

Deep Learning for EEG-Based Driver Fatigue Detection: A Systematic Review of Methods, Performance, and Future Directions

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Abstract—Driver fatigue remains a critical contributor to road accidents, necessitating reliable and real-time detection mechanisms. Electroencephalography (EEG) has proven effective in capturing neural signals associated with fatigue; however, challenges such as noise, subject variability, and manual feature extraction limit practical deployment. This paper presents a systematic review of deep learning approaches for EEG-based driver fatigue detection, highlighting their capacity to automate feature learning and enhance classification performance. Following PRISMA guidelines, relevant studies were identified across multiple scholarly databases and analyzed in terms of feature extraction methods, model architectures, and performance metrics. Results indicate that convolutional neural networks (CNNs), deep belief networks (DBNs), graph neural networks (GNNs), and hybrid frameworks consistently outperform traditional methods, achieving accuracy exceeding 99% in some cases. Hybrid strategies, including CNN-SVM and reinforcement learning models, demonstrate superior generalization and efficiency, while wavelet scattering and entropy-based features further improve robustness. Despite these advances, key challenges persist, including data quality, generalizability, interpretability, and ethical concerns regarding sensitive neural data. Future directions emphasize the need for large-scale standardized EEG datasets, lightweight and interpretable models for edge deployment, and privacy-preserving techniques such as federated learning.

Keywords— driver fatigue detection, electroencephalography (EEG), deep learning, feature extraction, convolutional neural networks (CNNs)

I. INTRODUCTION

Operating a vehicle requires a blend of visual and mental coordination, along with sustained concentration. Insufficient concentration can reduce a person's driving efficiency and result in adverse effects [1]. Fatigue is a multifaceted physiological condition that can lead to diminished mental and physical performance, as well as reduced alertness. It can arise from factors such as sleep deprivation, prolonged wakefulness, a disrupted circadian rhythm, or increased workload. Fatigue is often accompanied by drowsiness, which is a state characterized by the urge to sleep [2]. Driving fatigue is a key factor affecting driving performance, as it contributes to a large portion of traffic incidents. Globally, traffic accidents remain one of the leading causes of death and illness, often caused by fatigued and distracted drivers. The World Health Organization (WHO) reports that road traffic injuries ranked as the eighth leading cause of death worldwide, with approximately 1.35 million fatalities in 2018 [3].

Physiological signals are considered the most reliable for identifying fatigue, though challenges such as noise, signal complexity, and manual feature extraction limit accuracy. Deep learning has emerged as a promising solution by enabling automatic extraction of complex EEG features. This review systematically explores deep learning methods for EEG-based fatigue detection, evaluates their performance, and discusses their limitations. The review's key contributions include: (1) a comprehensive analysis of deep learning techniques for fatigue detection, (2) identification of current limitations and areas for improvement, and (3) guidance for future research in developing robust, generalizable, and interpretable EEG-based detection systems.

II. METHODOLOGY

A systematic literature review was conducted to ensure a comprehensive and unbiased review of literature on deep learning for EEG-based fatigue detection. The methodology follows established guidelines proposed by [4], and [5], incorporating structured processes for article identification, selection, and analysis. To improve transparency and traceability, the article selection process adhered to the PRISMA guidelines. PRISMA’s flow diagram in Fig. 1. visually captures the screening, inclusion, and exclusion process, ensuring clarity in reporting and minimizing bias. This rigorous approach supports the validity of the review and offers a replicable framework for future research in EEG-based fatigue detection using deep learning techniques.

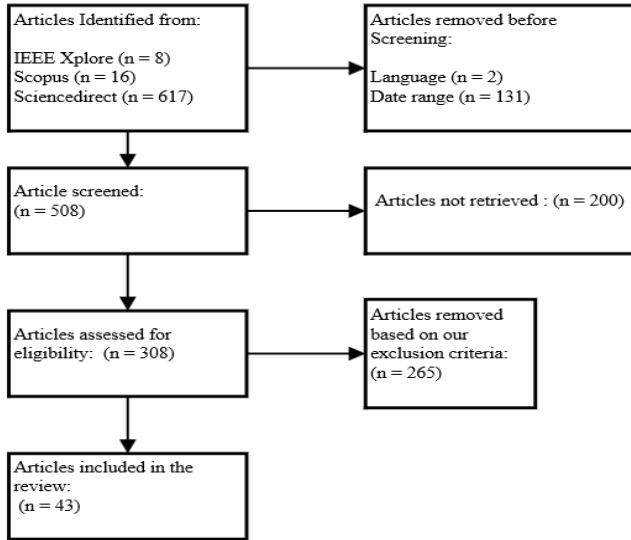


Fig. 1. Article selection process based on PRISMA template [6]

