



EEG-Based Driver Drowsiness Classification Using Support Vector Machine on Monotonous Road Driving Simulation

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Abstract

Driver drowsiness is a critical road safety issue responsible for thousands of traffic fatalities annually, particularly on monotonous road environments such as toll highways. This research introduces an Electroencephalography (EEG)-based driver drowsiness classification model using a Support Vector Machine (SVM) algorithm, with Observer Rated Sleepiness (ORS) as the ground truth. Data were collected from 22 licensed drivers who completed a 90-minute monotonic driving simulation in an ergonomics laboratory using the Muse S portable EEG device. The features extracted from the EEG consisted of mean and standard deviation for delta, theta, alpha, and beta band power each (14 in total) per one-minute epoch, as well as relative band power for each band and two ratios: the theta/alpha (θ/α) ratio and $(\theta+\alpha)/\beta$ ratio. Each classification was carried out using an SVM with a Radial Basis Function (RBF) kernel, and a One vs Rest (OvR) multi-class strategy, and the generalization power was validated using Leave-One-Subject-Out Cross Validation (LOSO-CV), which exhibits subject-independent generalization. Results showed an average LOSO-CV accuracy of 71.97% (SD = 14.67%) with a Macro-F1 score of 0.7187. The θ/α ratio was the most discriminative feature, increasing from -0.54 (alert) to 1.59 (severely drowsy). Analysis of drowsiness onset showed that physiological drowsiness onset occurred within the first 15 minutes of monotonous driving in 95.5% of subjects, much earlier than when drivers themselves reported feeling sleepy. The results of this study would provide strong evidence that portable EEG with SVM classification is a promising practical solution for real-time, accurate, and objective driver drowsiness detection in monotonous driving conditions.

Keywords: Drowsiness Detection, EEG, Monotonous Driving, Observer Rated Sleepiness, Support Vector Machine

1. INTRODUCTION

Driver drowsiness is a significant road safety concern and contributes to thousands of traffic accidents worldwide each year [1]. Drowsiness represents a transitional state between wakefulness and sleep, characterized by increased reaction time, reduced alertness, and impaired information processing [2], [3]. At more severe levels, drivers may experience microsleep, a brief episode of sleep lasting only a few seconds that occurs without conscious awareness, resulting in a temporary loss of responsiveness to road conditions despite appearing visually awake [4], [5]. This condition is commonly caused by sleep deprivation, prolonged driving duration, and monotonous driving environments [6], [7], and has been identified as a major risk factor for fatal crashes due to delayed or absent responses to traffic situations [8], [9].

The impact of drowsiness on road safety is reflected in the substantial number of traffic accidents worldwide. According to the World Health Organization (WHO) Global Status Report on Road Safety 2023, more than 1.2 million people die annually in road traffic crashes, with individuals aged 18–59 years representing the most affected group. Previous studies have estimated that drowsiness is involved in approximately 10–30% of road traffic accidents, although the actual prevalence is likely higher due to difficulties in objectively identifying fatigue-related incidents after a crash [8]. Importantly, many drowsiness-related crashes occur under normal weather, adequate lighting, and favorable road conditions, suggesting that the physiological state of the driver may represent a greater risk factor than external environmental conditions. These findings highlight the need for reliable methods capable of continuously monitoring driver alertness and detecting the onset of drowsiness before performance deteriorates to a dangerous level.

Electroencephalography (EEG) has been widely recognized as one of the most objective and sensitive physiological indicators for detecting driver drowsiness. Changes in brain activity, particularly increased power

in the alpha (8–12 Hz) and theta (4–8 Hz) frequency bands, have been strongly associated with declining alertness and the onset of microsleep [10], [11]. EEG enables real-time monitoring of brain electrical activity and can detect cognitive state changes within short time intervals, making it a promising technology for driver vigilance assessment [12]. Furthermore, recent advances in portable EEG technology have created opportunities for more practical and cost-effective driver monitoring systems compared with conventional clinical EEG equipment.

