Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 00 (2022) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

Transport Research Arena (TRA) Conference

How to Define a Safety Tolerance Zone for Speed? Insights from the i-DREAMS project

Eva Michelaraki[a]*, Marianthi Kallidoni[a], Christos Katrakazas[a], Tom Brijs[b], George Yannis[a]

[a]*National Technical University of Athens, Department of Transportation Planning and Engineering, 5 Heroon Polytechniou str., GR-15773, Athens, Greece*
[b]*3UHasselt, School for Transportation Sciences, Transportation Research Institute (IMOB), Agoralaan, 3590 - Diepenbeek, Belgium*

Abstract

Several factors of driver state negatively impact road safety, such as distraction (in-vehicle or external), fatigue and drowsiness, health issues and extreme emotions. The aim of the current study is to define a Safety Tolerance Zone (STZ) for speed, and integrate crash prediction and risk assessment. A naturalistic driving experiment was conducted and data from a representative sample (N=20 drivers) was utilized. Explanatory variables of risk and the most reliable indicators were assessed. A feature importance algorithm extracted from Extreme Gradient Boosting (XGBoost) was used to evaluate the significance of variables on forecasting STZ. Additionally, a Neural Network model was implemented for real-time data prediction. Results indicated a strong relationship between the STZ level for speed and the independent variables of headway, distance travelled and medium harsh braking events.

Peer-review under responsibility of the scientific committee of the Transport Research Arena (TRA) Conference

Keywords: i-DREAMS project; Safety Tolerance Zone; Speed; XGBoost; Bayesian Networks.

1. Introduction

Approximately, 1.25 million people die every year on roads worldwide, with millions more sustaining serious injuries and living with long-term adverse health consequences (World Health Organization, 2015). Globally, road crashes are one of the leading causes of death, especially among young people, as well as the number one cause of death among those aged 15–29 years (World Health Organization, 2008). Currently, road crashes are estimated to be the 9th leading cause of death across all age groups, and will also become the 7th dominant cause of death by 2030.

* Corresponding author. Tel.: +30-210-772-1265;
E-mail address: evamich@mail.ntua.gr

Peer-review under responsibility of the scientific committee of the Transport Research Arena (TRA) Conference

Several factors that affect the likelihood of a road traffic crash or a serious injury have been identified in the literature (Wang et al., 2021). These factors include the driver state, such as distraction, fatigue and drowsiness, health issues and extreme emotions and have been found to have a negative impact on road safety (Papantoniou et al., 2017; Pawelec, 2021). Moreover, differences in socio-cultural factors are still among the main determinants of road risks (Melinder, 2007). At the same time, technological developments make massive and disaggregated operator performance data easily available, for example, through new in-vehicle sensors that capture detailed driving style and contextual data (Hong et al., 2014). This creates new opportunities for the detection and design of customized interventions to mitigate the risks, increase awareness and upgrade driver performance, constantly and dynamically.

To exploit these opportunities, several machine learning techniques have been used in road safety analysis and traffic flow modelling. To begin with, Girma et al. (2019) proposed a deep learning model, (i.e. aLong Short Term Memory - LSTM model), in order to classify drivers according to their individual unique driving performance using vehicle telematics data. Results indicated that the proposed model's prediction accuracy remained satisfactory and outperformed other approaches despite the extent of inconsistencies induced in the dataset. Moreover, Chong et al. (2013) trained a fuzzy rule-based neural network to model the acceleration of a car-following vehicle. Fuzzy logic was used to discretize traffic state and action variables and reinforcement learning was used for the Neural Network (NN) to learn driving behavior patterns from naturalistic data.

