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Hybrid Modelling for Risky Driving Behavior Classification: Insights from Naturalistic Driving Study

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Introduction

Human error is a leading factor in the vast majority of traffic crashes, with studies showing that approximately 90-95% of all road crashes are linked to driver-related behaviors. These behaviors include speeding, violating traffic rules, distracted driving, fatigue, and driving under the influence of alcohol or drugs.

This study tackles the growing challenge of dangerous driving by employing hybrid machine learning models on naturalistic driving data. Central to the analysis is the **Safety Tolerance Zone (STZ)** framework, which categorizes behavior into Normal, Dangerous, and Avoidable Accident phases, as depicted in Figure 1. Real-time interventions and post-trip feedback aim to keep drivers within safe operational boundaries.

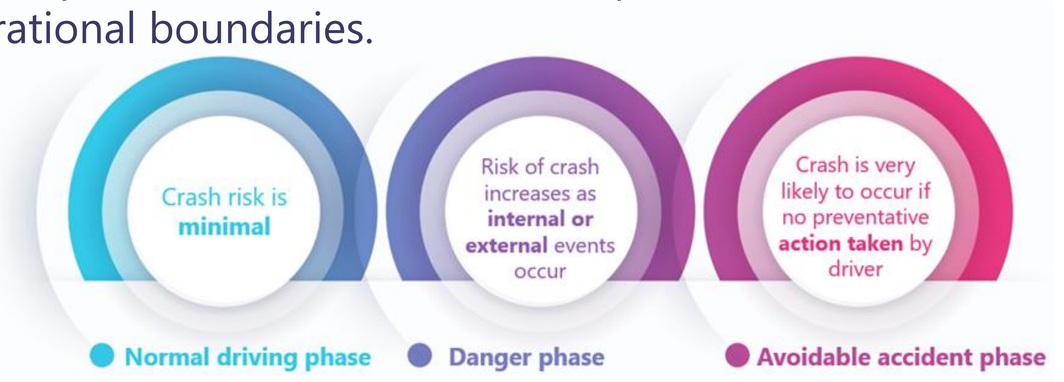


Figure 1: A schematic overview of the different driving phases of the STZ

Objectives

This aim of this paper is to predict **driving risk levels** based on real-world driving data

Naturalistic Driving Experiment

For the purpose of this analysis, a **naturalistic driving experiment** was conducted over a four-month period, divided into four distinct phases with participants from Belgium and the UK. A database consisting of 7163 trips and 147337 minutes of driving data (43 drivers) for Belgium and 8226 trips and 118175 minutes (26 drivers) for the UK was created. Figure 2 provides an overview of the different phases of the experimental design of the i-DREAMS on-road study.