A. Keywords

After defining the review's aim, keywords were carefully chosen to gather relevant articles within the study’s domain. To find closely related papers, searches were conducted on the titles and abstracts using the following keyword queries: ({EEE-based}) AND ({driver}), (deep AND learning) AND (EEG-based “fatigue detection”), and (deep AND transfer AND learning) AND (deep AND learning AND methods OR approaches AND EEG-based AND driver AND fatigue AND detection OR classification).

B. Searching the articles

The initial search was carried out on April 11, 2025, yielding 24 articles. The final search took place on April 15, 2025, resulting in a total of 617 articles. Articles deemed unrelated to the topic were excluded during the search process. Additionally, the search was restricted to articles published between 2015 and 2025, covering a span of ten years.

C. Academic databases

The academic databases used to extract articles are listed in Table I.

TABLE I. ACADEMIC DATABASES AND THEIR LINKS

Academic Databases	Web links
Scopus	https://www.scopus.com/
IEEE Xplore	http://ieeexplore.ieee.org/
ScienceDirect	http://www.sciencedirect.com/

III. LITERATURE REVIEW

A. Driver fatigue feature extraction methods in EEG-based data using Deep learning.

Electroencephalography (EEG) is a widely adopted physiological method for detecting driver fatigue, originally inspired by Richard Carton’s early discoveries of electrical brain activity and formalized by Hans Berger in 1924. EEG measures brain electrical signals across different frequency bands—Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), and Beta (13–30 Hz)—each associated with specific mental states such as deep sleep, fatigue, relaxation, and alertness. To capture accurate EEG data, electrodes are placed on the scalp using the standardized 10–20 system, particularly targeting the frontal (Fp1, Fp2, Fz) and central (C3, Cz, C4) lobes, where fatigue-related brain activity is most evident [7]. However, due to motion-induced noise during driving, preprocessing steps like bandpass filtering, notch filtering, and artifact correction are essential to enhance EEG signal quality and reliability for fatigue detection.

Feature extraction is the process of reducing the number of resources required to represent a large dataset. This technique involves creating new features from the original ones, ensuring that the new feature set captures most of the information contained in the original data [8]. Feature extraction remains a critical component in transforming raw EEG into machine-interpretable patterns. Traditional methods include Power Spectral Density (PSD), Wavelet Transforms, and statistical measures such as entropy and coherence. Deep learning models such as CNNs and DBNs have proven effective in automating hierarchical feature learning across both time and frequency domains.

Recent advances in driver fatigue detection leverage both video-based and EEG-based deep learning techniques. [9] introduced a Temporal-Spatial Network (TSNet), combining EfficientNet-v2 with adaptive attention modules to capture key temporal and spatial fatigue features from video sequences, achieving 89.42% accuracy on the NTHU-DDD dataset. [10] proposed an Attention-based Hybrid Neural Network (AHNN) utilizing EEG signals from the SEED-VIG dataset, integrating attention and 1D-CNN layers to achieve 92.97% and 97.86% accuracy for fine- and coarse-grained fatigue classification, respectively. [7] surveyed EEG-driven deep models, highlighting the superiority of deep learning over shallow methods in cognitive state classification using features like PSD and wavelet transforms. [11] combined DWT-based multilevel feature extraction with ReliefF-NCA hybrid selection (RFINCA), attaining 100% accuracy with K-NN. [12] reduced EEG noise using CNNs, extracting fractal and entropy

features to construct brain networks, which were classified using GNNs with 98.17% accuracy.

TABLE II. SUMMARY OF RELATED WORKS FOR DRIVER FATIGUE FEATURE EXTRACTION METHODS IN EEG-BASED DATA USING DEEP LEARNING.