The overall objective of the European H2020 i-DREAMS[†] project aims to define, develop test and validate the concept of the 'Safety Tolerance Zone' (STZ), with a smart Driver, Vehicle & Environment Assessment and Monitoring System. The term 'Safety Tolerance Zone', although abstract in nature, refers to a real phenomenon, i.e. self-regulated control over transportation vehicles by (technology assisted) human operators in the context of crash avoidance. Driving task complexity indicators (e.g. road layout, weather conditions, time of the day) and driver background factors (e.g. fatigue, distraction, sleepiness) are taken into consideration and a continuous real-time assessment is created in order to monitor and determine if a driver is within acceptable boundaries of safe operation (i.e. Safety Tolerance Zone). In addition, safety-oriented interventions and post-trip feedback are provided in order to prevent drivers from getting too close to the boundaries of unsafe operation.

The STZ is made up of three phases: Normal Driving phase, Danger phase and Avoidable Accident phase. Firstly, "Normal Driving" refers to the phase, where conditions at that point in time suggest that a crash is unlikely to occur and therefore, the crash risk is low and the operator is successfully adjusting their behavior to meet task demand. Secondly, the "Danger phase" is characterized by changes to the "Normal Driving" that suggest a crash may occur and thus, there is an increased crash risk. At this phase, a crash is not inevitable but becomes more likely. Lastly, the "Avoidable Accident" phase occurs when a collision scenario is developing, but there is still time for the operator to intervene to avoid the crash. In this phase, the need for action is more urgent to denote that if there are no changes or an evasive manoeuvre performed by the operator, a crash is very likely to occur.

Based on the above framework, the objective of the current study is to define a Safety Tolerance Zone for speed, and integrate crash prediction and risk assessment under a NN framework. To that aim, explanatory variables of risk and the most reliable indicators of task complexity and coping capacity, such as time headway, distance travelled, speed, forward collision, time of the day (lighting indicators) or weather conditions were assessed.

The paper is structured as follows. After this introduction, an overview of the data collected for the analysis is presented. Subsequently, a brief description of the methodological approach is provided. Subsequently, the significant findings are drawn and the results of the statistical analysis performed are summarized. Lastly, conclusions are highlighted and the limitations along with some proposals for further research are clearly stated.

2. Data collection

For the purpose of this research, a naturalistic driving experiment was carried out involving 20 drivers from Belgium, during a 3-month timeframe (from 21/07/2021 to 30/10/2021) and a large database of 757 trips was created. As the key output of the i-DREAMS project is an integrated set of monitoring and communication tools for intervention and support, state-of-the-art technologies and systems were utilized in order to monitor driving

[†] Further general project information can be found on the website: https://idreamsproject.eu

performance indicators. More specifically, data from the Mobileye system (Mobileye, 2022), a dash camera and the Cardio gateway (CardioID Technologies, 2022) which records driving behavior along with GNSS signals were used. In particular, the Mobileye systems is as a sensor network that measures parameters, like headway distance. Information about the current warning stage, as defined by Mobileye, were also collected for comparison with the i-DREAMS warning stage (i.e. normal driving, danger phase, avoidable accident phase). At the same time, information about the current state of the i-DREAMS platform were collected.

Explanatory variables of risk and the most reliable indicators of task complexity and coping capacity, such as time headway, distance travelled, forward collision or weather conditions were assessed. Particular emphasis was given to average speed and a new variable, namely STZ_speed, which takes into account the different levels of STZ for speed was created. Thus, the dependent variable was the level of the STZ for speed (i.e. STZ_speed), divided into three levels (i.e. Normal Driving phase: 0, Dangerous phase: 1, Avoidable Accident phase: 2).

Table 1 provides an overview of the variables examined along with their corresponding description.

Table 1. Driving performance indicators along with their corresponding description

(Source: Mobileye, Cardio, Data processing: NTUA)

Variable	Description
ME_AWS_hw_measurement_mean	Headway measurement (seconds)
ME_AWS_fcw_mean	Forward collision warning
ME_AWS_pcw_mean	Pedestrian collision warning
GPS_distances_sum	Distance travelled (km)
DEM_evt_ha_lvl_M_mean	Medium level harsh acceleration events
DEM_evt_hb_lvl_M_mean	Medium level harsh braking events
ME_AWS_time_indicator_median	Indicates lighting conditions (day, dusk, night)
ME_Car_wipers_median	Indicates weather conditions (wipers on/off)

