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Research Article

NeuroHybridNet: A Hybrid EEG Classification Model with Autoencoder-Enhanced Fractal-Wavelet Features

Hazret TEKİN

Şırnak University, Vocational School of Technical Sciences, hazrettekin@sirnak.edu.tr, Orcid No: 0000-0002-9379-721X

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* Corresponding author

ABSTRACT

Electroencephalography (EEG) signals offer a rich but complex source of information for assessing cognitive states, particularly in dynamic and high-stakes environments such as driver attention monitoring, where rapid and accurate detection of mental fatigue or distraction is critical for safety and performance.This study proposes WaveFrac-AE, a hybrid EEG classification model that combines time-frequency analysis, fractal dynamics, and nonlinear descriptors with Autoencoder-based dimensionality reduction. EEG signals representing three cognitive states—focused, distracted, and drowsy—are transformed into a compact latent space capturing both temporal and structural complexity. By fusing Continuous Wavelet Transform features with fractal measures (Petrosian, Hurst, DFA), the model achieves robust representation of non-stationary EEG dynamics. The Autoencoder component enhances generalizability by filtering noise and redundancy, enabling accurate and scalable mental state classification for real-time neuroergonomic applications. This hybrid approach has been tested with various machine learning algorithms—namely XGBoost, LightGBM, CatBoost, Random Forest, and Support Vector Machines (SVM). In subject-specific analyses, SVM achieved an average accuracy exceeding 97%, while the aggregated dataset—combining all subjects—yielded an accuracy surpassing 92%. Comparisons with contemporary studies suggest that this method occupies a competitive position and, in numerous cases, demonstrates higher performance. Consequently, the proposed model offers high-performance solution in driver attentiveness monitoring systems, thereby showing substantial potential for the development of early warning systems integrated into smart automobiles.

Introduction

In contemporary intelligent transportation systems, the real-time monitoring of driver attention levels has become a critical component for ensuring both road safety and passenger well-being. Particularly under prolonged and monotonous driving conditions, transitions in the driver's cognitive state—ranging from focused to distracted or drowsy—can significantly increase the risk of serious, and often fatal, traffic accidents [1]. To proactively detect and mitigate such high-risk scenarios, next-generation smart vehicles demand the integration of advanced technologies capable of continuously tracking and interpreting the driver's neural activity with precision and reliability [2]. At this point, portable EEG acquisition systems—either embedded into in-vehicle interfaces or designed as wearable devices for ergonomic use—offer a promising solution for uninterrupted assessment of attentional states, thereby contributing to enhanced situational awareness and driving safety [3]. Electroencephalography (EEG) signals are widely preferred for real-time observation of human brain activity due to their non-invasive nature and high temporal resolution. However, the inherently noisy structure, non-stationary behavior, and nonlinear dynamics of EEG signals pose significant challenges for accurate analysis and hinder the reliable detection of rapidly fluctuating attentional states in drivers [4]. Traditional approaches based on unidimensional or narrowband frequency analysis fail to fully capture this complexity, often overlooking transient fluctuations in attention [5]. Moreover, most feature extraction techniques reported in the literature rely on single-type and single-domain descriptors, typically constrained to either the time or frequency domain, while disregarding the fractal and chaotic properties inherently present in EEG signals [6]. This uni-dimensional perspective considerably limits the representational capacity of extracted features and constrains the ability of classification models to accurately distinguish between complex and overlapping cognitive states [7]. Consequently, hybrid models that integrate multiple complementary feature types—spanning time, frequency, and complexity domains—are increasingly favored alongside deep learning and advanced machine learning approaches, as they offer a more comprehensive characterization of EEG signals and improve the effectiveness of feature extraction. This enriched representation enhances the fidelity of mental state classification, particularly in real-time driver monitoring scenarios where nuanced cognitive dynamics must be reliably detected.

In the literature, subject-specific approaches are commonly employed in EEG-based mental state classification tasks, primarily due to the pronounced structural and functional variability of EEG signals across individuals [8]. These inter-individual differences are primarily attributed to factors such as cranial anatomy, electrode placement variability, and individual cognitive response patterns [9]. Although individually tailored models can capture subtle variations in EEG signals more effectively and thus achieve higher classification accuracy, the need to retrain the model for each new user imposes a significant cost in terms of time and computational resources—particularly in real-time applications [10]. To address these limitations, common-subject approaches have been developed, aiming to minimize the need for subject-specific calibration by training generalized models on EEG data collected from multiple individuals [11]. However, due to substantial inter-individual variability in EEG signals, the classification performance of these approaches is generally lower compared to subject-specific models [12]. This underscores the necessity of establishing a delicate balance between generalizability and classification accuracy in EEG-based attention monitoring systems.

This study introduces a novel hybrid framework for driver attention classification based on EEG signals, integrating diverse feature extraction techniques with deep representational learning through Autoencoder-driven dimensionality reduction. The proposed approach has been systematically assessed under both subject-specific and common-subject evaluation schemes, facilitating a rigorous comparison of the model's responsiveness to inter-individual variability and its capacity for cross-subject generalization. By leveraging this dual-paradigm assessment, the framework not only demonstrates adaptability to personalized neural patterns but also exhibits robustness in broader, population-level applications. The proposed approach—referred to as WaveFrac—aims to capture the complex patterns associated with varying levels of driver attention by holistically integrating features derived from multiple domains, including Continuous Wavelet Transform (CWT) and fractal descriptors such as Petrosian Fractal Dimension, Hurst Exponent, and Detrended Fluctuation Analysis (DFA). In this hybrid framework, the high-dimensional and noise-prone nature of EEG data is further addressed through an Autoencoder (AE) architecture, which transforms the input into a more compact and semantically meaningful latent representation. This dimensionality reduction not only enhances computational efficiency but also substantially improves the model's generalization capability. To comprehensively assess the classification performance of the proposed framework, a diverse set of machine learning algorithms—namely XGBoost, LightGBM, CatBoost, Random Forest, and Support Vector Machines (SVM) was utilized to discriminate between focused, distracted, and drowsy mental states. By validating the model across multiple classifiers and data variations, this strategy enhances the methodological rigor and demonstrates the adaptability, reliability, and robustness of the hybrid system in real-world driver attention analysis scenarios.

The originality of the proposed hybrid model lies in its integrative strategy that captures the structural complexity of EEG signals through the fusion of time-frequency, fractal, and statistical features—rather than relying on single-domain analyses, as commonly observed in prior studies [13]. By leveraging CWT for transient spectral dynamics, fractal measures (e.g., Petrosian, Hurst, DFA) for long-range signal dependencies, and Autoencoder-based dimensionality reduction to condense high-dimensional, noisy data into a more coherent latent space, the model preserves the strengths of each technique while mitigating their individual limitations. Furthermore, the framework has been rigorously evaluated under both subject-specific and common-subject paradigms using EEG data from five individuals, allowing for a comprehensive assessment of both personalization accuracy and cross-subject generalizability. This integrative and methodologically rigorous design distinguishes WaveFrac-AE as a novel and robust solution, capable of capturing the multidimensional nature of EEG signals while ensuring reliable performance across varying users and cognitive states.

The structure of this article unfolds across six integral sections. Following the introduction, the second section synthesizes key contributions from the literature on EEG-based mental state classification, critically examining the methodologies employed and the performance outcomes reported. The third section elaborates on the experimental framework, detailing the characteristics of the EEG dataset, participant demographics, and the data acquisition protocol. The fourth section presents the methodological core of the study, delineating the proposed hybrid classification architecture, which integrates time-frequency analysis via CWT, fractal dimension–based descriptors, Autoencoder-driven dimensionality reduction, and multiple machine learning classifiers. The fifth section reports the empirical findings under both subject-specific and common-subject paradigms, supported by performance metrics including classification accuracy, confusion matrices, and ROC analyses. The final section offers a holistic interpretation of the results, situates the study within the broader scientific context, and outlines prospective avenues for future exploration.

Literature Studies

In recent years, EEG-based mental state classification has attracted considerable attention due to its broad applications in monitoring driver fatigue, assessing mental workload, and detecting human stress. Researchers have explored various time-frequency analysis techniques, advanced feature-selection strategies, and deep-learning pipelines to address the complex, non-stationary nature of EEG signals. The following section reviews a series of representative studies, each contributing distinct insights into data preprocessing, feature extraction, or classification methodologies.

