**ABSTRACT**

Sleep stage classification is a crucial component of sleep research and clinical diagnosis, as it provides essential insights into sleep quality and disorders. Traditional methods often require multiple electroencephalogram (EEG) channels, making the setup cumbersome and uncomfortable for patients. This study proposes an attention-based deep learning approach for sleep stage classification utilizing single-channel EEG data, offering a more streamlined and patient-friendly solution. The proposed method leverages the power of attention mechanisms to focus on the most informative features in the EEG signal, thereby enhancing classification performance. Our approach involves preprocessing the raw EEG data to remove noise and artifacts, followed by feature extraction using convolutional neural networks (CNNs) to capture spatial patterns. These features are then processed by a recurrent neural network (RNN) to capture temporal dependencies, and an attention layer is applied to weigh the importance of different time steps. The final classification is achieved using a fully connected layer. Extensive experiments were conducted on publicly available EEG datasets, and the results demonstrate that our model outperforms traditional methods and state-of-the-art deep learning approaches in terms of accuracy and computational efficiency. Specifically, the attention mechanism significantly improves the model's ability to correctly classify different sleep stages, including wakefulness, REM sleep, and non-REM sleep stages (N1, N2, N3). This enhancement is attributed to the model's ability to dynamically focus on relevant parts of the EEG signal, which is particularly beneficial given the variability and complexity of sleep patterns. In conclusion, our attention-based deep learning framework represents a significant advancement in sleep stage classification using single-channel EEG data. By combining the strengths of CNNs, RNNs, and attention mechanisms, our model achieves superior performance while maintaining simplicity and cost-effectiveness. This work has the potential to transform sleep monitoring practices, offering a practical and efficient solution for both clinical and personal health applications.

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