

# Machine Learning for Physiological-Data-Based Driver Monitoring Systems: A Comparative Review and Experimental Case Study on Classification and Regression Approaches

## Fizyolojik Veriye Dayalı Sürücü İzleme Sistemleri İçin Makine Öğrenmesi: Sınıflandırma ve Regresyon Yaklaşımlarına Yönelik Karşılaştırmalı Bir Derleme ve Deneysel Örnek Olay Çalışması

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### Özet

Trafik kazaları, küresel çapta büyük kayıplara yol açan ciddi bir sorundur ve temelinde yorgunluk, dikkat kaybı ile uyku hali gibi insani faktörler yatar. Erken dönem ADAS sistemleri dış tehditleri ve araç dinamiklerini izleyerek daha çok reaktif (tepkisel) önlemlere odaklanırken, günümüzde proaktif (önleyici) Sürücü İzleme Sistemlerine (SİS) doğru temel bir paradigma değişimi yaşanmaktadır. Bu modern sistemler, kritik bir durum henüz ortaya çıkmadan riskleri tahmin edip önleyebilmek adına doğrudan sürücünün vücudundan alınan fizyolojik verileri kullanır. Bu çalışma, makine öğrenmesi (MÖ) modellerinin sürücü fizyolojik verilerini analiz etmede nasıl kullanıldığını incelemekte; sınıflandırma ve regresyon yaklaşımlarını karşılaştırmalı olarak ele alan kapsamlı bir literatür derlemesi sunmaktadır. Çalışmada temel fizyolojik ve davranışsal metrikler incelenmiş, çeşitli MÖ modellerinin uygulama alanları ve etkinlikleri analiz edilmiş; ayrıca veri değişkenliği, gerçek zamanlı işleme zorlukları ve sensör kısıtlamaları gibi kritik sorunlar tartışılmıştır. Derleme sonucunda, derin öğrenme yöntemlerinin artan gücü ve bu sistemlerin gerçek dünya koşullarında sağlam, genellenebilir bir şekilde çalışabilmesi için çok modlu sensör füzyonunun taşıdığı stratejik önem açıkça vurgulanmaktadır. Anahtar kelimeler: Makine Öğrenmesi (MÖ), Derin Öğrenme (DÖ), Sürücü İzleme Sistemi (SİS), Fizyolojik Sinyaller, ADAS

### Abstract

Traffic collisions remain a devastating global issue. Human error — specifically fatigue, loss of focus, and drowsiness — plays a massive role in these tragic events. Early Advanced Driver Assistance Systems (ADAS) mainly took a reactive approach, keeping an eye on external threats and vehicle movements. However, the automotive industry is currently undergoing a massive philosophical shift toward proactive Driver Monitoring Systems (DMS). Instead of waiting for a car to swerve, these modern setups look directly at the driver's own physiological data. By doing so, they can predict and neutralize

risks long before an actual emergency happens. This paper takes a deep dive into how researchers are applying machine learning (ML) models to analyze this physiological data, specifically comparing classification and regression techniques. The core behavioral and physical metrics are broken down, to evaluate how well different ML algorithms actually perform, and tackle the messy, real-world challenges like sensor limits and unpredictable data. Ultimately, this review points out that deep learning is rapidly taking over the field, and combining different types of sensors (multimodal fusion) is the smartest strategy for building reliable systems that work in chaotic, everyday driving conditions.

Keywords: Machine Learning (ML), Deep Learning (DL), Driver Monitoring System (DMS), Physiological Signals, ADAS

### 1. Introduction

Driving is a complex, dynamic task that requires drivers to continuously integrate visual input, cognitive judgment, and physical control [6]. This continuous demand on attention causes mental workload to fluctuate, at times pushing drivers toward inattention or fatigue — factors that are responsible for a substantial share of traffic accidents worldwide [7]. Existing driver-assistance technologies, such as lane-departure and forward-collision warnings, address this problem reactively: they intervene only after a hazardous situation has already begun to develop, rather than addressing its root cause, namely the compromised physiological or cognitive state of the driver [1].

Consequently, the automotive safety field is undergoing a shift from reactive interventions toward proactive Driver Monitoring Systems (DMS). Continuous assessment of physiological data provides a direct and objective measure of a driver's internal state [2], enabling predictive rather than reactive interventions. This need is amplified by the growing automation of driving tasks, which paradoxically increases the risk of driver disengagement and reduced vigilance.