To safely and systematically induce drowsiness, driving simulators have been widely employed in experimental studies. Driving simulators allow researchers to replicate monotonous driving conditions in a controlled environment without compromising participant safety while maintaining consistency in variables such as driving duration, road characteristics, and lighting conditions [13], [14]. Previous studies have demonstrated that driving simulators can effectively reproduce fatigue and drowsiness patterns comparable to those observed in real-world driving, making them suitable platforms for EEG-based drowsiness research [15], [16], [17].

As a reference for drowsiness labeling, Observer Rated Sleepiness (ORS) has been widely adopted because it is non-invasive and has demonstrated validity against both physiological and behavioral indicators. ORS has shown significant correlations with the Karolinska Sleepiness Scale (KSS), Slow Eye Movements (SEM), and EEG alpha and theta activity [18], [19]. Nevertheless, ORS is subject to limitations, including inter-rater variability and lower sensitivity in detecting subtle changes during the early stages of drowsiness [20]. Consequently, Combining, Observer Rated Sleepiness (ORS) with EEG signals may improve drowsiness detection accuracy by integrating behavioral observations with physiological measurements.

For the classification stage, Support Vector Machine (SVM) has been extensively applied in EEG-based studies due to its ability to handle high-dimensional and nonlinear data effectively [21], [22]. SVM has demonstrated strong performance in identifying complex patterns within EEG signals and has achieved high classification accuracy across various neuroergonomics applications [23], [24]. In addition, SVM offers strong generalization capabilities for medium-sized datasets and is less prone to overfitting than deep learning approaches, which typically require substantially larger amounts of labeled training data [25].

Despite the growing body of research on EEG-based drowsiness detection, several important gaps remain. Most existing studies have been conducted using populations and environmental conditions that differ from those found in Indonesia. Moreover, many studies rely on multi-channel clinical EEG systems that are impractical for real-world deployment and do not employ subject-independent validation schemes capable of evaluating model performance on previously unseen drivers. To date, studies specifically developing EEG-based driver drowsiness classification models using Indonesian driver populations, particularly under monotonous toll-road conditions such as those found in North Sumatra, remain limited.

This study aims to design a driver drowsiness level classification model based on EEG signals using an SVM algorithm, with ORS ratings serving as the ground truth labeling reference. Data were collected from 22 drivers using a portable Muse S EEG device during a simulated monotonous driving scenario, and the model was evaluated using a Leave-One-Subject-Out Cross-Validation (LOSO-CV) scheme to assess subject-independent generalizability.

The contributions of this work are: (1) a three-class drowsiness classification model (alert, mildly drowsy, severely drowsy) built on portable single-device EEG and validated through subject-independent evaluation; (2) integration of ORS as a behavioral-physiological labeling reference bridging observational and signal-based assessment; (3) demonstration of SVM generalizability to new drivers under monotonous driving conditions via LOSO-CV; and (4) a scientific foundation for developing portable, cost-effective drowsiness early warning systems applicable to real-world driving safety at scale.

2. MATERIALS AND METHOD

2.1. Research Design and Location

In this study, a quantitative experimental research design was implemented collecting Electroencephalography (EEG) signals and ORS scores from drivers over monotony driving simulation in a controlled manner. Experiments carried out in Ergonomics Laboratory, Department of Industrial Engineering, Faculty of Engineering, Universitas Sumatera Utara (USU) The laboratory features a driving simulator for performing controlled driving simulations and a Muse EEG device used to capture brain signals so researchers can conduct experimental physiological or cognitive research (under controlled conditions).

2.2. Participants

Twenty-two participants were recruited using judgment sampling (purposive sampling), selecting individuals with characteristics specifically relevant to the research objectives. This technique was chosen because the study requires subjects with specific characteristics not obtainable through random selection namely drivers with active driving experience capable of undertaking a 90-minute uninterrupted experimental protocol. Sample size determination of 22 subjects was based on EEG drowsiness detection studies using

LOSO-CV validation schemes, which typically involve 15–30 subjects to produce stable model generalization estimates.

