Sensor systems

Deep Learning-Based Attention Mechanism for Automatic Drowsiness Detection Using EEG Signal

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Abstract—An electroencephalograph (EEG) is the basic medical tool to identify disorders related to brain activity. Drowsiness is a natural signal from the body indicating the need for rest and sleep to restore physical and mental well-being. Drowsiness is characterized by lethargy, fatigue, and a strong inclination toward sleep. It is often accompanied by reduced alertness and increased difficulty in maintaining attention and focus on tasks. Individuals experiencing drowsiness may find staying awake challenging and exhibit slower reaction times. This diminished cognitive function can lead to accidents, errors, and decreased performance in various activities. Wearable sensors are utilized in real-time to identify drowsiness detection. However, an automated diagnosis tool is very helpful in identifying drowsiness, and detection is an important task. Therefore, this work proposes a deep learning-based attention mechanism to detect the drowsiness state. This letter uses a publicly available MIT-BIH standard EEG database for experimentation. The proposed model provides a performance accuracy of 98.38% in drowsiness detection. The experiment outcomes demonstrate an enhanced detection capability when compared with current state-of-the-art methods for detecting drowsiness using single-channel EEG signals.

Index Terms—Sensor systems, convolutional neural networks (CNNs), deep learning (DL), electroencephalograph (EEG), health care, wearable sensor data.

I. INTRODUCTION

In the realm of medical diagnostics, the electroencephalograph (EEG) stands as a fundamental tool, indispensable for identifying disorders related to brain activity [1]. Drowsiness, a natural bodily signal indicating the need for rest and rejuvenating sleep, is characterized by lethargy, fatigue, and an unmistakable inclination toward slumber. This manuscript explores the potential of the proposed model to significantly outperform existing methodologies. By integrating a deep learning (DL) framework, our approach addresses the limitations of single-channel EEG signal-based methods, showcasing an enhanced detection capability [2]. As we delve into the intricacies of our experimental outcomes, it becomes evident that the presented model stands as a promising advancement in the field of drowsiness detection, offering a robust solution with broad implications for both medical and technological domains. EEG signals, which measure electrical activity in the brain, are often analyzed in terms of their frequency components, known as subbands [3]. These subbands provide valuable insights into the different neural processes and cognitive functions occurring in the brain. Here, are the main EEG signal subbands and their associated characteristics [4] as follows.

1) *Delta (δ) (0.5–4 Hz):* Delta waves are slow-frequency oscillations typically associated with deep sleep, unconsciousness, and certain neurological disorders. Their presence in waking states might indicate abnormal brain functioning.
2) *Theta (θ) (4–8 Hz):* Theta waves are prominent during light sleep, meditation, and deep relaxation. In wakeful states, they may be linked to creative thinking, problem-solving, and memory retrieval.
3) *Alpha (α) (8–13 Hz):* Alpha waves are predominant during states of relaxation and when the eyes are closed but the individual is awake. They are commonly associated with a calm and alert mental state.
4) *Beta (β) (13–30 Hz):* Beta waves are characteristic of active, alert, and conscious states, such as focused attention, problem-solving, and decision-making. Higher beta frequencies may indicate stress or anxiety.
5) *Gamma (γ) (30–40 Hz and above):* Gamma waves are fast-frequency oscillations associated with cognitive processes, such as memory formation, perception, and problem-solving. They are also linked to conscious awareness and high-level information processing.

