Exploiting Surrogate Safety Measures and Road Design Characteristics towards Crash Investigations in Motorway Segments

Dimitrios Nikolaou

Transportation Engineer, PhD Candidate

Together with:
A. Dragomanovits, A. Ziakopoulos, A. Deliali,
I. Handanos, C. Karadimas, G. Yannis

The i-safemodels project

International Comparative Analyses of Road Traffic Safety Statistics and Safety Modeling

- **Project partners**:
  - NTUA Department of Transportation Planning & Engineering (www.nrso.ntua.gr)
  - OSeven Telematics (www.oseven.io)
  - Tongji University (https://en.tongji.edu.cn)
  - Third country partners: University of Central Florida (US), Purdue University (US), Loughborough University (UK), German Aerospace Center, DE
- **Duration of the project**:
  - 42 months (October 2019 – April 2023)
- **Operational Programme**:

  "Competitiveness, Entrepreneurship and Innovation" (EPAnEK) of the National Strategic Reference Framework (NSRF): Greece - China Joint R&D Projects.

Background (1/2)

- Motorways are typically the safest road environment; as the extension of the motorway network is associated with a reduction in road fatality rates, while other road types do not present the same positive safety effects (Albalate & Bel, 2012).

- The considerable improvement of Greek main road network from 750 km in 2007 of motorways to 2200 km in 2018 was a key factor for the reduction of road fatalities by 54% during the period 2010-2020 (ETSC, 2021).

- However, there is still space for improvement in road safety levels as 50 road fatalities were recorded on Greek motorways in 2019 and, towards this direction, a target of zero fatalities on motorways by 2030 has been set in the Greek Road Safety Strategic Plan for the period 2021-2030 (Yannis et al., 2022).

Background (2/2)

- However, budgets for road safety measures are **finite**.
- Regarding infrastructure improvements, several **quantitative methodologies** have been developed over the years, to enhance evidence-based decision making (e.g. crash analyses, inspections, assessment of the "in-built" safety of roads, etc.).
- A frequently used approach is offered through the application of **Crash Prediction Models** (CPMs), which require detailed data on crashes, geometric characteristics and traffic attributes.
- Apart from such characteristics, in recent years increased attention has been given to **Surrogate Safety Measures** (SSMs), which are parameters that describe attributes of the network or of the vehicle movement on roads and do not stem directly from or rely on crash data.

Objective

The objective of this research is threefold, and specifically to:

1. Investigate the relationship between road crash frequency in motorway segments and various explanatory variables based on road design characteristics and SSMs.

2. Create risk level clusters of the motorway segments based on crash and traffic data.

3. Compare the classification performance of five machine learning techniques for predictions of crash risk levels of motorway segments.

Data

- Injury and PDO road crashes (Olympia Odos Operation SA)
- Traffic (Olympia Odos Operation SA)
- Road geometry characteristics (Open GIS, CAD, Google Earth)
- Naturalistic driving metrics - SSMs (OSeven)

668 segments (200-600m length) of the Olympia Odos motorway.

- Average AADT (2018-2020): 10,786 vehicles/day
- Average trips per segment (6/2019-12/2020): 2,035 trips
- Road Crashes (2018-2020) 80 injury & 1,270 PDO

Table: Road crash, traffic, geometry and driver behaviour variables per segment.

Variable	Abbreviation	Min.	Max.	Mean
Number of through lanes	lanes	2	3	-
Length of motorway segment (km)	len_seg	0.20	0.60	0.53
Average Annual Average Daily Traffic Volume of motorway segment (veh/day) 2018-2020	avg_AADT_18_20	6,511	22,079	10,786
Posted speed limit (km/h)	speed_limit	90	130	121.7
Number of Total Road Crashes (Injury & Property Damage Only) 2018-2020	TotCr18_20	0.00	13.0	2.02
Number of Total Road Crashes (Injury & Property Damage Only) by segment length 2018-2020	TotCr18_20_len_seg	0.00	30.0	3.9
Curve 1 – Radius R (m)	Curve1	0.00	50,000	2,129
Curve 1 – Length of curve in segment (m)	Lcurve1_in_seg	0.00	600.0	218.2
Lane width (m)	lane_width	3.55	3.95	3.92
Paved inside shoulder width (m)	pav_ins_sh_width	0.50	1.75	0.69
Median width (measured from near edges of traveled way in both directions) (m)	median_width	2.25	23.50	4.96
Distance from edge of inside shoulder to barrier face (m)	dist_edginssh_barf	0.00	0.75	0.04
Paved outside shoulder width (m)	pav_out_sh_width	0.25	4.50	2.77
Distance from edge of outside shoulder to barrier face (m)	dist_edgoutsh_barf	0.00	3.25	0.82
Number of recorded trips	rec_trips	173	5,068	2,035
Average speed (all trips) (km/h)	avg_speed	77.0	153.0	115.9
Average number of harsh accelerations per trip (%)	avgha_pertrip_perc	0.00	9.83	0.21
Average number of harsh brakings per trip (%)	avghb_pertrip_perc	0.00	3.91	0.21
Average number of speeding events per trip (%)	avg_sp_ev_pertrip_perc	1.28	88.61	25.79