Driver-state monitoring has been studied by human-factors researchers for decades, drawing on foundational concepts such as the Yerkes–Dodson law of arousal [6]. Recent advances in

low-cost, high-fidelity sensing have accelerated interest from both academia and industry in monitoring driver state alongside vehicle state [6]. This interest has translated into regulatory action: the European Union mandated DMS in all new vehicle models beginning in 2024, and Euro NCAP now awards safety-rating credit to vehicles equipped with such systems [2]. Recent systematic reviews confirm that the field has grown rapidly across vision-based, physiological, and multimodal approaches, with an increasing share of studies now employing deep learning rather than classical pipelines [33], and highlight that distraction- and drowsiness-detection research remains dominated by visual modalities even as physiological and multimodal methods gain traction [34]. Complementary surveys of cognitive-state recognition report that deep learning became the dominant methodology in this space by 2023, alongside a broader movement toward multimodal physiological sensing [3], while a systematic review of driver-state detection technologies further catalogues the growing diversity of physiological and vehicular sensing approaches [35], and device-level reviews continue to track new wearable and health-monitoring hardware entering this application space [36].

Modern sensing technologies allow continuous, largely unobtrusive acquisition of physiological signals — including heart rate, respiration, and eye movement — while a person drives [6]. However, raw physiological data has limited value without interpretation, which is where machine learning becomes essential: ML algorithms are able to extract subtle, non-obvious patterns from complex biological signals that correspond to states such as drowsiness or distraction [10].

This paper reviews current machine learning strategies for interpreting driver physiological data, focusing on two complementary paradigms: classification, which assigns discrete driver states (e.g., "awake" versus "drowsy"), and regression, which predicts driver state on a continuous scale. Section 2 outlines the physiological and behavioral indicators used in this literature; Section 3 reviews the ML models applied to these indicators; Section 4 discusses evaluation metrics, data-quality challenges, and multimodal sensor fusion; Section 5 presents an original experimental case study applying several of these models to a physiological dataset; and Section 6 concludes with implications for future work.

2. Methods: physiological and behavioral indicators

2.1. Physiological measures from the human body

2.1.1. Cardiovascular markers

Heart rate (HR) and heart rate variability (HRV) are frequently examined because they provide a direct window into autonomic nervous system activity [6]. Under stress, fatigue, or cognitive overload, heart rate typically increases while HRV decreases, and these physiological shifts are often associated with degraded driving performance [12]. Electrocardiography (ECG) remains the gold-standard acquisition method, although its reliance on skin-contact electrodes limits comfort and practicality in everyday driving. Photoplethysmography (PPG) offers a less intrusive alternative with comparable diagnostic value [13].

2.1.2. Neurophysiological signals

Electroencephalography (EEG) captures the brain's electrical activity and is highly informative regarding alertness state. The slow  $\delta$  (0.5–4 Hz) and  $\theta$  (4–8 Hz) bands become dominant during the onset of sleep, whereas  $\alpha$  (8–14 Hz) and  $\beta$  (14–25 Hz) bands are associated with relaxed or actively attentive states [14]. A shift in spectral power from  $\beta$  toward  $\alpha$  and  $\theta$  activity is a reliable indicator of increasing drowsiness [14]. Electrooculography (EOG) is similarly effective for drowsiness detection, as it measures blink duration and Slow Eye Movements (SEM) [15]. Electrodermal activity (EDA, also referred to as GSR) quantifies sweat-gland activity via skin electrical resistance and serves as a proxy for mental workload [6].

2.2. Behavioral and vehicular cues

Camera-based facial monitoring provides an effective, non-invasive alternative to physiological sensing [16]. In-cabin cameras can detect heavy eyelids, yawning, and head-drooping behavior. A widely used metric is PERCLOS, defined as the percentage of time a driver's eyelids are at least 80% closed [8]. Vehicle-based indicators, such as irregular steering or lane-position drift, can likewise suggest a compromised driver state, although such measures must be interpreted cautiously, since poor road conditions or individual driving habits can confound the signal [19].

Table 1: Summary of physiological and vehicular signal types for driver state monitoring.

| Signal Type        | Derived Metric(s)                             | Indicator(s)          | Source             | Deployment              |
|--------------------|-----------------------------------------------|-----------------------|--------------------|-------------------------|
| Cardiovascular     | HR, HRV                                       | Workload, Stress      | ECG, PPG           | Contact / Non-contact   |
| Neurophysiological | EEG Bands ( $\delta, \theta, \alpha, \beta$ ) | Alertness, Drowsiness | EEG                | Invasive                |
| Ocular             | Blink Duration, SEM                           | Drowsiness            | EOG, Camera        | Contact / Non-intrusive |
| Autonomic (EDA)    | SCL, SCR                                      | Arousal, Workload     | GSR Sensor         | Contact                 |
| Behavioural        | PERCLOS, EAR, MAR                             | Drowsiness, Fatigue   | Camera             | Non-intrusive           |
| Vehicular          | Steering Angle, Lane Dev.                     | Fatigue, Aggression   | In-vehicle Sensors | Non-intrusive           |