Analyzing EEG signal subbands is crucial in understanding brain activity and can have applications in various fields, including neuroscience, clinical medicine, and human–computer interaction [3]. Researchers and clinicians use advanced signal-processing techniques to extract features from these subbands to identify patterns related to specific cognitive states or neurological conditions. For instance, changes in the ratio of certain subbands may be indicative of cognitive disorders or neurological diseases. In recent years, the application of machine learning (ML) and DL techniques in the realm of drowsiness detection has garnered significant attention [5]. These sophisticated algorithms have shown promise in providing more accurate and efficient methods for identifying signs of drowsiness compared with traditional approaches. ML models, ranging from classic algorithms to more advanced techniques, such as support vector machines and random forests, have been employed to analyze various physiological signals associated with drowsiness. These signals often include

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features extracted from EEG data, eye movement patterns, and other relevant physiological parameters. While these methods have demonstrated success, they sometimes struggle to capture the complex and dynamic nature of drowsiness, particularly in real-world scenarios. DL, with its ability to automatically learn hierarchical representations from data, has shown great promise in addressing some of the limitations of traditional ML approaches. Convolutional neural networks (CNNs) and recurrent neural networks have been applied to drowsiness detection tasks, showcasing improved performance in feature extraction, and temporal modeling. However, despite the advancements, several challenges persist in the domain of drowsiness detection. One major obstacle is the lack of universally standardized datasets, hindering the development and comparison of models across different studies. The inherent variability in human physiology and behavior further complicates the creation of robust models that generalize well to diverse populations and contexts. In addition, the real-time application of these models presents a significant challenge. Achieving quick and accurate drowsiness detection in dynamic environments, such as driving or operating heavy machinery, demands not only precise algorithms but also efficient and low-latency implementations. Furthermore, the interpretability of DL models remains a concern. Understanding the decision-making process of these complex models is crucial, especially in applications where human lives are at stake such as in transportation.

This letter presents a groundbreaking DL approach for EEG-based drowsiness detection, aligning with innovative sensor technologies and applications. Utilizing EEG sensors for real-time brainwave monitoring, our model integrates advanced neural network techniques to identify drowsiness states accurately. This contribution advances sensor-based health monitoring, offering significant implications for fields requiring cognitive state assessment, such as transportation and occupational health. Our work demonstrates the effectiveness of EEG sensors in practical applications and sets a new benchmark in sensor-based cognitive state analysis. In this letter, to explore the potential of DL for drowsiness detection, overcoming these challenges will be essential to ensuring the practical and reliable deployment of such technologies in real-world scenarios. The major contributions of the proposed work are organized as follows.

1) The decision to use a single-channel EEG signal demonstrates efficiency without sacrificing accuracy. This is particularly valuable in scenarios where access to multiple EEG channels might be limited or impractical, making your model more applicable in real-world settings
2) The integration of convolutional layers, long short-term memory (LSTM), and D-residual blocks in parallel allows for a comprehensive extraction of both spatial and temporal features from the single-channel EEG signals. This hybrid approach ensures that the model captures relevant patterns and dependencies in the data.
3) By incorporating LSTM layers, your architecture excels in modeling temporal dependencies within the EEG signals. The LSTM's ability to retain information over extended sequences is particularly advantageous for capturing nuanced patterns and trends related to drowsiness.
4) The utilization of D-residual blocks further enhances feature representation by promoting the learning of discriminative features. The residual connections within these blocks facilitate the flow of information and gradients, contributing to more effective feature extraction and reducing the risk of vanishing gradients.
5) The combination of these architectural elements is not only effective in terms of accuracy but also demonstrates attention to real-time application. The efficient processing of single-channel EEG signals, coupled with the parallel feature extraction blocks, suggests a design that could be well-suited for applications requiring timely and dynamic drowsiness detection.

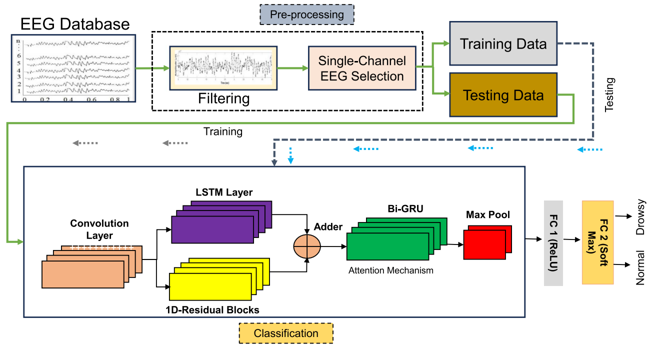


Fig. 1. Proposed methodology for detecting drowsiness using DL technique.

