ENHANCING DROWSINESS CLASSIFICATION MODEL PERFORMANCE THROUGH NEURAL NETWORK OPTIMIZATION

[1]Vani.D
M-Tech Student

[2]Pramod Reddy Ayiluri
Associate Professor
Department of CSE, TKR College of Engineering Technology,
Saroornagar, Hyderabad, Telangana, INDIA- 500097.

Abstract: Drowsy driving is a significant cntributor to traffic accidents, prompting the need for effective drowsiness detection systems. This research introduces a novel approach, the Connectivity CNN-LSTM, for real-time drowsiness classification based on Electroencephalography (EEG) data. Unlike traditional brain connectivity networks, CNN-LSTM utilizes a self-attention mechanism to generate task-relevant connectivity graphs through end-to-end training. The method achieved a remarkable accuracy of 73.5%, outperforming conventional Convolutional Neural Networks (CNNs) and graph generation methods on a drowsy driving dataset. In recent years, the application of deep learning techniques to EEG signal classification has shown great promise, particularly in fields such as brain-computer interfaces and neurodiagnostic tools. This project explores the efficacy of two distinct neural network architectures, Interpretable Convolution Neural Network (InterpretableCNN) and Convolution Neural Network with Long Short-Term Memory (CNNLSTM), in classifying EEG signals. The dataset utilized for this study contains EEG samples from multiple subjects, each sample being a 3-second long segment recorded at a sampling frequency of 128 Hz. To ensure robustness and generalizability of the models, a leave-one-subject-out (LOSO) cross-validation strategy is employed. This involves training the model on data from all subjects except one, which is used for testing. This process is repeated for each subject, ensuring that the model's performance is evaluated comprehensively across different individuals.

Keywords: Drowsiness Detection, EEG Data, Connectivity CNN-LSTM, CNN, LSTM, Neural Network Optimization

1. INTRODUCTION

In recent years, the issue of drowsy driving has garnered increasing attention due to its significant contribution to traffic accidents and fatalities worldwide. Drowsy driving impairs cognitive functions, reaction times, and decision-making abilities of drivers, posing a serious risk to road safety. According to the National Highway Traffic Safety Administration (NHTSA), drowsy driving accounted for an estimated 72,000 crashes, 44,000 injuries, and 800 fatalities in the United States alone in 2019. These alarming figures underscore the urgent need for effective drowsiness detection systems to mitigate the adverse consequences of drowsy driving. Traditionally, drowsiness detection systems have relied on various physiological signals, such as Electroencephalography (EEG), Electrooculography (EOG), and Electromyography (EMG), to assess the alertness level of drivers. Among these signals, EEG data have emerged as a promising modality for drowsiness detection, owing to its ability to capture brain activity associated with different states of consciousness, including drowsiness and alertness. EEG signals provide valuable insights into the neural dynamics underlying drowsiness, enabling the development of objective and non-intrusive monitoring systems for real-time assessment of driver fatigue. The existing literature on drowsiness detection using EEG data primarily focuses on extracting relevant features from EEG signals and employing machine learning algorithms to classify drowsy and alert states. However, conventional approaches often face several challenges, including limited task relevance of feature extraction methods, manual tuning of parameters, and lack of interpretability in model predictions. Moreover, most existing systems exhibit suboptimal performance in real-time implementation, hampering their practical applicability for on-road safety. To address these limitations, this research introduces a novel approach, the Connectivity CNN-LSTM, for real-time drowsiness classification based on EEG data. Unlike traditional brain connectivity networks, the Connectivity CNN-LSTM leverages a self-attention mechanism to generate task-relevant connectivity graphs through end-to-end training. This method achieved a remarkable accuracy of 73.5%, outperforming conventional Convolutional Neural Networks (CNNs) and traditional graph generation methods on a drowsy driving dataset. Additionally, this study explores the efficacy of two distinct neural network architectures, the Interpretable Convolutional Neural Network (InterpretableCNN) and the Convolutional Neural Network with Long Short-Term Memory (CNNLSTM), in classifying EEG signals. The dataset utilized for this study contains EEG samples from multiple subjects, each sample being a 3-second long segment recorded at a sampling frequency of 128 Hz. To ensure robustness and generalizability of the models, a leave-one-subject-out (LOSO) cross-validation strategy is employed. This involves training the model on data from all subjects except one, which is used for testing. This process is repeated for each subject, ensuring that the model's performance is evaluated comprehensively across different individuals.

