ISSN: 2634 - 8853

Journal of Engineering and Applied Sciences Technology

SCIENTIFIC Research and Community

Research Article

Open Access

A Deep Learning Approach for Automatic Sleep Stage Segmentation via Single Channel EEG Signals

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ABSTRACT

In this paper we develop and evaluates Convolutional Neural Network (CNN) models for automatic sleep stage segmentation using single-channel EEG signals from the Sleep-EDF dataset. We explored three architectures: CNN-CNN, CNN-CNN-Conditional Random Field (CRF), and CNN-Long Short-Term Memory (LSTM). The CNN-CNN-CRF model, incorporating a CRF layer for sequence labeling, demonstrated the highest performance with an accuracy of 89% and an F1 score of 82%, outperforming CNN-CNN (accuracy 87%, F1 score 81%) and CNN-LSTM (accuracy 71%, F1 score 76%). This approach surpasses existing state-of-the-art models by effectively capturing temporal dependencies between sleep epochs and ensuring consistent sequence labeling. The findings suggest that integrating CRFs with CNNs enhances classification performance, providing a robust solution for automated sleep stage segmentation. These results highlight the potential of deep learning in improving sleep analysis, with implications for sleep quality assessment and clinical applications.

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Received: March 11, 2025; **Accepted:** March 24, 2025; **Published:** March 31, 2025

Keywords: Sleep Stage Segmentation, EEG Signals, Deep Learning

Introduction

Accurate classification of sleep stages plays a crucial role in diagnosing and treating sleep-related disorders. In recent years, advancements in deep learning have transformed the field of medical signal processing, particularly in the automated analysis of electroencephalogram (EEG) data [1-3]. These developments have paved the way for novel approaches that leverage deep learning architectures to improve the accuracy, efficiency, and scalability of sleep stage segmentation. Earlier studies have explored various methods for sleep stage classification. Supratak et al., introduced DeepSleepNet, a two-step architecture comprising a Convolutional Neural Network (CNN) for feature extraction and a Long Short-Term Memory (LSTM) network for temporal sequence modeling [4]. This combination successfully captured the temporal patterns in EEG data, offering a significant improvement over traditional methods. Similarly, proposed a time-frequency analysis approach using Morlet wavelets and stacked sparse autoencoders, highlighting the effectiveness of wavelet-based feature extraction in modeling EEG signals [5]. Building on these works, this study investigates advanced CNN-based architectures for sleep stage segmentation. We propose and compare three models: CNN-CNN, CNN-CNN-Conditional Random Field (CRF), and CNN-LSTM. Each model is designed to exploit the temporal dependencies inherent in EEG signals while addressing the limitations of existing methods.

These innovative approaches highlight the potential of deep learning models in transforming how sleep stages are classified from EEG data [6,7]. By effectively encoding and modeling the complex patterns in EEG signals, these models offer promising tools for improving the assessment and understanding of sleep quality. By incorporating CRFs for sequence labeling, our approach emphasizes contextual consistency, making it particularly suited for sleep stage segmentation [8-11]. This paper focuses on evaluating these architectures using the Sleep-EDF dataset, a benchmark in sleep research. We aim to identify the model that best balances accuracy and robustness, paving the way for reliable applications in clinical and home-based sleep monitoring systems [12].

Methodology

This study uses the Sleep-EDF dataset and evaluates three models, CNN-CNN, CNN-CNN-CRF, and CNN-LSTM for sleep stage segmentation. Preprocessing ensures clean input data with subject-level separation. The models leverage CNNs for feature extraction, with CRF and LSTM layers capturing temporal dependencies. Training employed the Adam optimizer, and evaluations were based on accuracy and F1 scores, validated via 20-fold cross-validation to ensure robustness (Figure 1).