After an extensive data cleaning and preparation, the next step of the analysis involved a collinearity testing so that any highly correlated variables were excluded from the models. When two variables have an absolute value of correlation coefficient at least 0.6, then these two variables are highly correlated. Figure 1 indicatively shows the correlation coefficients between variables used in the models. No strong correlation among the examined variables was identified, as shown below:

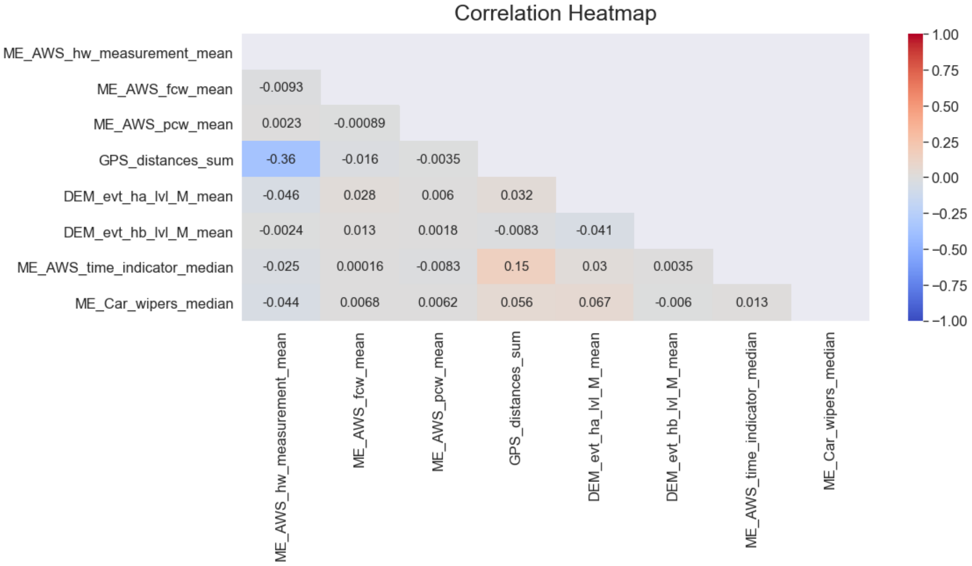

Fig. 1. Examined description correlation heatmap

3. Methodology

After the data collection, a feature selection algorithm (i.e. XGBoost) was applied in order to identify the most important features for predicting the STZ level. These features were then fed into an NN classifier to identify the STZ level. The following subsections describe the algorithms that were used in more detail.

3.1 XGBoost

XGBoost algorithms are optimized supervised ML algorithms encompassing multiple Classification and Regression Trees (CART). Due to its adaptability and effectiveness, XGBoost has been consistently outperforming competitor methodologies in numerous ML competitions (Nielsen, 2016). The algorithm is described extensively in the seminal work of Chen & Guestrin (2016). In short, if a mapping function is considered between variables:

$$\hat{y} = f(x_i) \tag{1}$$

where: y is the dependent (or response) variable, $\hat{y}$ is the predicted value of the dependent variable and x_i are the independent (or explanatory) n variables across i observations, then a regression tree ensemble model uses a number of functions K additively to predict y, so that:

$$\hat{y} = \varphi(x_i) = \sum_{k=1}^{K} f(x_i) \tag{2}$$

In XGBoost, three particular variable importance metrics were observed: (i) gain, describing the improvement in accuracy added by a feature to the branches it is located on, (ii) cover, describing the relative quantity of observations (or number of samples) concerned by a feature and (iii) frequency, describing the number of times a feature is used in all generated trees.

Therefore, following good ML practices, the hyperparameters of XGBoost algorithms should initially be tuned before their final executions, and their predictions should subsequently be evaluated with model evaluation metrics. It is important to note that the highly non-linear, tree ensemble structure of XGBoost makes it resilient against bias from multicollinearity effects (Guo et al., 2021).