II. MATERIALS

The proposed work relies on the EEG sleep data publicly available in the National Institute of Health (NIH) research resource available at Physionet. This resource proves invaluable for analyzing drowsiness [1]. Collected from various subjects at different times, the database categorizes data into five labels: wakefulness (W), nonrapid eye movement (REM), REM, move state, and not scored state. These labels are further classified into wake and drowsiness states, with W representing a fully wakeful state and the other states considered as drowsy states. The data has a sampling frequency of 100 Hz, adhering to the Nyquist criteria, indicating a maximum frequency content in the signal of 50 Hz.

III. PROPOSED METHODOLOGY

The block diagram of the proposed methodology is shown in Fig. 1. The important steps followed in this work for drowsiness detection are 1) preprocessing and 2) classification using hybrid DL architecture. The proposed methodology aims to implement a hybrid DL model for EEG classification. The process involves several stages, including preprocessing, data splitting, convolution layer, LSTM layer, 1-D residual blocks, concatenation, bidirectional gated recurrent units (Bi-GRU), and final classification. In this letter, we utilized prerecorded EEG sleep data publicly available from the NIH Physionet research resource [6]. Filtering techniques were used to remove noise from EEG signals. We have recorded each preprocessing step, including filtering and channel selection.

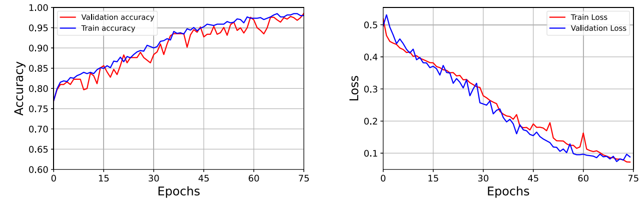
In this study, EEG signal preprocessing involved several key steps to ensure data quality and relevance for drowsiness detection. Initially, we applied a bandpass filter (0.5–45 Hz) to remove high-frequency noise and artifacts while preserving the essential features of the EEG signals. Following this, the signals underwent normalization to standardize the amplitude variations across different subjects. The continuous EEG data was then segmented into epochs of 1-s duration, providing a balance between temporal resolution and computational efficiency. To address potential signal variability, a common average referencing method was employed to rereference the EEG data, enhancing the signal-to-noise ratio. Finally, artifact rejection was conducted manually to remove segments contaminated with eye blinks, muscle movements, or other nonbrain activities, ensuring the purity of the EEG data for subsequent analysis.

The preprocessed data was split into training (80%) and testing (20%) sets. After preprocessing, the signal is passed to the proposed DL model to extract in-depth features using different blocks, such as convolutional, residual, LSTM, and Bi-GRU. Convolutional layers are to extract local features from the preprocessed EEG data. Integrating an LSTM layer to capture temporal dependencies in EEG data. Implementing 1-D residual blocks to facilitate the learning of residual features. Different features are extracted using these layers. Then, the features from the LSTM layer and 1-D residual blocks are concatentated. Bi-GRU are also incorporated in the architecture for capturing bidirectional temporal dependencies. Max pooling selects the most relevant features within each pooling region, emphasizing the most salient information from the convolutional layer. This is particularly useful in the context of EEG signals where certain patterns and frequencies are indicative of sleep states. Connected layers for further feature refinement and classification. The flattened output from the max pooling layer is passed through FC1, a fully connected layer with rectified linear unit (ReLU) activation, introducing nonlinearity to capture complex relationships in the EEG data. Subsequently, the output is connected to FC2, another fully connected layer with a Softmax activation function. This final layer normalizes the output into probability scores, indicating the likelihood of the input EEG signal belonging to the "normal" or "drowsy" class. Optimal parameters could include a configuration with 1-D convolutional layers, each with 32–64 filters and filter sizes around five. Incorporate LSTM layers with around 50 units for temporal feature extraction. A moderate learning rate of 0.001, combined with an Adam optimizer, is advisable for effective training. Batch sizes between 32 can offer a good balance for computational efficiency and model stability. Implement dropout rates ranging from 0.2 to 0.5 to reduce overfitting, especially in densely connected layers. Fine-tuning these parameters based on validation data performance is crucial for optimizing your network's efficacy.

