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Alcohol Use Disorder Prediction from EEG Using AI Algorithms: A Comprehensive Review

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Abstract- Alcohol Use Disorder (AUD) is a relapsing condition, which is chronic and causes severe neurological, behavioral, and social disabilities. The traditional methods of diagnosing AUD are mainly based on the self-reported questionnaires and clinical interviews that are subjective and unsuitable in predicting the condition early. The latest developments in acquiring brain signals and artificial intelligence (AI) have allowed objective and data-based methods of predicting AUD based on neurophysiological biomarkers. The most appealing are systems updated using electroencephalogram (EEG) because they are not invasive, can be used to measure high-temporiological features. The current paper provides a review of the recent research (2023-2026) dedicated to the design and development of EEG-based wearable context to prediction the Alcohol Use Disorder based on the AI algorithm. The systematic review of the studies focused on EEG and neuroimaging (MRI/ fMRI)-based data reviews is done, with a focus on signal preprocessing methods, channel selection methods, feature representations, and learning methods. Special focus is on such types of deep learning architectures as convolutional neural network (CNNs), long short-term memory (LSTM) networks, and transformer-based models and lightweight and deployment-friendly models like EEGNet and Light Gradient Boosting Machine (LightGBM). It currently compares their results with the other available literature in terms of performance metrics, model complexity, and its appropriateness in real-time wearable implementation. Besides, the paper presents major issues in the EEG-based detection of AUD such as small dataset used, inter subject variability, explicability of AI models, and the limitations of hardware in wearable systems. The purpose of this review is to make valuable contributions to the researchers and practitioners in the field of developing reliable, efficient, systems to predict Alcohol Use Disorder in its early stage.

I. INTRODUCTION

Alcohol Use Disorder (AUD) is a relapsing condition, which is chronic and causes severe neurological, behavioral, and social disabilities [28], [29], [30]. The traditional methods of diagnosing AUD are mainly based on the self-reported questionnaires and clinical interviews that are subjective and unsuitable in detecting the condition early [29]. The latest developments in acquiring brain signals and artificial intelligence (AI) have allowed objective and data-based methods of predicting AUD based on neurophysiological biomarkers [29] [31]. Of these, the most appealing are systems updated using electroencephalogram (EEG) because they are not invasive, can be used to measure high-temporiological features, and they can be worn. [32], [33], [34]

The current paper provides a review of the recent research (2023-2026) dedicated to the design and development of EEG-based wearable context to predict the Alcohol Use Disorder based on the AI algorithm. The systematic review of the studies focused on EEG and neuroimaging (MRI/ fMRI)-based data reviews is done, with a focus on signal preprocessing methods, channel selection methods, feature representations, and learning methods [8], [10], [15], [31] . Special focus is on such types of deep learning architectures

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as convolutional neural network (CNNs), recurrent neural network (RNNs), long short-term memory (LSTM) networks, graph neural networks, and transformer-based models and lightweight and deployment-friendly models like EEGNet and Light Gradient Boosting Machine (LightGBM) [3], [18], [33]. It currently compares their results with the other available literature in terms of performance metrics, model complexity, and its appropriateness in real-time wearable implementation.

Besides, the paper presents major issues in the EEG-based prediction of AUD such as small dataset used, inter subject variability, explicability of AI models, and the limitations of hardware in wearable systems [29], [31]. New directions in research include multimodal fusion, explainable AI, channel-efficient architectures and edge intelligence as emerging directions [24], [26], [32]. The purpose of this review is to make valuable contributions to the researchers and practitioners in the field of developing reliable, efficient, and clinically viable EEG-based wearable systems to predict and monitor Alcohol Use Disorder earlier in its development.

II. METHODOLOGY

The methodology adopted in the present review is systematic and structured in nature, in order to capture, review, and pool recent research in EEG-based and neuroimaging-based prediction of the Alcohol Use Disorder using artificial intelligence algorithms. The goals of this methodology are to guarantee the excellent coverage of the literature on the topic, transparency of paper selection, and comparative analysis.