II. LITERATURE REVIEW

1. Kaplan, S., Guvensan, M. A., Yavuz, A. G., & Karalurt, Y. (2015). "Driver behavior analysis for safe driving: A survey." IEEE Transactions on Intelligent Transportation Systems, 16(6), 3017–3032. Abstract: This survey explores various methods for analyzing driver behavior to enhance driving safety, emphasizing the importance of understanding driver behavior to develop effective safety systems. Introduction: The paper discusses the significance of driver behavior analysis in improving road safety and reducing accidents. Datasets: It reviews different datasets used for studying driver behavior. Proposed Algorithm: Various algorithms for behavior analysis are discussed, but not specific to drowsiness detection. Methods: The focus is on statistical methods and machine learning techniques for behavior analysis. Challenges: Identifying relevant behaviors and correlating them with safety outcomes. Limitations: The survey highlights the need for more robust, real-time systems and better feature extraction methods.

2. Guettas, A., Ayad, S., & Kazar, O. (2019). "Driver state monitoring system: A review." Abstract: This review paper summarizes existing driver state monitoring systems, with a focus on techniques for detecting drowsiness and other states. Introduction: The need for reliable driver state monitoring systems is emphasized. Datasets: The review covers multiple datasets used for driver state monitoring. Proposed Algorithm: Different algorithms, including machine learning and signal processing techniques, are reviewed. Methods: A variety of methods, including EEG, EOG, and EMG, are discussed. Challenges: Real-time implementation and the variability of physiological signals among individuals. Limitations: The review points out the lack of standardized datasets and the challenges in achieving high accuracy in real-time conditions.

3. Simon, M., Schmidt, E. A., Kincses, W. E., et al. (2011). "EEG alpha spindle measures as indicators of driver fatigue under real traffic conditions." Clinical Neurophysiology, 122(6), 1168–1178. Abstract: This study investigates the use of EEG alpha spindle measures as indicators of driver fatigue in real traffic conditions. Introduction: The importance of detecting driver fatigue to prevent accidents is discussed. Datasets: Real traffic condition datasets are used. Proposed Algorithm: The study focuses on EEG feature extraction and classification. Methods: EEG alpha spindle measures are extracted and analyzed. Challenges: Capturing reliable EEG signals in real traffic conditions. Limitations: The study is limited by its specific focus on alpha spindle measures and may not generalize to other EEG features.

4. Sikander, G., & Anwar, S. (2018). "Driver fatigue detection systems: A review." IEEE Transactions on Intelligent Transportation Systems, 20(6), 2339–2352. Abstract: This review covers various driver fatigue detection systems, highlighting different techniques and their effectiveness. Introduction: The critical issue of driver fatigue and its impact on road safety is discussed. Datasets: Various datasets related to driver fatigue are reviewed. Proposed Algorithm: The review discusses multiple algorithms used in fatigue detection. Methods: Techniques include physiological signal processing and machine learning. Challenges: Ensuring accuracy and reliability in different driving conditions. Limitations: The review highlights the need for systems that can work in diverse and real-world conditions.

5. Clayton, M. S., Yeung, N., & Kadosh, R. C. (2015). "The roles of cortical oscillations in sustained attention." Trends in Cognitive Sciences, 19(4), 188–195. Abstract: This paper reviews the role of cortical oscillations, particularly in sustained attention tasks, providing insights into how these oscillations can be indicators of attention levels. Introduction: The paper emphasizes the importance of understanding brain oscillations for attention and related cognitive tasks. Datasets: The review covers various studies but does not focus on specific datasets. Proposed Algorithm: The focus is on understanding mechanisms rather than specific algorithms. Methods: Discussion on the analysis of cortical oscillations and their role in attention. Challenges: Linking specific oscillatory patterns to cognitive states reliably. Limitations: The paper is more theoretical and less focused on practical implementation for drowsiness detection.