Participants were required to: (1) hold an active Class A driving license for at least 2 years since first obtaining this license; (2) be aged between 20 and 45 years; (3) have refrained from caffeine, alcohol, or alertness-affecting medications for a minimum of six hours prior to the experiment; (4) have achieved appropriate sleep (minimum of 6 continuous hours off nightly sleep) during the night preceding the experiment; (5) comply with inclusion criteria without or minimal illness or health condition(s)/disorder(s); and finally, but perhaps most importantly they must be willing to perform the full 90-minute experimental protocol without breaks.

2.3. Research Instruments

In a single session, each participant performed a 90-min monotonic driving simulation. In this study, the simulator allowed for a continuous toll road setting without distractions from traffic or shift of visual stimulus to help induce drowsiness in a controlled manner. Before the data collection, the Muse S was completely charged and linked with a smartphone through the Mind Monitor app. The device was placed on the participant's head in such a way that signals from all four electrodes were stable. Before starting the simulation participants sat quietly for 1–2 min for EEG baseline calibration. Continuous EEG recording and video recording were performed over the complete 90 min session. The per-second band power values in CSV format were stored.

2.4. Experimental Protocol

Each participant completed a 90-minute monotonous driving simulation in a single session. The simulation replicated a continuous toll road scenario without traffic interactions or visual distractions to systematically induce drowsiness. EEG was recorded continuously throughout the session using the Muse S device, while simultaneous video recording was conducted to support ORS assessment. Participants were instructed to drive as they would normally, without being informed about the specific hypotheses of the study to minimize behavioral bias.

2.5. Observer Rated Sleepiness (ORS)

The Driving with ORS was assessed by a trained observer coding video recordings of each participant driving sessions [26]. Data throughout the full sleep study was recorded at one-minute intervals in the following levels, where ORS0 (alert) eyes blinking normally without yawning and a stable upright body posture; ORS1 mildly drowsy, no effort to stay awake some eye lid closure but will open eyes on command, reliable scoring of consistency with use of time, monotonous scale; ORS2 severely drowsy half-closed eyes with vacant gaze accompanied by specific criteria (frequent yawning occur every minute between nodding). This resulted in 90 ORS labels per subject for a total of 1980 labels across all 22 subjects.

ORS was chosen as ground truth since it reflects objective third-party observations of sleepiness-related behavior (as opposed to self-report measures such as the KSS which are affected by stigma). It has been shown to correlate positively with KSS, lateral vehicle deviation and slow eye movements as well as EEG alpha and theta activity, demonstrating its convergent validity[18][27].

2.6. EEG Signal Processing and Feature Extraction

The Mind Monitor application recorded the EEG data of each participant in comma-separated values (CSV) file format, with internal Fast Fourier Transform (FFT)-based calculation for band power estimates at each second. Segments of data were split into epochs by calendar minute (90 epochs per subject, 1,980 for the entire cohort). The segmentation aligned with the per-minute ORS labels to create a labeled dataset for supervised learning.

Fourteen features were extracted per epoch: (a) mean band power for delta, theta, alpha, and beta (4 features); (b) standard deviation of band power for the same four bands (4 features); (c) relative band power for each band, calculated as $\text{Relative Power}(\text{band}) = \text{Mean}(\text{band}) / (\text{Mean}(\delta) + \text{Mean}(\theta) + \text{Mean}(\alpha) + \text{Mean}(\beta))$ (4 features); (d) theta/alpha (θ/α) ratio, a primary indicator of drowsiness as theta increases while alpha decreases; and (e) the $(\theta+\alpha)/\beta$ ratio, reflecting low-to-high frequency transitions during wake-to-sleep transitions.

Epoch completeness analysis confirmed that 95.1% of all 1,980 epochs contained at least 51–59 valid seconds (mean = 58.0 s, median = 59.0 s), indicating consistent recording quality throughout. Only epochs with more than 10 valid seconds were retained; one epoch was excluded on this basis ($N = 1$).

2.7. SVM Classification Model

SVM, an algorithm that separates data classes through a maximum-margin hyperplane in feature space [33], was used for classification. Due to the complex and non-linear overlap of EEG patterns at various levels of drowsiness, we used the Radial Basis Function (RBF) kernel, which is defined as:

$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$ where x_i and x_j are 14-dimensional EEG feature vectors, $\|x_i - x_j\|^2$ its squared Euclidean distance between the two points; where γ controls how much influence a single training example has over the area around it on decision boundary.