Acı et al. distinguished three cognitive conditions—focused, unfocused, and drowsy—by combining short-time Fourier transform (STFT) with an SVM classifier, surpassing 96% accuracy [14]. Building on similar aims in driver drowsiness detection, Alreshidi et al. proposed a multimodal framework for detecting pilots' mental states using EEG signals, combining automated preprocessing, Riemannian geometry-based feature extraction, and hybrid ensemble learning. Their method achieved 86% accuracy on EEG data collected from 18 pilots in flight simulations [15]. Nuamah and Seong likewise achieved high accuracy in detecting multiple cognitive load levels in a driving-simulator environment by leveraging well-labeled tasks and advanced EEG features, consistently surpassing 90% [16]. Hag et al. developed a stress detection framework using frontal EEG signals, salivary alpha-amylase levels, and machine learning classifiers under two induced stress levels. Their SVM-based model achieved a classification accuracy of 93.2%, utilizing optimal features from functional connectivity and temporal-spectral EEG domains [17]. Rahman et al. analyzed EEG signals to classify mental states using ten different machine learning algorithms, with hyperparameter tuning via RandomSearchCV. Among the models, SVM achieved the highest accuracy of 95.36%, followed closely by Gradient Boosting and XGBoost classifiers [18]. Zeng et al. proposed a cross-subject fatigue detection model (GDANN) that integrates Domain-Adversarial Neural Networks with GANs to overcome inter-subject variability in EEG signals. Their model achieved an average accuracy of 91.63%, outperforming traditional classifiers in EEG-based fatigue detection tasks [19]. Kimmatkar and Babu developed an EEG-based emotion detection system to classify 12 subtle emotional states and evaluated the impact of meditation music therapy on mental state regulation. Using Chirplet transform features and a multimodel classifier approach, their system achieved successful emotion recognition and demonstrated a 75% positive emotional shift with music therapy intervention [20]. Sharma et al. proposed a stress detection method based on short-duration EEG signals, utilizing entropy features extracted via stationary wavelet transformation. Their SVM model, optimized using the Whale Optimization Algorithm, achieved a high classification accuracy of 97.26%, demonstrating the method's reliability for timely stress recognition [21]. Kamińska et al. investigated EEG-based stress classification in a virtual reality environment using relaxing and stressful VR scenes, monitored via the EMOTIV EPOC Flex system. Among several classifiers tested, MLP and SVM achieved the highest accuracy of 96.42% when all EEG frequency bands were used [22]. Rajendran et al. analyzed EEG signals from 25 subjects under stress and non-stress conditions using DWT-based sub-band energy features and statistical validation via the Wilcoxon signed-rank test. Their cubic SVM classifier achieved 95.83% accuracy and maintained 89.74% accuracy when validated on an external EEG dataset [23].

Dataset and Experimental Material

In this study, EEG recordings were collected from five neurologically healthy adults across seven experimental sessions per participant, with the first two serving as acclimatization and the remaining five for data collection [14]. On average, each participant contributed five sessions, totaling approximately 25 hours of EEG data. During each 35–55-minute session, participants engaged in a passive task using Microsoft Train Simulator, aiming to maintain train speed within set limits with minimal control input. Three cognitive states—focused (0–10 min), unfocused (10–20 min), and drowsy (20–30 min)—were defined based on temporal segments. EEG signals were recorded using the Emotiv Epoc neuroheadset from seven active electrodes (F7, F3, P7, O1, O2, P8, AF4), sampled at 128 Hz, and wirelessly transmitted via Bluetooth. One sample per second was labeled according to cognitive state, yielding segmented data across the three conditions. Table 1 summarizes dataset specifications, and Figure 1 shows a representative raw EEG waveform from one channel.

Table 1. Overview of the EEG dataset characteristics [14]

Feature	Description
Number of Participants	5 (Healthy, voluntary students)
Number of Sessions (Experiments)	7 per participant (first 2 for training/adaptation, last 5 for actual data collection)
Duration of Each Session (min)	35–55 min (average ~40 min)
Total Recording Duration	Approximately 25 hours (5 participants × 5 sessions × ~1 hour)
EEG Device	Emotiv Epoc (128 Hz sampling rate, 0.2–43 Hz frequency band)
Electrodes Used	7 main electrodes: F7, F3, P7, O1, O2, P8, AF4 (modified placement)
Mental States	1) Focused 2) Unfocused 3) Drowsy

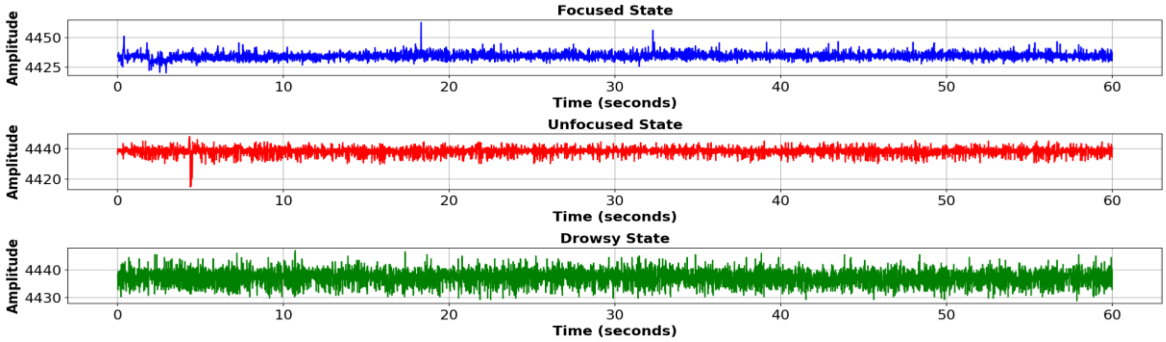

Figure 1. Raw EEG waveforms associated with three cognitive conditions

Methodology

This study presents WaveFrac-AE, a hybrid EEG classification framework that integrates handcrafted multiscale features with deep representation learning. The model fuses CWT–based time-frequency descriptors and nonlinear fractal metrics to construct a robust representation of cognitive states. CWT enables high-resolution, scale-continuous analysis, capturing localized EEG oscillations with statistical and energy-based measures such as mean, standard deviation, skewness, kurtosis, and wavelet entropy variants (Shannon, Rényi) [24]. The choice of CWT over the more conventional Discrete Wavelet Transform (DWT) is motivated by its superior ability to provide continuous, high-resolution analysis across all time and scale levels [25]. CWT is preferred in this study over DWT due to its finer spectral sensitivity, which is crucial for capturing the transient dynamics and subtle cognitive fluctuations in nonstationary EEG signals [26]. To capture EEG's long-range and scale-invariant dynamics, this study employs PFD, Hurst Exponent, and DFA as fractal analysis complements CWT by quantifying global nonlinear patterns and persistent temporal structures, enriching the model's representation for cognitive state classification [27].

To enhance classification accuracy and reduce complexity, all extracted features are compressed into a compact latent space using an Autoencoder. Unlike traditional reduction methods, the Autoencoder preserves key discriminative patterns while suppressing noise and redundancy, making it essential for refining the hybrid wavelet-fractal feature set. This integration not only strengthens generalization but also complements the dual-domain representation, enabling more robust EEG-based attention state classification. To evaluate classification performance, the proposed model was tested using multiple algorithms (SVM, Random Forest, XGBoost, LightGBM, CatBoost), enabling a comprehensive assessment of its robustness and generalizability across learning paradigms. This strategy highlights how the hybrid feature set interacts with diverse classifiers, revealing consistent gains in accuracy and adaptability. The integration of deep features encoding traditional classifiers significantly boosts discriminative power, validating the model's effectiveness for EEG-based mental state classification. The study's multi-classifier evaluation reveals the model's strong adaptability and enhanced discriminative power, resulting in improved accuracy and generalization for EEG-based mental state classification. The overall structure of the proposed hybrid model is illustrated in Figure 2, detailing each stage of the framework with concise process descriptions.

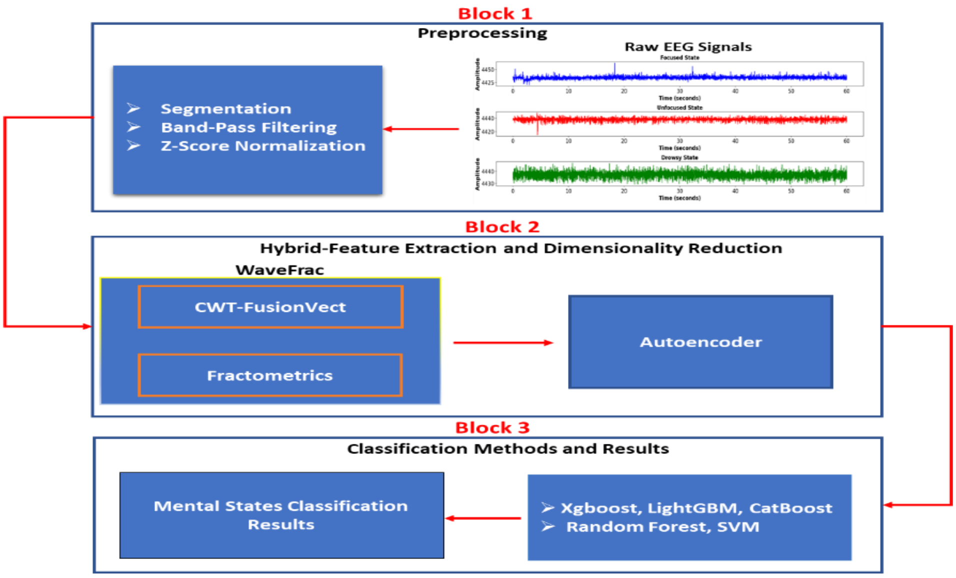

Figure 2. Block diagram of the proposed EEG-based classification pipeline

➢ **Block 1 (Preprocessing):** Raw EEG signals are segmented, band-pass filtered (0.5–45 Hz) to remove noise, and then normalized using Z-score to standardize amplitudes, ensuring clean and consistent input for analysis.

➢ **Block 2 (Feature Extraction & Dimensionality Reduction):** In the proposed WaveFrac architecture, two complementary feature sets—CWT-FusionVect (derived from time-frequency coefficients via statistical moments, energy measures, and entropy-based descriptors) and Fractometrics (capturing fractal complexity via PFD, Hurst, and DFA)—are extracted from EEG signals. These high-dimensional descriptors are then fused and compressed using an Autoencoder to generate a compact latent representation, enabling robust and scalable mental state classification.