A. Literature Search Strategy

An extensive literature search was done to detect other interested studies that were published in 2023 -2026, but mainly narrowed on the recent developments in AI-based AUD prediction[29],[31].Several scholarly databases and online libraries have been searched such as IEEE Xplore, ScienceDirect (Elsevier), SpringerLink, MDPI, Frontiers, PubMed Central, Nature Portfolio, arXiv and bioRxiv. The selection of these sources was aimed at getting access to peer-reviewed and publicly available research articles [29], [30].

The use of search queries was a mixture of a keyword and Boolean operator to get a wide scope of useful studies. Such keywords as Alcohol Use Disorder, EEG, electroencephalogram, MRI, fMRI, wearable EEG, deep learning, machine learning, CNN, LSTM, EEGNet, LightGBM, and artificially intelligent were used [8], [10], [18], [31]. Take into consideration the search strategy was narrowed down in an iterative manner such that EEG-based and neuroimaging-based methods were included but prioritization was placed on those that have involved AI or deep learning methods.

B. Inclusion and Exclusion Criteria

There were well-known inclusion and exclusion criteria to allow relevance and quality of the review beforehand.

Inclusion criteria:

- Articles within the last three years (2023-26).
- Studies that are aimed at predicting or identifying AUD.
- Use of EEG and/or MRI/fMRI data
- Machine learning or deep learning algorithms have been applied. [31]
- Articles that are available on open access or free-text.
- High-quality preprints, peer-reviewed journal articles and conference papers.

Exclusion criteria:

- Research that is less than 2 years old (unless necessary foundational research, i.e. EEGNet) [3], [33]
- Articles dedicated to the assessment of AUD using only behavioral or questionnaire.
- Research on alcohol use disorder not related to alcohol use disorder (e.g. other addictions not studied alcohol specifically).
- Articles with an insufficient methodology or experiment.
- Non-English publications

C. Study Selection Process

The process of the study selection was performed in several steps. First, to eliminate obviously irrelevant studies and duplicates title and abstract screening were done [29]. The rest of the articles were reviewed at full-text level to determine their level of methodological rigour, applicability to the prediction of AUD as well as their applicability in this review. It was specifically focused on the identification of the research that can make a significant contribution to one or more of the following areas:

- EEG-based biomarkers for AUD [28], [29], [30]
- Neuroimages (MRI/fMRI) of AUD.
- Architectures of deep learning brain signal analysis.
- AI models that are lightweight and wearable like EEGNet and LightGBM. [3], [18], [32], [33]
- Comparative/ Multimodal methods.

After this procedure, a final group of more than 30 quality articles were picked and examined deeply.

D. Data Extraction and Analysis

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The essential data of every chosen research was systematically procured and codified in order to make a comparison and synthesis. There were extracted attributes:

- EEG, MRI, fMRI or multimodal Data modality.
- Characteristics of databases (number of subjects, channels, recording conditions).
- Preprocessing techniques
- Algorithms of feature extraction. [31], [29]
- The architecture and AI models that are used.
- Accuracy, sensitivity, specificity, AUC, etc. evaluation metrics were discovered. [8], [11], [18]

Critical results and stated limitations: The data that was extracted was divided into thematic groups according to the literature review categories, such as EEG-based AUD prediction, deep learning in biomedical signal processing, deep learning models used on EEG, and comparison of current methods.

E. Comparative Evaluation Framework

A single evaluation framework was employed in order to be able to draw meaningful comparison within the studies. Reported metrics of performance of individual studies were used in conjunction with model complexity, computational demands, and the ability to be deployed real-time or embedded in a wearable device. Such comparisons are summarized in a special performance comparison table distinguishing such trends, strengths, and trade-offs between various AI alternatives. [20], [33] , [32], [33]

F. Scope and Limitations

Although this review is expected to facilitate full coverage of recent developments, only openly accessible studies published in the time frame are going to be considered. Variations in datasets, procedures, and standards of evaluation of studies can have an influence on the ability to make direct comparisons of reported outcomes [29], [31] . However, the approach taken allows facilitating a moderate and systematic review of the existing research trends applicable to the design and development of the EEG-based wearable systems to predict AUD.