Finally, because drowsiness labels were present in three ORS classes, multi-class SVM was performed using the One-vs-Rest (OvR) strategy by constructing three binary classifiers: SVM₀ (ORS 0 vs {ORS 1, ORS 2}), SVM₁ (ORS 1 vs {ORS 0, ORS 2}) and SVM₂ (ORS 2 vs {ORS 0, ORS 1}). The classifier with the largest decision score made the final classification.

Leave-One-Subject-Out Cross Validation (LOSO-CV) scheme was applied both for training and testing, allowing us to assess subject-independent generalizability by leaving each fold as test set with one subject as a test set and 21 others as the training subjects. Hyperparameters C and γ were tuned using logarithmic grid search ($C \in \{10^{-2}, 10^{-1}, \dots, 10^3\}$; $\gamma \in \{10^{-4}, 10^{-3}, \dots, 10^0\}$) with nested cross-validation on training data. You use z-score standardization during feature normalization, where the mean and standard deviation are computed from training data on each fold.

Then, a last model was trained on all 1,980 epochs with median parameters from LOSO-CV ($C = 10$, $\gamma = 0.0550$, KernelScale = 3.01511) in order to classify new drivers not belonging to the training data. Evaluation Metrics The performance of the best Hyperparameter tuned-optimized models were evaluated using metrics such as Accuracy, Precision, Recall, F1-score per class and Macro-F1 score.

2.8. Drowsiness Onset Detection

Onset of drowsiness analysis was conducted to determine the first minute during which each driver exhibited at least one drowsy state across the 90-minute session. Onset was then classified into two categories: (1) Mild Onset -first minute of ORS ≥ 1 sustained for at least-two consecutive-minutes; (2) Severe Onset -first minute of ORS=2-sustained-at-least 2- consecutive minutes. To ensure that there were no momentary fluctuations in the EEG detectable over a two-minute period falsely categorizing participants as having (or not having) mental phenomena, we imposed a continuity requirement of two minutes for both sleep and wake. Onset was calculated (as a difference between true ORS labels and SVM predictions) separately for each participant and assessed whether our model can detect the onset early enough.

3. RESULTS AND DISCUSSION

3.1. EEG Signal Preprocessing

Electroencephalography (EEG) preprocessing in this study was performed by the device- and application-level pipelines Muse S for acquisition and Mind Monitor for recording and band-power estimation without a custom offline preprocessing chain. The Muse S applies an internal analog bandpass filter during acquisition to attenuate frequencies outside the physiologically relevant EEG range (approximately 1–50 Hz), reducing DC drift and high-frequency electrical noise. Mind Monitor computes per-second absolute band power estimates using an FFT-based algorithm for the delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) bands and writes these values continuously to CSV. These built-in filtering and spectral-decomposition steps constitute the primary preprocessing layer for all EEG data in this study. No additional offline processing (e.g., independent component analysis, manual artifact rejection, or adaptive filtering) was applied; this limitation of consumer-grade EEG acquisition is discussed further in Section 3.7 (Limitations and Future Work).

Artifact handling (eye blinks and motion) relied on procedural measures in the absence of a dedicated artifact-rejection pipeline. First, each session began with a 1–2 minute baseline stabilization period during which participants sat quietly to allow the EEG signal to stabilize and to provide a reference window for signal-quality assessment. Second, epoch-level completeness filtering excluded epochs containing fewer than 10 valid seconds of recording. Of 1,980 total epochs, only one epoch was excluded by this criterion; 95.1% of epochs contained 51–59 valid seconds (mean = 58.0 s, median = 59.0 s). Residual transient artifacts (e.g., isolated eye blinks) were not removed individually; because features were computed as per-minute means and standard deviations across 51–59 seconds of data, brief transient artifacts had minimal influence on epoch-level feature values.