Methodological Background (1/2)

Negative Binomial Regression

- Widely used for count data modelling.
- Generalization of Poisson regression.
- Preferred when overdispersion exists in crash count data.

Hierarchical Clustering

- Hierarchy of clusters based on the agglomerative approach.
- Each observation starts in its own cluster and pairs of clusters are merged as one moves up the hierarchy.
- Clusters are visually represented in a dendrogram.

Classification Algorithms

- Logistic Regression: linear classification model employing the logistic function.
- Decision Tree: non-parametric model with hierarchical structure (nodes - dataset features, branches - possible values, leaves - classification labels).
- Random Forest: ensemble learning technique with independent decision trees. DTs' outcomes are combined (majority vote or a vote of confidence).
- Support Vector Machine: finds the solution hyperplane for maximal separation of classes in high-dimensional feature space.
- K-NN: simple classifier based on the labels of K nearest neighbors.

Methodological Background (2/2)

Classification Performance Metrics

- **Accuracy** (fraction of predictions that are correctly classified) ➔ (TP + TN)/P + N
- **Precision** (fraction of correct predictions for a certain class) ➔ TP/(TP + FP)
- **Recall** (fraction of instances of a class that were correctly predicted) ➔ TP/(TP + FN)
- **F1-Score** (harmonic mean of Precision and Recall) ➔ 2 * (Precision * Recall)/(Precision + Recall)
- **Macro-averaged**: Precision, Recall, F1-Score

SHAP values

- **Model-agnostic method** drawing from coalitional game theory.
- Provide a **measure of contribution** of each feature to the prediction of a particular instance in a model.
- Defined as the **difference** between the expected model output and the output when that feature is excluded.

Crash Frequency Regression Model

- Dependent variable of the developed NB regression: "TotCr18_20"

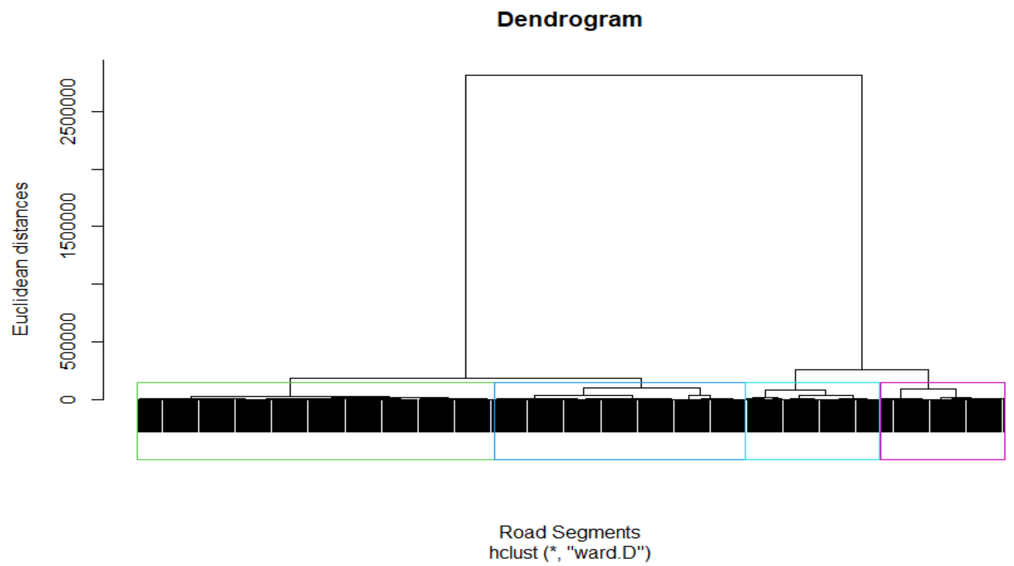
Independent variables	Estimate	Std. Error	z value	Pr(|z|)	VIF
(Intercept)	-1.23636	0.199	-6.216	<0.001	-
avg_AADT_18_20	0.00007	0.000	12.394	<0.001	1.017
avgha_pertrip_perc	14.75934	4.192	3.521	<0.001	1.071
avghb_pertrip_perc	30.00911	6.770	4.433	<0.001	1.037
len_seg	1.93453	0.330	5.856	<0.001	1.055
AICc	2333.837				