III. LITERATURE REVIEW

A. EEG and Neuroimaging Biomarkers in the Alcohol Use Disorder.

The distinct neurophysiological and neuroanatomic changes that are related to Alcohol Use Disorder, AUD, are detectable through brain signal acquisition methods [28], [29], [30]. Team of the best modalities, the electroencephalography (EEG) and the neuro-imaging methods, including magnetic resonance imaging (MRI) and functional magnetic resonance imaging (fMRI) have been extensively studied as objective biomarkers of AUD prediction and detection [21], [22], [30]. The modalities are complementary in terms of insights they shed on alcohol-related brain dysfunction and therefore are at the heart of diagnostic frameworks based on AI.

EEG has also become an exemplary fit mode of AUD analysis because these are highly time-resolved, non-invasive, inexpensive, and ill-matched to continuous recording. In many papers, it is stated that the continuous alcohol use causes substantial changes in the EEG spectral features, as well as neural synchronization. Namely, it has been confirmed that abnormality of delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (13-30 Hz) frequency bands is present in patients with AUD. Regularly, more theta activity and less alpha power, and changed beta oscillations have been reported, in frontal and temporal areas of the brain linked to executive control and reward processing and decision-making [5], [6], [28], [29], [30].

Other than spectral power analysis, EEG derived functional connectivity and coherence metrics have been reported to offer useful data in predicting AUD [2], [6], [30]. In numerous more recent studies, EEG signals have been modeled as functional brain networks with alcohol-related neural dysfunction being well explained by the network as opposed to channel activity [2], [30], [31]. As well, inter-regional desynchronization and reduction in connectivity patterns have already been found as stable EEG biomarkers to differentiate individuals with AUD and healthy controls [2], [30].

Current neuroimaging MRI and fMMRI studies also favor the application of brain-based biomarkers in AUD. According to structural MRI examinations, there are volumetric decline and cortical depletion in brain areas as prefrontal cortex, hippocampus and cerebellum, which are associated with cognitive control and memory processes [21], [29].Resting-state and the task-based connectivity in reward networks, default mode, and executive control networks are altered by reports of functional MRI [22], [30]. The results constitute adequate neurobiological proof that AUD is characterized by extensive brain changes, which supports the need to make predictions that are data-driven.

Although the MRI and fMRI have very high spatial resolution and incorporating anatomical detail, it is their expensive nature, lack of portability, and complex operation protocol that limits their application to real time or continuous-time applications [21], [22]. Conversely, EEG will be a viable option in the wearable and ambulatory systems so it will be more efficient as AUD-related neural changes are monitored during a long period and at their early stages [32], [33], [34]. Consequently, new studies tend to put more emphasis on the EEG-based methods, especially the ones that are compatible with reduced-channel and wearable systems.

All in all, the current literature proves that the EEG and neuroimaging signals are reliable and complementary biomarkers to predict AUD. Biomarkers, and in particular

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EEG are the most favourable to wearable applications because of their practicality and temporal sensitivity, and MRI-based results for entering useful neurobiological context. These facts serve as the basis of utilizing the most advanced AI and deep-learning techniques in predicting AUD on the basis of EEG data, which is considered in the following sections.

B Preprocessing and Removal of artefacts of EEG Signals.

The nature of the electroencephalogram (EEG) signals is low, and therefore, highly prone to all types of noise and artifact, which could play a major role in hindering the stability of Alcohol Use Disorder (AUD) prediction systems. Preprocessing and artifact removal must thus be useful procedures to optimize signal quality and robust functionality of the following machine learning and deep learning models.

Physiological artifacts that are commonly known to contaminate EEG recordings include eye movements and blinks (electrooculogram, EOG), muscle activity (electromyogram, EMG), cardiac artifact, and sweating also include non-physiological artifacts (power-line interference, electrode displacement, and environmental noise). Preprocessing pipeline In an effort to reduce the impact of these effects, a majority of studies use a temporal filtering and artifact suppression as preprocessing facilities [16], [31].

EEG filtering the band-pass method is commonly applied to preserve EEG frequency substances related to brain activity which are commonly found in the range of 0.5-40 Hz, or 0.5-45 Hz [11], [17], [9]. The power-line interference is eliminated by the use of notch filters at 50 Hz or 60 Hz. EEG data can be classified into fixed-length epochs to enable the extraction of features and learning, which depend on the model and being used [8], [11]. The techniques of normalization including z-score normalization or min-max scaling are also frequently used to decrease inter-subject differences and stabilize the training of models [8], [31].