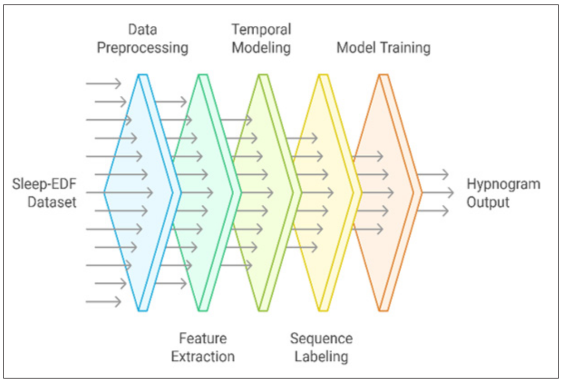

Figure 1: Proposed Sleep Stage Segmentation Framework

Approach

This study introduces a CNN-CNN-CRF model for sleep stage segmentation (Figure 5), uniquely combining the feature extraction power of CNNs with the sequence-labeling capability of Conditional Random Fields (CRFs). The integration of CRFs ensures contextual consistency by learning transition probabilities between consecutive sleep stages, a limitation in standard CNN models (Figure 1). Unlike traditional methods, this approach directly addresses the challenge of temporal dependencies in EEG signals without requiring extensive hyperparameter tuning. This novel architecture demonstrates improved performance and robustness, establishing it as a reliable tool for automated sleep analysis (Figure 2).

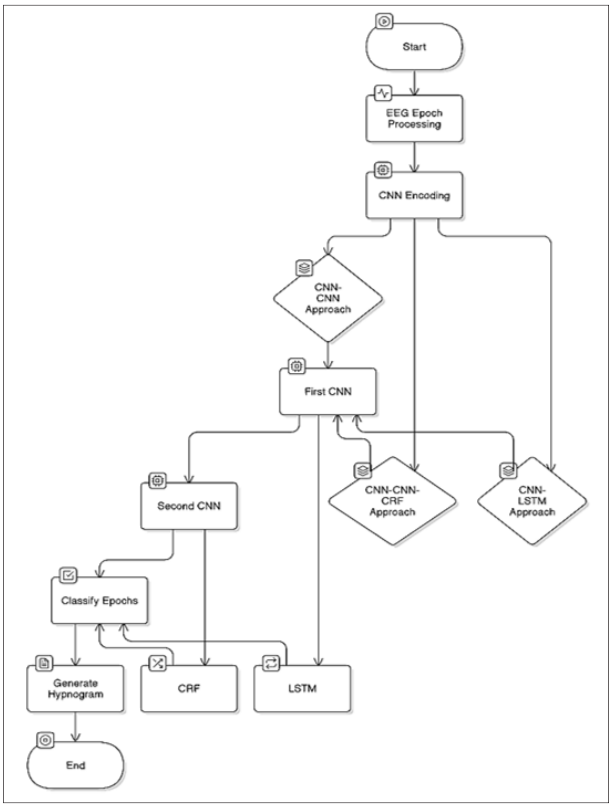

Figure 2: The Proposed CNN-CNN-CRF Architecture: Combines the feature extraction strength of CNNs with the sequence-labeling ability of CRFs, ensuring contextual consistency by modeling transition probabilities between sleep stages. This approach addresses temporal dependencies in EEG signals efficiently, offering enhanced performance and robustness for automated sleep stage analysis

Dataset & Data Preprocessing

The dataset utilized in this study is the publicly available Sleep-EDF dataset, collected by [12]. This dataset consists of EEG sleep recordings from 20 subjects, with 19 of them having two full nights of sleep data. We used pre-processing scripts provided by Supratak et al., to prepare the data for analysis [4]. To ensure unbiased evaluation, the dataset was divided into training and test sets such that no individual appears in both sets simultaneously. The input data consists of sequences of 30-second EEG epochs (Figure 3), with each epoch labeled according to the sleep stage: Wake (W), Non-Rapid Eye Movement stages N1, N2, N3, and Rapid Eye Movement (REM).

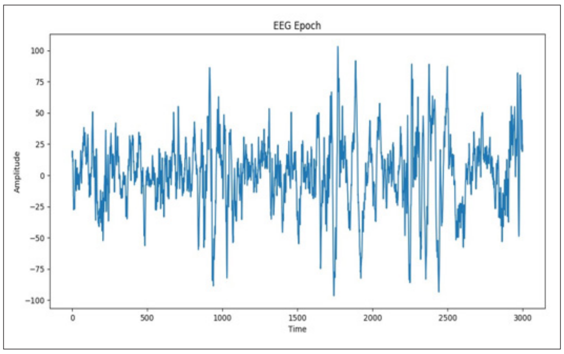

Figure 3: EEG Epoch

This labeling provides a clear categorization of the sleep stages, allowing for precise training and testing of our model. By maintaining a strict separation between training and testing subjects, the integrity of the model's evaluation is preserved, ensuring that the results accurately reflect its ability to generalize across different individuals (Figure 4). This approach enhances the reliability of the sleep stage classification process and facilitates its application in clinical settings (Figure 2).

