13th Symposium of the European Association for Research in Transportation (hEART2025)
10-12 June 2025, Munich, Germany

Driver and road environment assessment for identifying Safety Tolerance Zone using machine learning techniques

Eva Michelaraki[1], Thodoris Garefalakis[1], Constantinos Antoniou[2], Tom Brijs[3], George Yannis[1]

[1] National Technical University of Athens, Department of Transportation Planning and Engineering, Athens, Greece
[2] Technical University of Munich, Chair of Transportation Systems Engineering, Munich, Germany
[3] UHasselt, School for Transportation Sciences, Transportation Research Institute (IMOB), Hasselt, Belgium

Introduction

Human operator does not however act in isolation. They are an **integral part of the transport system** which is made up of a complex interaction of drivers, vehicles, infrastructure, other environmental factors and the rules and regulations that govern them.

The concept of the **Safety Tolerance Zone (STZ)** attempts to describe the point at which self-regulated control is considered safe (Michelaraki et al., 2022). Simply described, it is the zone where the demands of the driving task are balanced with the ability of the driver to cope with them. The STZ comprises three phases: normal driving, danger and avoidable accident phase, as depicted in Figure 1.

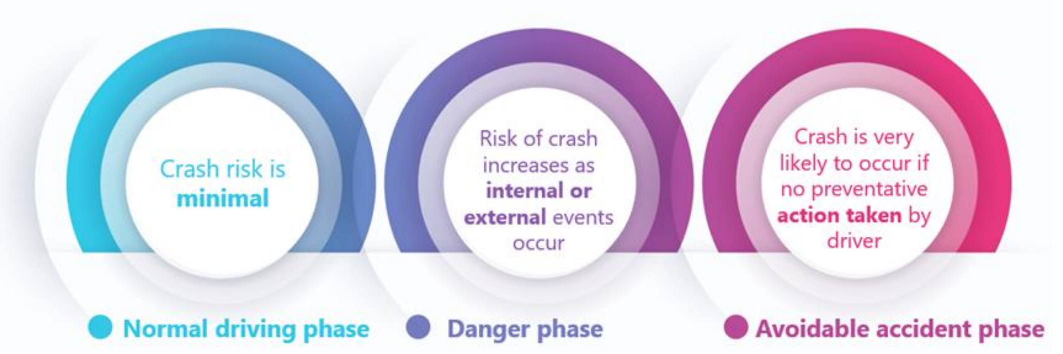

Figure 1: A schematic overview of the different driving phases of the STZ

Objectives

This aim of this paper is to assess **driver, road and environment** indicators for the identification of STZ using machine learning techniques.

The Simulator Experiment

For the purpose of this analysis, a **simulator experiment** was carried out involving 55 drivers (with total duration of 2 months) and a database consisting of 165 trips (55 drivers x 3 driving scenarios) was created. The most prominent driving behavior indicators, such as speeding, headway, duration, distance and harsh events were assessed. The simulator trials consisted of three phases, as depicted in Figure 2.

Scenario 1 (Baseline)	• Intervention: NO • Description: a reference period to monitor driving behaviour without interventions • Duration: 15 minutes
Scenario 2	• Intervention: Real-time • Description: an intervention scenario influencing driving behaviour with fixed timing thresholds (and/or message and/or display) • Duration: 15 minutes
Scenario 3	• Intervention: Real-time • Description: an intervention scenario with modifying condition influencing driving behaviour with variable timing thresholds (and/or message and/or display) • Duration: 15 minutes

Figure 2: Three phases of the simulator experiment

A custom car simulator **developed by DriveSimSolutions** was designed (Figure 3), allowing for creation of custom scenarios and data collection at every simulation update frame. It is also visualized on a triple monitor setup consisting of three 49 inch 4K monitors, providing an 135° field of view (Figure 4).

Figure 3: Car simulator developed by DriveSimSolutions, using OEM Peugeot 206 parts

Figure 4: Example of an intersection in STISIM Drive 3

Methodology

- A feature importance analysis (i.e. **Extreme Gradient Boosting - XGBoost**) was implemented to evaluate the significance of various variables in forecasting STZ.
- Machine learning analysis (i.e. **Neural Networks**) was applied to make accurate and data-driven predictions by identifying complex patterns between task complexity and coping capacity on crash risk.
- A comprehensive assessment of the performance of three machine learning classifiers (i.e. **Decision Trees, Random Forests and k-Nearest Neighbors**) was performed to predict STZ levels for speeding.