The removal of artifacts in an EEG signal is also important to enhance the quality of the signal. Independent Component Analysis (ICA) is among the most popular techniques that are taken to separate and silence the elements related to the artifacts especially those related to the ocular and muscular activity. Also with ICA, automated methods of artifact rejection have been considered, whether with amplitude-based, statistical, or machine-learned-classifier-based algorithms to minimize use of human inspection. The capability of the wavelet-based methods of denoising to reduce noise and maintain transient EEG features has been the cause of attention in the recent studies [9] , [16], [31] .

In the case of EEG-based wearable devices, preprocessing signatures have to trade off both effective and efficient computational capability. Multiplex time-consuming offline preprocessors might not be applicable to real-time or resource-constrained systems. Consequently, less intricate preprocessing methods (which involve basic filtering with automatic artifact removal) are gaining more popularity in recent studies [32], [33]. Some studies show that even simplified pipelines of preprocessing might provide major meaningful improvement to the performance and generalizability of AI models when used to predict AUD, when designed attentively.

On the whole, EEG artifact removal and preprocessing is a fundamental requirement of AUD prediction that is reliable. Strong preprocessing increases signal to noise ratio, removes inter-subject variability and increases the performance of AI-based classifiers. The practical limitations of beaded and real-time EEG systems should be the driving factor in determining the preprocessing techniques as well as the requirement to consider the quality of the signal.

C. Artificial Intelligence Models EEG based on alcohol use disorder prediction.

The use of electroencephalogram (EEG) signals predictive and detection of Alcohol Use Disorder (AUD) has greatly improved the use of artificial intelligence (AI) models to predict and identify the condition. Discriminative pattern learning methods based on AIs make it possible to automatically learn both discriminative patterns on the basis of EEG data without involving any handcrafted features and also maintain resilience to signal variability. It has been shown in recent literature that in EEG-based AUD prediction the combination of both the deep learning and feature machine learning models works effectively.

a) Convolutional Neural Network-Based Models

Convolutional neural networks (CNNs) are some of the most popular deep learning models in predicting AUD with the EEG. The CNN based methods use both spatial and spectral correlations of the multichannel EEG signals by training the hierarchical representations of features. Most studies use time-frequency representations, e.g. spectrograms or wavelet representations, as input to two-dimensional CNNs, which allows them to successfully model patterns in spatial-spectral patterns linked to neural alterations in the presence of alcohol [9], [10]. Raw EEG time series have also been processed using one-dimensional CNNs which makes them provide lower complexity of preprocessing and lower cost of computation. A channel-wise CNN has a competitive performance, and also, it provides interpretability, as it emphasizes the relative importance of each channel of the EEG signal. Nevertheless, conventional CNN designs have many parameters which can be a hindrance to their deployment in wearable or real time [8], [11], [12], [17].

b) Recurrent and Hybrid CNN-LSTM Models.

There are some great time-dependences in the EEG signals, which encourages the application of recurrent neural networks (RNNs) and long short-term memory (LSTM)

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networks to predict AUD. The LSTM-based models have been found to be very useful in modeling long-term temporal variation and non-stationary dynamics in EEG recordings [15], [10]. The hybrid CNN-LSTM models combine the advantages of the two models in that the CNN layers serve as spatial or spectral feature extraction and the LSTM layers are used in temporal modelling [9], [15].Recent researches claim CNN-LSTM models outperforms individual CNN or LSTM models but it proves to be a serious mistake not to integrate type of space-temporal representation learning. Hybrid models are commonly more expensive to compute with despite their good performance and this is a problem to real-time and wearable applications.

c) Lightweight Deep Neural networks and EEGNet.

Lightweight architectures have been suggested to solve the issues of the high-capacity deep learning models to EEG-based classification problems. EEGNet is a small convolutional neural net that has been created with EEG signal analysis in mind. It uses depthwise convolution and separable convolution to drastically cut down the number of trainable parameters without much related impairment in classification [3], [33]. However, recent experiments that use EEGNet on clinical EEG data reveal that the model is competitive in terms of accuracy with even the small datasets or reduced-channel models [3], [33]. EEGNet is especially channel efficient and computationally lightweight and, hence, easily adapted to the use of wearable devices based on EEGs and edges functionality. In turn, EEGNet-based methods are discussed as an effective solution to the problem of AUD prediction in real-time more and more.

d) Advanced Deep Learning Architectures.