3.2 Neural Networks

A NN is a simplified model which works by simulating a large number of interconnected processing units that resemble abstract versions of neurons. In addition, NNs can approximate a wide range of predictive models with minimal demands on model structure and assumption. The processing units are arranged in layers. In particular, these models consist of three main parts: an input layer, with units representing the input fields; one or more hidden layers; and an output layer, with a unit or units representing the target field(s). The units are connected with varying connection strengths. Input data are presented to the first layer, and values are propagated from each neuron to every neuron in the next layer. Thus, a result is delivered from the output layer.

Moreover, NNs generate a prediction for each record, examining individual records, as well as making adjustments to the weights whenever it makes an incorrect prediction. The aforementioned processing is repeated many times, and the network continues to improve its predictions until one or more of the stopping criteria have been met. It should be mentioned that all weights are random and the answers derived from the net are probably nonsensical.

In the case of aggregating N road safety performance indicators into one combined index, a typical composite indicator takes the following form (Nardo et al., 2005):

$$y = \sum_{i=1}^{n} w_i x_i \tag{3}$$

where: y represents the composite index, x_i the i^{th} normalized indicator and w_i the weight assigned to x_i.

3.3 Model evaluation metrics

In order to compare the classification performance of the several configurations (hyperparameters and mix of considered inputs), well-established machine learning error metrics were calculated. The following metrics were utilized, based on the confusion matrix, which provides True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) metrics.

Accuracy, which represents the proportion of correctly classified observations, is defined as:

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{4}$$

Precision, which quantifies the number of positive class predictions that actually belong to the positive class, is defined as:

$$Precision = TP/(TP + FP) \tag{5}$$

Recall, also known as True Positive Rate, is defined as:

$$Recall = TP/(TP + FN) \tag{6}$$

F-means, which combines precision and recall into a single measure, is defined as:

$$F - means = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{7}$$

The structure methodology along with the proposed characteristics to estimate the STZ for speed is depicted in the following flowchart in Figure 2:

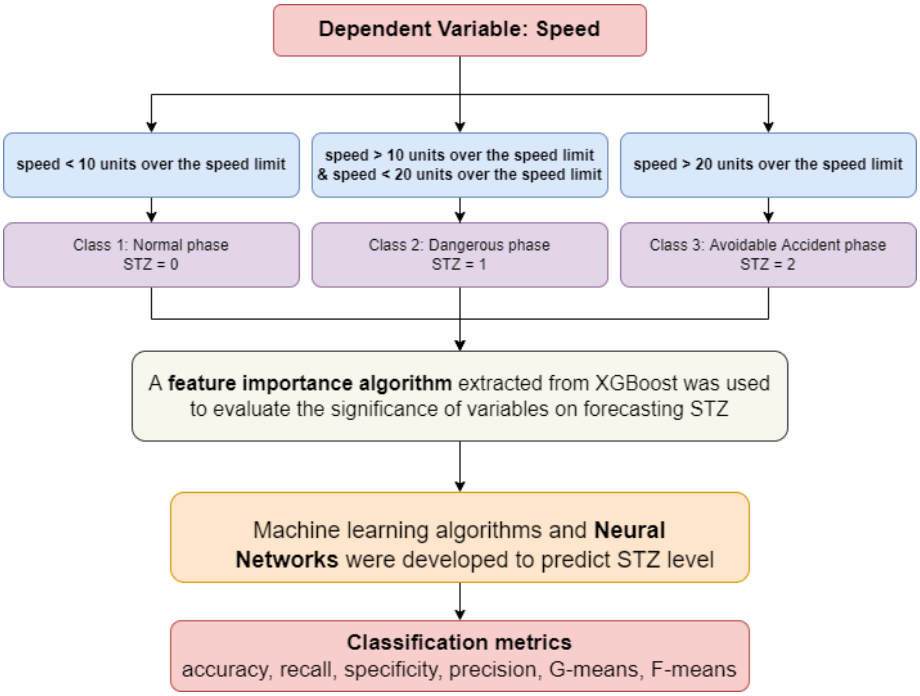

Fig. 2. Proposed methodology for the definition of the Safety Tolerance Zone (STZ) for speed