### 3. Machine learning paradigms for driver state analysis

#### 3.1. Driver state classification: categorical detection

##### 3.1.1. Traditional machine learning

Traditional ML algorithms dominated the field prior to the widespread adoption of deep learning. Support Vector Machines (SVMs), for example, have proven effective at detecting impaired driving; combining physiological and vehicle-movement features, researchers achieved approximately 70% classification accuracy [21]. Random Forest classifiers also perform well when provided with hand-crafted features such as eye aspect ratio (EAR), effectively separating alert from drowsy drivers [23].

##### 3.1.2. The rise of deep learning

Convolutional Neural Networks (CNNs) have substantially advanced the field, particularly for the analysis of video streams and raw physiological signals [3]. Numerous well-established architectures have been applied to the drowsiness-detection problem, including VGG16, MobileNet, ResNet50V2, and AlexNet [16]. Reported results are often striking: one study

achieved 99.71% accuracy with ResNet50V2 on the NITYMED database [26], while another employed an ensemble of CNNs operating solely on in-vehicle sensor data and achieved a 94.2% detection rate [20].

#### 3.2. Driver state regression: continuous prediction

##### 3.2.1. Continuous physiological metrics

Rather than assigning discrete labels such as "awake" or "asleep," regression models predict driver state on a continuous scale, which is well suited to variables such as PERCLOS or seat-pressure distribution [9]. XGBoost has demonstrated particularly strong performance in this context: one study predicting PERCLOS achieved an RMSE of 3.847 and an adjusted  $R^2$  of 0.996 [18].

##### 3.2.2. Predicting subjective states

The Karolinska Sleepiness Scale (KSS), a 9-point self-report instrument, is commonly used and correlates strongly with objective EEG measures [28]. Regression-based estimation of KSS enables multi-stage warning architectures, for example issuing a mild alert at KSS level 5, an intensified alert at level 7, and an autonomous braking or pull-over response at level 9.

Table 2: Comparative Overview of Machine Learning Models for Driver State Detection.

| Model                       | Type           | Typical Input        | Performance              | Key Strength                  |
|-----------------------------|----------------|----------------------|--------------------------|-------------------------------|
| SVM                         | Classification | HRV, blink duration  | 70% accuracy             | Effective with small datasets |
| Random Forest               | Classification | EAR, MAR             | High accuracy            | Robust; diverse data types    |
| CNN (ResNet50V2, MobileNet) | Classification | Image/video streams  | Up to 99.71%             | Automates feature extraction  |
| Ensemble CNN                | Classification | In-vehicle sensors   | Up to 94.2%              | Handles multiple states       |
| XGBoost                     | Regression     | Physiological/behav. | RMSE=3.847, $R^2$ =0.996 | Efficient, explainable        |
| Functional Lin. Reg.        | Regression     | Physiological vars.  | ~90% accuracy            | Interpretable models          |

### 4. Performance metrics, datasets, and multimodal fusion

#### 4.1. Evaluation metrics for robustness

Accuracy alone can be misleading, particularly when the underlying dataset is imbalanced [20]. For classification tasks, Precision, Recall, and F1-score provide a more complete picture of model behavior [9]. For regression tasks, RMSE and MAE remain the standard metrics for quantifying prediction error [18].

#### 4.2. Challenges in data collection and generalization

Achieving reliable performance in a controlled simulator does not guarantee equivalent performance under real-world driving conditions, and generalization remains a significant challenge [20]. Inter-individual physiological variability — arising from genetic, cultural, and situational factors — means that a stress-induced heart-rate response can differ substantially between

individuals [30]. Consequently, it is not unusual for model accuracy to fluctuate by several percentage points across different test sessions or conditions [30]. Sensor-comfort trade-offs compound this challenge: high-fidelity sensors such as EEG caps are often impractical for continuous everyday use, while low-cost, non-intrusive cameras are highly sensitive to lighting conditions and frequently degrade in performance after dark [19].

#### 4.3. Overcoming limitations with multimodal sensor fusion

Multimodal sensor fusion addresses the limitations of any single sensing modality. By combining physiological signals, facial-camera feeds, and steering-wheel inputs, researchers obtain a substantially more complete representation of driver state [4]. No individual sensor is fully reliable on its own; fused approaches have been reported to push F1-scores as high as 96.10% [9]. Industry implementations, such as those from Rheinmetall and BlackBerry, similarly demonstrate that combining camera and radar data is central to building systems that are robust in real-world deployment.