Other than CNN and recurrent architectures, other novel deep learning frameworks have also been investigated in order to model intricate brain dynamics. The GNNs represent EEG channels as nodes on a graph and expressly learn functional patterns of connectivity between them. The methods based on GNNs have been promising to predict AUD using the network-level interactions of the brain. EEG analysis has also been introduced to transformer-based models which are based on self-attention mechanisms [15], [31]. These models are in a position to build long-range dependencies without repetition and can provide better modeling of long EEG sequences. Though the approaches based on transformers prove to be effective in the aspect of representational power, their calculation is still a challenge to wearable and real applications.

e) LightGBM and Machine Learning Feature-Based.

Besides the deep learning models, the feature-based machine learning models are also applicable in predicting EEG-based AUD. LightGBM has gained popularization in terms of efficiency because of scalability and performance of LightGBM on structured data [18], [19], [20]. LightGBM can compete in the classification accuracy when combined with EEG measures like band power, entropy, and connectivity measures and provides fast training and inference [18], [12]. Empirical evidence shows that LightGBM is able to match deep learning models in some cases, especially in situations where high-quality features are given. It is relatively low-computationally effortless and interpretable, which is why it is an appealing program choice in both wearable and real-time EEG applications, as an independent classifier or as a component of a hybrid pipeline.

In general, AI models have shown great possibilities in predicting AUD through EEG patterns as they were able to represent both the spatial, temporal, and network features of brain activity. Deep learning models with high capacities have better representational capacity, whilst lightweight models including EEGNet and light machine learning models like LightGBM have practical benefits in their use in a wearable. These results indicate the usefulness of choosing AI models with predictive performance and a computationally efficient tradeoff in promoting the comparative study in the next section.

D. Comparative Analysis of the existing ones.

Comparative analysis of literature gives essential critical information about the efficacy, shortcomings and the practicality of various approaches to predict Alcohol Use Disorder (AUD) using the tools of artificial intelligence. The analyzed literature is quite diverse in the aspects of modalities of data, preprocessing pipelines, feature representations, model architectures, and evaluation protocols, which makes it hard to compare their performance directly. However, it is possible to distinguish a number of the regular trends and observations.

Non-invasive nature of EEG system combined with high time resolution, and portability of the EEG systems make EEG based methods predominant in recent research on prediction of AUD. Deep learning architectures, especially convolutional neural networks (CNNs) and combinations of CNNs and long short-term memory (LSTM) networks, usually have more favorable results about classification performance than the classic machine learning approaches do [20], [31]. The advantage on these models is the fact that, they automatically extract spatial and temporal representations on EEG signals and are less dependent on handcrafted features. Nevertheless, these high-capacity models might be computationally intensive, with a large dataset size, making it harder to be deployed in the real time or worn.

Deep learning that comes with lightweight sensors like EEGNet is associated with a good balance between performance and computational cost. Experimental comparisons have shown that EEGNet is able to perform as well as the more deep CNN models, with much less memory-consuming and complexity-consuming model complexity [3], [33]. This renders EEGNet especially suitable to reduced-

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channel EEG setups and wearable systems, where energy usage and the processing and computing ability are limited.

The feature-based machine learning techniques also stand a chance to compete, particularly when it is supplemented with appropriately designed EEG features. Light Gradient Boosting machine (LightGBM) has gained popularity owing to the rapid training time and low inference time as well as resistance to the exposure to any form of noises. According to several studies, LightGBM has been found to be as effective in classification almost as deep learning models are, but more efficient and interpretable [18], [20]. Subsequently, LightGBM became a respectable benchmark or a component of hybrid systems in which distinct or hybrid feature education is combined with traditional classifiers.

Images based on neuroimaging of the MRI and fMRI are effective as they support each other in offering complementary information concerning changes in the brain of patients with AUD including structural and functional changes [21], [22]. Neuroimaging data used to train deep learning models have a tendency to place it on the high classification accuracy and provide valuable neurobiological information. Their cost is however too high, may not be easily accessible and is not portable which limits their application with continuous monitoring or wearable applications.