- Crash frequency is positively correlated with the average AADT, showing that as traffic volume increases, the number of road crashes increases as well.
- Harsh accelerations and harsh brakings have a positive relationship with the dependent variable, indicating that as the number of these two harsh driving behaviour events increases, crash frequency also increases.
- This finding confirms that harsh driving behaviour events present a statistically significant positive correlation with historical crash records indicating that these metrics can be meaningfully considered as reliable SSMs.
- Lastly, crash frequency is higher for motorway segments with higher length, as length serves as an exposure parameter.

Definition of Crash Risk Levels

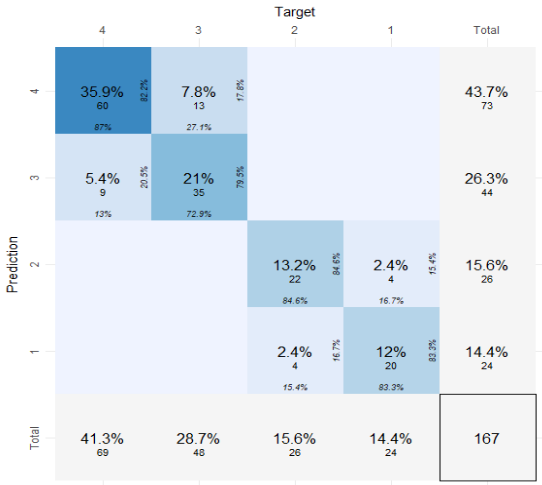
Agglomerative hierarchical clustering

- The Euclidean distance between single observations of the dataset and Ward's minimum variance method as the linkage criterion were used.
- The variables considered for the formation of the risk level clusters of the motorway segments correspond to the number of total road crashes by segment length and the respective AADT of each segment.
- The selection of the number of clusters was based on the produced dendrogram.
- Four distinct clusters representing crash risk levels of the examined segments emerged from the hierarchical clustering procedure, ranging from more risk-prone, potentially unsafe locations to more safe locations.

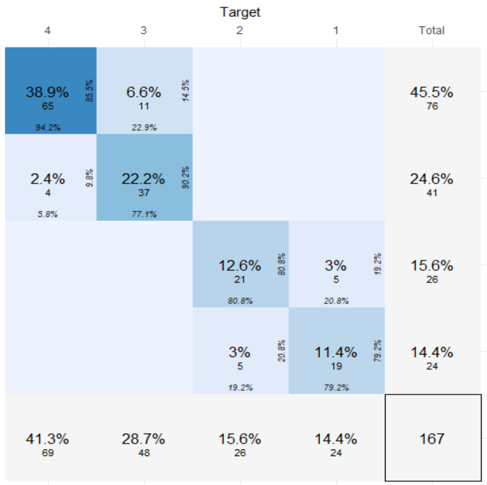


Crash Risk Level	Count of Segments	Average "TotCr18_20_len_seg"	Average "avg_AADT_18_20"
1	96	7.57	20,876
2	104	4.55	17,218
3	193	3.25	8,086
4	275	2.76	6,726
Total	668	3.87	10,786

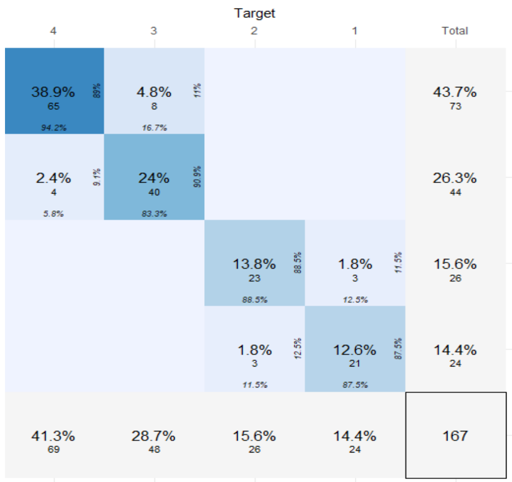
Crash Risk Level Classification Models



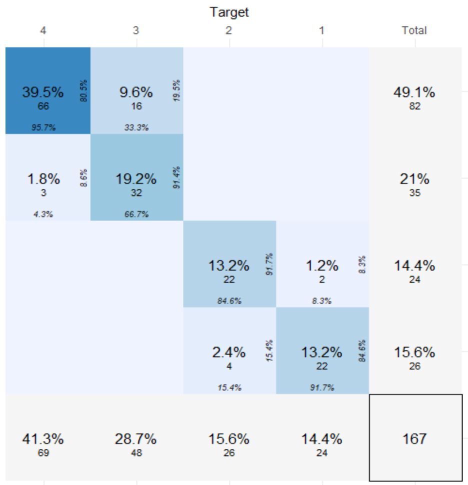
Logistic Regression (LR)