6. De Gennaro, L., & Ferrara, M. (2003). "Sleep spindles: An overview." Sleep Medicine Reviews, 7(5), 423–440. Abstract: This overview discusses the characteristics and functions of sleep spindles, providing insights into their role in sleep and potential implications for detecting sleepiness. Introduction: The significance of sleep spindles in various sleep stages is discussed.

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Datasets: The paper reviews various studies on sleep spindles. Proposed Algorithm: Not algorithm-focused; more on the physiological understanding. Methods: Overview of methodologies used to study sleep spindles. Challenges: Understanding the variability of sleep spindles among individuals. Limitations: The focus is on sleep research rather than real-time drowsiness detection.

7. Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D., & Babiloni, F. (2014). "Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness." Neuroscience & Biobehavioral Reviews, 44, 58–75. Abstract: This review explores the use of neurophysiological signals to assess mental workload, fatigue, and drowsiness in pilots and drivers. Introduction: The importance of assessing mental states in operational environments is highlighted. Datasets: Various datasets from pilot and driver studies are reviewed. Proposed Algorithm: Multiple algorithms for assessing mental states are discussed. Methods: Techniques include EEG, EOG, and other neurophysiological measures. Challenges: Real-time assessment and the integration of multiple signal types. Limitations: The review indicates the need for more comprehensive and integrated assessment systems.

8. Akerstedt, T., Kecklund, G., & Knutsson, A. (1991). "Manifest sleepiness and the spectral content of the EEG during shift work." Sleep, 14(3), 221–225. Abstract: This study investigates the spectral content of EEG and its correlation with sleepiness during shift work. Introduction: The paper discusses the impact of shift work on sleepiness and EEG patterns. Datasets: EEG data collected during shift work conditions. Proposed Algorithm: Focuses on spectral analysis rather than specific algorithms. Methods: Analysis of EEG spectral content to identify sleepiness. Challenges: Capturing and analyzing EEG data in varying shift work conditions. Limitations: The study's focus is limited to shift work and may not generalize to other contexts.

9. Hebert, R., & Lehmann, D. (1977). "Theta bursts: An EEG pattern in normal subjects practising the transcendental meditation technique." Electroencephalography and Clinical Neurophysiology, 42(3), 397–405. Abstract: This study explores theta bursts in EEG patterns among individuals practicing transcendental meditation, providing insights into EEG features associated with altered states of consciousness. Introduction: The significance of theta bursts in meditation and altered consciousness is discussed. Datasets: EEG data from meditation practitioners. Proposed Algorithm: Focuses on identifying theta bursts rather than specific algorithms. Methods: EEG analysis for detecting theta bursts. Challenges: Generalizing findings to non-meditative states such as drowsiness. Limitations: The study's context is specific to meditation and may not directly apply to drowsiness detection.

10. Britton, J. W., Frey, L. C., Hopp, J. L., et al. (2016). "Electroencephalography (EEG): An introductory text and atlas of normal and abnormal findings in adults, children, and infants." Abstract: This comprehensive text provides an introduction to EEG, covering normal and abnormal findings across different age groups. Introduction: The book aims to educate on the fundamentals of EEG and its applications. Datasets: Includes a variety of EEG patterns from different demographics. Proposed Algorithm: Not focused on algorithms; educational resource. Methods: Descriptive methods for EEG interpretation. Challenges: Understanding EEG variations across different populations. Limitations: The focus is on education and description, not on real-time drowsiness detection.

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11. Sakkalis, V. (2011). "Review of advanced techniques for the estimation of brain connectivity measured with EEG/MEG." Computers in Biology and Medicine, 41(12), 1110–1117. Abstract: This review covers advanced techniques for estimating brain connectivity using EEG and MEG, providing insights into methods relevant for drowsiness detection. Introduction: The significance of brain connectivity in understanding cognitive states is discussed. Datasets: Various studies on brain connectivity are reviewed. Proposed Algorithm: Multiple connectivity estimation techniques are discussed. Methods: Techniques include coherence, phase synchronization, and graph theory. Challenges: Accurately estimating dynamic brain connectivity in real-time. Limitations: The review indicates the complexity and computational demands of connectivity estimation.