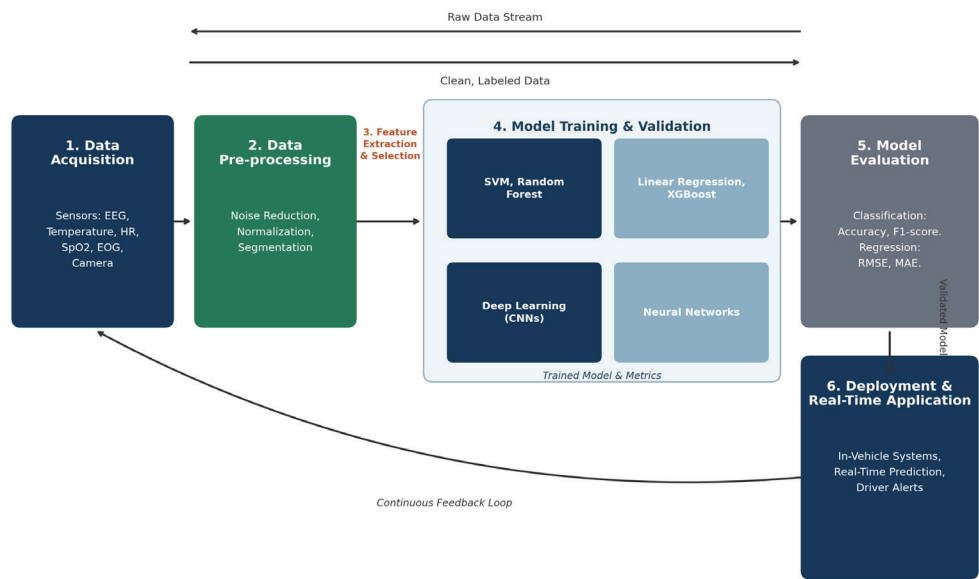


Figure 1: Driver State Analysis Flowchart in This Study.

5. Experimental study: ML models on physiological dataset

To evaluate these concepts empirically, the publicly available Kaggle Driver Physiological Dataset [37] was used, which provides continuous recordings of three physiological channels — body temperature, heart rate, and peripheral oxygen saturation (SpO2) — collected from [authors: please confirm exact sample size, sensor hardware, and sampling protocol] under simulated driving conditions. Records containing missing values or physiologically implausible readings (e.g., SpO2 outside the 70–100% range) were removed prior to analysis, and raw body-temperature readings were converted from Fahrenheit to Celsius. The resulting features were standardized (zero mean, unit variance) and expanded into a five-dimensional feature space [authors: please confirm the specific derived variables used to expand from three raw signals to five features] before Principal Component Analysis (PCA) was applied, reducing the feature space to two principal components that jointly explained over 90% of the total variance. The dataset was then partitioned into training and test subsets using an 80/20 split, with class balance verified between the stressed (Driver State  $\geq 7$ ) and non-stressed (Driver State  $< 7$ ) groups.

5.1. Regression results

Three regression algorithms were evaluated for their ability to predict the driver's continuous state: Linear Regression, a Decision Tree, and a Random Forest.

Table 3: Regression Model Results.

| Model             | MSE  | RMSE | MAE  | R <sup>2</sup> |
|-------------------|------|------|------|----------------|
| Linear Regression | 1.59 | 1.26 | 0.90 | 0.70           |
| Decision Tree     | 0.31 | 0.56 | 0.15 | 0.94           |
| Random Forest     | 0.23 | 0.48 | 0.20 | 0.96           |

The Random Forest Regressor substantially outperformed the alternative models ( $R^2 = 0.96$ ,  $RMSE = 0.48$ ), demonstrating strong generalization without evidence of overfitting to noise in the training data. Linear Regression performed considerably worse ( $R^2 = 0.70$ ), consistent with the expectation that physiological relationships are rarely well approximated by a linear model.

5.2. Classification results

The models were then evaluated on a binary classification task: whether the driver was stressed (Driver State  $\geq 7$ , class 1) or relatively calm (Driver State  $< 7$ , class 0).