Authors	Data Modality	Extraction Method	Classification Method	Accuracy	Key Findings
[9]	Video data	Temporal-Spatial Adaptive Module (TSAM) with EfficientNet-v2	Temporal-Spatial Network (TSNet), ATFM	89.42% (NTHU-DDD dataset)	Deep learning method for spatiotemporal analysis, captures continuous fatigue patterns from video data using temporal and spatial attention mechanisms.
[10]	EEG signals	Attention-based Hybrid Neural Network (AHNN), 1D convolutions	Fine-grained and coarse-grained fatigue	92.97% (fine-grained), 97.86% (coarse-grained)	Individual-based feature selection for subject-specific EEG analysis, high classification accuracy for driver fatigue detection in both subject-dependent/independent setups.
[7]	EEG signals	Power Spectral Density (PSD), Wavelet transforms	Artificial Neural Networks, BNNs	High accuracy (varies)	Survey on EEG-based neural networks, highlights the effectiveness of deep learning over shallow models in detecting fatigue using frequency-domain features.
[11]	EEG signals	1D Discrete Wavelet Transform (DWT), Binary Pattern (BP), Statistical features	k-Nearest Neighbors (k-NN)	100%	Hybrid method for feature selection (RFINCA) and multilevel feature extraction from EEG, achieving high classification accuracy in detecting driver fatigue.
[12]	EEG signals	Singular Value Entropy, Fractal Dimensions, Functional Brain Network (FBN)	Graph Neural Network (GNN)	98.17%	Integrated CNN for noise reduction and GNN for classifying brain networks, high accuracy in detecting fatigue, even in noisy environments.

B. Discussion

Table II. highlight the growing impact of deep learning in EEG-Based driver fatigue detection. Models such as CNNs, Deep Belief Networks, and hybrid architectures consistently outperformed traditional methods like Power spectral density, by effectively capturing complex spatiotemporal and frequency-domain features. Techniques including Wavelet Packet Transform (WPT), Singular Value Entropy, and Phase Lag Index (PLI), when integrated with deep learning, enhance feature robustness and classification accuracy. The use of attention mechanisms, convolutional layers, and multilevel extraction across temporal and spectral domains enables better adaptation to subject-specific EEG patterns. In conclusion,

deep learning approaches demonstrate superior accuracy, sensitivity, and specificity, establishing them as more effective and reliable than conventional techniques for real-time fatigue detection.

C. Deep Learning Models in Fatigue Detection in terms of Performance

[1] achieved a remarkable 99.9% accuracy using a hybrid CNN-SVM model with Optuna-driven hyperparameter tuning, illustrating the benefit of combining deep and classical models. [13] employed Proximal Policy Optimization in a deep reinforcement learning (DRL) framework, reaching 99.3% accuracy and enabling real-time attention monitoring via edge computing. [14] leveraged Wavelet Scattering Networks with SVM, achieving 99.39% accuracy and superior computational

efficiency over CNN and LSTM. [15] proposed EEMD-based PSD feature extraction combined with PSO-H-ELM, yielding 97.53% accuracy, showcasing robustness in dynamic conditions. [16] presented a 12-layer ConvNet for end-to-end EEG analysis, attaining 97.02% accuracy and demonstrating adaptability across scenarios. [17] introduced clustering-based brain network imaging with PCNN classification, achieving

96.7% accuracy and enhancing early fatigue detection. [18] compared Autoencoder and Weighted KNN, with Autoencoder slightly outperforming at 99.7%, affirming deep learning's edge in EEG classification. Collectively, these models exhibit strong generalization, high precision, and real-time feasibility, with hybrid and adaptive architectures offering the best balance between accuracy and computational efficiency.