Inspection of extracted features revealed negative values in certain ratio and relative-power features, particularly at ORS 0 and in epochs with low valid-second counts where band power had not stabilized. Specifically, 22 epochs showed θ/α ratio values below -5 , and 383 epochs exhibited negative Relative Theta values attributable to early-session band-power fluctuations. These epochs were retained in the analysis for two reasons: (1) their proportion relative to the full 1,980-epoch dataset was small (e.g., 19.4% for negative Relative Theta), and (2) the SVM classifier with Radial Basis Function (RBF) kernel is relatively robust to moderate feature outliers through margin maximization, provided outliers do not dominate the training distribution. The impact of these artifacts and outliers was assessed implicitly via LOSO-CV, which tests generalization across subjects including those with higher artifact prevalence.

Prior to SVM training, all 14 features were normalized using z-score standardization applied separately within each LOSO-CV fold. Normalization parameters (mean μ and standard deviation σ) were computed

exclusively from each fold's training set (21 subjects) and applied to the corresponding test subject's data as shown in equation 1.

$$\tilde{x} = (x - \mu_{\text{train}}) / \sigma_{\text{train}} \quad (1)$$

This fold-specific normalization prevents data leakage from test to training data and ensures that LOSO-CV generalization estimates reflect true subject-independent performance. For the final model trained on all 1,980 epochs, normalization parameters were computed from the full training dataset.

3.2. EEG Feature Characteristics per ORS Class

The descriptive statistics of EEG features across the three ORS classes are presented in Table 1. The table summarizes the mean values of frequency-domain EEG parameters obtained from 1,980 epochs, providing an overview of the changes in brain activity patterns associated with increasing drowsiness levels.

Table 1. Mean EEG Feature Values per ORS Class (N = 1,980 Epochs)

Feature	ORS 0 – Alert (n=600)	ORS 1 – Mild (n=768)	ORS 2 – Severe (n=612)
Mean Theta	−0.7416	10.9583	20.3939
Mean Alpha	15.9407	23.0674	17.6616
Relative Theta	0.0248	0.1138	0.2017
Relative Alpha	0.2643	0.2949	0.2085
θ/α Ratio	−0.5420	0.5043	1.5931
$(\theta+\alpha)/\beta$ Ratio	−0.9533	1.8111	2.9202

Mean Theta increased progressively from −0.74 (ORS 0) to 10.96 (ORS 1) and 20.39 (ORS 2), confirming theta activity as a strong marker of drowsiness onset. Relative Theta rose from 0.025 to 0.202, while Relative Alpha declined from 0.264 to 0.209, reflecting a shift in brain dominance from high- toward low-frequency activity consistent with established drowsiness neurophysiology. The θ/α ratio was the most discriminative feature, with values exceeding 1.0 serving as a clear threshold for the alert-to-severe-drowsiness transition. The $(\theta+\alpha)/\beta$ ratio increased from −0.95 to 2.92, further confirming low-frequency dominance in the severely drowsy state.

Some negative values appear in ratio and relative power features at ORS 0, attributable to outlier epochs with very low N_{Detik} values, where recorded band power was not yet stable. Specifically, 22 epochs showed $\text{Ratio_TA} < -5$ and 383 epochs had negative Relative Theta calculation artifacts from band power fluctuations in the early seconds of recording. These epochs were retained in analysis as their overall impact on model training was minimal given the full dataset size of 1,980 epochs.

3.3. ORS Label Distribution

The ORS label distribution across all 1,980 epochs showed a relatively balanced spread: 600 epochs (30.3%) labeled ORS 0 (alert), 768 epochs (38.8%) labeled ORS 1 (mildly drowsy), and 612 epochs (30.9%) labeled ORS 2 (severely drowsy). This balanced distribution is favorable for SVM training as it minimizes the risk of classification bias due to class imbalance.

Substantial inter-individual variability was observed in ORS distribution per subject. The earliest drowsiness onset occurred at minute 2 (S011 and S016), while the latest was at minute 54 (S010). Subjects S007 and S008 showed heavy drowsiness dominance with 61 and 56 ORS 2 epochs respectively, while S006, S017, and S010 were dominated by the alert state with 57, 64, and 61 ORS 0 epochs.

3.4. SVM Classification Performance (LOSO-CV)

Table 2 presents the per-subject LOSO-CV accuracy results across all 22 folds. The overall mean accuracy was 71.97% with a standard deviation of 14.67%.