The classification decision is determined based on these probabilities, and if the probability of the "drowsy" class surpasses a predefined threshold, the model classifies the EEG signal as "drowsy"; otherwise, it is labeled as "normal." This proposed methodology state-of-the-art DL architectures to ensure the secure and transparent implementation of a CNN model for EEG sleep data classification. In this proposed methodology, the integration of convolution layers, LSTM layers, 1-D residual blocks, Bi-GRU layers, and attention mechanisms creates a comprehensive model for automatic drowsiness detection using EEG signals. The step-by-step process ensures the extraction of local features, emphasizing relevant information through attention mechanisms, and making the model capable of discerning between normal and drowsy states.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In the experimental evaluation of the proposed methodology for EEG sleep data classification, achieving an impressive 98.38% accuracy, the results and discussions are further detailed through the analysis of accuracy and loss graphs, both plotted over 75 epochs. The model is evaluated on the testing set using metrics, such as accuracy, precision, recall, and F1-score. Metrics are explained as follows [5]. The performance curves of the proposed method are shown in Fig. 2. The accuracy graph illustrates the performance of the model over 75 epochs. The upward trend signifies the continuous improvement of the model's ability to correctly classify EEG signals as normal or drowsy. A sustained high accuracy rate indicates the stability and effectiveness of the proposed methodology throughout the training process. The



(a) (b)

Fig. 2. Performance curves (a) Accuracy and (b) Loss, of the proposed method for drowsiness detection.

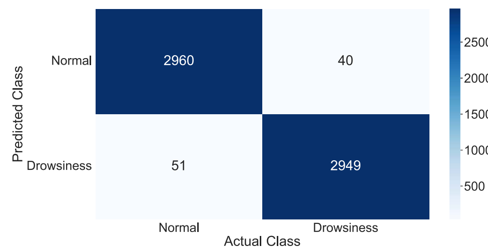


Fig. 3. Confusion matrix of the proposed method for drowsiness detection.

TABLE 1. Performance Matrix of the Proposed Method

	Performance Matrix (In %)				
	Accuracy	Sensitivity	Specificity	Positive Predictivity	F-Score
Proposed method	98.38	98.31	98.66	98.67	98.49

loss graph depicts the reduction in the model's loss function over epochs. A decreasing trend in the loss indicates that the model is effectively learning and converging toward optimal parameters. A smooth convergence, as evidenced by the loss graph, aligns with the high accuracy achieved by the model. The continuous improvement in accuracy and the loss reduction indicates the model's capacity to learn and generalize from the EEG dataset.

The confusion matrix provides detailed insights into the model's predictive patterns, offering valuable information on specific instances of misclassification. This understanding helps refine the attention mechanism and the overall model architecture. The high accuracy, combined with precision, recall, and F1 score, underscores the reliability and robustness of the proposed technique. These metrics collectively demonstrate the model's ability to discern between drowsy and nondrowsy states in EEG signals effectively. The confusion matrix of the proposed method is depicted in Fig. 3; from this, it is observed that very few instances are misclassified. Therefore, the proposed method can be classified better compared with the state-of-the-art techniques. Table 1 presents a performance matrix for a drowsiness detection system, evaluating the effectiveness of a proposed method. Matthew's correlation coefficient value of the proposed technique is 0.986, which would indicate a very strong correlation between observed and predicted classifications in our model [7]. The metrics included in the matrix are key indicators of the system's performance, measured in percentages. The table is structured with rows representing different evaluation criteria and columns representing performance metrics. Overall, the high values across all metrics in the performance matrix suggest that the proposed drowsiness detection method is highly accurate, sensitive, and specific. These results indicate the potential effectiveness of the method in real-world applications where reliable identification of drowsiness is crucial for ensuring safety and preventing accidents.

