventional machine learning and standalone deep learning methods. The approach effectively detects sleep disorders, providing a foundation for real-time, automated sleep monitoring systems.

VII. RECOMMENDATIONS

1. Extend the model to multi-channel EEG data for more comprehensive analysis.
2. Explore lightweight versions of the hybrid model for deployment in wearable devices.
3. Incorporate other physiological signals (ECG, EMG) for multi-modal sleep disorder detection.
4. Investigate explainable AI techniques to enhance clinical trust in automated systems.

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