Table 2. LOSO-CV Accuracy and Optimal Parameters per Subject

Fold	Subject	Accuracy (%)	Best C	Best γ
1	S001	63.33	1	0.1
2	S002	70.00	1	0.1
3	S003	53.33	100	0.01
4	S004	80.00	1	0.1
5	S005	74.44	10	0.01
6	S006	84.44	10	0.1
7	S007	73.33	100	0.01
8	S008	80.00	1	0.1
9	S009	81.11	1	0.1
10	S010	82.22	1	0.1

Fold	Subject	Accuracy (%)	Best C	Best γ
11	S011	83.33	1	0.1
12	S012	90.00	1	0.1
13	S013	73.33	1,000	0.001
14	S014	75.56	100	0.01
15	S015	34.44	10	0.01
16	S016	84.44	1	0.1
17	S017	85.56	100	0.01
18	S018	84.44	1,000	0.01
19	S019	41.11	10	0.01
20	S020	57.78	10	0.1
21	S021	64.44	1	0.1
22	S022	66.67	100	0.01
Mean		71.97 $\pm$ 14.67		

Table 3 presents the per-class evaluation metrics obtained from the complete LOSO-CV evaluation. The performance of the SVM model was assessed using precision, recall, and F1-score for each ORS class to evaluate its ability to distinguish between different levels of drowsiness. These metrics provide a more detailed interpretation of classification performance beyond overall accuracy by highlighting the reliability and balance of predictions across classes.

Table 3. SVM Classification Metrics per ORS Class

Class	Precision	Recall	F1-Score	Support
ORS 0 (Alert)	0.7601	0.6867	0.7215	600
ORS 1 (Mild Drowsy)	0.7019	0.7604	0.7300	768
ORS 2 (Severe Drowsy)	0.7079	0.7010	0.7044	612
Macro-F1	–	–	0.7187	1,980

The Macro-F1 score of 0.7187 reflects balanced performance across all three classes. ORS 1 achieved the highest F1-score (0.7300) with a recall of 0.7604, indicating the model's greatest reliability in detecting transitional drowsiness. ORS 0 had the highest precision (0.7601), meaning that when the model predicts an alert state, this prediction is most likely correct. ORS 2 showed the lowest F1-score (0.7044), though the difference from other classes was marginal.

From a road safety perspective, recall of ORS 2 at 0.7010 indicates the model correctly identified 7 out of 10 severe drowsiness cases. False negatives in ORS 2 (missed severe drowsiness) carry greater safety consequences than misclassifications in other classes, making improvement of ORS 2 recall a priority for future model development.

Confusion matrix analysis showed that the largest classification errors occurred at class boundaries: 112 ORS 0 epochs were misclassified as ORS 1 (18.7%), and 136 ORS 2 epochs were misclassified as ORS 1 (22.2%). This pattern is expected given ORS 1's transitional nature, with EEG features overlapping adjacent classes. The parameter combination $C=1$, $\gamma=0.1$ was most frequently selected (10 of 22 folds), suggesting that moderate regularization and broad kernel scope generalize best across subjects.

Per-subject accuracy ranged from 34.44% (S015) to 90.00% (S012). Subjects with lower accuracy S015 (34.44%) and S019 (41.11%) likely possessed idiosyncratic EEG patterns insufficiently represented in training data from the other 21 subjects. Subjects with high accuracy S012 (90.00%), S017 (85.56%), S006 (84.44%), S016 (84.44%), S018 (84.44%) showed EEG patterns consistent with the general population. This inter-subject variability is a well-known challenge in subject-independent EEG-based drowsiness detection systems.

3.5. Final Classification Model and Mathematical Representation

A final SVM model was trained on all 1,980 epochs using median parameters from LOSO-CV ($C = 10$, $\gamma = 0.0550$, $\text{KernelScale} = 3.01511$). Table 4 summarizes the final model parameters.