➢ **Block 3 (Classification Methods and Results):** Autoencoder-derived features are classified into cognitive states (focused, unfocused, drowsy) using algorithms like SVM, Random Forest, and boosting methods. Performance is evaluated via 5-fold cross-validation using accuracy, confusion matrices, and ROC curves.

Preprocessing

During the preprocessing stage, raw EEG signals are first segmented into fixed-length time windows to structure the analysis of temporal dynamics. Each segment is treated independently, enabling localized examination of cognitive patterns. After segmentation, a band-pass filter (0.5–45 Hz) is applied to remove irrelevant frequency components and retain those associated with cognitive activity. A fifth-order Butterworth filter with zero-phase distortion is employed to preserve signal integrity during this step. Finally, Z-score normalization is performed to reduce inter-channel variability and standardize signal amplitudes, ensuring that the model is not biased by differences in magnitude across channels or recording sessions. All preprocessing operations—including segmentation, filtering, and normalization—are applied uniformly across all subjects and EEG channels to guarantee methodological consistency. These steps enhance the quality and relevance of the data, preparing it for reliable feature extraction. Figure 3 illustrates sample EEG signals before and after preprocessing, highlighting the effectiveness of the pipeline in isolating clean signal components across different cognitive states.

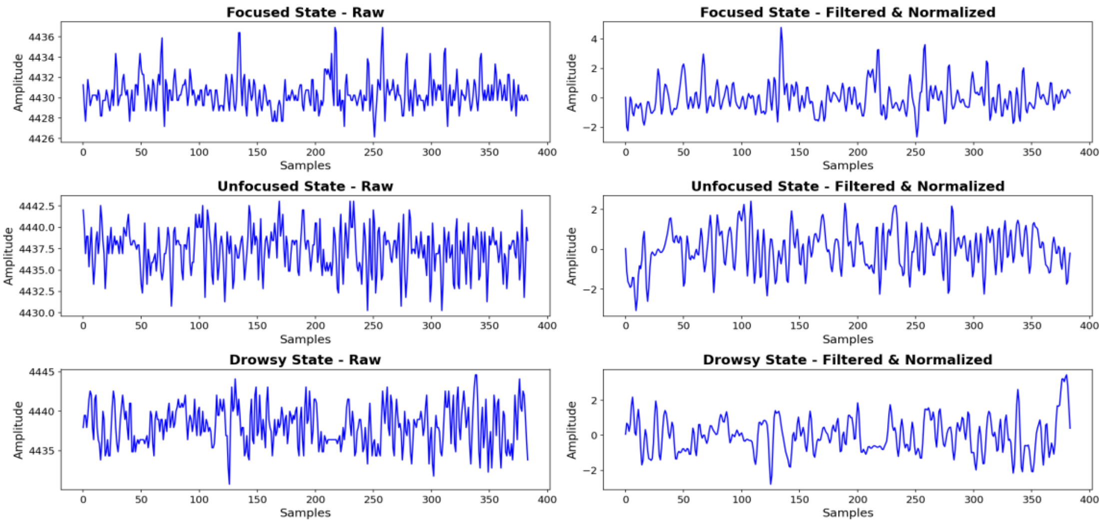

Figure 3. EEG signal raw vs. filtered-normalized

Hybrid Feature Extraction and Dimensionality Reduction

CWT-derived multiscale features for EEG dynamics

EEG is a powerful non-invasive method for tracking brain activity, but its complex, dynamic nature requires time-frequency analysis to accurately capture neural oscillations linked to cognitive and clinical states [28]. Unlike the Fourier Transform, which provides only global frequency content, and the STFT, which suffers from fixed resolution, CWT offers multi-resolution analysis—making it ideal for capturing transient, time-varying neural patterns in EEG signals [29]. While CWT is traditionally employed to compute time-frequency coefficients, this study emphasizes a more advanced usage: extracting diverse statistical, energy-based, and entropy-driven features from the wavelet coefficients to map subtle neural dynamics. These descriptors—mean, standard deviation, skewness, kurtosis, and entropy measures—complement fractal features such as Petrosian, Hurst, and DFA, which capture structural irregularity and self-similarity in EEG signals. This fusion creates a synergistic feature space, where CWT highlights transient patterns and fractals model inherent complexity. To extract CWT coefficients, the Continuous Wavelet Transform is applied to EEG signals as formulated in Equation (1), enabling a multi-scale decomposition that captures localized time-frequency patterns essential for feature derivation.

$$CWT(a,b) = \int_{-\infty}^{\infty} x(t)\psi^{*}_{a,b}(t)dt \qquad (1)$$

In Equation (1), x(t) denotes the input signal, $\psi_{a,b}^*(t)$ represents the scaled and shifted wavelet function, a is the scale parameter, and b corresponds to the time-shift parameter. The wavelet coefficients obtained through the CWT encapsulate the time-frequency characteristics of EEG signals and serve as a rich source for extracting informative features. To capture cognitive-related neural dynamics, various features were extracted from CWT coefficients, including statistical (mean, std, skewness, kurtosis), energy-based, and entropy measures (Wavelet, Rényi, Shannon). Together, they provide a rich representation of signal amplitude and spectral complexity, enhancing mental state classification. The corresponding mathematical formulations and notations for these features are presented in the equations below. The mean represents the arithmetic average of the wavelet coefficients. In the mathematical expression provided in Equation (2), μ denotes the mean value, N is the total number of samples in the signal and, C_i refers to the individual wavelet coefficients.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} C_i \tag{2}$$

The standard deviation quantifies the extent to which the wavelet coefficients deviate from their mean, reflecting the dispersion of the data around the average value. In Equation (3), σ denotes the standard deviation, N represents the total number of samples in the signal, C_i corresponds to the individual wavelet coefficients, and μ is the mean of the coefficients.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=0}^{n}(C_i - \mu)^2} \tag{3}$$

Skewness is utilized to assess the asymmetry in the distribution of wavelet coefficients, while kurtosis captures the presence of extreme values in the EEG signal, thereby enabling the detection of abrupt changes in neural activity. The mathematical formulations corresponding to these two measures are provided in Equations (4) and (5), respectively. In these equations, Sk denotes the skewness, Ku represents the kurtosis, σ is the standard deviation, N is the total number of samples in the signal, C_i indicates the wavelet coefficients and μ refers to their mean value.

$$Sk = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{C_i - \mu}{\sigma}\right)^3 \tag{4}$$

$$Ku = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{C_i - \mu}{\sigma}\right)^4 - 3 \tag{5}$$

Energy-based features offer a powerful means of analyzing the distribution of energy across different frequency bands in EEG signals, serving as key indicators in the identification of cognitive processes and neurological disorders. Wavelet energy quantifies the energy concentration of the EEG signal at various scales, while relative wavelet energy computes the proportion of energy at each scale, thereby facilitating the interpretation of EEG activity within specific frequency bands. The corresponding mathematical formulations for wavelet energy and relative energy are provided in Equations (6) and (7), respectively.

$$E = \sum_{i=1}^{N} C_i^2 \tag{6}$$

$$RE = \frac{E_{scale}}{\sum_{all\_scales} E} \tag{7}$$

In Equations (6) and (7), N denotes the total number of signal samples, C_i represents the wavelet coefficients, E corresponds to the wavelet energy, and RE denotes the relative wavelet energy. The RE value is calculated as the ratio of the energy at each scale (Escale) to the total energy across all scales.

Entropy-based features derived from the CWT are employed to quantify the complexity and irregularity of EEG signals, with Wavelet Entropy specifically serving as a measure of signal disorder and proving useful in the detection of events such as epileptic seizures and alterations in consciousness levels [30]. Rényi Entropy is utilized to analyze the information density and uncertainty embedded within EEG signals, providing a generalized framework for quantifying signal complexity beyond traditional entropy measures [31]. Shannon Entropy, on the other hand, is employed to characterize the relationship between EEG dynamics and underlying cognitive processes [32]. The following equations present the mathematical formulations corresponding to Wavelet Entropy, Rényi Entropy, and Shannon Entropy, respectively.

$$E_i = \sum_{i=1}^{N} |C_i(t)|^2 \ , \ p_i = \frac{E_i}{\sum_{j=1}^{N} E_j} \ , \ H = -\sum_{i=1}^{N} p_i \log p_i \tag{8}$$

In Equation (8) E_i represents the energy distribution of the wavelet coefficients obtained through the CWT. This energy distribution is normalized to form a probability distribution denoted by pi representation. The symbol H denotes the wavelet entropy, which is computed by taking the logarithm of the probability distribution components to quantify the signal's degree of disorder.

$$p_i = \frac{|C_i|^\alpha}{\sum_{j=1}^{N} |C_j|^\alpha} \ , \ H_\alpha = \frac{1}{1-\alpha} \log \sum_{i=1}^{N} p_i^\alpha \tag{9}$$

In Equation (9) p_i denotes the normalized probability distribution derived from the wavelet coefficients. The parameter α defines the order of the entropy and controls the sensitivity of the measure to the distribution's structure. H_α represents the Rényi entropy, which is computed by applying a logarithmic function to the probability distribution, with its value influenced by the chosen α parameter.

$$p_i = \frac{|C_i|}{\sum_{j=1}^{N}|C_j|}\ ,H_s = -\sum_{i=1}^{N} p_i \log_2 p_i \tag{10}$$

Equation (10) presents the mathematical formulation of Shannon entropy, utilizing the same notations as described in the previous entropy measures. The logarithmic expression with base 2 is employed to quantify information in bits. Shannon entropy evaluates the information content of EEG signals by analyzing the distribution of CWT coefficients: higher entropy values indicate a more homogeneous and complex signal distribution, whereas lower entropy values suggest that the energy is concentrated in fewer coefficients, reflecting a more regular and less complex signal structure. The Morlet wavelet was used in this study for its balanced time-frequency resolution, ideal for transient EEG analysis [33]. Figure X displays the CWT scalograms of EEG signals corresponding to focused, unfocused, and drowsy cognitive states. EEG signals across different cognitive states show noticeable diversity in their time-frequency energy patterns. These variations emphasize the non-stationary and dynamic nature of EEG signals. Given the diversity and temporal evolution observed in the scalograms, it is insufficient to rely solely on raw CWT coefficients. Instead, we extract higher-order statistical (mean, standard deviation, skewness, kurtosis), energy-based, and entropy features (Shannon, Rényi, Wavelet entropy) that effectively summarize the signal's structural and spectral behavior over time. This approach enables the model to capture both transient activations and underlying complexity, providing a discriminative feature space well-suited for mental state classification. The use of CWT-derived features is thus not arbitrary but grounded in the visually evident variability across cognitive conditions, as exemplified by the scalograms.

