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Research Paper

Predictive models for road traffic sign: Retroreflectivity status, retroreflectivity coefficient, and lifespan

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ABSTRACT

This study addresses the critical safety issue of declining retroreflectivity values of road traffic signs, which can lead to unsafe driving conditions, especially at night. The paper aims to predict the retroreflectivity coefficient values of these signs and to classify their status as acceptable or rejected (in need of replacement) using machine learning models. Moreover, logistic regression and survival analysis are used to predict the median lifespans of road traffic signs across various geographical locations, focusing on signs in Croatia and Sweden as case studies.

The results indicate high accuracy in the predictive models, with classification accuracy at 94% and an R2 value of 94% for regression analysis. A significant finding is that a considerable number of signs maintain acceptable retroreflectivity levels within their warranty period, suggesting the feasibility of extending maintenance checks and warranty periods to 15 years which is longer than the current standard of 10 years. Additionally, the study reveals notable variations in the median lifespans of signs based on color and location. Blue signs in Croatia and Sweden exhibit the longest median lifespans (28 to 35 years), whereas white signs in Sweden and red signs in Croatia show the shortest (16 and 10 years, respectively). The high accuracy of logistic regression models (72–90%) for lifespan prediction confirms the effectiveness of this approach. These findings provide valuable insights for road authorities regarding the maintenance and management of road traffic signs, enhancing road safety standards.

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1. Introduction

Road traffic signs play a crucial role to ensure safe navigation on roads by conveying important information to drivers. They need to be visible and legible both day and night. However, due to the specific conditions during night-time, their visibility is much more important at night compared to daytime (Saleh and Fleyeh, 2021). Poor visibility of road traffic signs at night can result in drivers missing important information and causing confusion, potentially leading to crashes. Retroreflective sheeting helps to ensure that road traffic signs are visible in low light conditions by reflecting light from vehicle headlights back to the driver (Ré et al., 2011).

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Retroreflective sheeting functions by utilizing tiny glass beads or prismatic elements to reflect light to the source (Ré et al., 2011), making the sign better visible. The effectiveness of the sign material in reflecting light is measured by the retroreflectivity coefficient (RA). In this study, the terms “retroreflectivity” or (RA) are used instead of “retroreflectivity coefficient” to describe the property of road traffic signs that reflect light to the source.

The main problem with road traffic signs is that their retroreflectivity deteriorates over time, and if they fall below the required level for visibility, the signs must be replaced. In some countries, visual inspection is employed, which lacks objectivity, while in others, signs are replaced once their warranty period expires. Road authorities use various in-suite inventory methods, such as measuring retroreflectivity through a handheld retroreflectometer to assess the condition of road traffic signs and ensure they meet the minimum acceptable levels of retroreflectivity specified by regulations, for example, the European standards (European Committee for Standardization, 2007). However, these methods can be tedious, time-consuming, expensive, and risky for maintenance personnel (Siegmann et al., 2005).

To explore an alternative to the traditional in-suite inventory methods, this study aims to predict the status and values of road traffic signs' retroreflectivity using machine learning techniques. By training models on two datasets collected from Sweden and Croatia, the study improves the accuracy and reliability of the predictive models and evaluates their generalization and performance. The study also highlights the importance of several variables, such as area, height, and location of road traffic signs for the predicting models.

This study contributes to improving knowledge regarding the deterioration of retroreflective sheeting and its implications for sign specification and purchasing decisions. Its findings provide a solid foundation to improve strategies and approaches in maximizing the longevity and effectiveness of retroreflective sheeting. The proposed machine learning methods and models offer a reliable and low-cost tool for predicting the retroreflectivity status of road traffic signs and values of retroreflectivity.

Furthermore, the study explores the crucial aspect of durability by examining the long-term performance and resilience of retroreflective sheeting under various conditions and usage scenarios. By considering factors such as sheeting class, color, GPS positions, area, height from ground level, distance to road, and location of road traffic signs, the study provides a comprehensive understanding of the material's durability over time.

The rest of the paper is organized as follows: The literature review is presented in Section 2. In Section 3, the methods and materials are presented including the description of data, models, and algorithms used. The results and the performance of the proposed models for each algorithm are given in Section 4. Finally, conclusions are drawn in Section 5.

2. Literature review

The prediction of road traffic sign service life and retroreflectivity has been the focus of several studies. In 1988 the first attempt was made to predict the replacement month of warning signs, considering factors such as sheeting type, color, orientation, climate, age, pollution, and salt spray (Swargam, 2004). However, the model was limited to yellow signs and achieved an R^2 value of 50% to 64%. In 1992, regression models were formulated to estimate retroreflectivity but with the poor performance of R^2 values ranging from 20% to 50% (Black et al., 1992).

In 2002, linear regression models were developed, with the most significant factors being sign age, orientation, and distance from the road (Wolshon et al., 2002). A study in 2004 (Swargam, 2004) found artificial neural networks to be more accurate than regression models, with an average accuracy of 65.27% compared to regression models' 9.99% to 33.52%. Nine regression models were used in 2006, with age being the dominant predictor and R^2 values between 20% and 50% (Rasdorf et al., 2006). Regression analyses in 2009 found retroreflectivity minimums were reached 8–15 years after installation, with R^2 values between 19% and 52% (Immaneni et al., 2009).