Table 4. Final SVM Model Parameters

Parameter	Description	Value
Kernel	Kernel function	Radial Basis Function (RBF)
C	Box constraint (regularization)	10
γ (gamma)	RBF kernel parameter	0.0550
KernelScale	Kernel scale ($1/\sqrt{2\gamma}$)	3.01511
Multi-class strategy	Classification approach	One-vs-Rest (OvR)
Input features	Feature vector dimension	14
Training data	Total training epochs	1,980 epochs

The RBF kernel function used in the final model is defined as known in equation 2.

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2) = \exp(-0.0550 \|x_i - x_j\|^2) \quad (2)$$

where x_i and x_j are 14-dimensional EEG feature vectors of two compared epochs, $\|x_i - x_j\|^2$ is the squared Euclidean distance, and $\gamma = 0.0550$ controls the influence range of each data point on the shape of the decision boundary. Under the One-vs-Rest strategy, the final model comprises three binary decision functions, as shown in equation 3.

$$\begin{aligned} f_0(x) &= \sum \alpha_i^0 \cdot y_i^0 \cdot K(x_i, x) + b_0 \rightarrow \text{ORS 0 vs } \{\text{ORS 1, ORS 2}\} \\ f_1(x) &= \sum \alpha_i^1 \cdot y_i^1 \cdot K(x_i, x) + b_1 \rightarrow \text{ORS 1 vs } \{\text{ORS 0, ORS 2}\} \\ f_2(x) &= \sum \alpha_i^2 \cdot y_i^2 \cdot K(x_i, x) + b_2 \rightarrow \text{ORS 2 vs } \{\text{ORS 0, ORS 1}\} \end{aligned} \quad (3)$$

where α_i are Lagrange coefficients obtained from the optimization process, y_i are binary labels (+1 or -1), and b is the bias term. The final classification decision is determined by the classifier with the highest score as shown in equation 4.

$$\hat{Y} = \operatorname{argmax}_k f_k(\tilde{x}), \quad k \in \{0, 1, 2\} \quad (4)$$

where $\tilde{x} = (x - \mu) / \sigma$ is the feature vector normalized using the mean (μ) and standard deviation (σ) of the full training data.

The model consists of three binary classifiers with the following support vector counts: SVM₀ (ORS 0 vs others): 800 SVs; SVM₁ (ORS 1 vs others): 1,077 SVs; SVM₂ (ORS 2 vs others): 842 SVs; Total: 2,719 SVs. SVM₁ carries the most support vectors (1,077), consistent with ORS 1 as a transitional class with the greatest feature overlap between adjacent classes. The total SVs (2,719) exceeding the training data count (1,980) indicates that a single epoch can serve as a support vector in multiple classifiers, as expected behavior in OvR multi-class implementations.

3.6. Drowsiness Onset Detection

Table 5 presents onset detection results for all 22 subjects. All 22 subjects experienced mild drowsiness onset during the session, with actual onset ranging from minute 2 to minute 54 (mean: 7.4 min). Critically, 21 of 22 subjects (95.5%) showed onset within the first 15 minutes.

Table 5. Drowsiness Onset Detection Results per Subject

Subject	Mild Onset Actual (min)	Mild Onset Pred. (min)	Severe Onset Actual (min)	Severe Onset Pred. (min)
S001	3	1	9	3
S002	8	1	11	11
S003	6	1	8	1
S004	5	5	29	24
S005	5	1	15	5
S006	4	3	84	—
S007	7	1	13	1
S008	8	2	19	4
S009	5	1	6	9
S010	54	7	—	—
S011	2	16	57	—
S012	10	11	42	42
S013	3	1	5	1
S014	6	1	26	1
S015	5	1	6	4
S016	2	2	—	3
S017	3	14	75	—
S018	5	5	—	—
S019	5	1	17	1
S020	8	20	14	—
S021	5	1	19	2
S022	4	1	18	1

The SVM model detected mild drowsiness onset in all 22 subjects with a mean predicted onset of 4.4 minutes earlier than observer-rated onset in 68.2% of cases. The median absolute onset prediction error was 4.0 minutes, with 68.2% of predictions within a 5-minute window of actual onset. The tendency toward earlier

SVM prediction indicates that EEG signals capture pre-behavioral drowsiness markers before they manifest in observable behavior a key advantage of physiological over behavioral monitoring.