Table 4: Classification performance comparison of models for driver state detection.

| Model         | Accuracy | Prec. 0 | Rec. 0 | F1 0 | Prec. 1 | Rec. 1 | F1 1 |
|---------------|----------|---------|--------|------|---------|--------|------|
| Logistic Reg. | 0.88     | 0.81    | 0.81   | 0.81 | 0.91    | 0.91   | 0.91 |
| Decision Tree | 0.99     | 0.97    | 0.99   | 0.98 | 0.99    | 0.99   | 0.99 |
| Random Forest | 0.98     | 0.95    | 1.00   | 0.98 | 1.00    | 0.98   | 0.99 |

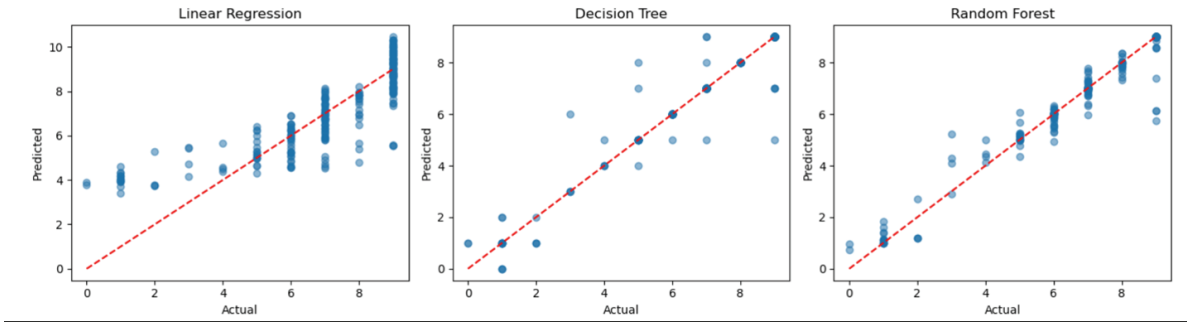


Figure 2: Regression Plots: Actual vs. Predicted Values.

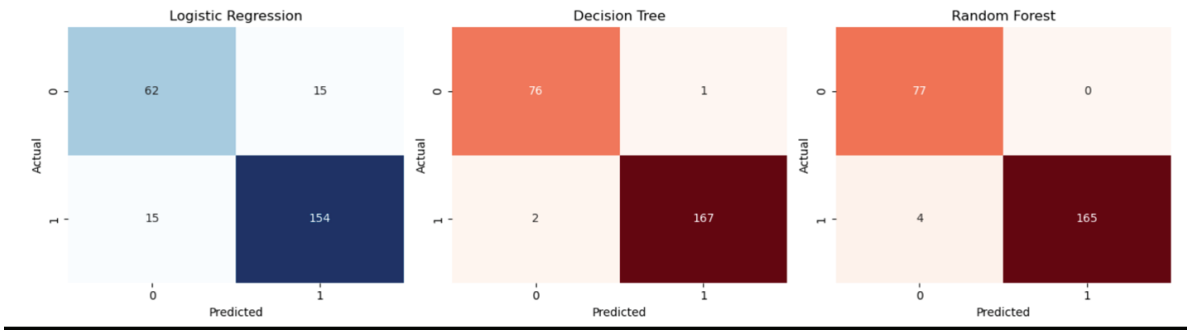


Figure 3: Confusion Matrices for Classification Models.

Both the Decision Tree and Random Forest classifiers achieved high accuracy, exceeding 98%. Random Forest in particular achieved perfect recall for the calm state (class 0) and an AUC approaching 1.00. Logistic Regression, despite its simplicity, still achieved a respectable 87.8% accuracy. These results indicate that tree-based ensemble methods are highly effective for classifying driver state from physiological data.

5.3. Feature importance and permutation analysis

Model interpretability analysis revealed that SpO2 consistently emerged as the dominant predictive variable across all models. Body temperature ranked second in importance, while heart rate contributed comparatively less to model decisions. A permutation importance test confirmed that this ranking was robust rather than incidental (Table 5). Partial Dependence

Plots (PDPs) further revealed a clear trend: higher SpO2 values were strongly associated with classification as the stressed state. This finding is biologically plausible, as variation in blood oxygen saturation is closely linked to overall physiological and cognitive state.

Table 5: Permutation Importance of Features.

| Feature          | Importance Mean | Importance Std |
|------------------|-----------------|----------------|
| SpO2             | 0.38            | 0.02           |
| Body Temperature | 0.09            | 0.02           |
| Heart Rate       | 0.05            | 0.01           |

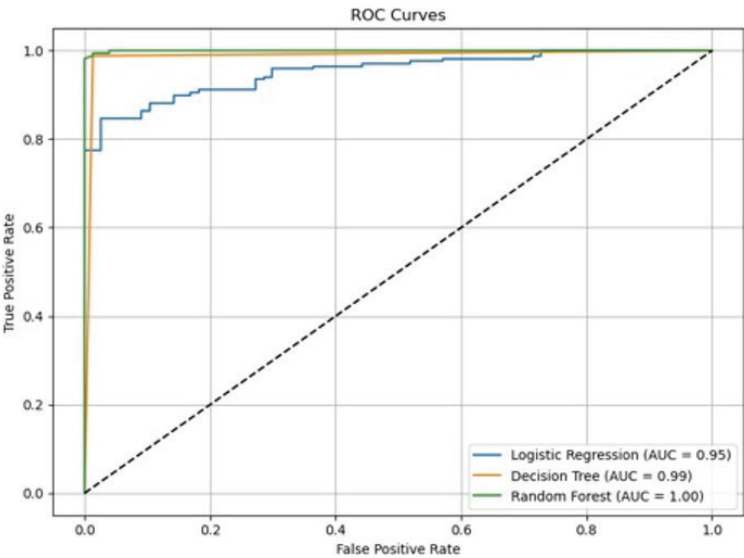


Figure 4: ROC Curves for Classification Models.