A 2010 study evaluated sign sheeting against retroreflectivity and color criteria, finding that most products failed in color chromaticity before retroreflectivity (Brimley et al., 2011). In 2017, regression models were developed to predict the retroreflection of road traffic signs mounted in Zagreb, with an average coefficient of determination between 55% and 60% (Babić et al., 2017).

In 2021, a neural network-based deep learning model was used for road traffic sign retroreflectivity prediction, achieving an R^2 value of 97.6%, while polynomial regression models achieved an R^2 of 75.9% (Alkhulaifi et al., 2021).

Algorithms, including Random Forest, Artificial Neural Network, and Support Vector Machines, were used in 2022 (Saleh and Fleyeh, 2022) to predict the retroreflectivity status of road traffic signs with an overall high accuracy, precision, recall, and F1 scores of 98%. Also, in 2022, two logarithmic regression models were found to be the best-fitting models for predicting retroreflectivity in Sweden and Denmark, with R^2 values of 50% and 95% (Saleh et al., 2022). The first model identified age, direction, GPS positions, color, and sheeting class of road traffic signs as significant predictors, while the second model used age, color, and sheeting class of road traffic signs.

The existing literature lacks comprehensive exploration in the domain of road traffic sign retroreflectivity prediction. Specifically, there is a notable research gap in enhancing the performance of the regression predictive model, extending the array of predictor variables, and applying classification predictive models. Addressing this void is vital for achieving more accurate prediction of the retroreflectivity and service life for road traffic signs.

Regarding the methodology, survival analysis is a common technique for estimating the time until an event occurs and is widely used in fields like medicine and engineering. However, this approach has not been adopted in studying the functional

service life of traffic signs. Research in this area has primarily relied on regression models to determine when road signs become inadequate due to reduced visibility. This indicates a potential area for further exploration and application of survival analysis in this domain.

3. Methods-material and experiments

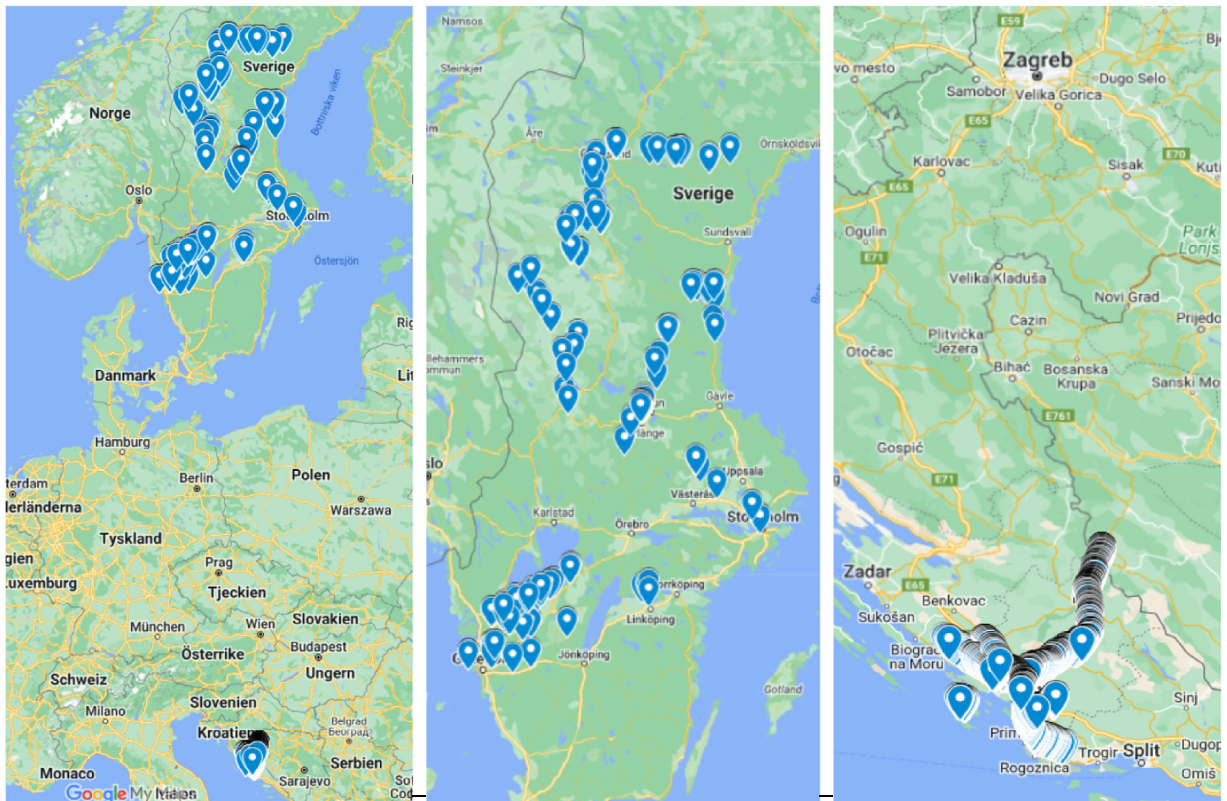
3.1. Data collection and pre-processing

The study utilized two datasets, the first was sourced from road traffic signs in Sweden (Saleh and Fleyeh, 2022; Kjellman et al., 2018; Saleh et al., 2023), and the second was gathered in Croatia using similar methods as depicted in Fig. 1.A.