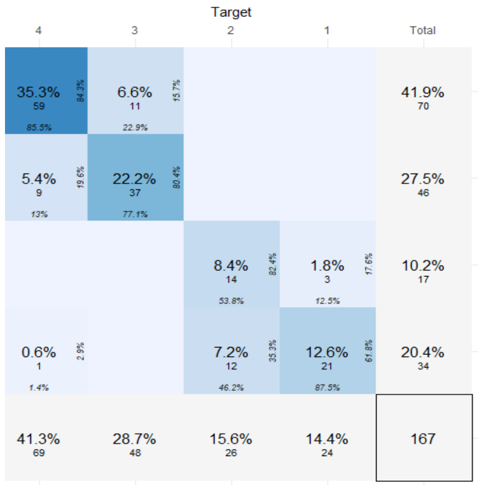
Decision Tree (DT)



Random Forest (RF)



Support Vector Machine (SVM)



K-Nearest Neighbor (K-NN)

- **Response variable:** Crash Risk Level
  Predictors: lanes, lane_width, Curve1, Lcurve1_in_seg, median_width, pav_ins_sh_width, pav_out_sh_width, dist_edginssh_barf, dist_edgoutsh_barf, speed_limit, avg_speed, avg_sp_ev_pertrip_perc, avghb_pertrip_perc, avgha_pertrip_perc
- The **training subset (75%)** was used to train the models, while the **test subset (25%)** was used to evaluate their performance.
- **Overall accuracies**: 89.3% for RF, 85.1% for DT, 85.1% for SVM, 82.1% for LR and 78.4% for K-NN.
- **RF classification model** was the best performing model, based on both the overall accuracy and the per-class metrics.

	LR	DT	RF	SVM	K-NN
Crash Risk Level	**Precision (%)**				
1	83.3	79.2	87.5	84.6	61.8
2	84.6	80.8	88.5	91.7	82.4
3	79.5	90.2	90.9	91.4	80.4
4	82.2	85.5	89.0	80.5	84.3
Macro-averaged	82.4	83.9	89.0	87.0	77.2
Crash Risk Level	**Recall (%)**				
1	83.3	79.2	87.5	91.7	87.5
2	84.6	80.8	88.5	84.6	53.8
3	72.9	77.1	83.3	66.7	77.1
4	87.0	94.2	94.2	95.7	85.5
Macro-averaged	82.0	82.8	88.4	84.7	76.0
Crash Risk Level	**F1 score (%)**				
1	83.3	79.2	87.5	88.0	72.4
2	84.6	80.8	88.5	88.0	65.1
3	76.1	83.1	87.0	77.1	78.7
4	84.5	89.7	91.5	87.4	84.9
Macro-averaged	82.1	83.2	88.6	85.1	75.3

SHAP values (1/2)

- SHAP values were provided for the RF model in order to deal with the difficult challenge of interpreting its results.
- To create a representative instance of motorway segments, the median values of the continuous predictors were used.
- Medians were preferred instead of the mean values, as it can be concluded that the predictors are not normally distributed based on the outcomes of Shapiro-Wilk normality tests, skewness and kurtosis values.

Abbreviation	Shapiro-Wilk (p-value)	Skewness	Kurtosis	Median
lane_width	< 0.001	-2.42	10.48	3.95
Curve1	< 0.001	5.74	42.56	950.00
Lcurve1_in_seg	< 0.001	0.49	2.27	197.65
median_width	< 0.001	3.86	23.58	4.93
pav_ins_sh_width	< 0.001	1.63	11.43	0.75
pav_out_sh_width	< 0.001	-0.85	3.68	3.00
dist_edginssh_barf	< 0.001	3.19	15.79	0.00
dist_edgoutsh_barf	< 0.001	0.96	3.13	0.50
speed_limit	< 0.001	-1.16	2.82	130.00
avg_speed	< 0.001	-1.27	6.31	118.00
avg_sp_ev_pertrip_perc	< 0.001	0.11	3.29	32.00 %
avghb_pertrip_perc	< 0.001	4.73	31.30	0.07 %
avgha_pertrip_perc	< 0.001	10.03	121.58	0.08 %