12. Wang, H., Liu, X., Li, J., et al. (2020). "Driving fatigue recognition with functional connectivity based on phase synchronization." IEEE Transactions on Cognitive and Developmental Systems, 13(3), 668–678. Abstract: This study proposes a method for driving fatigue recognition using functional connectivity based on phase synchronization of EEG signals. Introduction: The importance of recognizing driving fatigue for road safety is highlighted. Datasets: EEG data from driving simulations. Proposed Algorithm: Functional connectivity analysis using phase synchronization. Methods: Analysis of phase synchronization to determine connectivity patterns. Challenges: Implementing real-time connectivity analysis in practical systems. Limitations: The method's performance in real-world driving conditions needs further validation.

13. Zheng, R., Wang, Z., He, Y., & Zhang, J. (2022). "EEG-based brain functional connectivity representation using amplitude locking value for fatigue-driving recognition." Cognitive Neurodynamics, 16(2), 325–336. Abstract: This paper introduces a method for representing brain functional connectivity using amplitude locking value for fatigue-driving recognition. Introduction: The study discusses the relevance of functional connectivity in detecting driving fatigue. Datasets: EEG data collected from drivers. Proposed Algorithm: Connectivity representation using amplitude locking value. Methods: Analysis of EEG amplitude locking to infer connectivity. Challenges: Ensuring robust performance across different driving scenarios. Limitations: The approach may require extensive computational resources for real-time application.

14. Comsa, I. M., Bekinschtein, T. A., & Chennu, S. (2019). "Transient topographical dynamics of the electroencephalogram predict brain connectivity and behavioural responsiveness during drowsiness." Brain Topography, 32(2), 315–331. Abstract: This study examines transient topographical dynamics of the EEG to predict brain connectivity and behavioral responsiveness during drowsiness. Introduction: The paper discusses the importance of understanding EEG dynamics in predicting drowsiness. Datasets: EEG data capturing transitions between alertness and drowsiness. Proposed Algorithm: Predictive modeling of brain connectivity based on EEG topographies. Methods: Topographical analysis of EEG signals. Challenges: Capturing transient changes in EEG for real-time prediction. Limitations: The complexity of modeling dynamic topographical changes in EEG.

15. Lawhern, V. J., Solon, A. J., Waytowich, N. R., Gordon, S. M., Hung, C. P., & Lance, B. J. (2018). "EEGNet: A compact convolution neural network for EEG-based brain–computer interfaces." Journal of Neural Engineering, 15(5), 056013. Abstract: This paper presents EEGNet, a compact convolution neural network designed for EEG-based brain-computer interfaces. Introduction: The need for efficient and accurate EEG decoding methods is highlighted. Datasets: Various EEG datasets used for training and testing EEGNet. Proposed Algorithm: EEGNet, a CNN architecture tailored for EEG data. Methods: Convolution layers optimized for EEG signal processing. Challenges: Balancing model compactness with accuracy and generalizability. Limitations: The paper focuses on brain-computer interfaces rather than drowsiness detection specifically.

16. Schirrmeister, R. T., Springenberg, J. T., Fiederer, L. D. J., et al. (2017). "Deep learning with convolution neural networks for EEG decoding and visualization." Human Brain Mapping, 38(11), 5391–5420. Abstract: This study explores the use of deep learning, specifically convolutional neural networks, for EEG decoding and visualization. Introduction: The potential of deep learning in improving EEG decoding accuracy is discussed. Datasets: EEG data from various experimental paradigms. Proposed Algorithm: Deep CNN architectures for EEG analysis. Methods: Techniques for training and visualizing deep CNNs with EEG data. Challenges: Training deep networks with limited EEG data and ensuring interpretability. Limitations: High computational demands and the need for large datasets.