The first dataset that illustrated in Fig. 1.B consisted of 695 records collected in 2018 and 2021 from road traffic signs in Sweden (Saleh et al., 2023). The signs' ages ranged from brand new to 44 years old, and the dataset included variables such as age, sheeting class, color, sign direction, GPS positions, coefficient of retroreflection (RA), and daylight chromaticity. The data comprised road traffic signs in white, red, yellow, and blue colors, and in classes 1, 2, and 3.

The second dataset was collected between 2015 and 2020 from 14 151 road traffic signs in the city of Šibenik-Knin in southern Croatia, as depicted in Fig. 1. C. The data was collected by the Department for Traffic Signaling at the Faculty of Transport and Traffic Sciences, University of Zagreb, and included road traffic signs aged from new to 37 years old. The collected data comprised the coefficient of retroreflection of retroreflective material in four colors (white, red, yellow, and blue) and three classes (1, 2, and 3). The variables included in this dataset were age, sheeting's class, color, direction, GPS positions, height, area, location, and distance to the road.

For both datasets, the retroreflectivity of road traffic signs was measured using a handheld retroreflectometer, as shown in Fig. 2. The retroreflection coefficient (RA) was measured at 5° entrance angle (β_1) and 0.33° observation angle (α) (Wolshon et al., 2002). The GPS positions and direction (orientation) of the signs were also recorded, and an image of each sign was captured using the retroreflectometer. The direction refers to the azimuth angle to which the sign is facing. The amount of reflected light by each sheeting differs across the grades (sheeting classes) of retroreflective sheeting, with sheeting class 1 reflecting less and sheeting class 3 reflecting the most.



A. All road traffic signs

B. Signs in Sweden

C. Signs in Croatia

Fig. 1. The locations of the road traffic signs included in the analyzed data.



Fig. 2. Data Collection in Sweden Using a Handheld Retroreflectometer by the Author.

All road traffic signs with missing measurements or information are removed from the dataset before they are analyzed and the resultant dataset is shown in [Table 1](#). Furthermore, the original datasets had an imbalance in terms of retroreflectivity status, with a severe skew in the distribution ratio of the minority status to the majority status (also shown in [Table 1](#)). To address this issue, a Random Oversampling technique was employed to generate new samples for the minority status (rejected) by sampling with replacement. This resulted in a new balanced dataset with equal representation of both status categories ([Table 1](#)). Additionally, normalization was employed to scale the dataset by casting the data variables to a range between zero and one, which is required when there are big differences in the ranges of different variables ([Ali et al., 2014](#)).

3.2. Study design

This study employed two types of predictive models to determine road traffic signs' retroreflectivity status and values. A classification model was used to predict whether a road traffic sign was accepted or rejected based on its level of retroreflectivity, while a regression model was employed to predict retroreflectivity values. To accomplish these two tasks, three machine-learning algorithms namely Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Networks (ANN) were utilized.

A train-test split was used for evaluating the models. The split was performed on the data with 20% of the data assigned to the test set and held out to evaluate regression models. The original data sets were used in regression models while over-sampled data sets were used in the classification models.

The effectiveness of these models was compared in terms of their accuracy. [Fig. 3.A](#) and [3.B](#) provide an overview of the models used in the study.