4. Results

A feature importance algorithm extracted from Extreme Gradient Boosting (XGBoost) was used to evaluate the significance of variables on forecasting STZ and select the most appropriate independent variables. GPS distance travelled, headway measurement and medium level harsh braking events were the most important factors of all examined indicators. The parameters of task complexity (i.e. car wipers and time indicator) were less significant, while forward collision warning and pedestrian collision warning variables had a negligible impact on STZ speed. Figure 3 provides an overview of the feature importance of independent variables based on XGBoost algorithm.

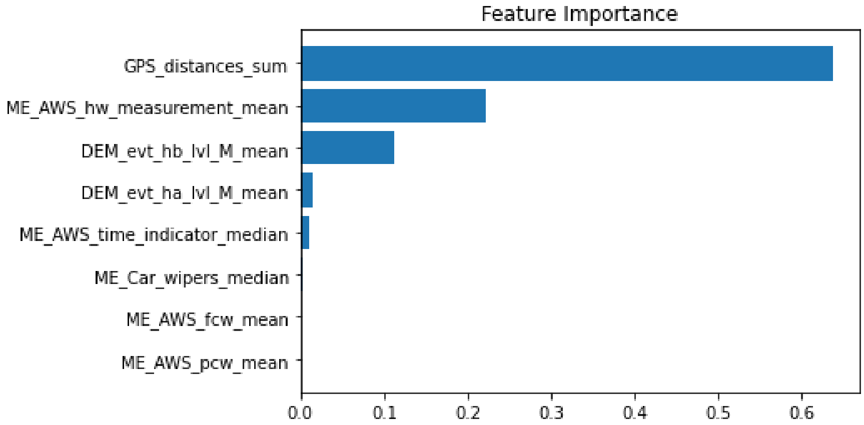

Fig.3. XGBoost feature importance of independent variables

A dataset of 50,000 rows was used and a feed-forward multilayer perceptron NN model was implemented. Based on the feature importance and the significance of the relevant indicators, there were three neurons in the input layer (i.e. headway measurement, medium level harsh braking events and distance travelled) and one neuron in the output layer (i.e. STZ), as shown in Figure 4.