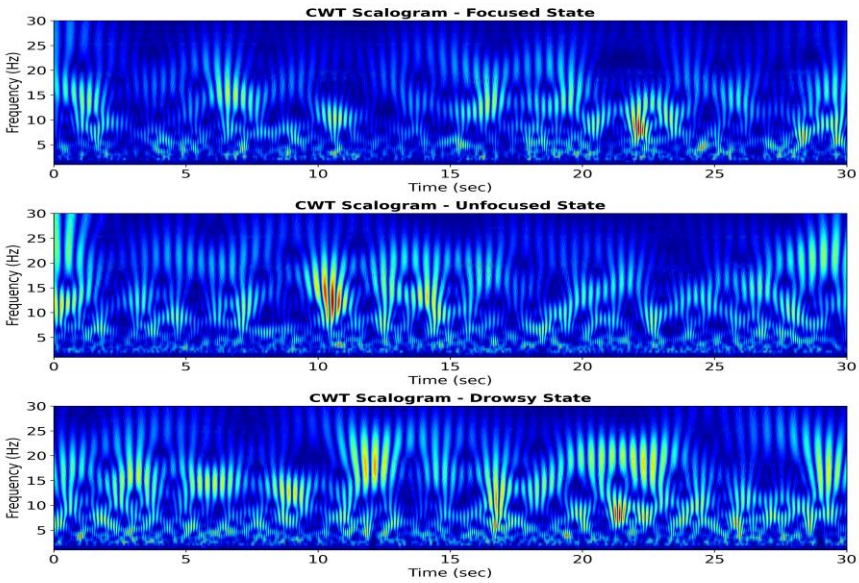

Figure 4. CWT-based scalograms of EEG signals for different mental states

Fractal Features

Fractal dimension analysis is a widely employed technique for quantifying the complexity and irregularity of biomedical signals, and it plays a critical role in uncovering the underlying dynamics of EEG data, which inherently exhibit nonlinear and fractal characteristics [34]. While the CWT is highly effective for performing time-frequency analysis of EEG signals, it does not directly quantify intrinsic properties such as signal irregularity, complexity, or long-range temporal dependencies [35]. Fractal features are employed in this study to capture the nonlinear, self-similar, and scale-invariant properties inherent in EEG signals—characteristics that conventional linear methods often fail to represent. These features provide critical insight into the long-term dependencies and complex temporal dynamics of brain activity, which are essential for distinguishing cognitive states. Among them, PFD offers a compact yet sensitive measure of signal irregularity by quantifying zero-crossings, making it particularly effective in detecting subtle, transient changes in neural activity. The mathematical formulation of PFD is given in Equation (11).

$$\mathrm{PFD} = \frac{\log \mathrm{N}}{\log \mathrm{N} + \log\left(\frac{\mathrm{N}}{\mathrm{N} + 0.4\mathrm{N}_{\delta}}\right)} \tag{11}$$

In Equation (11), N denotes the total number of signal samples, N_{δ} represents the number of sign changes (zero-crossings) in the first derivative of the signal. This method is directly linked to signal regularity: a signal exhibiting high variability and frequent fluctuations (i.e., high-frequency components) will result in a lower PFD value, whereas a more regular and structured signal will yield a higher PFD. The Hurst exponent is a statistical measure used to evaluate the long-term dependency and predictability of a time series. It yields a value within the range of $0 \leq \mathrm{H} \leq 1$, where the magnitude of H indicates the degree of persistence or anti-persistence in the signal. The mathematical formulation of the Hurst exponent is provided in Equation (12).

$$H = \lim_{N \to \infty} \frac{\log\left(\frac{R}{S}\right)}{\log N} \tag{12}$$

In Equation (12), N denotes the length of the time series, R represents the range between the maximum and minimum values within the cumulative signal, and S refers to the standard deviation of the series. The ideal range of the Hurst exponent depends on the intrinsic characteristics of the EEG signal under analysis, as different cognitive or physiological states may manifest varying degrees of long-term temporal correlation. DFA is a robust technique used to evaluate long-range correlations and scale-dependent dynamics within time series data. It quantifies how the residual variance evolves after removing local trends from the signal, thereby capturing the underlying self-similarity and temporal organization. The mathematical formulation of the DFA method is presented in the equations below.

$$Y(k) = \sum_{i=1}^{k} (x_i - \bar{x}) \tag{13}$$

In Equation (13), *Y(k)* represents the cumulative sum of the signal, where, x_i denotes the original signal values and $\bar{x}$ is the mean of the series. In the subsequent step, the integrated signal is divided into non-overlapping segments of equal length *n*, and a linear trend is fitted to each segment. After detrending each window, the fluctuation function *F(n)* is computed as shown in Equation (14), which quantifies the variance of the residuals from the local trends across all segments.

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (Y(k) - Y_n(k))^2} \tag{14}$$

In Equation (14), $Y_n(k)$ denotes the local trend estimated within each segment, and *N* represents the total number of segments. The fluctuation function *F(n)* is computed for various window sizes *n*, and the scaling behavior of the signal is characterized by plotting *F(n)* against *n* in a log-log plot. The slope of this plot defines the DFA exponent, which serves as a quantitative indicator of long-range correlations. This exponent has been widely employed in EEG studies for applications such as sleep stage analysis, epilepsy detection, and the classification of consciousness levels [36].

Fractal features—PFD, Hurst Exponent, and DFA—complement CWT by capturing nonlinear dynamics and long-range correlations that time-frequency analysis alone may overlook. Each metric targets a distinct aspect of signal complexity: PFD reflects structural irregularity, Hurst indicates long-term memory, and DFA captures scale-invariant fluctuations. Figure 5 provides a visual comparison of three fractal-based features—PFD, Hurst Exponent, and DFA Exponent—across different mental states. The violin plots display the overall distribution and variability of each feature for the three classes (focused, unfocused, and drowsy), while the KDE plots illustrate their density profiles, revealing how these features vary between cognitive conditions. Among the three, PFD shows the most noticeable separation between mental states, suggesting it is particularly effective at capturing signal irregularities related to attentional changes. The DFA Exponent also demonstrates distinct class-dependent patterns, especially in the focused condition, while the Hurst Exponent provides additional insight into long-term signal trends, albeit with more overlap between classes. The integration of PFD, Hurst, and DFA provides a richer, physiologically grounded EEG representation, enhancing the model's ability to detect subtle cognitive transitions. This strengthens the overall accuracy and generalizability of the WaveFrac-AE framework, especially in real-time applications like driver monitoring

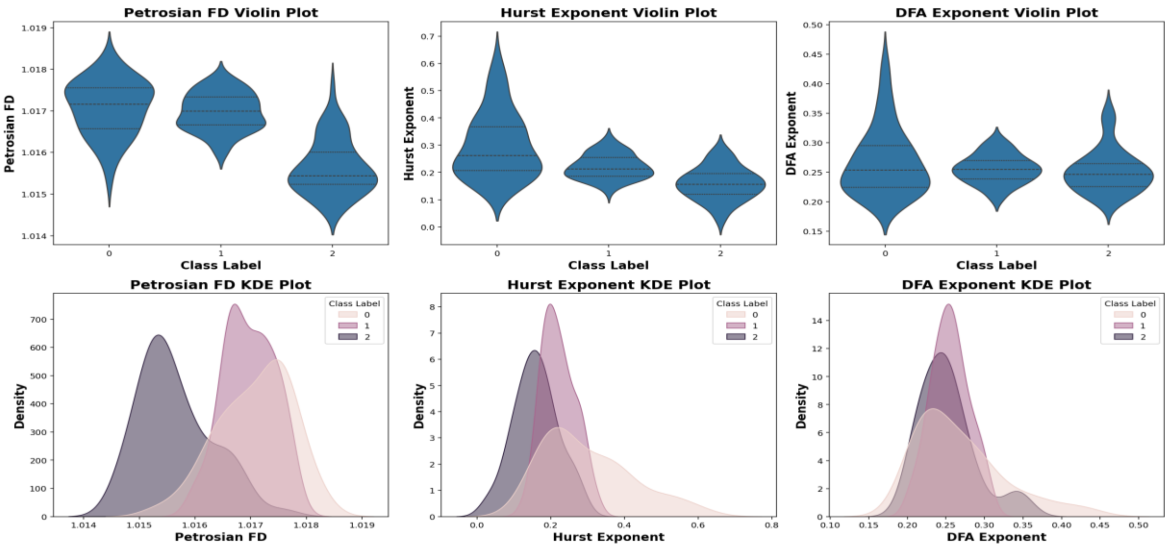

Figure 5. Class-wise distributions of EEG nonlinear features: Petrosian FD, Hurst, and DFA measures

Feature Dimensionality Reduction (Autoencoder)

EEG signals, owing to the inherent complexity of underlying biological processes, are characterized by high dimensionality, substantial noise, and multi-component structure. To enhance classification accuracy and computational efficiency in EEG-based mental state recognition, this study employs an Autoencoder-based dimensionality reduction technique that compresses the data into a more compact and information-dense latent representation by capturing its intrinsic patterns through a neural network architecture [37]. Unlike traditional dimensionality reduction techniques, Autoencoders not only reduce data dimensionality but also generate latent representations that preserve salient patterns, thereby enabling the extraction of more discriminative features for downstream classification tasks [38]. In this study, an Autoencoder is used to compress the high-dimensional feature space—derived from CWT and fractal descriptors (PFD, Hurst, DFA)—into a lower-dimensional, informative representation. This process reduces noise and redundancy while preserving key features essential for classification. The model's architecture and parameters are detailed in Table 2 and Figure 6, respectively.