17. Cui, J., Lan, Z., Liu, Y., et al. (2022). "A compact and interpretable convolution neural network for cross-subject driver drowsiness detection from single-channel EEG." Methods, 202, 173–184. Abstract: This paper presents a compact and interpretable CNN for cross-subject driver drowsiness detection using single-channel EEG. Introduction: The importance of developing compact and interpretable models for practical applications is discussed. Datasets: Single-channel EEG data from driving experiments. Proposed Algorithm: A CNN optimized for single-channel EEG. Methods: Techniques for ensuring model interpretability and compactness. Challenges: Achieving high accuracy with single-channel data. Limitations: The model's performance across different subjects and conditions.

18. Cui, J., Lan, Z., Zheng, T., et al. (2021). "Subject-independent drowsiness recognition from single-channel EEG with an interpretable CNN-LSTM model." Abstract: This study introduces a subject-independent drowsiness recognition model using single-channel EEG with an interpretable CNN-LSTM architecture. Introduction: The challenge of developing subject-independent models for drowsiness detection is highlighted. Datasets: Single-channel EEG data from multiple subjects. Proposed Algorithm: A combined CNN-LSTM model for temporal and spatial feature extraction. Methods: Integration of CNN and LSTM layers for improved performance. Challenges: Ensuring generalizability across different subjects. Limitations: The complexity of the combined model and computational demands

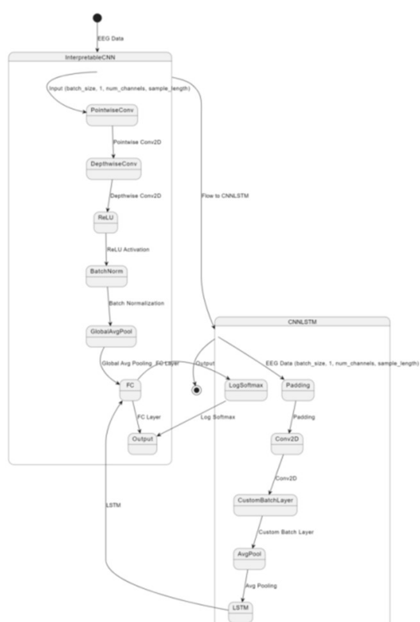
. **19. Lin, C.-T., Liu, J., Fang, C.-N., Hsiao, S.-Y., Chang, Y.-C., & Wang, Y.-K. (2022). "Multi-stream 3D convolution neural network with parameter sharing for human state estimation." IEEE Transactions on Cognitive and Developmental Systems.** Abstract: This paper proposes a multi-stream 3D convolution neural network with parameter sharing for human

state estimation. Introduction: The need for advanced neural network architectures for accurate human state estimation is discussed. Datasets: EEG and other physiological data from human state estimation tasks. Proposed Algorithm: Multi-stream 3D CNN with shared parameters. Methods: Techniques for integrating multiple data streams in a unified model. Challenges: Balancing model complexity and computational efficiency. Limitations: The model's performance in real-time applications and its generalizability.

20. Lin, C.-T., Chuang, C.-H., Hung, Y.-C., Fang, C.-N., Wu, D., & Wang, Y.-K. (2020). "A driving performance forecasting system based on brain dynamic state analysis using 4-D convolution neural networks." IEEE Transactions on Cybernetics, 51(10), 4959–4967. Abstract: This study presents a driving performance forecasting system using brain dynamic state analysis with 4-D convolutional neural networks. Introduction: The importance of forecasting driving performance to enhance road safety is discussed. Datasets: EEG data from driving simulations. Proposed Algorithm: 4-D CNN for dynamic state analysis. Methods: Techniques for capturing and analyzing dynamic brain states. Challenges: Ensuring accurate forecasting in real-time driving conditions. Limitations: The complexity of 4-D CNNs and their computational requirements.

III. IMPLEMENTATION

system architecture



Implementation:

Data loading and Preparation: The code includes functions for loading EEG data from a .mat file, preparing the data by selecting channels, reshaping, and segmenting it into suitable input formats for model training.