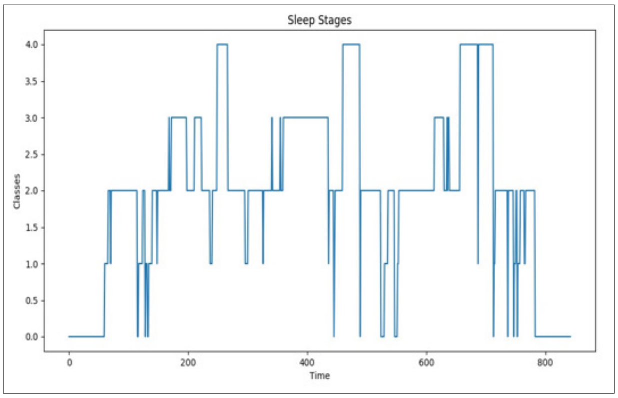

Figure 4: Sleep Stages Through the Night

Model Architectures

CNN-CNN: This model employs a two-step CNN architecture. The first CNN extracts spatial features from individual EEG epochs, while the second CNN captures temporal dependencies between consecutive epochs for sequence labeling.

CNN-CNN-CRF: Building on CNN-CNN, this model integrates a Conditional Random Field (CRF) layer for sequence labeling. The CRF enforces contextual consistency, improving the accuracy of sleep stage transitions.

CNN-LSTM: This architecture combines a CNN for feature extraction with an LSTM network to model temporal patterns. LSTMs excel at capturing long-term dependencies in sequential data, making them suitable for sleep stage segmentation.

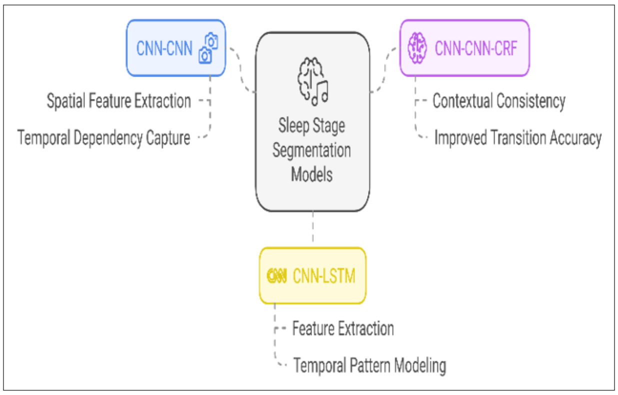

Figure 5: An Overview of Sleep Stage Segmentation Models

Training and Evaluation

Models were trained using the cross-entropy loss function, optimized with Adam. Hyperparameters, including learning rate and batch size, were tuned empirically. Performance metrics such as accuracy and F1 score were computed to evaluate the models. The CNN-CNN-CRF model was further assessed against state-of-the-art methods using 20-fold cross-validation, ensuring robustness and generalizability.

Experiment

In this study, we implement a two-step model architecture that utilizes a 1D Convolutional Neural Network (CNN) to process each EEG epoch, followed by either another 1D CNN or an LSTM network to label the sequence of epochs and generate the final hypnogram. This approach enables the model to consider contextual information when predicting sleep stages for each epoch (Figure 2, 5). To evaluate different modeling strategies, we compare three approaches:

CNN-CNN

This model uses a 1D CNN for both encoding each EEG epoch and labeling the sequence. The first CNN extracts features from the individual epochs, while the second CNN processes these features over the sequence to classify each epoch within its temporal context.