TABLE III. SUMMARY OF DEEP LEARNING MODELS IN FATIGUE DETECTION IN TERMS OF PERFORMANCE

Authors	Approach/Technique	Key Findings	Classification Accuracy	Discussion
[1]	Optimized CNN-SVM hybrid learning for multi-channel EEG data. Optuna framework used for hyperparameter tuning.	CNN-SVM achieved 99.9% accuracy with reduced training time (4 seconds). Combines deep learning's feature extraction with machine learning's efficiency.	99.9%	Demonstrates hybrid learning's potential for high precision and efficiency.
[13]	EEG-informed Deep Reinforcement Learning (DRL), with Proximal Policy Optimization (PPO) for real-time monitoring.	PPO outperformed DQN, achieving 99.3% accuracy in classifying attention states. Enabled real-time interventions using edge computing.	99.3%	Highlights DRL's advantage in safety-critical applications using EEG data.
[14]	Wavelet Scattering Network (WSN) for feature extraction; SVM for classification.	Achieved 99.33% accuracy in real driving settings; 99.39% for SEED-VIG dataset. Outperformed CNN and LSTM in efficiency and simplicity.	99.33% - 99.39%	Excellent for real-time and computationally efficient fatigue detection.
[15]	Power Spectral Density (PSD) features from EEMD; PSO-H-ELM classifier.	Achieved 97.53% accuracy, sensitivity of 98.27%, and specificity of 96.79%. Outperformed traditional entropy-based methods.	97.53%	Robust and effective for capturing fatigue-related EEG patterns.
[16]	12-layer ConvNet with data augmentation for multi-channel EEG in real driving.	Attained 97.02% accuracy, sensitivity of 97.76%, and F-measure of 97.19%. Eliminated manual feature extraction.	97.02%	Automatic and scalable method for various EEG-based applications.
[17]	Clustering on Brain Networks (CBNs) to extract spatio-temporal features; PCNN for pattern recognition.	Achieved 96.7% accuracy. Reduced signal mixing and improved early fatigue detection.	96.7%	Demonstrated potential for early warnings in real-world settings.
[18]	Comparison of deep learning (Autoencoder) and machine learning (Weighted KNN) for EEG classification.	Autoencoder achieved 99.7% accuracy, slightly outperforming Weighted KNN at 99.6%.	99.7% (Autoencoder), 99.6% (KNN)	Demonstrated both approaches' effectiveness for real-time fatigue detection.

D. Discussion

Table III. highlights the effectiveness of various deep learning models in EEG-based driver fatigue detection. Hybrid models like CNN-SVM and DRL approaches such as PPO demonstrate superior accuracy (up to 99.9%) and real-time performance. Feature-specific techniques like Wavelet Scattering Networks and EEMD-based PSD extraction offer both accuracy and computational efficiency. End-to-end ConvNets eliminate manual feature engineering, while clustering methods and Autoencoders enhance early detection. This implies that deep learning and hybrid frameworks consistently outperform traditional methods, offering robust, scalable, and efficient solutions for real-world fatigue monitoring.

E. Public Datasets Used in EEG-Based Driver Fatigue Detection

Several publicly available EEG datasets have been instrumental in advancing driver fatigue detection research. The DEAP dataset, although primarily designed for emotion analysis, has been repurposed for fatigue studies due to its comprehensive EEG recordings. Similarly, the SEED dataset offers valuable insights with its multimodal approach, including EEG data, which researchers have utilized to explore fatigue detection methodologies. These datasets provide standardized benchmarks, facilitating the development and comparison of fatigue detection algorithms.

IV. RESULTS AND DISCUSSIONS

A. Data quality and complexity

Data quality and complexity pose significant challenges in applying deep learning models for EEG-based fatigue detection. EEG signals are inherently complex, characterized by high temporal and spatial resolution, and are often contaminated by noise from sources such as muscle movements, eye blinks, and external electrical interference. This noise complicates the preprocessing stage, requiring advanced filtering and artifact removal techniques, which can be computationally intensive and may inadvertently distort the signal. Moreover, the quality of EEG recordings can vary significantly due to differences in electrode placement, equipment sensitivity, and individual scalp properties, leading to inconsistencies in the data. Additionally, EEG data is highly non-linear and subject to individual variability, influenced by factors like age, gender, and health conditions, making it difficult to generalize across populations. Addressing these complexities requires robust preprocessing pipelines, data augmentation techniques, and the collection of diverse datasets, which are resource-intensive and challenging to standardize.

B. Model generalization

Model generalization is a critical limitation in EEG-based fatigue detection using deep learning. EEG signals are highly individualized, influenced by factors such as age, gender, health status, and even emotional states, making it difficult for models trained on one population to perform well on another. This variability leads to a lack of robustness and limits the applicability of these models across diverse user groups. Additionally, deep learning models often overfit to the training

data, especially when datasets are small or lack diversity, resulting in reduced performance on unseen data. The scarcity of large, labeled, and representative EEG datasets further exacerbates this issue. Domain shifts, such as differences in equipment, electrode placement, or recording conditions, can also significantly affect model accuracy. To enhance generalization, researchers must focus on creating standardized protocols, leveraging transfer learning, and developing domain adaptation techniques, which require additional effort and computational resources.