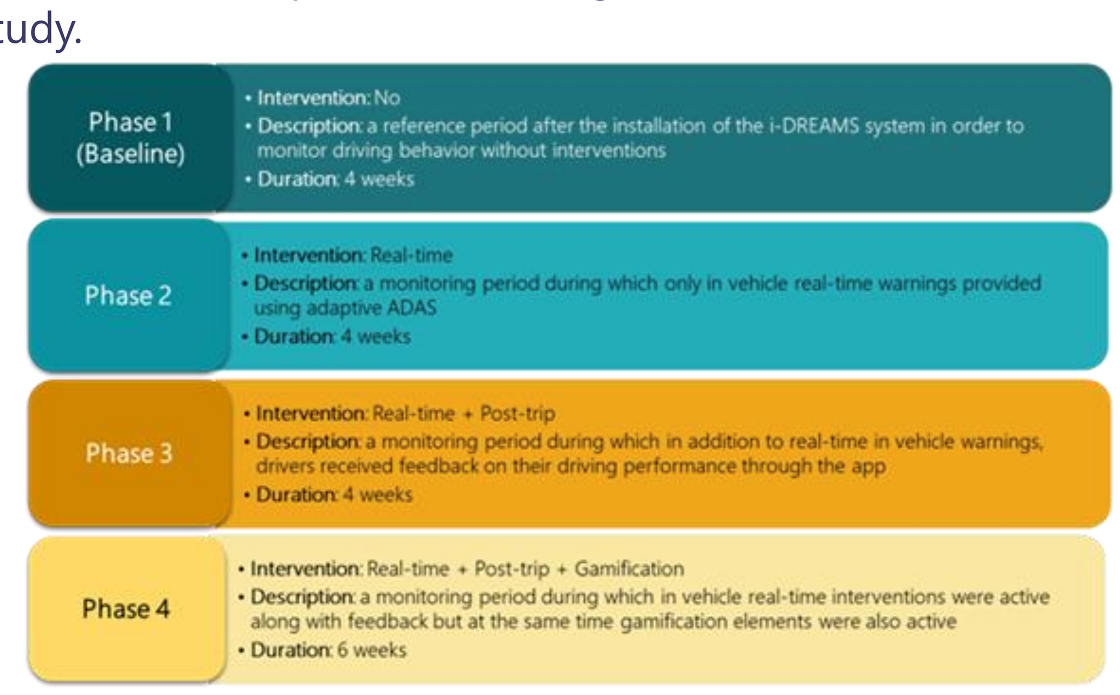


Figure 2: Overview of the different phases of the experimental design

A Data collection employed several cutting-edge technologies, including an **OBD-II device** installed in each vehicle to capture hundreds of driving parameters. The **Mobileye system**, integrated with mobile networks, further facilitated data gathering without user interaction. To categorize driving behavior, each 30-second interval of the trip was assigned to one of three safety levels: Normal, Dangerous, or Avoidable Accident. These levels were determined based on intervention thresholds from the literature and the classification of variables such as speed and headway distances

Methodology

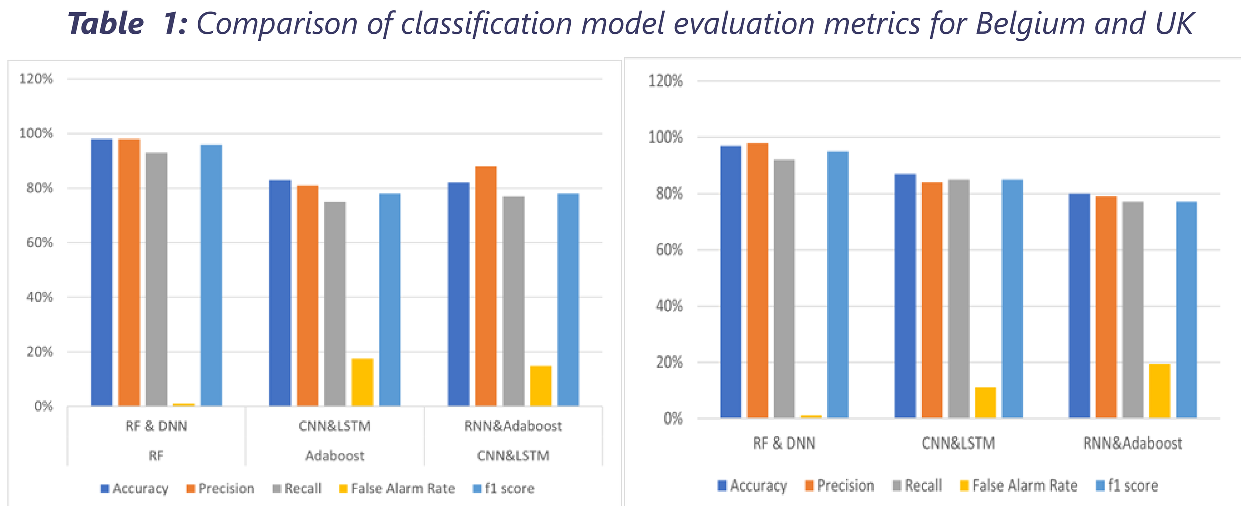
- A classification approach was applied to identify Safety Tolerance Zone (STZ) levels, using **three hybrid machine learning models**:
  1. Deep Neural Network – Random Forest (DNN–RF)
  2. Convolutional Neural Network – Long Short-Term Memory (CNN–LSTM)
  3. Recurrent Neural Network – AdaBoost (RNN–AdaBoost)
- Driving behavior was categorized into three risk levels—Normal, Dangerous, and Avoidable Accident—based on **speed** and **headway thresholds**, using 30-second time windows.
- **Feature selection** was performed through a Random Forest permutation method. The most influential variables included **total distance, average speed, harsh acceleration, and harsh braking**.
- Synthetic Minority Over-sampling Technique (**SMOTE**) was applied to address class imbalance across the STZ categories.
- A multi-metric evaluation (accuracy, precision, recall, F1-score, false positive rate) was conducted to assess classifier performance across both countries.
- Model interpretability was enhanced using the Local Interpretable Model-Agnostic Explanations (**LIME**) algorithm, offering transparency into the influence of individual driving features on classification outcomes.