CNN-CNN-CRF

In this configuration, a 1D CNN encodes each epoch, and then a combination of a 1D CNN and a Conditional Random Field (CRF) is used for sequence labeling. The CRF adds a probabilistic framework that considers dependencies between neighboring epochs, potentially improving the accuracy of sleep stage classification by enforcing consistency in the sequence labeling.

CNN-LSTM

This approach also uses a 1D CNN for epoch encoding but employs an LSTM for sequence labeling. The LSTM is adept at capturing temporal dependencies, making it well-suited for analyzing sequences of sleep epochs where the order and transitions between stages are crucial.

By comparing these models, we aim to identify the most effective approach for accurate and context-aware sleep stage classification (Figure 7), leveraging the strengths of CNNs for feature extraction and either CNN, CRF, or LSTM for capturing temporal patterns and relationships (Figure 6,7).

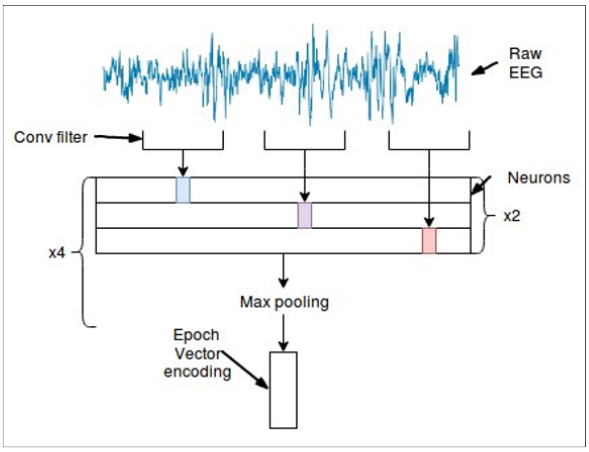

Figure 6: Epoch Encoder

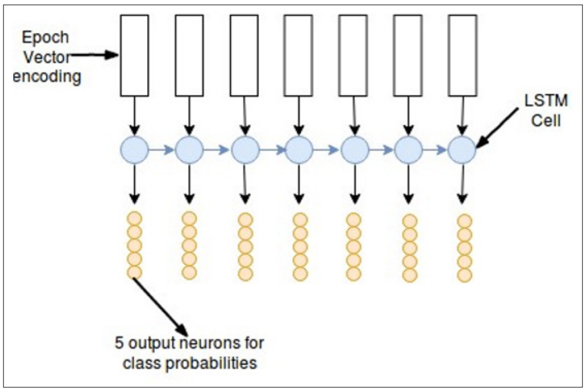

Figure 7: Sequential Model for Epoch Classification

Result

Sequential Model Comparison

The LSTM-based model showed the lowest accuracy because LSTMs typically need extensive parameter tuning—such as adjustments to learning rate, batch size, and regularization—to perform well, which was not thoroughly conducted in this study. In contrast, the CNN-CRF model outperformed the CNN-only model, demonstrating that the CRF component effectively learns the transition probabilities between sleep stages. This result highlights the advantage of incorporating CRFs, which can enhance the model's ability to capture the dependencies between consecutive epochs, leading to more accurate sleep stage classification (Table 1).

Table 1: Proposed Models Results

Model	Accuracy	F1
CNN-CNN	0.87	0.81
CNN-CNN-CRF	0.89	0.82
CNN-LSTM	0.71	0.76

Comparison To the State of Art

The CNN-CNN-CRF approach performs well, even when compared to state-of-the-art methods (Figure 8), especially when evaluated using a 20-fold cross-validation setup. In this setup, training and test sets are kept independent, ensuring that no subject appears in both sets. Predictions are made within this cross-validation framework, allowing for comprehensive evaluation. Metrics are then calculated based on predictions across the entire dataset, confirming the robustness of this approach. This methodology highlights the model's ability to generalize effectively and demonstrates its potential in accurately classifying sleep stages (Figure 9, 10).