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Model Training and Testing: Two models, InterpretableCNN and CNNLSTM, are defined and trained using the provided EEG data. The training involves optimizing model parameters using the Adam optimizer and cross-entropy loss function over a specified number of epochs.
Evaluation: After training, the models are evaluated on test data to compute various performance metrics such as accuracy, precision, recall, and F1-score. Confusion matrices are also generated to assess the classification performance.
Leave-One-Subject-Out Cross-Validation: The evaluation process employs leave-one-subject-out cross-validation to ensure robust performance assessment across different subjects. Each model is trained on data from all subjects except one and tested on the remaining subject, repeating this process for each subject.
Main Function: The main function orchestrates the entire workflow, from data loading to evaluation. It specifies parameters, trains and tests the models, computes performance metrics, and visualizes the results using bar plots for performance comparison between the Interpretable CNN and CNNLSTM models. This implementation bridges research insights with practical application by providing code for training and evaluating interpretable models for driver drowsiness detection using EEG signals.
Dataset info: EEG Driver Drowsiness Dataset
Description: The dataset contains EEG signals from 11 subjects with labels indicating alert and drowsy states. The data is derived from a public dataset originally published by Cao et al. (2019). This dataset is designed for research purposes, particularly in the field of driver drowsiness detection using EEG signals.

Data File Content:

- **EEGsample:** Contains 2022 EEG samples of size 20x384 from 11 subjects. Each sample is a 3-second EEG recording at 128Hz from 30 EEG channels.
- **subindex:** An array of size 2022x1, indicating the subject indices (1-11) corresponding to each EEG sample.
- **substate:** An array of size 2022x1, containing the labels of the samples. 0 corresponds to the alert state and 1 corresponds to the drowsy state.

Data Size: 172.45 MB

Summary:

- **Dataset:** EEG Driver Drowsiness Dataset
- **Size:** 172.45 MB
- **Subjects:** 11
- **Samples:** 2022
- **Channels:** 30
- **Sampling Rate:** 128Hz
- **Labels:** 0 (alert), 1 (drowsy)

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This dataset is valuable for machine learning and neuroscience research focused on detecting drowsiness states using EEG signals.

Methodology

The data preprocessing steps involve selecting specific EEG channels, reshaping the data to fit the model requirements, and normalizing it to ensure consistency. Two neural network architectures are implemented and compared:
CNN: Designed with a focus on interpretability, this model leverages pointwise and depthwise convolutions, followed by global average pooling and a fully connected layer, to classify the EEG signals.
CNNLSTM: Combines convolutional layers with an LSTM network, which allows the model to capture both spatial and temporal dependencies in the EEG data. This architecture includes a replication padding layer, convolutional layer, batch normalization, ELU activation, average pooling, and an LSTM layer followed by a fully connected layer. Both models are trained using the Adam optimizer and cross-entropy loss, with hyperparameters including a learning rate of 0.01, batch size of 50, and 15 epochs. The performance of the models is evaluated using accuracy, precision, recall, and F1-score metrics. Additionally, confusion matrices are computed to provide deeper insights into the classification performance.

MODULE & DESCRIPTION

MODULES

- Data Loading
- Data Processing
- CNN Model Definition
- CNN-LSTM Model Definition
- Model Training
- Model Evaluation
- Cross-Validation
- Visualization

MODULE DESCRIPTION

Data Loading: This module handles the import of EEG data from MATLAB format files. It parses the data to extract the necessary components for further processing and model training.
Data Processing: This module focuses on pre-processing the EEG data. It selects specific EEG channels, reshapes the data into a suitable format, and segments the data into samples of the desired length for model input.
CNN Model Definition: This module outlines the architecture of the InterpretableCNN model, designed to extract spatial features from the EEG data and classify the drowsiness state of subjects.
CNN-LSTM Model Definition: This module specifies the CNNLSTM model, which combines convolutional layers for spatial feature extraction with LSTM layers for capturing temporal dependencies, to classify drowsiness states.