Severe drowsiness (ORS 2) onset was detected in 19 of 22 subjects by actual ORS assessment. The model correctly predicted no severe onset for S010 and S018, but incorrectly predicted onset for S016 (minute 3, no actual severe onset). The model failed to detect severe onset in S006 (actual minute 84), S011 (minute 57), S017 (minute 75), and S020 (minute 14), subjects who showed high EEG variability. The concentration of onset within the first 15 minutes carries critical implications: drowsiness warning systems must be activated from the first minute of monotonous driving, not only after visible behavioral signs emerge.

3.7. Physiological vs. Subjective Drowsiness Gap

The preliminary survey indicated that 72.7% of respondents identified monotonous roads as the primary drowsiness trigger. This received strong physiological confirmation: all 22 subjects developed drowsiness during the monotonous simulation, with Mean Theta increasing from -0.74 (ORS 0) to 20.39 (ORS 2) and the θ/α ratio rising from -0.54 to 1.59 . Monotonous driving objectively induces drowsiness across the entire subject population, aligning with the subjective majority perception.

The most significant finding is the substantial discrepancy between subjectively perceived and physiologically measured drowsiness onset. The preliminary survey indicated that 27.3% of respondents first felt drowsy after 30–60 minutes, and 25.8% after 1–2 hours of driving. In contrast, EEG data showed that 95.5% of subjects experienced physiological drowsiness onset before minute 15, with a mean actual onset of just 7.4 minutes. The SVM model detected onset at an even earlier mean of 4.4 minutes. This gap potentially 20–50 minutes represents a critical safety blind spot. The phenomenon, known as sleepiness unawareness, implies that relying on driver self-awareness as a safety mechanism is fundamentally insufficient.

Furthermore, the preliminary survey reported that more than 30% of respondents had experienced microsleep indicators (not remembering events from the previous seconds), and approximately 20% had experienced unintentional lane departures. This study provides direct physiological validation: 19 of 22 subjects (86.4%) experienced severe drowsiness (ORS 2) during the session, with the $(\theta+\alpha)/\beta$ ratio increasing from -0.95 (alert) to 2.92 (severely drowsy), confirming dominant low-frequency brain activity characteristic of the pre-microsleep state. These results establish that subjectively reported symptoms are supported by objectively measurable brain wave changes.

4. CONCLUSION

This study successfully developed and validated an EEG-based driver drowsiness classification model using Support Vector Machine (SVM) with Observer Rated Sleepiness (ORS) as ground truth in a monotonous driving simulation, yielding three principal conclusions:

First, Electroencephalography (EEG) signals exhibit consistent, progressive changes with increasing drowsiness. Mean Theta increased from -0.74 (alert) to 20.39 (severely drowsy), Relative Theta rose from 0.025 to 0.202 , and Relative Alpha declined from 0.264 to 0.209 . The θ/α ratio was the most discriminative feature, with values exceeding 1.0 serving as a clear marker of the alert-to-severe-drowsiness transition. The $(\theta+\alpha)/\beta$ ratio increased from -0.95 to 2.92 , confirming dominant low-frequency brain activity in the severely drowsy state.

Second, the SVM model with a Radial Basis Function (RBF) kernel and One vs Rest (OvR) multi-class strategy achieved a Leave-One-Subject-Out Cross Validation (LOSO-CV) mean accuracy of 71.97% (Macro-F1 = 0.7187), within the 70–80% range reported in the literature for subject-independent EEG drowsiness detection. The final model ($C=10$, $\gamma=0.0550$, 2,719 support vectors) successfully detected mild drowsiness onset in all 22 subjects with a median prediction error of 4.0 minutes and 68.2% of predictions within a 5-minute window.

Third, a critical safety finding is that physiological drowsiness onset via EEG occurs at a mean of 7.4 minutes into monotonous driving, while drivers subjectively estimate onset at 30–60+ minutes a potential 20–50 minute discrepancy. This sleepiness-unawareness blind spot cannot be addressed solely through driver self-monitoring. Future research should explore increased EEG channel counts, subject-adaptive models, deep learning approaches, and real-world validation to further improve practical applicability and detection accuracy.

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