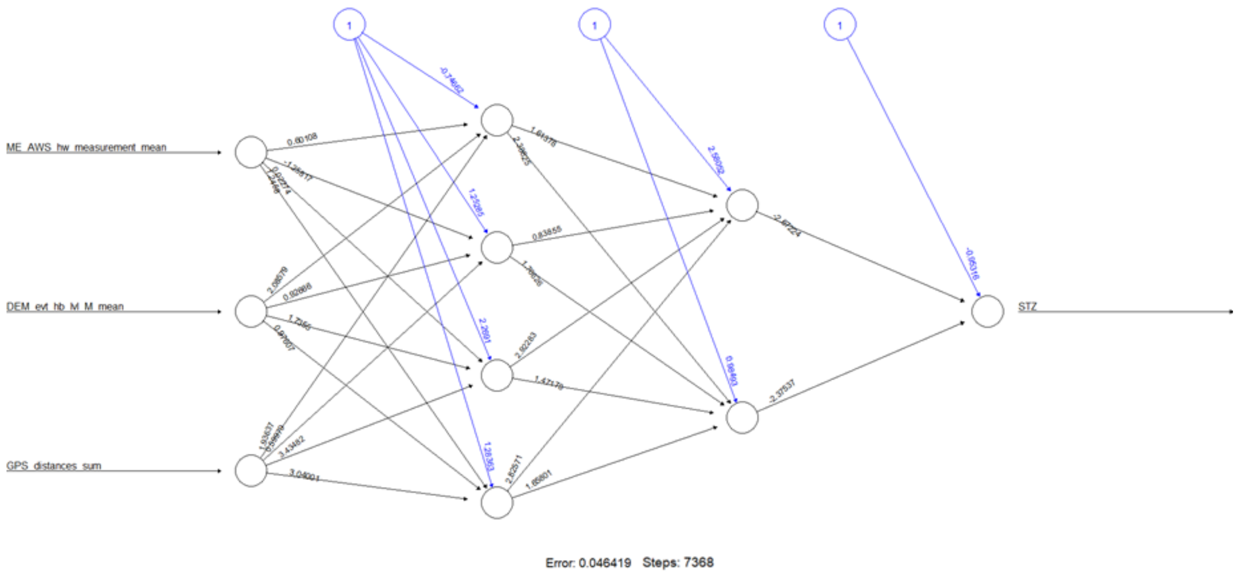

Fig. 4. The multi-layer Neural Network model layout for STZ

Then, a confusion matrix which contains three rows and three columns and reports the number of false positives, false negatives, true positives, and true negatives was created. This allows more detailed analysis than the proportion of correct classifications (e.g. accuracy, precision, recall). It should be mentioned that accuracy refers to how close a measurement is to the true or accepted value, while precision refers to how close measurements of the same item are to each other. Table 2 provides the assessment of classification model.

Table 2. Assessment of classification model

	0	1	2	Total
Accuracy	0.62	0.82	0.75	0.72
Precision	0.97	0.56	0.40	0.68
Recall	0.61	0.54	0.46	0.57
F-means	0.75	0.55	0.47	0.62

**0 refers to normal phase, 1 refers to dangerous phase, 2 refers to avoidable accident phase*

5. Discussion

Following the formulation and explanation of the required functions, machine learning algorithms were utilized for the STZ prediction regarding the variable of speed and the results were then incorporated into the integrated NN model for predicting STZ speed. Based on the confusion matrix calculated, the variable STZ speed holds the result of dividing the sum of True Positives and True Negatives over the sum of all values in the matrix. All analyses were conducted in R-studio (R Core Team, 2019). The data were split into 75% train and 25% test in order to evaluate the models. It should be mentioned that class 0 refers to normal phase, class 1 refers to dangerous phase, while class 2 refers to avoidable accident phase.

Focusing on the results of all classes combined, both classifiers achieve 72% accuracy, 68% specificity and 57% recall. First of all, the total accuracy means that the model is 72% accurate in making a correct prediction. Moreover, the model was 68% accurate regarding a positive sample and 57% accurate on predicting safety-critical classes (i.e. “Dangerous” and “Avoidable Accident”), which means that the model can be trusted in its ability to detect positive samples in a moderate degree.

It should be noted that Normal Driving included the majority of available data and thus was predicted with 97% precision and 61% recall, while Dangerous Driving classification presented 56% precision and 54% recall. The Avoidable Accident phase, which included only the 4% of the test set, presented the lowest rates, i.e. 40% precision and 46% recall in STZ. Overall, the aforementioned findings indicated that both methods could predict adequately the Safety Tolerance Zone but the imbalance of the dataset posed difficulties in correctly identifying all classes.

The current study possesses certain limitations. Firstly, the sample size of the analysis was relatively small and could be expanded if the models are going to be generalized. Secondly, drivers’ demographic characteristics, such as age, gender, education level, driving experience or mental health state were not included in the analysis. In addition, the influence of psychological status of participants, such as driver distraction, anger, sleepiness or fatigue were not examined in the present study, as only the driver data from the naturalistic driving experiment were used. Taking into consideration that drivers react differently under different circumstances with respect to traffic conditions (i.e. high, medium or low traffic volumes), it would be of great interest to investigate average speed using traffic and driver data.

Future research efforts could consider additional drivers’ age groups, while larger datasets from across the world could enhance the analysis procedure. The investigation of other significant factors could be also included in the future. For instance, the presence of a passenger, the drug abuse, the alcohol consumption or the seat belt use constitute some of the high risk factors that cause road crashes. As per future research directions, the examination of additional methods of analysis could be applied. In particular, imbalanced learning as well as factor analysis and microscopic data analysis of the database collected could be implemented through econometric techniques, and deep learning.