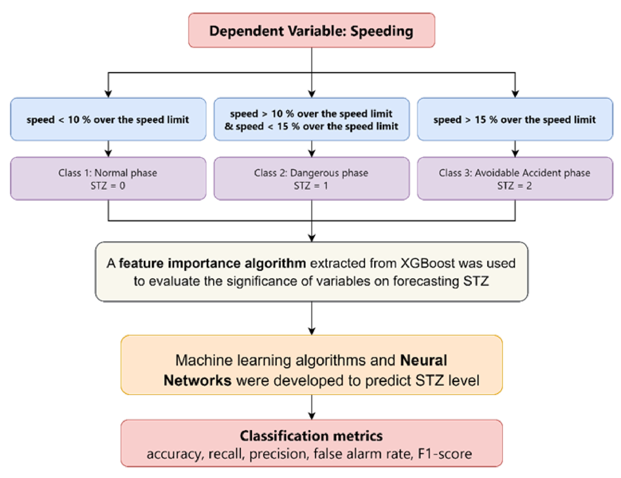

Figure 5: Proposed methodology for the definition of the STZ for speeding

Results

As shown in Figure 6, distance travelled, headway, harsh accelerations, harsh brakings and time indicator emerged as the **most important factors** among all examined indicators. Conversely, car wipers found to be less significant. Lastly, variables related to forward collision warning and pedestrian collision warning had a negligible impact on STZ speeding.

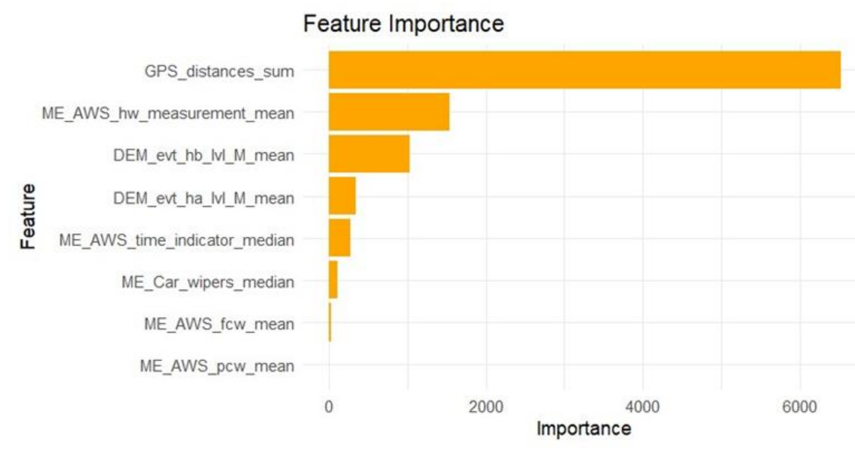

Figure 6: XGBoost feature importance of independent variables for speeding

Based on the feature importance and the significance of the relevant indicators, a dataset of 745,251 rows from the simulator experiment was used and a feed-forward multilayer perceptron NN model was implemented. The data were split into 80% train and 20% test in order to evaluate the models. The model was run with deep neural networks, making use of **two hidden layers** (represented by circles in the middle of the diagram) where the computations take place. It should be noted that STZ1 speeding refers to normal phase, STZ2 refers to danger phase, while STZ3 refers to avoidable accident phase.

NNs achieved exceptional predictive accuracy, with an **accuracy rate of up to 85%**, demonstrating the model's robustness in identifying positive cases and its effectiveness in detecting safety-critical scenarios.

