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Driving Risk prediction over a repetitive driving pattern

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Driving risk assessment remains a critical challenge in global road safety, a problem exacerbated by the 1.19 million annual fatalities recorded due to human error. While significant research has focused on complex and unpredictable driving environments, a substantial portion of daily road use occurs under highly repetitive conditions, such as standardized commutes for office workers or professional logistics personnel. These scenarios introduce unique psychological and physiological risks, including decreased vigilance, habituation to environmental hazards, and a dangerous increase in risk-taking behavior driven by overconfidence. Predicting and monitoring risk in these monotony-prone environments is therefore essential to prevent accidents related to reduced cognitive engagement.

To address these limitations, this study proposes a predictive framework leveraging a sensor fusion approach within a specific experimental context designed to simulate repetitiveness. The research was conducted with a cohort of 54 participants (28 males and 26 females), each of whom participated in 12 distinct sessions, requiring them to drive 4 laps along the same standardized track. This structured approach yielded a robust dataset that captured the subtle evolution of driving patterns and physiological responses over time. The predictive framework developed in this research integrates vehicle dynamics with human-centric metrics. Beyond standard kinematic data, the study incorporated physiological signals, such as heart rate (HR) and stress levels, alongside demographic factors to create a holistic driver profile.

A critical aspect of this research is the objective quantification of driving risk used to label the dataset. Unlike studies relying solely on subjective self-reports, we implemented a dynamic kinematic thresholding method governed by a velocity-dependent acceleration metric. Safety boundaries are defined by thresholds, derived by equation 1, that establish a non-linear relationship between the vehicle's speed and its permissible longitudinal and lateral forces.

$$\sqrt{a_x^2 + a_y^2} = g \cdot \left[0.198 \cdot \left(\frac{V}{100}\right)^2 - 0.592 \cdot \left(\frac{V}{100}\right) + 0.569\right] \tag{1}$$

Data points remaining within these boundaries are classified as "Low Risk," while excursions beyond these limits are categorized as "High Risk." An entire lap is evaluated and labeled based on the cumulative number of unsafe instances—moments where the vehicle exceeds these predefined thresholds. This aggregate metric allows for the categorization of each lap into distinct risk levels (Low, Medium, and High), reflecting the overall safety of that specific run.

- **Low Risk:** Less than 5% of the points fall outside the safety thresholds.
- **Medium Risk:** Between 5% and 8% of the points fall outside the thresholds.
- **High Risk:** More than 8% of the points are classified as unsafe.

Furthermore, the study explores a predictive approach rather than a purely descriptive one. The physiological and kinematic metrics collected during a completed lap are utilized as features to predict the risk level of the subsequent lap. This temporal forecasting approach aims to identify early warning signs of behavioral degradation, potentially allowing for proactive interventions before a high-risk event occurs. The classification system was based on the XGBoost algorithm, ensuring high-performance handling of the non-linear feature space. To ensure robustness and generalizability, the model was evaluated using a Stratified 5-Fold Cross-Validation approach. The resulting findings show that the classifier achieved a mean accuracy of 90.6% (±3.5%). Overall results are shown in Table 1. By bridging the gap between physical vehicle thresholds and biometric driver data, this study provides a scalable methodology for driving risk prediction in repetitive driving tasks, facilitating a necessary shift toward proactive road safety systems.

Table 1: Classification Report.

Driving risk level	Precision	Recall	F1-score	Support
Low risk	93.8%	95.0%	94.4%	481
Medium risk	74.5%	70.5%	72.5%	112
High risk	92.1%	92.1%	92.1%	88