6. Conclusions

The present research aimed to define a Safety Tolerance Zone (STZ) for speed and integrate crash prediction and risk assessment. For that purpose, data collected from a naturalistic driving experiment with a sample of 20 drivers were utilized. Explanatory variables of risk and the most reliable indicators, such as time headway, distance travelled, speed, forward collision, time of the day (lighting indicators) or weather conditions were assessed.

A feature importance algorithm extracted from Extreme Gradient Boosting (XGBoost) was used to evaluate the significance of variables (i.e. headway, forward collision warning, pedestrian collision warning, distance travelled, harsh acceleration and braking events as well as lighting and weather conditions) on forecasting STZ. In addition, a

Neural Network model was implemented for real-time data prediction, taking into account the most important and significant risk indicators.

Results indicated a strong relationship between STZ_speed and the independent variables of headway, distance.travelled and medium harsh braking events. However, imbalanced learning could enhance classification results, in order for all three STZ levels to be correctly identified in real-time.

Acknowledgements

This research was funded by the European Union's Horizon 2020 i-DREAMS project (Project Number: 814761) funded by European Commission under the MG-2-1-2018 Research and Innovation Action (RIA).

References

CardioID Technologies (2022). Heartmetrics Experts. Last assessed 15/05.22. Retrieved from: https://www.cardio-id.com/automotive/.

Chen, T., & Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining (pp. 785-794).

Chong, L., Abbas, M. M., Flintsch, A. M., & Higgs, B. (2013). A rule-based neural network approach to model driver naturalistic behavior in traffic. Transportation Research Part C: Emerging Technologies, 32, 207-223.

Girma, A., Yan, X., & Homaifar, A. (2019). Driver identification based on vehicle telematics data using LSTM-recurrent neural network. In 2019 IEEE 31st International Conference on Tools with Artificial Intelligence (ICTAI) (pp. 894-902). IEEE.

Guo, M., Yuan, Z., Janson, B., Peng, Y., Yang, Y., & Wang, W. (2021). Older pedestrian traffic crashes severity analysis based on an emerging machine learning XGBoost. Sustainability, 13(2), 926.

Hong, J. H., Margines, B., & Dey, A. K. (2014). A smartphone-based sensing platform to model aggressive driving behaviors. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (pp. 4047-4056).

Melinder, K. (2007). Socio-cultural characteristics of high versus low risk societies regarding road traffic safety. Safety science, 45(3), 397-414.

Mobileye (2022). An Intel Company. Last assessed 15/05.22. Retrieved from: https://www.mobileye.com/

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, H., & Giovannini, E. (2005). Handbook on constructing composite indicators: methodology and user guide. Organisation for Economic Cooperation and Development (OECD). Statistics Working Paper JT00188147, France.

Nielsen, D. (2016). Tree boosting with xgboost-why does xgboost win" every" machine learning competition? (Master's thesis, NTNU).

Papantoniou, P., Papadimitriou, E., & Yannis, G. (2017). Review of driving performance parameters critical for distracted driving research. Transportation research procedia, 25, 1796-1805.

Pawelec, K. (2021). State of health, fatigue, psychophysical, and psychological characteristics, and their influence on road traffic safety. An evaluation attempt. Cybersecurity and Law.

Wang, Z., Huang, S., Wang, J., Sulaj, D., Hao, W., & Kuang, A. (2021). Risk factors affecting crash injury severity for different groups of e-bike riders: A classification tree-based logistic regression model. Journal of safety research, 76, 176-183.

World Health Organization (2015). Global status report on road safety 2015. World Health Organization. https://apps.who.int/iris/handle/10665/189242.

World Health Organization. (2008). The global burden of disease: 2004 update. World Health Organization. https://apps.who.int/iris/handle/10665/43942.

XGBoost developer team (2021). XGBoost Documentation. Official website. Available from: https://xgboost.readthedocs.io/en/latest/index.html [Accessed 07/10/2021].