Results

The hybrid classification models were evaluated using naturalistic driving data from Belgium and the UK. The **DNN–RF** model achieved the **highest performance** across both datasets

Dataset	Model	Accuracy	Precision	Recall	FPR	F1-score
Belgium	RF & DNN	98%	98%	93%	0.96%	96%
	CNN & LSTM	83%	81%	75%	17.5%	78%
	RNN & Adaboost	82%	88%	77%	14.9%	78%
UK	RF & DNN	97%	98%	92%	1.36%	95%
	CNN & LSTM	87%	84%	85%	11.11%	85%
	RNN & Adaboost	80%	79%	77%	19.4%	77%

Table 1: Comparison of classification model evaluation metrics for Belgium and UK



a) b)

Figure 3: Comparison of classification model evaluation metrics for a) Belgium and b) UK

The **DNN–RF model** showed superior ability to detect risky behavior (high recall), while maintaining low false alarms (low FPR), making it highly suitable for safety-critical applications.

Feature Importance

Top predictive features:

1. Total distance traveled
2. Average speed
3. Mean level of harsh acceleration
4. Mean level of harsh braking

These features collectively capture both **strategic driving tendencies** (e.g., speed, trip length) and **tactical behaviors** (e.g., abrupt acceleration or braking), providing a comprehensive picture of driving risk.

Results

Regional Insights via LIME

To further interpret the model decisions, the Local Interpretable **Model-Agnostic Explanations (LIME)** technique was applied:

- In Belgium, **harsh acceleration** and **harsh braking** were the dominant predictors, suggesting a behavioral pattern characterized by abrupt or aggressive maneuvers.
- In the UK, the model emphasized **total travel distance** and **average speed** as more influential, possibly reflecting the impact of longer, high-speed trips on driver fatigue and attention.

These regional differences highlight how **driving style, infrastructure**, and **traffic conditions** may influence risk factors differently across countries.

Dataset	Feature	Value
Belgium	GPS_spd_mean	0.14
	GPS_distances_sum	0.31
	DEM_evt_ha_lvl_L_mean	2.00
UK	DEM_evt_hb_lvl_L_mean	0.56
	GPS_spd_mean	0.29
	GPS_distances_sum	0.58

Table 2: LIME results for Belgium and UK

Conclusions

- A key outcome of the study is the idenfication of specific driving behaviors, particularly harsh acceleration, harsh braking, and total driving distance, as significant indicators of driver safety.
- The hybrid modeling approach, combining **DNN-RF**, was particularly successful, consistently delivering **high accuracy** across both countries.
- The study highlighted that **harsh acceleration** and **braking** were dominant risk factors in Belgium, in the UK, **longer travel distances** and **higher speeds** posed greater risks.
- A major innovation is the use of **LIME algorithm** to interpret the models' decision-making processes. Predictions ere made interpretable, enhancing trust and applicability in real-world settings.
- These results support the integration of such models into **ADAS systems**, **driver coaching tools**, and **regional safety policies**.
- **Future research** should expand the dataset to include more drivers and integrate driver demographics, phycological factors, and environmental variables. Such extensions would support even more tailored and effective risk prediction framaworks.

Acknowledgments

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