3.3. Variable importance

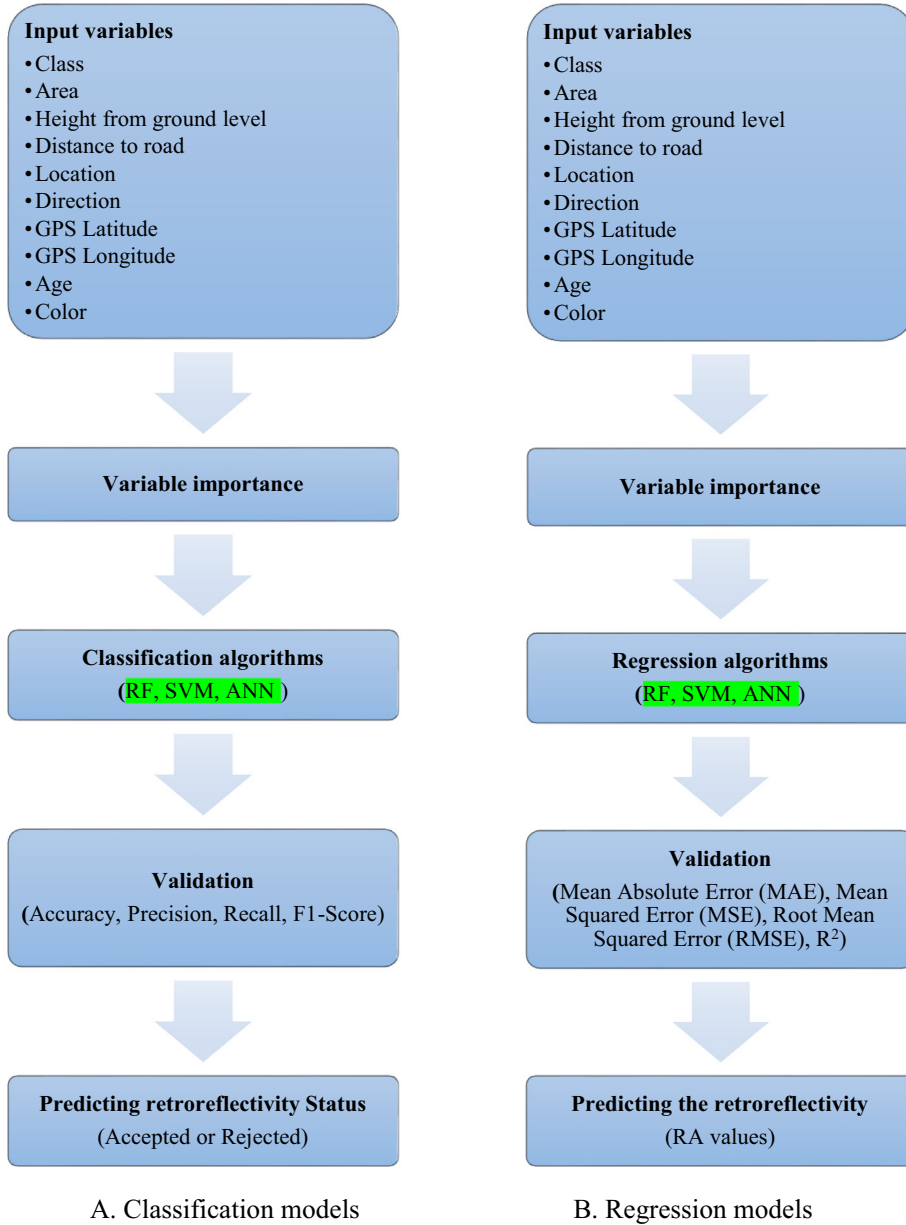
In predictive modeling, the identification and selection of important variables are crucial for optimizing the accuracy, and generalization of new data. Variable selection not only reduces model complexity but also enhances interpretability, particularly when dealing with a large number of potential predictors, thereby mitigating the risk of overfitting. To measure the importance of input variables, this study utilized permutation variable importance measurement. This approach involves determining the increase in prediction error of the model after permuting the values of each variable. By applying this methodology, valuable insights into the strength and direction of relationships between predictors and the outcome were obtained.

Through a comprehensive literature review, it was revealed that previous studies have not explored the influence of road traffic sign height, area, and location on retroreflectivity. Consequently, selecting these variables and analyzing their importance can provide crucial insights for improving the performance of predictive models. By identifying the most influential factors, models can be optimized to accurately predict the retroreflectivity of road traffic signs.

Table 1

The size of the datasets (rows).

	Sweden	Croatia
Original data	695	14 151
Cleaned data	636	10 755
Accepted road traffic signs	439	9045
Rejected road traffic signs	197	1 710
Distribution ratio (accepted/rejected)	44.9%	18.9%
Oversampled data	878	18 090

**Fig. 3.** Summary of the models.

3.4. Algorithms

Three machine learning algorithms were used in both classification and regression models:

3.4.1. Random forest (RF)

RF is an ensemble learning technique for classification, regression, and other tasks. It constructs multiple decision trees during training (Saleh et al., 2023). In classification, the output is determined by the class most frequently chosen by the trees, whereas for regression, it involves the average prediction of individual trees.

3.4.2. Support vector machines (SVM)

In classification, SVM segregates data points into distinct classes using a hyperplane (Saleh et al., 2023), minimizing misclassification errors. In regression SVM identifies the best-fitting hyperplane for data points in a continuous space (Saleh et al., 2023), while minimizing prediction errors.

3.4.3. Artificial neural networks (ANN)

In classification tasks, ANNs classify observations into discrete classes using input data. ANNs can proficiently manage both categorical and numeric inputs in this context. However, when dealing with categorical variables, encoding is imperative to effectively handle them as the dependent variable. In contrast, in regression ANNs, output variables (numeric dependent variables) are predicted based on inputs, and ANNs remain capable of handling diverse input types, categorical or numeric (Swargam, 2004; Saleh and Fleyeh, 2022; Saleh et al., 2023).

3.5. Validation

The accuracy, precision, recall, and F1-Score were calculated to evaluate classification models (Saleh and Fleyeh, 2022). The accuracy score, which measures how many labels the model got right out of the total number of predictions, was mainly used to compare the performance of the classification models.

Mean absolute error (MAE), Mean squared error (MSE), Root mean squared error (RMSE), and coefficient of determination (R^2) were calculated to evaluate regression models. The RMSE, MAE, and MSE have a value of zero if the regression model fits the data perfectly and R^2 has a value of one if the regression model fits the data perfectly (that means if MSE is zero) (Ré et al., 2011; Alkhulaifi et al., 2021). Both RMSE and R^2 were used in this study to quantify how well the regression model can fit the dataset.

3.6. Predicting the lifespan of road traffic signs according to retroreflectivity

This study employs two distinct statistical methods to predict the lifespan of road traffic signs as determined by their retroreflectivity: logistic regression and the Kaplan-Meier estimator.

3.6.1. Logistic regression

Logistic regression is a predictive analysis used primarily in statistics and machine learning to model the probability of a certain class or event (Maalouf, 2011). In the context of this study, logistic regression is used to predict the probability of a road traffic sign reaching the end of its lifespan based on its retroreflectivity values. The logistic regression model is expressed by Eq. (1).

$$P(Y = 0) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \dots + \beta_n X_n)}} \quad (1)$$

where $P(Y = 0)$ is the probability of the sign reaching the end of its lifespan, $\beta_0, \beta_1, \dots, \beta_n$ are the coefficients, and X_1, \dots, X_n are the predictors.