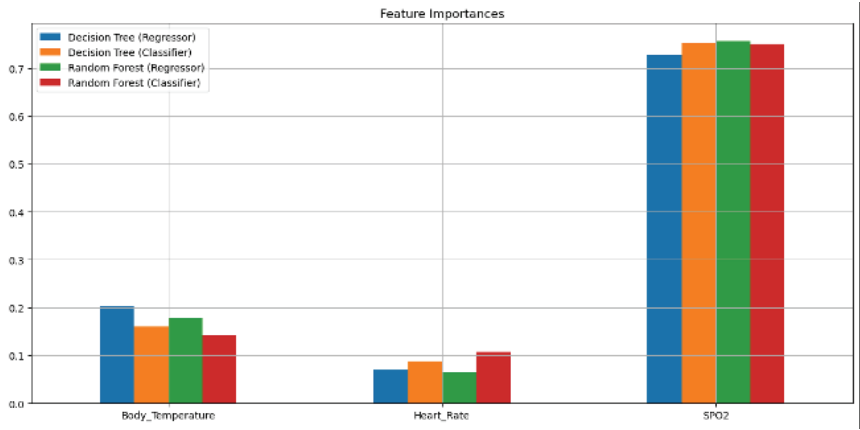


Figure 5: Feature Importance Across Regression and Classification Models.

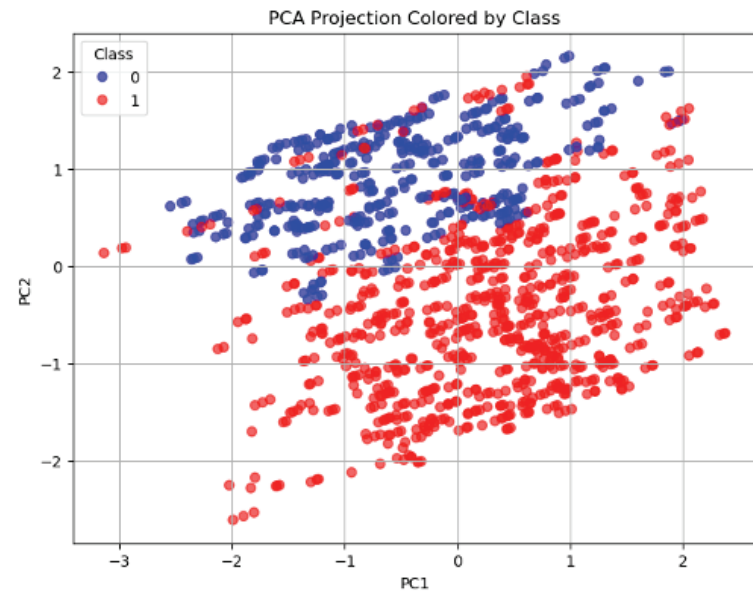


Figure 6: Principal Component Analysis (PCA) Projection Colored by Class.

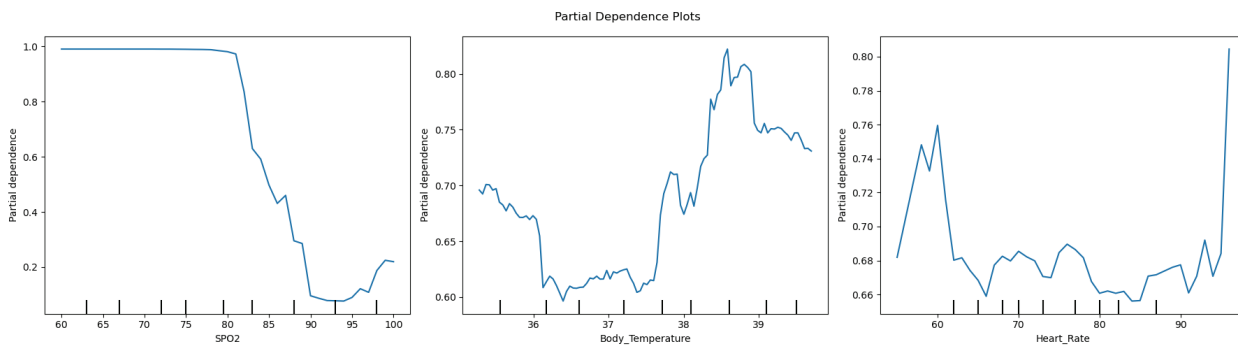


Figure 7: Partial Dependence Plots (PDP) for Top Features.