Table 2. Hyperparameters of the proposed Autoencoder model

Structural Element	Details
Encoder	Three fully connected layers: 1024 → 512 → 256 (latent space)
Decoder	Two fully connected layers: 512 → 1024 → input_dim
Normalization & Regularization	Batch Normalization after each layer Dropout rate: 0.35
Output Layer	Linear activation to reconstruct original input
Optimization	AdamW optimizer Learning rate: 0.0005 Weight decay: 1e-4
Training Strategy	MAE loss Early Stopping based on validation error stagnation

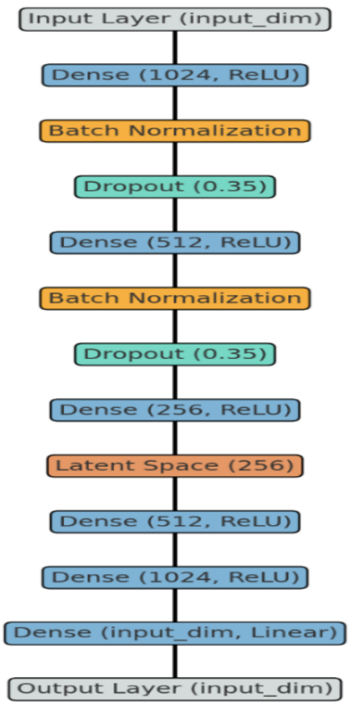

Figure 6. Autoencoder structural diagram

The proposed Autoencoder uniquely integrates time-frequency and fractal EEG features into a low-dimensional latent space, enhancing feature discriminability. Its architecture employs progressive compression—from 1024 to 256 units—combined with Batch Normalization and Dropout (rate = 0.35) to enhance training stability and prevent overfitting. The use of the AdamW optimizer with weight decay (1e-4) is a deliberate choice to improve convergence and prevent weight explosion, while the learning rate (0.0005) balances convergence speed and stability. MAE loss minimizes reconstruction error, and Early Stopping avoids overtraining. Together, these design choices support a more generalizable and efficient model, distinguishing WaveFrac-AE from standard Autoencoder applications in EEG analysis.

Machine Learning Algorithms Employed in the Classification Framework

EEG signals are highly complex, nonlinear, and non-stationary, making them difficult to model with traditional statistical methods. Their dynamic structure requires advanced learning algorithms to effectively capture temporal and structural variations [39]. In this context, tree-Tree-based models like Random Forest, XGBoost, LightGBM, and CatBoost use hierarchical partitioning and ensemble learning to capture complex decision boundaries and improve classification. In contrast, SVM maps data to higher-dimensional spaces to identify optimal hyperplanes, enabling precise separation of cognitive states.

Support Vector Machines (SVM)

Support Vector Machines (SVM) are widely adopted supervised classifiers in statistical learning due to their high accuracy and effectiveness in handling complex, high-dimensional data structures. This method constructs an optimal separating hyperplane by projecting samples into a higher-dimensional feature space to maximize the margin between classes, and it remains effective on non-linearly separable datasets through the use of kernel functions. To enhance generalizability and mitigate overfitting, careful tuning of hyperparameters such as C and gamma is essential; C controls the trade-off between margin maximization and classification error, while gamma defines the influence of individual data points on the decision boundary. Moreover, by relying solely on support vectors during the classification process, the algorithm enhances computational efficiency and significantly reduces processing costs.

Random Forest

Random Forest is a robust ensemble learning algorithm that constructs multiple decision trees using randomly selected data subsets and features via bootstrap aggregation (bagging), combining their outputs through majority voting or averaging for final prediction. This structure enhances generalization and reduces overfitting by promoting model robustness against data variability. The *n_estimators* parameter, which defines the number of trees, plays a crucial role in model accuracy; however, increasing it may lead to higher computational costs. The high channel-wise variability in EEG signals makes Random Forest's random feature selection advantageous for identifying salient attributes; however, its reliance on numerous independent decision trees can result in prolonged computation times when applied to large-scale EEG datasets.

XGBoost (Extreme Gradient Boosting)

XGBoost, a gradient boosting-based decision tree algorithm, is widely recognized for its exceptional computational efficiency and predictive accuracy, particularly when dealing with large-scale datasets [41]. It iteratively builds decision trees that correct the residuals of previous ones, thereby progressively minimizing prediction errors through a stepwise optimization process. Its application in biomedical signal classification—especially EEG—is largely attributed to its advanced branch and leaf optimization mechanisms, which significantly enhance class separability within complex signal patterns [42]. Moreover, the incorporation of both L1 and L2 based ensemble models and kernel-based classifiers—particularly Support Vector Machines (SVM)—have emerged as powerful modeling alternatives for EEG-based mental state classification, owing to their ability to handle complex decision boundaries and capture non-linear patterns within high-dimensional neurophysiological data [40].

regularization techniques mitigates overfitting and reinforces generalizability, while its histogram-based processing architecture enables scalable modeling with reduced computational overhead in high-dimensional EEG datasets [43].

LightGBM (Light Gradient Boosting Machine)

LightGBM is a gradient boosting framework that functions similarly to XGBoost but achieves greater computational efficiency and reduced memory usage, making it particularly well-suited for large-scale biomedical data analysis [44]. By adopting a leaf-wise tree growth strategy, LightGBM enhances the precision of decision boundaries, thereby facilitating a more nuanced interpretation of complex medical signals such as EEG [45]. One of its most prominent advantages lies in the use of Gradient-based One-Side Sampling (GOSS), which selectively discards low-gradient instances during training [46]. This approach not only improves generalization but also significantly reduces training time especially when modeling the non-stationary and high-dimensional nature of EEG signals

CatBoost (Categorical Boosting)

CatBoost is a gradient boosting algorithm specifically designed to handle categorical data more effectively, making it a robust choice for modeling inter-subject variability in EEG signals [47]. One of its key strengths lies in its ability to automatically encode categorical features, enabling the model to optimize decision boundaries without extensive preprocessing. Furthermore, CatBoost employs symmetric tree structures during training, allowing for more balanced learning. This architectural feature enhances the model's ability to generalize across diverse individuals, capturing subtle variations in EEG patterns while maintaining classification consistency and robustness [48].

Experimental Results

To systematically evaluate the classification performance, adaptability, and generalization capability of the proposed WaveFrac-AE framework, the study implements two distinct experimental paradigms: the subject-specific and common-subject approaches. In the subject-specific setting, independent models are trained and evaluated for each participant, enabling the assessment of personalized classification performance and the model's suitability for individual-level applications. Conversely, the common-subject paradigm involves pooling EEG data from all participants to train a single unified model, allowing the evaluation of inter-subject generalization and the model's scalability in broader, real-world contexts. In both paradigms, the unified feature set—comprising time-frequency descriptors (via CWT) and nonlinear complexity measures (PFD, Hurst, DFA)—is reduced using an Autoencoder to extract the most salient and discriminative components while minimizing noise and redundancy.

To ensure a comprehensive and unbiased performance evaluation, five state-of-the-art machine learning classifiers—XGBoost, LightGBM, CatBoost, Random Forest, and SVM—were employed. For each model, predefined search spaces were established, and systematic hyperparameter optimization was carried out using a grid search procedure combined with five-fold stratified cross-validation. A fixed random seed was applied during all experiments to preserve class balance, reduce the risk of overfitting, and guarantee reproducibility. Importantly, all classifiers were evaluated under the same cross-validation framework, which enabled a fair and systematic comparison of adaptability, stability, and generalization capacity across different learning algorithms. The final hyperparameter configurations obtained through this optimization process are summarized in detail in Table 3.