C. Interpretability

Interpretability is a significant limitation in using deep learning models for EEG-based fatigue detection. These models often function as "black boxes," making it difficult to understand how they process and derive decisions from complex EEG data. This lack of transparency poses challenges in validating the model's predictions, particularly in critical applications such as fatigue monitoring in driving or aviation, where trust in the system is paramount. Clinicians and practitioners require clear explanations of the patterns or features the model considers indicative of fatigue to ensure reliability and compliance with safety standards. Moreover, without interpretability, identifying and addressing biases in the model becomes challenging, potentially leading to unfair or inaccurate predictions across different user groups. Efforts to improve interpretability, such as employing techniques like saliency maps, Layer-wise Relevance Propagation (LRP), or attention mechanisms, are essential but add complexity to model development and may compromise computational efficiency.

D. Real-time Performance

Real-time performance is a critical limitation in EEG-based fatigue detection using deep learning. Real-time applications, such as fatigue monitoring for drivers or operators, require models that can process EEG signals rapidly and deliver accurate predictions with minimal latency. However, deep learning models, especially complex architectures like recurrent neural networks (RNNs) or transformers, often involve high computational demands that challenge real-time processing capabilities. The preprocessing of EEG data, including artifact removal and feature extraction, further adds to the computational overhead, making it difficult to achieve the necessary speed. Additionally, the deployment of such models on portable or edge devices is constrained by limited hardware resources, such as reduced memory and processing power, which compromises real-time applicability. Balancing the trade-off between model complexity and processing speed while maintaining prediction accuracy remains a significant hurdle. Optimizing models through techniques like lightweight architectures and on-device inference is essential but often requires advanced engineering efforts.

E. Ethical and Privacy Concerns

Ethical and privacy concerns present significant challenges in applying deep learning models for EEG-based fatigue detection. The collection of EEG data involves capturing highly sensitive and personal neural activity, which raises privacy issues related to unauthorized access, misuse, or data breaches. Ensuring informed consent and maintaining user

anonymity are critical but can be complex when dealing with large datasets or cross-border collaborations. Additionally, ethical concerns arise around potential misuse, such as using EEG data to monitor employees' fatigue levels without their knowledge or consent, which infringes on individual autonomy and privacy. Bias in data collection and model training can also lead to unfair outcomes, disproportionately affecting certain demographic groups. Furthermore, the potential for over-reliance on automated systems raises concerns about accountability, especially in high-stakes scenarios like aviation or healthcare. Addressing these issues requires robust legal frameworks, transparent data practices, and the implementation of secure, ethical AI systems.

V. FUTURE DIRECTIONS

A. Creation of Standardized, Large-Scale Datasets

Future research should prioritize the development of standardized, large-scale EEG datasets that encompass diverse populations. Such datasets should include variations in age, gender, health status, and environmental conditions to enhance the generalizability of fatigue detection models. Standardization in data collection protocols, electrode placements, and preprocessing techniques will facilitate more consistent and comparable results across studies. Additionally, publicly accessible repositories can encourage collaboration and accelerate advancements in the field by providing researchers with the necessary resources to train and validate robust deep learning models.

B. Advances in Transfer Learning and Domain Adaptation Techniques

Enhancing model generalization through transfer learning and domain adaptation is essential for mitigating cross-domain variability in EEG-based fatigue detection. Transfer learning can leverage knowledge from related tasks or larger datasets to improve model performance on specific applications with limited data. Domain adaptation techniques can align feature distributions across different environments, such as transitioning from laboratory settings to real-world scenarios. These approaches can reduce the need for extensive subject-specific calibration, making models more adaptable and scalable for diverse user groups and operational contexts.

C. Integration of Multimodal Data

Incorporating multimodal data, such as combining EEG with other physiological metrics (e.g., heart rate, eye movement) or behavioural indicators (e.g., driving patterns), can provide a more comprehensive assessment of fatigue. Multimodal approaches can enhance the robustness and accuracy of fatigue detection systems by capturing a wider range of indicators and compensating for the limitations of individual data sources. Future research should explore the synergistic effects of different data modalities and develop methods for effective data fusion and feature integration to create holistic fatigue monitoring solutions.

VI. CONCLUSION

EEG-based fatigue detection has emerged as a promising area of research, with deep learning models enabling high accuracy in detecting fatigue-related patterns. These

advancements have paved the way for the development of automated fatigue detection systems in applications like driver monitoring and workplace safety. However, the limitations highlighted underline the complexity of translating research into practical solutions. While current methods show strong performance in controlled settings, their generalizability and real-world applicability remain limited. Addressing these challenges requires collaborative efforts to improve data quality, model robustness, and real-time deployment, alongside the establishment of ethical guidelines and standard protocols.

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