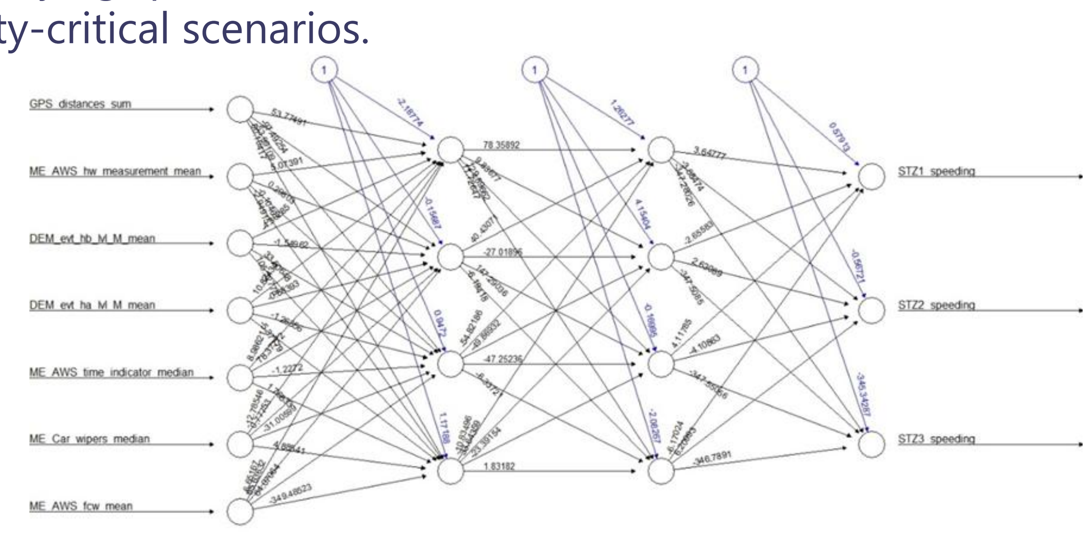

Figure 7: The multi-layer Neural Network model layout for STZ speeding

Classification Results

Table 1 provides the assessment of classification model for speeding. Overall, RF demonstrates the best performance with a **high accuracy of 89.1%,** precision of 90.8% and recall of 87.5%. DT shows moderate performance with an accuracy of 85.2%, precision of 85.3% and recall of 83.1%. kNN performs the lowest among the three, with an accuracy of 81.5%, precision of 78.3% and recall of 79.6%.

Figure 8 depicts the bar chart, comparing the performance of three classifiers for speeding. It can be observed that **RF consistently outperforms the other two classifiers** in all metrics, showing the highest scores. DT and kNN show relatively close performance, with kNN generally having the lowest scores among the three. These metrics indicated that the model was highly accurate in making correct predictions and excels in identifying positive samples, as evidenced by its high precision.

Table 1: Evaluation metrics for classification models for speeding

Model Fit measures	0	1	2	Total
Accuracy				
DT	0.887	0.853	0.816	0.852
RF	0.930	0.878	0.865	0.891
kNN	0.825	0.803	0.818	0.815
Precision				
DT	0.873	0.866	0.821	0.853
RF	0.952	0.815	0.888	0.908
kNN	0.833	0.789	0.771	0.783
Recall				
DT	0.860	0.834	0.801	0.831
RF	0.891	0.872	0.863	0.875
kNN	0.843	0.788	0.759	0.796
F1 Score				
DT	0.815	0.792	0.733	0.804
RF	0.878	0.741	0.713	0.849
kNN	0.803	0.687	0.652	0.791

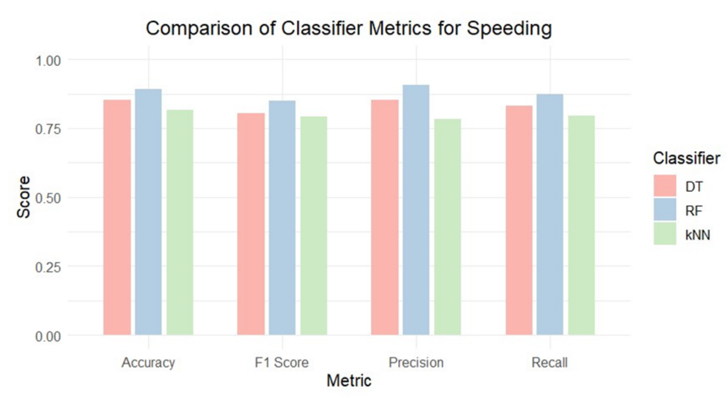

Figure 8: Comparison of classifier metrics of machine learning techniques for speeding

Conclusions

- The effectiveness of the NN models in **predicting speeding levels was encouraging**; the level of STZ can be predicted with an exceptional accuracy.
- The three machine learning classifiers (DT, RF, kNN) had **insightful results** in terms of accuracy and precision.
- Results indicated that **RF models outperformed** the DT and kNN models across all metrics, making them the most effective for predicting speeding.
- The DT **model showed satisfactory performance**, while the kNN model consistently had the lowest but moderate scores, indicating that it is the least effective for this task.
- The performance variations observed underscored the importance of selecting the right model based on data characteristics and **precision-recall trade-offs**, essential for real-world applications.
- Future research could explore **additional methods of analysis**, such as imbalanced learning, factor analysis and models that account for unobserved heterogeneity. Econometric techniques could also be applied.

Acknowledgments

The research was funded by the EU H2020 i-DREAMS project (Project Number: 814761) funded by European Commission under the MG-2-1-2018 Research and Innovation Action (RIA).

Contact Information:
Eva Michelaraki, PhD, Research Associate NTUA
Department of Transportation Planning and Engineering
Email: evamich@mail.ntua.gr
Website: https://www.nrso.ntua.gr/p/evamich/