Table 3. Hyperparameter configurations of the classification models used in the study

Classifier	Main Parameters
XGBoost	n_estimators=200 learning_rate=0.02 max_depth=4 subsample=0.6 colsample_bytree=0.6
LightGBM	n_estimators=200 learning_rate=0.02 num_leaves=31 max_depth=4 subsample=0.6 colsample_bytree=0.6
CatBoost	iterations=200 learning_rate=0.02 depth=4 verbose=0
Random Forest	n_estimators=100 max_depth=3
SVM	kernel='rbf' C=2 gamma='scale' probability=True

Table 4 summarizes the subject-specific classification results using the WaveFrac+AE framework across five participants and five machine learning algorithms. The findings clearly underscore the strength of personalized modeling in EEG-based attention classification. Support Vector Machines (SVM) consistently delivered the highest accuracies—for example, 97.52% for Subject 1 and 97.33% for Subject 4—demonstrating its superior ability to capture subject-specific EEG dynamics. SVM achieved the best performance since the RBF kernel can effectively model complex non-linear decision boundaries, while the margin maximization principle provides strong generalization across different subjects. XGBoost and LightGBM also performed well, with XGBoost achieving 91.67% for Subject 5, highlighting the effectiveness of gradient boosting in handling high-dimensional EEG features. CatBoost yielded moderate results, performing best for Subject 5 (85.60%) but showing reduced accuracy for others, especially Subject 3 (73.96%). Random Forest recorded the lowest performance overall, with particularly poor results for Subject 3 (67.35%), indicating its limited capability to model complex EEG structures. These results confirm that WaveFrac+AE, particularly when paired with SVM, offers high accuracy and robustness in subject-specific settings—making it a strong candidate for individualized EEG-based mental state monitoring.

Table 4. 5-Fold subject-specific accuracies of WaveFrac-AE across machine learning models

Subject	XGBoost		LightGBM		CatBoost		Random Forest		SVM	
	Mean (%)	± SD (%)	Mean (%)	± SD (%)	Mean (%)	± SD (%)	Mean (%)	± SD (%)	Mean (%)	± SD (%)
S1	91.43	2.25	90.95	2.72	82.19	5.15	79.52	2.12	97.52	0.85
S2	89.62	3.11	88.86	3.45	79.62	3.37	73.52	3.58	96.95	1.54
S3	81.93	4.79	83.19	3.97	73.96	4.94	67.35	5.43	90.00	1.97
S4	90.19	2.93	90.19	1.52	81.33	2.88	77.43	1.22	97.33	0.65
S5	91.67	1.66	91.31	1.97	85.60	3.94	83.21	2.45	96.19	1.23
Average (Mean± SD)	**88.97**	**2.95**	**88.90**	**2.73**	**80.54**	**4.06**	**76.21**	**2.96**	**95.60**	**1.25**

Figure 7 presents subject-specific confusion matrices, offering a detailed class-level view of each classifier's ability to distinguish between focused, distracted, and drowsy states. These visualizations support the accuracy results in Table 4, further emphasizing the advantages of SVM. SVM stands out with consistently high precision and balanced classification across all classes, particularly for Subjects S1, S2, and S4, where true positive rates are notably strong and inter-class confusion is minimal. In comparison, XGBoost and LightGBM maintain strong overall performance but show occasional confusion in detecting the distracted state, often misclassifying it as focused or drowsy—indicating less distinct decision boundaries for intermediate cognitive states. CatBoost performs moderately, while Random Forest shows clear limitations, with frequent misclassifications between distracted and drowsy states. This suggests a lower capacity to model the nonlinear, non-stationary nature of EEG data. Overall, Figure 7 reinforces the superiority of SVM in subject-specific EEG classification, highlighting its robustness and class-wise balance—making it particularly suitable for applications requiring accurate and fine-grained mental state differentiation.

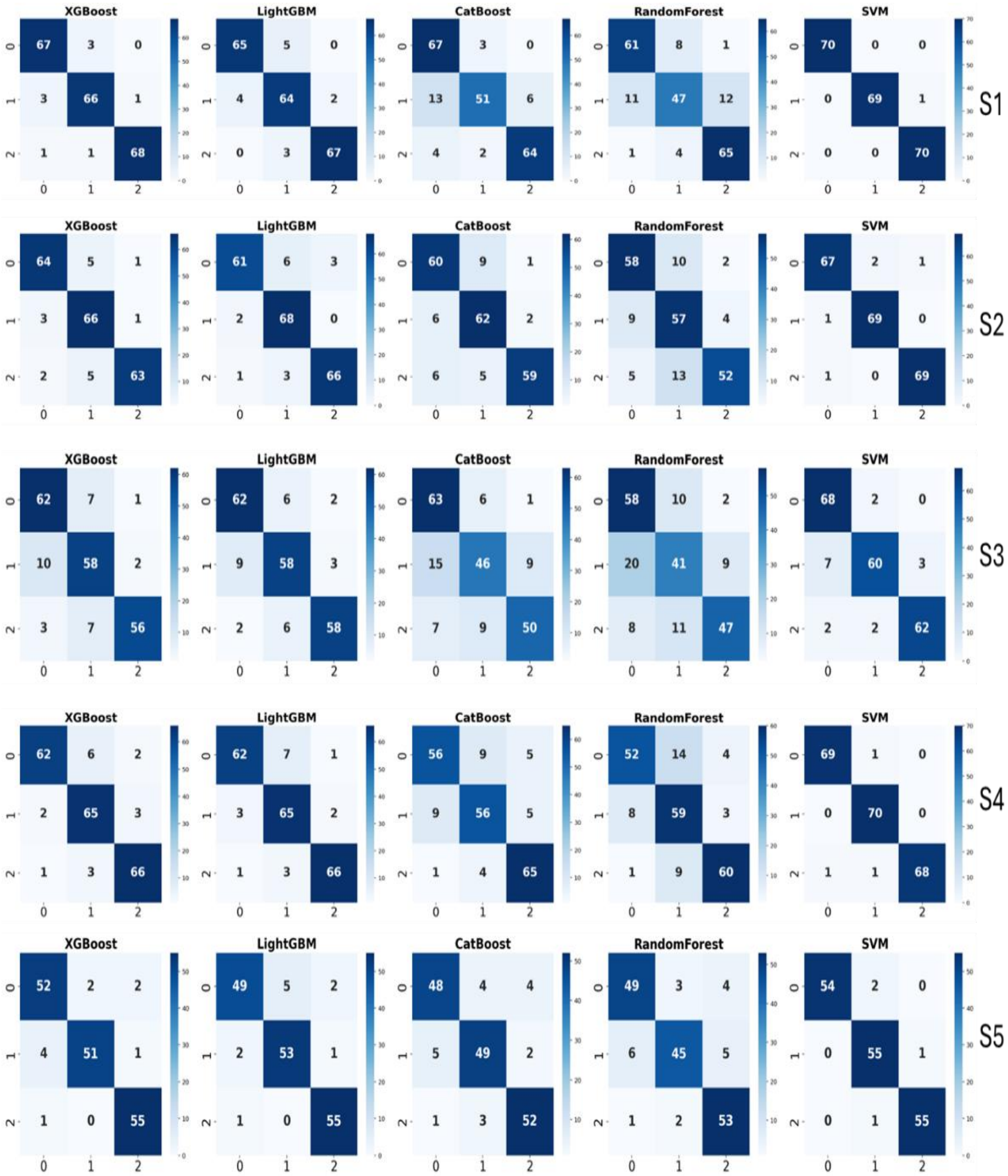

Figure 7. Confusion matrices of subject-specific classification results for each machine learning model across five subjects (S1–S5)

To provide a more comprehensive evaluation beyond overall accuracy, Figure 8 presents ROC curves and AUC scores to assess classifier performance beyond overall accuracy, focusing on sensitivity-specificity trade-offs across subjects (S1–S5) and classifiers. SVM achieved near-perfect AUCs (1.00 for four subjects, 0.98 for S3), confirming its superior precision and generalizability in modeling nonlinear EEG patterns. XGBoost and LightGBM also showed strong performance (AUCs 0.95–0.99), while CatBoost and Random Forest lagged slightly (AUCs 0.90–0.95 and 0.85–0.92, respectively), indicating lower class discrimination. Overall, ROC analysis reaffirms SVM as the most reliable model for EEG-based mental state classification.