SHAP values (2/2)

- The SHAP values can be positive (green bars) or negative (red bars) for each crash risk level, depending on whether the feature has a positive or negative contribution to the prediction for that class.
- It can be observed that this representative motorway segment is more likely to belong to the lowest crash risk level, which corresponds to overall safer locations with lower traffic volumes and road crashes by segment length than the motorway segments between the first and the third crash risk level.
- The harsh acceleration related variable does not make a significant contribution to the prediction of the segment crash risk level.
- The results of this investigation suggest that harsh brakings may be more pertinent than harsh accelerations for predicting the crash risk level of motorway segments overall.

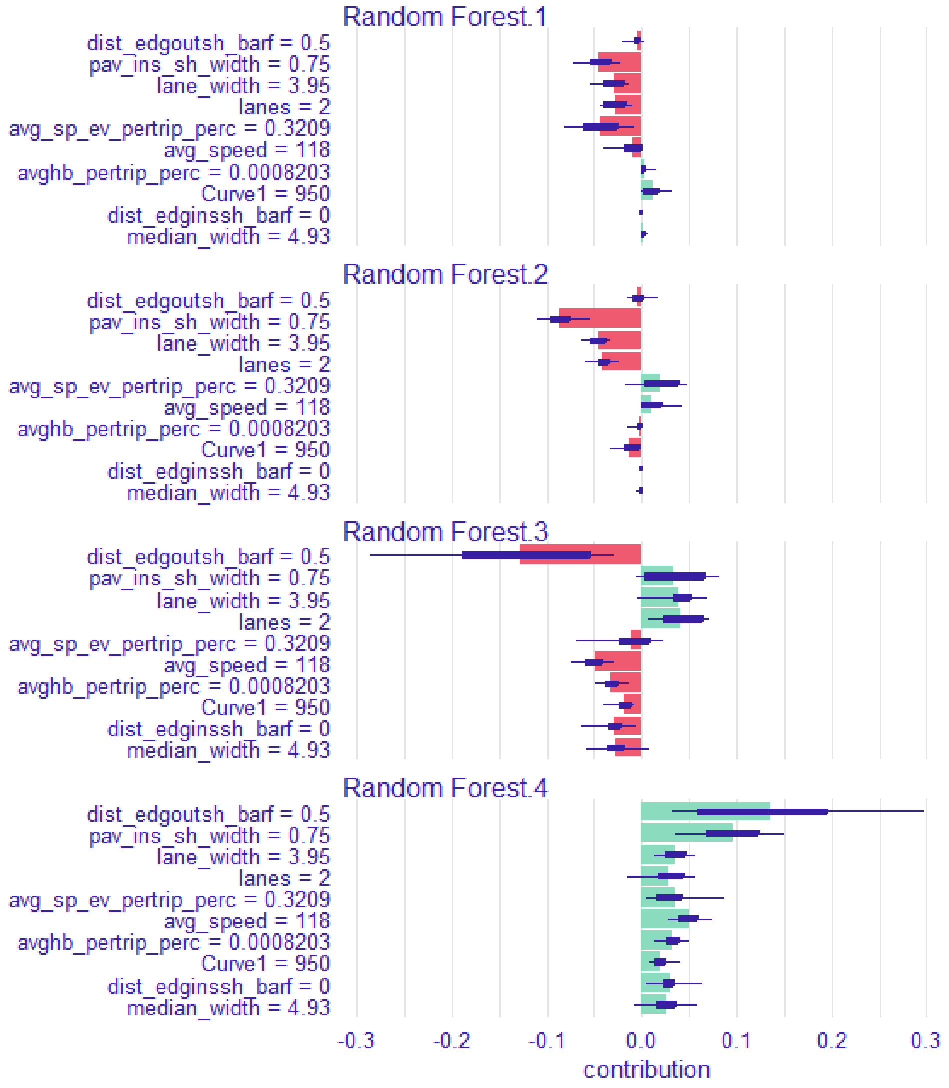


Figure: SHAP values for the RF model and a representative motorway segment

Key Conclusions

- The positive and statistically significant relationship between crash frequency and harsh driving behaviour events demonstrates that such events can be a valid subcategory of naturalistic SSMs.

- The overall and per crash risk level classification performance of the developed RF model was very high indicating that this approach could be utilized as a quite promising proactive approach for the identification and prioritization of potential hazardous motorway segments.

- Harsh brakings may be more pertinent than harsh accelerations for predicting the crash risk level of motorway segments overall.

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