## 6. Conclusions

This experimental case study demonstrates that machine learning models can accurately track and predict physiological driver state. Among the features examined, SpO2 emerged as the most influential predictor. For continuous-state prediction, the Random Forest Regressor performed best, achieving an  $R^2$  of 0.96; for discrete-state classification, the Random Forest Classifier again performed best, achieving approximately 98.4% accuracy. These results are consistent with known physiological relationships, as blood-oxygen saturation is closely linked to human stress response and cognitive performance.

The broader field has evolved considerably beyond classical machine learning toward deep learning and complex multimodal sensor fusion, and the present experimental results — obtained from a comparatively simple, single-modality tabular dataset using classical models — should be interpreted within that context. As reviewed in Section 3.1.2 and Section 4.3, CNN-based architectures and multimodal fusion pipelines have achieved substantially higher and more robust performance than the classical models evaluated here when applied to richer, higher-dimensional sensor streams such as video or multi-channel physiological recordings

[3,4,9,16,20,26,33,34]. A natural extension of this work is therefore to apply deep learning architectures (e.g., 1D-CNNs or LSTM networks) to time-resolved physiological signals, and to augment the present single-modality dataset with complementary sensing channels — such as facial video or EEG — to evaluate whether multimodal fusion yields the accuracy and robustness gains reported elsewhere in the literature; this extension was beyond the scope of the tabular, session-level dataset used in the present case study and is identified here as a priority for future work. Beyond this, the industry must focus on several additional priorities. First, more comfortable sensing modalities (e.g., remote photoplethysmography, rPPG) are needed. Second, models must be developed that adapt to inter-individual physiological variability. Third, Explainable AI (XAI) techniques should be prioritized so that regulators and end users can trust these systems. Finally, validated algorithms must be shown to operate reliably in real time within an actual vehicle.

## Acknowledgment

The data utilized in this specific experimental portion was retrieved from the Kaggle Driver Physiological Dataset. The

raw body temperature data was converted into Celsius before running the analyses.