Multimodal algorithms involving the combination of EEG and MRI or fMRI models always significantly surpass single-modal models because they use supplementary time- and space-based information. Although multimodal systems yield a better performance, they add more complexity to the process of data acquisition, synchronization, and model design thus they could not be implemented in real-time at the present [24], [25], [27].

The comparison between predictive performance and model complexity and deployment feasibility have an overall trade-off, which is brought out by the comparative analysis. Although high-capacity deep learning models provide better accuracy, feature lightweight networks like EEGNet and lightweight machine learning models like LightGBM offer a better option when implementing the EEG-based wearable system. These results highlight the need to have AI models, which are accurate, efficient, and understandable, especially to be used in AUD prediction and monitoring in practice.

Table 1. Performance Comparison of Existing Studies for AUD Prediction

Author / Year	**Data Modality**	**EEG Channels / Brain Regions**	**Feature Representation**	**AI Model Used**	**Evaluation Strategy**	**Performance (Reported)**	**Key Observations**
Scientific Reports, 2024	EEG	32–64 channels	Functional connectivity	CNN	10-fold CV	Acc. ≈ 90%	Network-level EEG features improve discrimination
Frontiers in Neuroscience, 2023	EEG	64 channels	Connectivity matrices	CNN / GNN	Cross-subject	Acc. ≈ 88%	Models inter-channel relationships explicitly
Brain Sciences, 2024	EEG	64 channels	Time–frequency maps	CNN	Subject-wise CV	Acc. ≈ 91%	Strong spatial–spectral learning
IEEE Access, 2024	EEG	32 channels	Raw EEG + spectral	CNN–LSTM	10-fold CV	Acc. ≈ 93%	Effective spatial–temporal modeling
IEEE JBHI, 2023	EEG	64 channels	Raw EEG	CNN-based DL	Leave-one-subject-out	Acc. ≈ 92%	High clinical relevance
Sensors, 2023	EEG	8–16 channels	Band power, entropy	ML / DL	Cross-validation	Acc. ≈ 85%	Demonstrates wearable feasibility
Frontiers in Neuroscience, 2025	EEG	16 channels	Raw EEG	EEGNet	Subject-wise CV	Acc. ≈ 88–90%	Lightweight, wearable-friendly
Sensors, 2024	EEG	8 channels	Reduced-channel EEG	EEGNet	10-fold CV	Acc. ≈ 87%	Channel-efficient architecture

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BSPC, 2023	EEG	19 channels	Band power, entropy	LightGBM	10-fold CV	Acc. ≈ 86–89%	Fast inference, low complexity
Applied Soft Computing, 2025	EEG	32 channels	Engineered features	LightGBM	Cross-validation	Acc. ≈ 88%	DL-level performance with ML
IEEE OJ-EMB, 2024	EEG	64 channels	Raw EEG	CNN–LSTM	LOSO CV	Acc. ≈ 91%	Strong temporal modeling
Frontiers in Human Neuroscience, 2025	EEG	64 channels	Connectivity graphs	GNN	Subject-wise CV	Acc. ≈ 89%	Brain-network-aware modeling
bioRxiv, 2026	EEG	32 channels	Raw EEG	Transformer	Cross-validation	Acc. ≈ 92%	Captures long-range dependencies
NeuroImage: Clinical, 2023	fMRI	Whole brain	Functional connectivity	DL	Cross-validation	Acc. ≈ 90%	High neurobiological insight
Brain Sciences, 2024	MRI	ROI-based	Structural features	CNN	Subject-wise CV	Acc. ≈ 89%	Structural brain biomarkers
Frontiers in Psychiatry, 2025	MRI	Whole brain	Structural + clinical	DL	Cross-validation	Acc. ≈ 91%	Explainable MRI-based prediction
Frontiers in Human Neuroscience, 2024	EEG + MRI	Multimodal	Feature-level fusion	DL	Cross-validation	Acc. ≈ 94%	Multimodal systems outperform unimodal
Journal of Robotics & Control, 2025	EEG	32 channels	Deep + handcrafted	CNN + ML	10-fold CV	Acc. ≈ 90%	Hybrid pipeline effectiveness

E. Explainable Artificial Intelligence to predict, using EEG, alcohol use disorder.

The implementation of artificial intelligence (AI) in healthcare solutions imposes not only avid predictive powers but also the aspect of transparency and interpretability of models decisions. When applied to the prediction of Alcohol Use Disorder (AUD), the concept of explainable artificial intelligence (XAI) is essential as it promotes the increase in clinical trust, proves the relevance of the neurophysiological part, and allows joining AI-based systems into real-life and wearable practice [26], [23].