3.6.2. Kaplan-meier estimator

Kaplan-Meier estimator, also known as the product-limit estimator, is a non-parametric statistic used to estimate the survival function from lifetime data (George et al., 2014). In this study, Kaplan-Meier estimator is used to estimate the duration the road signs remain functional based on their retroreflectivity. Kaplan-Meier estimator is particularly useful for handling censored data, which is common in lifespan studies. The estimator is given by Eq. (2).

$$S(t) = \prod_{t_i \leq t} \left(1 - \frac{d_i}{n_i}\right) \quad (2)$$

where $S(t)$ is the survival probability at time t , d_i is the number of events (end of lifespan) at t_i , and n_i is the number of subjects at risk of the event at t_i .

Logistic Regression is used for binary outcomes (Event versus No Event) while the Kaplan-Meier estimator is used for survival analysis, where the outcome is the time until an event occurs. Logistic regression assesses the influence of retroreflectivity on the probability of a sign reaching the end of its lifespan, while Kaplan-Meier estimator provides an empirical survival function for the signs based on observed lifespans.

4. Results and discussion

4.1. Variable importance

The importance of the variables for classification and regression models was examined using RF, SVM, and ANN algorithms to select the appropriate variables for each model to obtain the best results. Fig. 4 shows the importance score of the variables for the classification models while Fig. 5 presents the importance score for regression models. The “importance score” is determined by calculating the difference between the baseline model's performance (the original model) and the performance achieved when the values of a particular variable are permuted. The importance of variables varies between different models, generally, age, sheeting class, and color were the most important variables for predicting the retroreflectivity and its status. Therefore, considering these three variables helps road authorities in achieving the goal of using sustainable and durable road traffic signs.

Age was the most important variable for predicting retroreflectivity status when analyzing the data from Croatia. It was also the most important variable when using RF and ANN classification models on the data from Sweden while the sheeting class was the most important variable for predicting retroreflectivity status using SVM classification models on the data from Sweden. Over time, the retroreflective properties of road traffic signs deteriorate due to exposure to different weather conditions and dirt, therefore, older signs are likely to have lower retroreflectivity levels compared to newer signs. Hence, age is an important variable to consider when predicting the retroreflectivity status of road traffic signs. However, it was noticed that age is the third important variable in Swedish data using SVM (Fig. 4) due to differences in the classifiers used to calculate variables importance.

In Croatia, retroreflective sheeting class 3 is only used if there is a necessity to emphasize the importance of the road traffic sign. This explains why only 15% of the road traffic signs in the Croatian dataset belong to sheeting class 3, while 51% were in sheeting class 1 and 34% in sheeting class 2. The Swedish data contains 41% of road traffic signs in sheeting class 1, 16% in sheeting class 2, and 43% in sheeting class 3. This can be a reason why the sheeting class is the most important variable in the Swedish data while it comes in third place in the Croatian data.

The sheeting class was the most important variable for predicting retroreflectivity in both datasets, using RF, SVM, and ANN regression models. In the second place comes color and in the third place comes age. Color is the second most important variable for predicting retroreflectivity in both datasets which are nearly as important as sheeting class. Certain classes and colors are associated with higher or lower retroreflectivity levels, therefore, the sheeting class and color variables are more important than any other variable in predicting retroreflectivity.