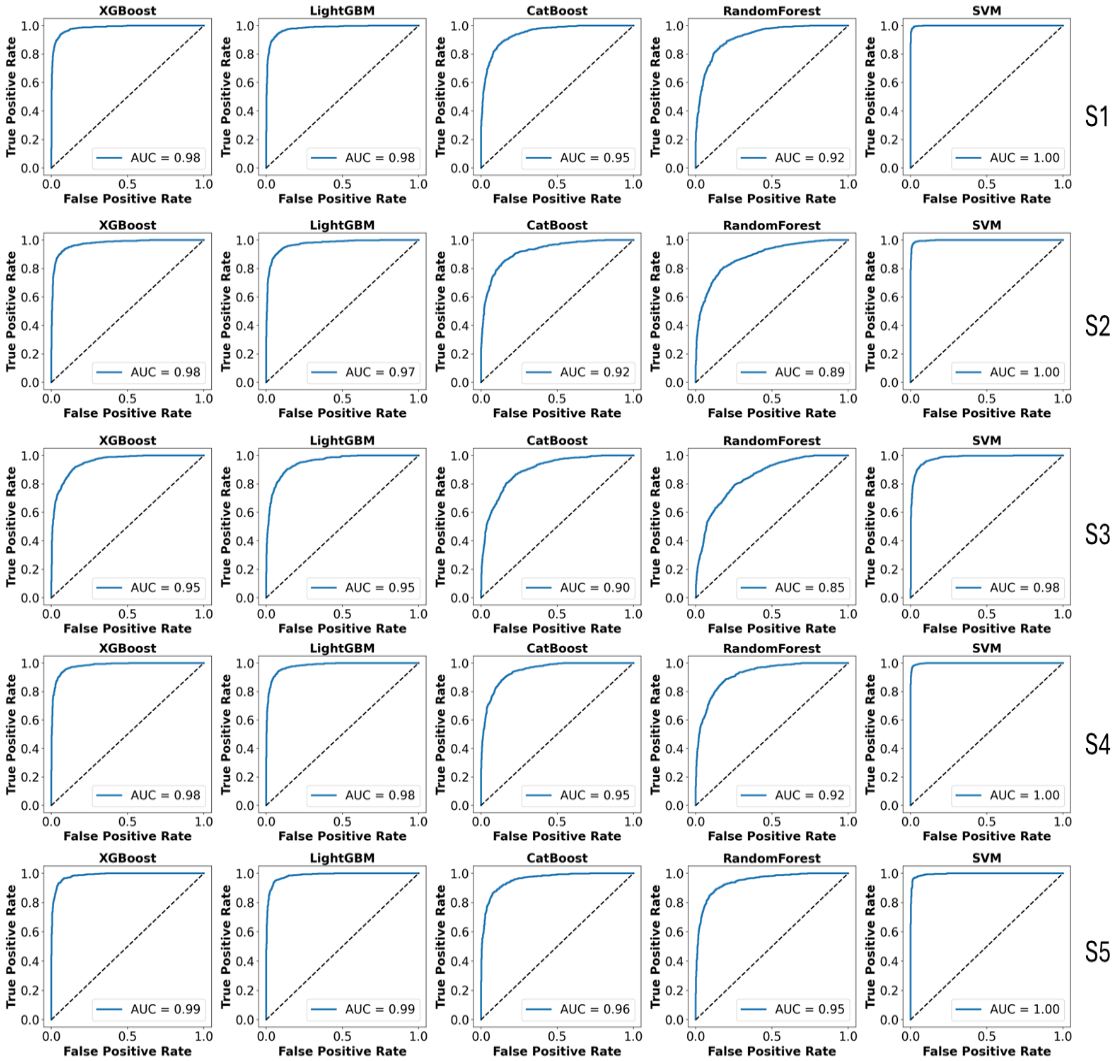

Figure 8. ROC curves and corresponding AUC values for subject-specific classification across five subjects and five classifiers.

To rigorously evaluate the WaveFrac+AE framework, its components—CWT-only features, fractal-only features, and hybrid features without Autoencoder—were tested separately. Results showed that models using isolated feature sets or omitting dimensionality reduction performed significantly worse. As shown in Table 5 and Figure 9, WaveFrac+AE + SVM outperformed all other configurations, achieving an average accuracy of 95.6%. This represents a 5.7% improvement over WaveFrac without Autoencoder, 14.5% over CWT-only, and 30.1% over fractal-only models. Importantly, the model's standard deviation decreased from 4.84 to 3.10, indicating better cross-subject consistency. These findings confirm that fusing CWT's time-frequency features with fractal metrics, and compressing them via an Autoencoder, yields a more robust, discriminative, and generalizable EEG representation—making WaveFrac-AE + SVM the most effective and reliable solution for multi-class mental state classification.

Table 5. Subject-wise test accuracies (%) of competing EEG pipelines (Fractal + SVM, CWT + SVM, WaveFrac + SVM, WaveFrac-AE + SVM)

Subject	Fractal+SVM	CWT+SVM	WaveFrac+SVM	WaveFrac + AE +SVM
S1	69.52	88.48	94.09	97.52
S2	66.38	81.52	90.24	96.95
S3	60.93	70.56	80.55	89.92
S4	67.69	84.29	93.11	97.33
S5	63.02	80.76	91.31	96.19
Mean ± SD	65.51 ± 3.26	81.12 ± 6.66	89.87 ± 4.84	95.60 ± 3.10

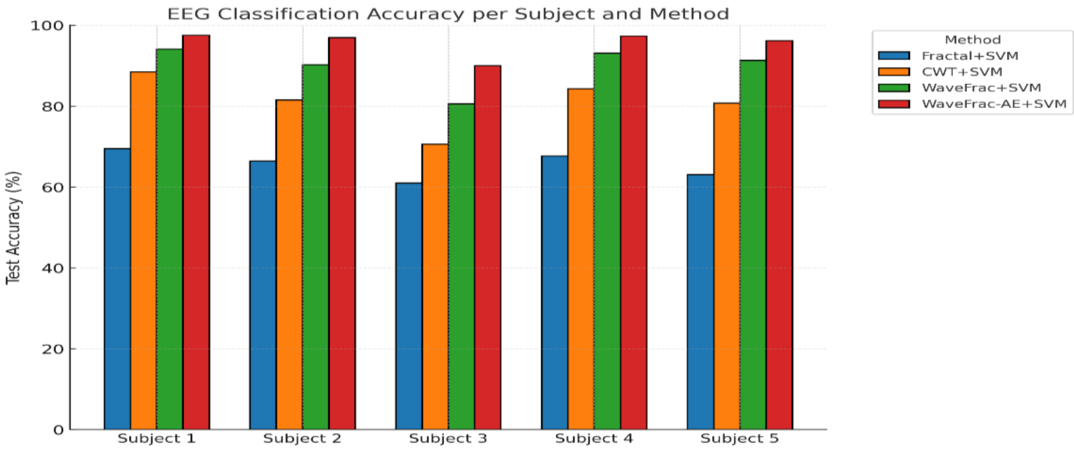

Figure 9. Per-subject accuracy profile highlighting the superiority of the proposed WaveFrac-AE + SVM over baseline methods

Figure 10 illustrates the benchmarking results obtained by comparing the proposed hybrid feature extraction method (WaveFrac-AE) with its individual components, namely fractal-based and time–frequency (CWT, WaveFrac) representations. For each feature type, classification accuracies were computed across all five subjects using five-fold cross-validation, and the mean values were subsequently averaged to provide a comprehensive comparison. The bar graph presents the performance of all classifiers (XGBoost, LightGBM, CatBoost, Random Forest, and SVM), thereby enabling a systematic evaluation of how different learning algorithms respond to alternative feature representations. The results clearly demonstrate that the hybrid WaveFrac-AE features consistently outperform their individual counterparts across classifiers, with SVM achieving the highest accuracy levels. This confirms the effectiveness of combining fractal and time–frequency information under an autoencoder-based dimensionality reduction framework, resulting in more discriminative and robust representations of EEG signals.

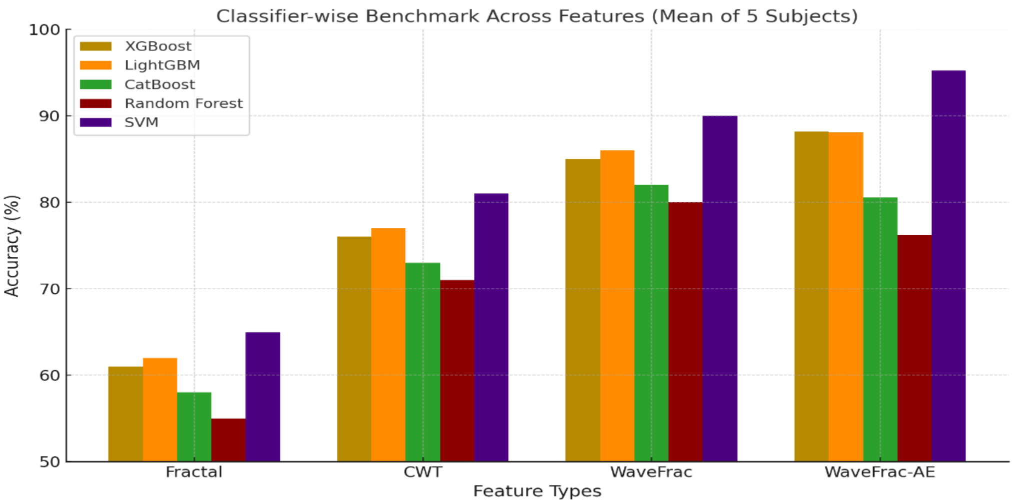

Figure 10. Benchmarking of feature sets across classifiers (Mean of 5 subjects)

All previous analyses were performed on a subject-specific basis, assessing classification performance individually. However, to evaluate the generalizability of the proposed WaveFrac-AE framework, additional experiments were conducted under a common-subject paradigm, where EEG data from all five subjects were combined to train a single, unified model. In this approach, the aggregated dataset was partitioned into five folds for stratified cross-validation. In each iteration, four folds were used for training and the remaining fold for testing, ensuring that all subjects contributed to both the training and testing phases. This setup provides a more rigorous test of the model's robustness against inter-subject variability. As shown in Table 6, SVM achieved the highest accuracy at 92.03%, significantly outperforming other classifiers—XGBoost (78.67%), LightGBM (78.54%), CatBoost (71.36%), and Random Forest (69.17%). These results demonstrate SVM's strong ability to handle the complex, nonlinear structure of EEG data across diverse individuals. The consistently high performance of WaveFrac-AE + SVM confirms its capacity to generalize well, despite challenges posed by inter-individual differences in EEG signals, making it a robust solution for real-world, population-wide cognitive monitoring.

Table 6. 5-Fold average accuracy of the proposed WaveFrac-AE model for common-subject attention state classification

Models	**Mean Accuracy (%)**	**± SD (%)**
XGBoost	78.67	3.29
LightGBM	78.54	2.47
CatBoost	71.36	3.93
RandomForest	69.17	4.76
SVM	92.03	1.78

Figure 11 displays confusion matrices from the best-performing folds of each classifier under the common-subject paradigm, illustrating class-wise performance across the three attention states: focused, unfocused, and drowsy. SVM stands out with the most balanced performance—achieving 95% accuracy for classes 0 and 1, and 91% for class 2—aligning with its top overall accuracy of 92.03% (Table 6). XGBoost and LightGBM also performed reasonably well, particularly for class 2 (84%), but showed confusion between focused and unfocused states, suggesting less clear decision boundaries. CatBoost delivered moderate results, especially struggling with class 1 (66% accuracy), while Random Forest performed weakest overall, achieving only 58% for class 1 and displaying frequent misclassification between unfocused and drowsy states. Overall, Figure 10 reinforces that SVM not only leads in accuracy but also provides superior class-wise precision and balance, making it the most robust and generalizable model for EEG-based mental state classification across individuals.