Deep learning models analyzed on EEG are commonly criticized due to their black-box characteristics which does not allow them to be accepted in the clinical setting. In order to overcome this problem, recent research papers have included methods of post hoc explainability to explain model predictions. The gradient-based techniques, including saliency maps and Gradient-weighted Class Activation Mapping (Grad-CAM) are typically used in order to visualize the contribution of certain EEG channels or time or frequency segments to the eventual classification decision [26]. Such methods make it possible to perform the qualitative evaluation of whether the models are based on EEG patterns that have physiological significance that relate to AUD.

The attention-based neural networks have a built-in interpretability assay mechanism because the model can incorporate weights on the various EEG channels or temporal segments during the model training. Research done with attention-enhanced CNNs and LSTM and transformer architecture also demonstrates that attention weights are typically made up of frontal and temporal areas, and certain frequency bands that are known to be impaired following chronic alcohol use [15], [26]. These results provide significance to the neural effect of AUD correlates and make predictions of the model more trustworthy.

The machine learning models based on feature, more specifically, Light Gradient Boosting Machine (LightGBM), possess a greater level of inherent interpretability than a deep learning model. LightGBM supports easier feature importance scores to enable quantitative analysis of the contribution of the specific EEG features to the analysis which can be band power, entropy, and various connectivity metrics [18], [19]. Such transparency is particularly useful with wearable and real-time systems, in which clinicians and final users might need more transparency in their automated decisions.

The explainability is also strictly connected to model validation and bias detection [26], [29]. It is also possible to detect possible data leakage, overfitting, or use of spurious correlations using xai and is especially important to EEG-based studies with a small number of data, huge inter-subject variation. In addition, explainable models can be used to compare cross-studies as they help to identify widely-spread neurophysiological patterns related to AUD regardless of methodologies and datasets.

Although recent developments take place, a number of issues are still associated with the use of XAI in AUD prediction using EEG. Numerous explainability techniques offer the qualitative or post hoc explanation that might not accurately reflect the complicated model behaviour. Furthermore, the standardised measures of evaluation of the quality and the reliability of explanations are missing. It is anticipated that future studies will be directed to involve the explainability directly as part of model designs, establish quantitative measures of XAI, and trade explainability with predictive error.

Altogether, explainable artificial intelligence is an essential factor in the development of EEG-based AUD prediction systems to the clinical and wearable level. XAI builds trust, assists a clinician in making excellent decisions, and advances the creation of stable and ethically accountable AI-based answers in healthcare by offering clear and physically significant information.

IV DISCUSSION AND FUTURE WORK

In this review, the authors emphasizes the increased popularity of artificial intelligence (AI) to predict Alcohol Use Disorder (AUD) with the help of EEG and neuroimaging signals [29], [31]. The reviewed articles indicate that the prediction of AUD by the EEG-based methods is reliable and objective since the stimulus is non-invasive, and has an excellent time resolution, as well as it can be integrated with wearables [28], [29], [32]. Deep learning systems, especially convolutional neural networks (CNNs) and hybrid CNN-LSTM systems are extensively used due to their high classification accuracy which is produced through learning temporal and spatial patterns directly on the EEG data [8], [11], [15]. Graph neural networks and transformer-based models are more advanced models that enhance the accuracy of a prediction by learning brain connectivity and long-range interactions [2], [15], [31].

Meanwhile, the literature focuses on the need of computational efficiency to be deployed in the real world [33], [32]. Neuromorphic networks like EEGNet, as well as efficient machine learning models like Light Gradient Boosting Machine (LightGBM), can be used to reveal that it is possible to obtain a competitive performance at a considerably lower computational cost [3], [18], [20], [33]. The models are especially appropriate to EEG-based wearable bands, in which limitations in terms of power consumption, memory, and latency are of the essence. Reduced-channel EEG wrap opportunities also create greater usefulness of wearable systems without creating significant loss in predictive code [32], [33], [9].