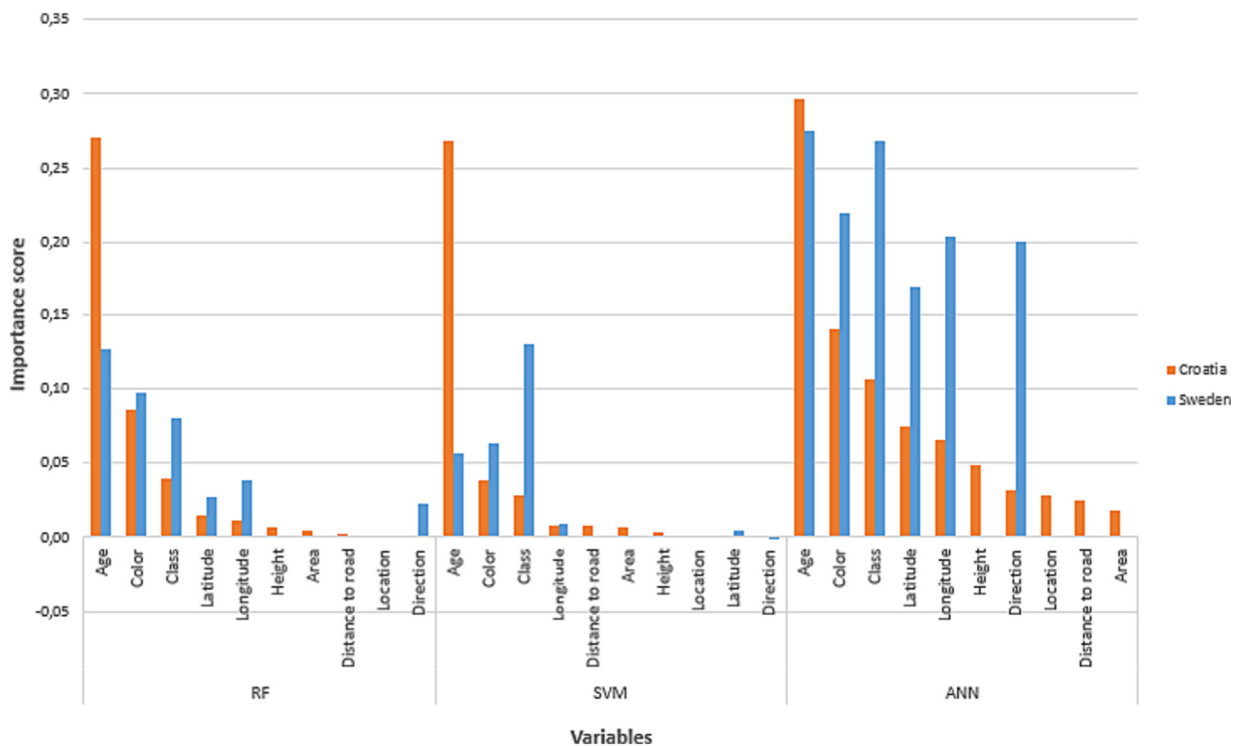


Fig. 4. Variable Importance to retroreflectivity status.

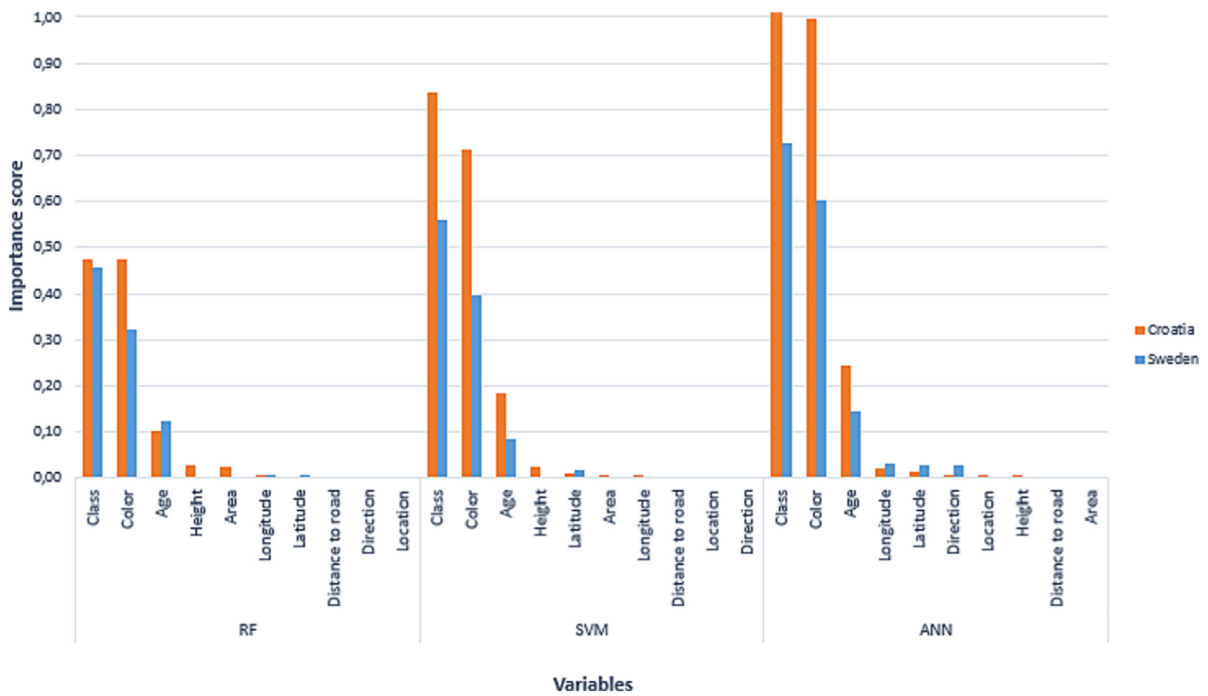


Fig. 5. Variable Importance to retroreflectivity (RA).

Generally, there is a range of important scores among the variables, with some variables having higher scores than others and even the same variable having high or low scores in different models. It is not uncommon for the importance score of a variable to differ across different models or algorithms. The reason for this is that each model has its way to evaluate the importance of variables based on its underlying assumptions, biases, and constraints. Different models may have different architectures and parameter settings that affect the way they evaluate the importance of variables. Even the correlated, noisy, and irrelevant variables can affect the importance scores of these variables across different models.

4.2. Predicting the lifespan of road traffic signs according to retroreflectivity

To predict the age at which the status of retroreflectivity transitions from accepted to rejected, logistic regression was utilized. Fig. 6 displays the ages at which road traffic signs with red, blue, yellow, and white retroreflective sheeting were rejected/accepted in the Swedish dataset.

Fig. 7 depicts the relationship between the age and status of retroreflectivity (accepted or rejected) for red, blue, yellow, and white retroreflective sheeting in data from Croatia.