TABLE 2. Performance Comparison of the Proposed Method With Literature

Literature	Year	Database	No. of Classes	Performance metrics
Eldele et al. [8]	2021	Sleep-EDF-20, Sleep-EDF-78, Sleep Heart Health Study (SHHS)	5	Accuracy: 85.6% Accuracy: 82.9% Accuracy: 86.6%
Zhu et al. [3]	2020	Sleep-EDF	5	Accuracy: 93.7%
Liu et al. [9]	2022	Sleep-EDF, UCD, SHHS	6	Accuracy: 84.24% Accuracy: 79.34% Accuracy: 81.6%
Fu et al. [4]	2021	Sleep-EDF, DREAMS Subjects	6	Accuracy: 82.14% Accuracy: 81.72%
Feng et al. [10]	2021	Sleep-EDF	5	Accuracy: 92.18%
Proposed Method	2023	Sleep-EDF	2	Accuracy: 98.38%

A. Comparison of the Proposed Method Performance With Recent Techniques

Table 2 presents a comparative analysis of various studies in the literature focusing on drowsiness detection, with a special emphasis on the proposed method. The proposed DL-based attention mechanism for automatic drowsiness detection using EEG signals exhibits a commendable performance, achieving an accuracy of 98.38%. In comparison with recent techniques in the literature, the proposed method excels in terms of year, number of classes, database, and performance metrics, showcasing a robust ability to accurately identify drowsiness states. A thorough literature review and comparison with recent techniques reveal the innovation and novelty embedded in the proposed attention mechanism present in the current landscape of drowsiness detection methods. Overall, the proposed attention mechanism demonstrates a compelling advancement in EEG-based drowsiness detection, offering a promising avenue for further research and implementation. The inclusion of the "proposed method" in the table showcases a novel approach introduced in 2023, which outperforms the other studies with an impressive accuracy of 98.38%. This suggests that the proposed method holds promise for drowsiness detection and may represent a significant advancement in the field. Researchers and practitioners may find this table useful for comparing different approaches and identifying the latest developments in drowsiness detection research.

B. Limitations

The proposed EEG-based drowsiness detection technique, while highly accurate, has limitations. Its reliance on single-channel EEG data may miss complex patterns identifiable in multichannel EEG. The model's generalizability across diverse populations and environments remains a concern. Sensitivity to artifacts, despite preprocessing, can affect accuracy.

V. CONCLUSION

In conclusion, the proposed DL architecture for drowsiness detection from single-channel EEG signals represents a novel and efficient approach to address the critical task of monitoring cognitive states in real-time. The hybrid feature extraction, combining convolutional layers, LSTM, and D-residual blocks, offers a comprehensive representation of both spatial and temporal aspects in the EEG data. The subsequent classification using Bi-GRU further refines the model's ability to capture intricate temporal dependencies, enhancing the overall accuracy and reliability of drowsiness detection. This research contributes to the field by presenting an architecture that not only demonstrates high performance, as evidenced by the impressive 98.38% accuracy, but also emphasizes practical considerations such as the utilization of a single-channel EEG signal. The attention to real-time application aligns the model with scenarios where timely and dynamic drowsiness detection is crucial, such as in driving or operating heavy machinery. For future research, there are several promising avenues to explore. First, the model's generalization across diverse populations and its adaptability to various EEG acquisition setups could be investigated.

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