## 7. References

- [1] NHTSA, "Driver Assistance Technologies," accessed Sep. 2025. [Online]. Available: <https://www.nhtsa.gov/vehicle-safety/driver-assistance-technologies>
- [2] KORE Wireless, "What Is a Driver-Monitoring System (DMS)?" accessed Sep. 2025.
- [3] K. Jin, A. Rubio-Solis, R. Naik, D. Leff, J. Kinross, and G. Mylonas, "Human-Centric Cognitive State Recognition Using Physiological Signals: A Systematic Review of Machine Learning Strategies Across Application Domains," *Sensors*, vol. 25, no. 13, Art. 4207, 2025. doi: 10.3390/s25134207
- [4] ResearchGate, "Multimodal Fatigue Detection in Drivers via Physiological and Visual Signals," 2024.
- [5] ResearchGate, "ECG-based fatigue driving detection model," 2024.
- [6] E. T. Solovey, M. Zec, E. A. Garcia Perez, B. Reimer, and B. Mehler, "Classifying Driver Workload Using Physiological and Driving Performance Data: Two Field Studies," *Proc. ACM CHI '14*, 2014.
- [7] Y. Sun, "An In-Vehicle Physiological Signal Monitoring System for Driver Fatigue Detection," *TRB*, 2011.
- [8] T. Abe, "PERCLOS-based technologies for detecting drowsiness: current evidence and future directions," *SLEEP Advances*, vol. 4, no. 1, zpad006, 2023. doi: 10.1093/sleepadvances/zpad006
- [9] ResearchGate, "Driver Fatigue Transition Prediction in Highly Automated Driving," 2020.
- [10] SPIE, "Assessing Deep Learning Techniques for Human Driving Behavior Prediction," 2025.
- [11] BlackBerry QNX, "What Is a Driver Monitoring System?" accessed Sep. 2025.
- [12] S. Narayanan et al., "Estimating Markers of Driving Stress through Multimodal Physiological Monitoring," arXiv:2507.14146, 2025.
- [13] Eventiotic, "Physiological Measurements for Determining Driver's State," 2020.
- [14] PMC, "Driving Drowsiness Detection Using Spectral Signatures of EEG," *Frontiers in Neuroscience*, 2023.
- [15] PMC, "An EOG Sensor's Ability to Detect Driver Drowsiness," 2023.
- [16] MDPI Applied Sciences, "AI- and Deep Learning-Powered Driver Drowsiness Detection," vol. 15, no. 3, 2025.
- [17] IRJET, "Machine Learning Based Driver Monitoring System," vol. 10, no. 12, 2023.
- [18] Univ. of Michigan, "Predicting Driver Fatigue in Automated Driving with Explainability," 2021.
- [19] IRJET, "Driver Drowsiness Detection System," vol. 8, no. 5, 2021.
- [20] PMC, "Ensemble CNN to Detect Drowsy Driving with In-Vehicle Sensor Data," 2021.
- [21] A. Shi et al., "SVM Classification of Drunk Driving Behaviour," *Int. J. Environ. Res. Public Health*, vol. 14, no. 1, 2017.
- [22] ResearchGate, "SVM Classification of Drunk Driving Behaviour," 2017.
- [23] IJARST, "Driver Drowsiness Detection using ML and DL," 2023.
- [24] PMC, "Deep Learning in Physiological Signal Data: A Survey," *IEEE Rev. Biomed. Eng.*, 2020.
- [25] ResearchGate, "DL Model for Driver Drowsiness Detection in Low-Light Conditions," 2023.
- [26] MDPI Applied Sciences, "CNN-Based Approach for Driver Drowsiness Detection," vol. 13, no. 13, 2023.
- [27] TOJDAC, "Regression Model for Driving Fatigue Detection Based on Seat Pressure Distribution," vol. 8, 2018.
- [28] T. Åkerstedt and M. Gillberg, "Subjective and objective sleepiness in the active individual," *Int. J. Neuroscience*, vol. 52, pp. 29–37, 1990.
- [29] V. Putilov and O. Donskaya, "Construction and Validation of EEG Analogues of the KSS," Semantic Scholar, 2014.
- [30] ResearchGate, "Detecting Stress During Real-World Driving Tasks Using Physiological Sensors," 2003.
- [31] Rheinmetall, "Sensor Fusion," 2023.
- [32] insideAI News, "Using Machine Learning with Health Data: Challenges and Pitfalls," 2017.
- [33] O. F. Hassan, A. F. Ibrahim, M. A. Makhoul, and B. Hafiz, "Intelligent driver monitoring systems: a survey of drowsiness detection technologies for road safety," *Artificial Intelligence Review*, Springer, 2026. doi: 10.1007/s10462-026-11505-w
- [34] A. Dontoh, S. Ivey, L. Sirbaugh, A. Danyo, and A. Aboah, "Visual Dominance and Emerging Multimodal Approaches in Distracted Driving Detection: A Review of Machine Learning Techniques," arXiv:2505.01973, 2025.
- [35] M. S. AL-Quraishi, S. S. A. Ali, M. AL-Qurishi, T. B. Tang, and S. Elferik, "Technologies for detecting and monitoring drivers' states: A systematic review," *Heliyon*, vol. 10, no. 20, e39592, 2024. doi: 10.1016/j.heliyon.2024.e39592
- [36] L. Melders, R. Smigins, and A. Birkavs, "Recent Advances in Vehicle Driver Health Monitoring Systems," *Sensors*, vol. 25, no. 6, Art. 1812, 2025. doi: 10.3390/s25061812
- [37] Kaggle (user: gowrishankarachari), "Driver Physiological Dataset," accessed 2025. [Online]. Available: <https://www.kaggle.com/datasets/gowrishankarachari/driver-physiological-dataset>

## Özgeçmişler



**Dr. Baris Aykent** is a dynamics and controls expert specializing in real-time software development for ground and aerial vehicles, including UAVs. He holds a PhD in Control Engineering from Arts et Métiers ParisTech (2013), an MSc in System Dynamics & Control from Istanbul Technical University, and a BSc in Mechanical Engineering from Yıldız Technical University. Over a career spanning Germany (BAST-Daimler-UniBw), France (Renault), and Türkiye (Hexagon, Profen, Togg, Altinay, and Evry), he has led development of driver-assistance and vehicle-control systems such as ESC, TCS, ABS, EPS, BMS, and Hill Assist Control across MIL/SIL/HIL/DIL/VIL environments, most recently serving as Head of Control Software at Evry. His expertise also spans driving simulators and motion/simulator sickness, system identification, Kalman filtering, and machine learning (including FFNN, NARX, and reinforcement learning) applied to autonomous and electric vehicle systems. He currently lectures on Applied AI in Automotive Systems at both MEF University and Işık University, and has authored several Springer book chapters on ESC and vehicle control.