The performance of the logistic regression model on road signs varies between Sweden and Croatia, as shown in Table 2. In Sweden, it shows high effectiveness for red signs with an accuracy of 0.88 and similarly high precision, recall, and F1-score. For blue, white, and yellow signs, the model demonstrates good accuracy of 0.72 to 0.82 but lower precision for blue signs at 0.68. In Croatia, the model has high performance on white and yellow signs with accuracies of 0.93 and 0.90 respectively, and consistently high precision, recall, and F1-scores. However, it shows less performance for red signs with an accuracy of 0.78, and slightly better performance for blue signs compared to Sweden, with an accuracy of 0.83. Overall, the model is most effective for white and yellow signs in Croatia and red signs in Sweden, with varying degrees of effectiveness for other colors. The high accuracy and balanced performance of these logistic regressions make them a reliable tool for predicting the lifespan of road traffic signs.

In Croatia, after 25 years, only 2 to 4% of road traffic signs with red, yellow, and white sheeting were considered acceptable, according to Fig. 8. On the other hand, in Sweden, approximately 30–55% of road traffic signs remained acceptable after the same period (25 years). However, when considering road traffic signs with blue sheeting, after 25 years, 78% and 37% of them were accepted in Sweden and Croatia, respectively.

It is worth noting that according to Croatian regulations, the coefficient of retroreflection of road traffic signs should be checked within 10 years, before the expiration of the warranty period for the road traffic sign. Based on the results shown in Fig. 8, about 62–94% of road traffic signs in Croatia remained acceptable within the 10 years (during the warranty period). Even in Sweden, about 71–95% of road traffic signs remain acceptable within 10 years. Therefore, this study suggests checking the retroreflectivity of signs first after 15 years to assess their performance beyond the warranty period.

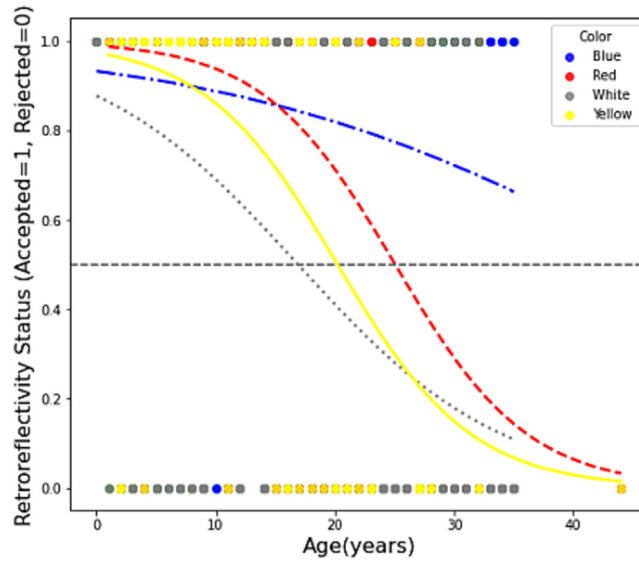


Fig. 6. Logistic regression analyses of the age of road traffic signs in Sweden.

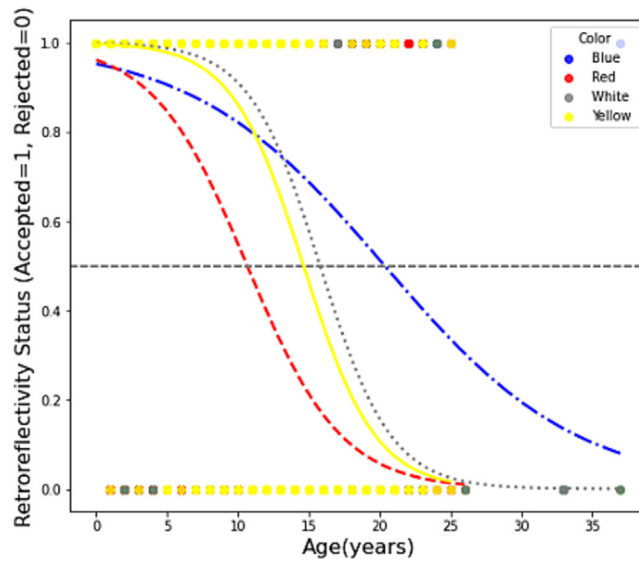


Fig. 7. Logistic regression analyses of the age of road traffic signs in Croatia.

Table 2

Performance of logistic regression models.

Color	Sweden				Croatia			
	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score
Blue	0.82	0.68	0.82	0.74	0.83	0.73	0.83	0.77
Red	0.88	0.87	0.88	0.86	0.78	0.76	0.78	0.77
White	0.72	0.72	0.72	0.72	0.93	0.91	0.93	0.91
Yellow	0.82	0.82	0.82	0.81	0.90	0.89	0.90	0.89

Generally, the age of Swedish road traffic signs lies between 0 to 44 years while the age of Croatian road traffic signs lies between 0 to 37 years. In the Croatian data, the older road traffic signs were categorized as sheeting class 1 (up to 37 years old), while classes 2 and 3 were up to 19 and 15 years old, respectively. Moreover, there were fewer road traffic signs in sheeting class 3 in the Croatian data. This could explain why the accepted road traffic signs after 25 years were higher in