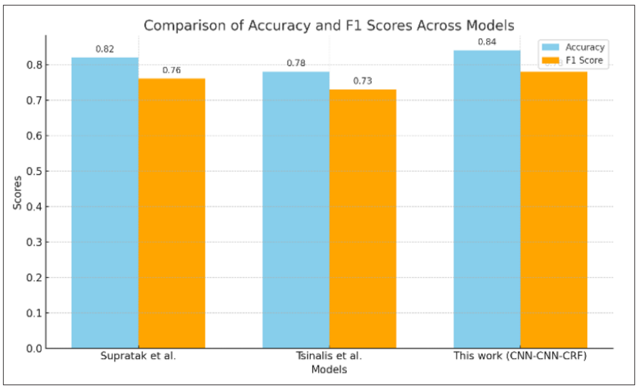

Figure 8: Comparison with Existing Models and Their Approach

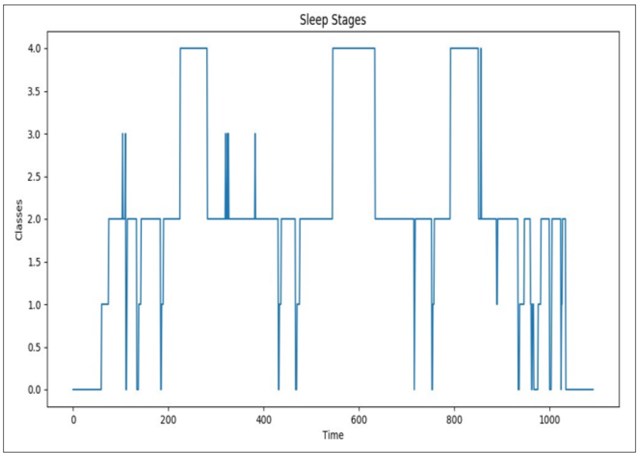

Figure 9: Ground Truth Hypnogram Example

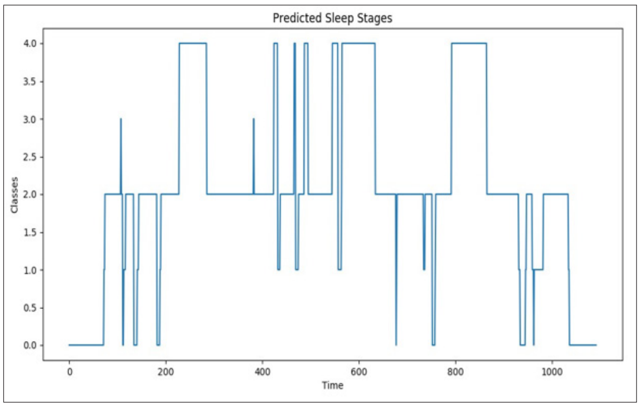

Figure 10: Predicted Hypnogram example

Discussion

The results of this study demonstrate the effectiveness of integrating sequence labeling mechanisms with CNNs for sleep stage segmentation. Among the tested models, the CNN-CNN-CRF approach consistently outperformed alternatives, achieving superior accuracy and F1 scores. This highlights the importance of incorporating contextual information, as the CRF layer enforces consistency across consecutive sleep stages, addressing limitations of standard CNNs. In contrast, the CNN-LSTM model underperformed, likely due to insufficient hyperparameter tuning and the challenges of training LSTMs on relatively small datasets. While LSTMs are theoretically well-suited for sequential data, their sensitivity to parameter configurations may limit their practical application without extensive optimization. When compared to state-of-the-art methods, the CNN-CNN-CRF model demonstrated comparable or improved performance, underscoring its robustness and potential for real-world applications. The use of 20-fold cross-validation further ensured the reliability of results, with minimal risk of overfitting. Future research could explore hybrid architectures that combine the strengths of CRFs and LSTMs or investigate transfer learning to enhance generalizability. Expanding the dataset with additional subjects or modalities, such as multi-channel EEG or other physiological signals, could also improve model performance and applicability in diverse clinical scenarios.

Conclusion

In this paper evaluated multiple approaches for sleep stage segmentation using the Sleep-EDF dataset, demonstrating that the CNN-CRF model outperforms both LSTM-based and CNN-only models. The CNN-CRF approach effectively leverages transition probabilities between sleep stages, enhancing segmentation accuracy. Despite the potential of LSTMs, their need for extensive parameter tuning limited their performance in this study. Overall, the results highlight the advantages of integrating CRFs with CNNs for capturing temporal dependencies and achieving superior sleep stage classification.

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