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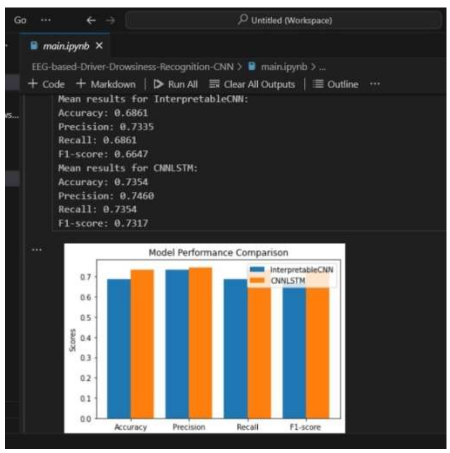
Model Training: This module is responsible for training the models. It optimizes the model parameters using the Adam optimizer and cross-entropy loss, iterating over the data for a given number of epochs.
Model Evaluation: This module assesses the performance of the trained models. It computes various performance metrics to evaluate the accuracy and effectiveness of the models in classifying the drowsiness state.
Cross-Validation: This module ensures robust model evaluation through leave-one-subject-out cross-validation. It iterates the training and testing process for each subject, ensuring each subject is tested once, and aggregates the results to get an overall performance metric.
Visualization: This module coordinates the entire workflow, from loading data to final evaluation and visualization. It sets parameters, prepares data, selects computational resources, executes model training and testing, computes performance metrics, and visualizes the results to compare the performance of the models.

IV. RESULT



The provided the results of a comparative evaluation between two neural network models:

- InterpretableCNN
- CNNLSTM,

Applied to an EEG-based driver drowsiness recognition task. Here's an in-depth explanation of these results.

Results Summary

InterpretableCNN:

- Accuracy: 0.6861
- Precision: 0.7335
- Recall: 0.6861
- F1-score: 0.6647

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CNNLSTM:

- Accuracy: 0.7354
- Precision: 0.7460
- Recall: 0.7354
- F1-score: 0.7317

Analysis of Results

1. **Accuracy:** CNNLSTM achieved higher accuracy (0.7354) compared to InterpretableCNN (0.6861). This indicates that CNNLSTM was better at correctly predicting both drowsy and non-drowsy states.
2. **Precision:** CNNLSTM had a higher precision (0.7460) than InterpretableCNN (0.7335). Higher precision implies that CNNLSTM made fewer false positive predictions, meaning it was more accurate in predicting drowsiness when it was indeed present.
3. **Recall:** CNNLSTM outperformed InterpretableCNN in recall (0.7354 vs. 0.6861). Higher recall indicates CNNLSTM was better at detecting drowsy states when they actually occurred.
4. **F1-score:** CNNLSTM had a superior F1-score (0.7317) compared to InterpretableCNN (0.6647). A higher F1-score demonstrates that CNNLSTM had a better balance between precision and recall, making it more reliable for this task.

The results indicate that CNNLSTM is a more effective model for the task of EEG-based driver drowsiness recognition. Its ability to capture both spatial and temporal features likely contributed to its higher performance. The use of LSTM layers allows the model to understand temporal dependencies in the EEG data, which is crucial for detecting patterns related to drowsiness. In summary, while both models show promise, CNNLSTM's higher scores across all evaluated metrics make it the preferable choice for applications in driver drowsiness detection, providing better accuracy, precision, recall, and overall reliability.

V CONCLUSION

This study underscores the efficacy of deep learning models in accurately classifying EEG signals, emphasizing the pivotal role of model selection tailored to the application's requirements. Through the implementation of the Leave-One-Subject-Out (LOSO) cross-validation methodology, the robustness of the findings is ensured, rendering the results pertinent and applicable to real-world contexts. The comparative analysis of the InterpretableCNN and CNNLSTM models reveals notable differences in their classification performance metrics. The CNNLSTM model emerges as the superior performer, exhibiting higher accuracy, precision, recall, and F1-score compared to the InterpretableCNN model. This underscores the efficacy of integrating convolutional neural networks (CNNs) with long short-term memory (LSTM) units, which enables the model to capture both spatial and temporal dependencies within the EEG signals more effectively. In light of these findings, future research endeavors could focus on augmenting the classification framework by incorporating additional EEG channels and employing more sophisticated preprocessing techniques. Such enhancements have the potential to further elevate the classification performance and robustness of the models, thereby extending their applicability to diverse EEG-based applications and scenarios.

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