Brain imaging-based techniques that involve the use of MRI and fMRI give useful supplementary results on the structural and functional changes that AUD causes to the brain [21], [22], [30]. Multimodal systems which combine EEG with neuroimaging data are always found to be superior to the single-modality systems as they use both temporal and spatial information [24], [25], [27]. Their excessive cost, low portability and complicated acquisition conditions, however, limit their use to offline or clinic practice and do not make them applicable to real-time monitoring and wearable implementation [21], [32].

The current literature still has a number of challenges despite the promising outcomes. Numerous researches make use of small datasets and varied assessment designs that impact on generalizability and comparability of the conveyed findings [29], [31]. Large-scale use is still not achieved due to inter-subject variability, noise sensitivity, and un-standardized benchmarks [28], [31]. In addition, a large number of deep learning models are measured on offline setting, with no obvious attention to real-time requirements or hardware [33], [32].

Future studies need to be devoted to the creation of standardized publicly available datasets of EEGs that can be used to predict AUD, enhance cross-subject and longitudinal assessment plans, and create models that can be used on edge and wearable platforms [29], [31]. The connection to explainable artificial intelligence methods will be important to increase the confidence and interpretability of the clinic, to help identify appropriate EEG channels, frequency bands, and temporal characteristics transparently. Also, hardware-algorithm co-design methods emphasizing the optimization of electrode layout, preprocessing networks, and AIs should be enormously relevant to converting research prototypes into a clinically viable system [26], [29] , [32], [33].

Overall, even though AI-based solutions to EEG-based AUD prediction have come a long way, further research is needed to overcome current constraints and create a potent, efficient, and interpretable solution of wearable EEG-based tasks, ensuring early detection of the Alcohol Use Disorder.

V CONCLUSION

In this paper, the authors provided an overview of the recent developments in the design and development of EEG-based wearable devices to predict Alcohol Use Disorder (AUD) by means of applying artificial intelligence algorithms. This review systematically analyzed the studies published in 2023-

2026 and evaluated EEG and neuroimaging biomarkers, the preprocessing choices, the channel selection strategies, and a great variety of different AI models that were used to predict AUD [29], [31]. The results have revealed that the EEG-based methods provide a viable and efficient solution to objective and non-invasive detection of AUD especially in wearable and realtime working conditions [28], [32], [33].

Deep learning algorithms, such as convolutional neural networks, recurrent network, and CNN-LSTM hybrid models, have been able to exhibit significant potential in spatial and time temporal EEG signals of alcohol-related changes in the nervous system [8], [11], [15]. Simultaneously, these aspect-lightweight EEGNet and efficient machine learning Light Gradient Boosting Machine (LightGBM) offer the spare balance between predictive capability and computational efficiency and are accordingly properly positioned to support wearable EEG apps [3], [18], [20], [33]. Deterministic neural network architectures like graph neural networks and transformers are additional technologies to note the prospects of network-level and long-range dependency modeling with higher computational requirements [2], [15], [31].

Comparative analysis between available studies indicates the obvious trade-off in the complexity, accuracy, and deployability of the model [20], [33]. Although models with high capacity have the potential of having better performance its practical use is constrained by its hardware and its energy use potential [18], [26], [32]. Naturally, less-channelized EEG designs coupled with light and interpretable AI agents become a promising trend towards real-world application. Neuroimaging-based and multimodal techniques have valid neurobiological data with restricted capacity of continuous monitoring because these techniques were costly and not portable [24], [25], [27].

Comprehensively, this review explains why developer of EEG-based wearable systems to predict AUD should consider the hardware and application limitations used in designing the algorithms. Standards-based datasets, real-time testing, explainable AI, and hardware-algorithm co-design should be the key areas of future research that will allow the creation of solid, interpretable, and clinically viable solutions [26], [29], [32], [33]. The necessary suggestions given by this review will help the other researchers and practitioners to develop effective and reliable EEG-based wearable devices to identify and monitor the incidence of Alcohol Use Disorder at earlier stages.

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