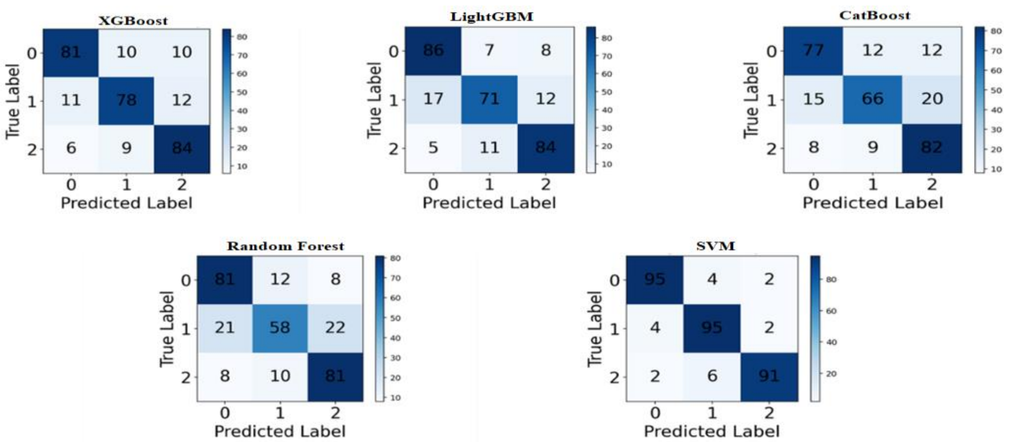

Figure 11. Confusion matrices of each classifier in the common-subject paradigm

Figure 12 presents ROC curves for all classifiers under the common-subject EEG modeling setup, offering a detailed view of each model's class discriminability. The SVM classifier achieved the highest AUC (0.98), confirming its strong ability to separate classes with minimal error, even amidst inter-subject variability. XGBoost and LightGBM also performed well, each with AUCs of 0.92, indicating effective pattern recognition and reliable class separation. In contrast, CatBoost (AUC = 0.89) and especially Random Forest (AUC = 0.87) showed reduced discriminative capability, with Random Forest's curve indicating higher misclassification. Overall, the ROC analysis confirms that SVM not only leads in accuracy but also excels in sensitivity and specificity, reaffirming its robustness and reliability for generalized EEG-based mental state classification

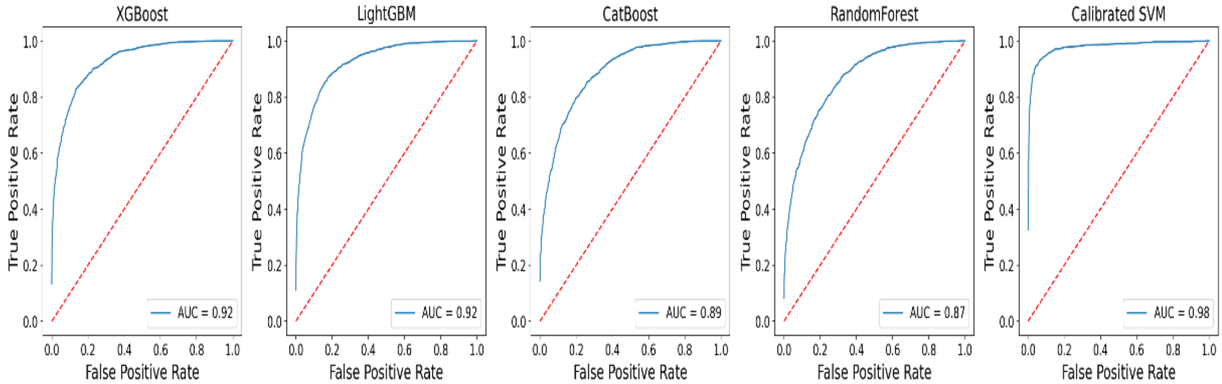

Figure 12. ROC curves and AUC scores of classifiers in the common-subject paradigm.

As summarized in Table 7, reported accuracies in EEG-based mental state classification vary considerably across studies, ranging from 83% to 97.2%, largely due to differences in datasets, number of classes, and evaluation strategies. In particular, Li et al. [51] achieved 97.2% using CWSTR-Net, which is numerically very close to the accuracy obtained in this study (97.52%). Although the numerical gain of 0.3% should not be overstated in the absence of identical datasets and train–test partitions, it is important to note that our study addresses the same number of mental state classes as Li et al. [51]. Under this comparable setting, the proposed method achieves performance that is highly competitive with, and in some cases slightly superior to, state-of-the-art approaches, highlighting its robustness and reliability. The significance of our contribution lies not merely in the numerical accuracy but in the methodological framework. Unlike prior works that rely exclusively on deep learning architectures (e.g., Wu et al. [50]) or kernel-based models (e.g., Wang et al. [52]), our approach integrates hybrid feature representations (WaveFrac-AE) with a robust SVM classifier. This combination effectively balances handcrafted signal characteristics with representation learning, leading to consistently high accuracies across all subjects. These findings confirm that the proposed methodology is both competitive and reliable within the current landscape of EEG-based mental state classification. While absolute superiority cannot be claimed without standardized benchmarking across datasets, the results clearly demonstrate that our framework provides a strong alternative to existing methods. In this respect, the study makes a meaningful contribution by achieving accuracy levels that are competitive with, and in some instances exceed, the best-reported results in the literature, while offering methodological novelty that enhances robustness and interpretability.

Tablo 7. Comparative analysis of mental state classification methods in EEG studies

Literature Studies	Dataset	Number of Mental State Classes	Method	Accuracy (%)
Zhang et al. [49]	EEG	2	Recurrent 3D-CNN	89.0
Wu et al. [50]	EEG	3	Deep Stacked Contractive Autoencoder	91.6
Li et al. [51]	EEG	3	CWSTR-Net	97.2
Wang et al. [52]	EEG	2	Multiple Kernel Learning (MKL)+SVM	84.3
Zeng et al. [53]	EEG	2	Generative-Domain-Adversarial Neural Network(GDANN)	91.63
Sonnleitner et al. [54]	EEG	2	Regularized Linear Discriminant Analysis (LDA)	92.0
Cao et al. [55]	EEG–fNIRS	3	SVM	83.0
Venkat and Chinara [56]	EEG	2	Wavelet Packet Transform+ Extra Trees Classifier	85.3-94.45
This study	**EEG**	**3**	**WaveFrac-AE + SVM**	**97.52**

Discussing and Conclusion

This study provides both theoretical and practical insights into EEG-based mental state classification. The proposed WaveFrac-AE framework integrates time–frequency features (via CWT) and fractal measures (PFD, Hurst, DFA), which are subsequently compressed using an Autoencoder to capture both short-term fluctuations and long-term dependencies. This hybrid design addresses the limitations of traditional narrow-band analyses by better modeling the complex, nonlinear, and non-stationary nature of EEG signals, thus offering a more comprehensive and interpretable representation of brain activity.

From a practical perspective, the study demonstrates that high-dimensional EEG features can be efficiently reduced while preserving critical information. This reduction significantly lowers computational complexity, which is a valuable step toward real-time feasibility. In particular, the consistently strong performance of SVM indicates that such hybrid representations are well-suited for classification tasks under constrained settings. While the accuracies achieved (over 97% for subject-specific and ~92% for common-subject evaluations) are promising, they should be interpreted with caution given the limited number of participants and the use of a controlled simulator environment. These results therefore serve as an encouraging proof of concept rather than a definitive claim of readiness for deployment in safety-critical systems.

Several limitations remain. The small participant pool restricts generalizability, as EEG signals are highly subject-dependent. More diverse populations are needed to validate robustness across users. Moreover, simulator-based recordings may not capture external artifacts and behavioral variations observed in real-world driving, where motion artifacts, fatigue, and environmental noise can degrade signal quality. While leave-one-subject-out validation would offer stronger insights into inter-subject generalization, the dataset size prevented its application; instead, a common-subject paradigm was adopted as a practical compromise.

Future work should extend this framework through multimodal integration (e.g., combining EEG with ECG, eye-tracking, or fNIRS) to enhance the robustness of cognitive state detection. In addition, expanding evaluations to larger, multi-subject datasets will be essential for improving the generalizability of the findings across diverse populations. Beyond the current hybrid WaveFrac-AE design, future studies will also investigate the integration of entropy-based measures and the use of alternative dimensionality reduction and compression techniques (in addition to Autoencoder), thereby enriching feature representations and reducing redundancy. Transfer learning strategies could further facilitate rapid adaptation to new users with minimal calibration. Finally, testing the framework in real-world driving and industrial environments will provide critical insights into its feasibility and practical deployment within advanced driver-assistance and neuroergonomic systems.

In summary, the study contributes a novel hybrid framework that demonstrates competitive performance and methodological robustness, while acknowledging the need for further validation before drawing strong conclusions regarding safety-critical applications.

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Informed consent: Not applicable.

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