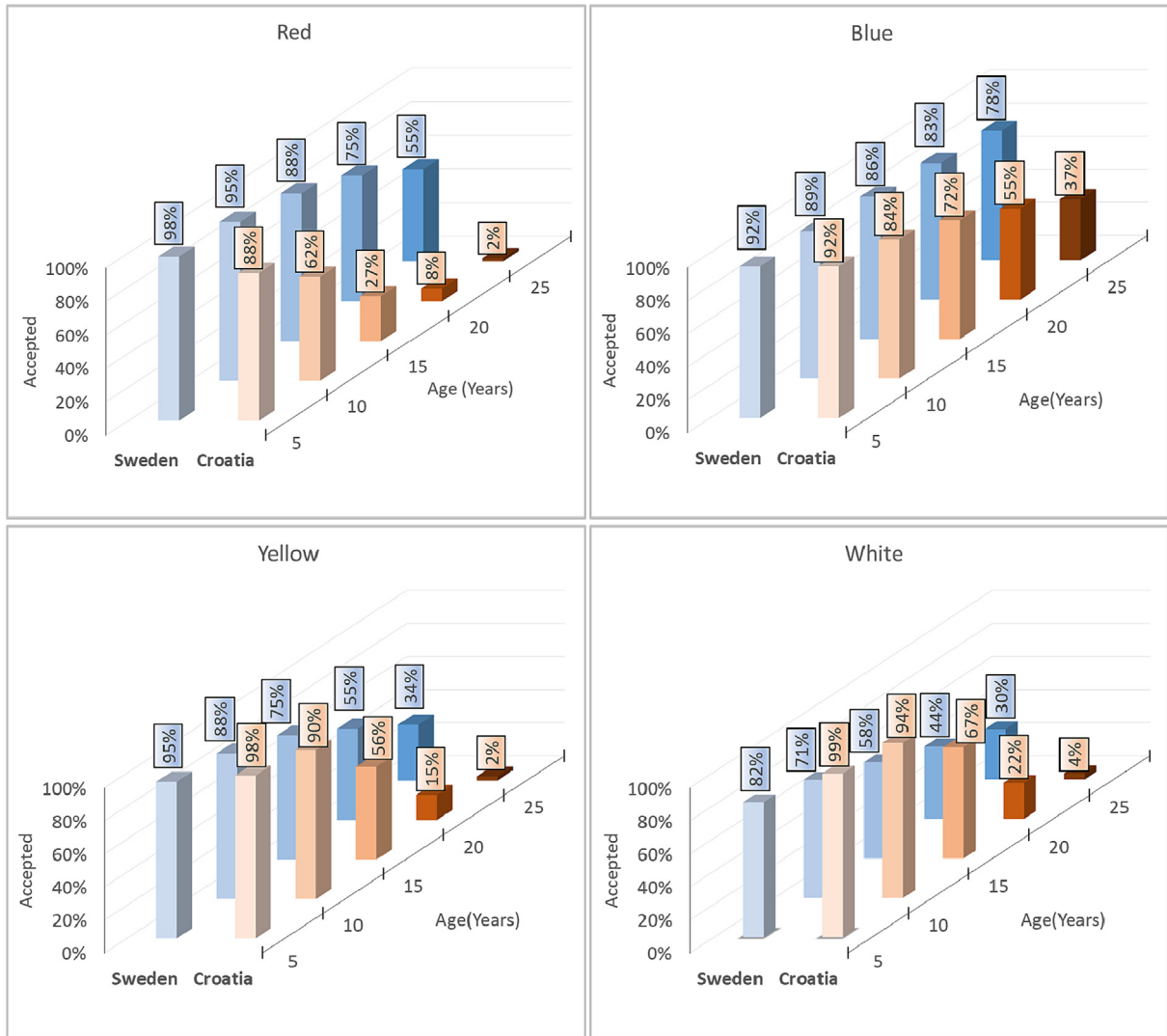


Fig. 8. Accepted road signs for ages of 5–25 years, Logistic Regression Analysis.

Sweden than in Croatia. The age distribution per sheeting class in each dataset is the reason why road traffic signs in the Swedish data are expected to have a longer lifespan compared to those in the Croatian data.

Maintenance of road traffic signs is a process that involves routine inspections, cleaning, and replacement of faded or damaged signs to ensure their visibility and legibility for drivers. The frequency and standards of maintenance may differ based on guidelines and regulations established by road authorities in each country, such as Sweden and Croatia. The maintenance of road traffic signs can potentially impact the collected data on the age and retroreflectivity of road traffic signs in each country. If road traffic signs are well-maintained, they may have been replaced more frequently, leading to a different distribution of ages and retroreflectivity values than those of poorly maintained signs. As new retroreflective sheeting has a longer lifespan and its retroreflectivity lasts longer, the proper maintenance of road traffic signs can influence the collected data on age and retroreflectivity.

Factors such as traffic volume, climate, and geographic location can affect the retroreflectivity of road traffic signs (Saleh and Fleyeh, 2021). In areas with higher traffic volume and harsher weather conditions, road traffic signs may deteriorate more quickly, resulting in a shorter lifespan and lower retroreflectivity. Additionally, the location of the road traffic signs, such as being in direct sunlight or a shaded area, can affect their retroreflectivity (Saleh et al., 2022).

Comparing the situation in Sweden and Croatia, the weather conditions in these regions are different. Sweden has a cold climate with more precipitation, while Croatia has a Mediterranean climate with hot and dry summers. The traffic volume may also vary between the regions, with Sweden having more heavily trafficked highways and Croatia having more rural roads. These differences could potentially impact the age and retroreflectivity of road traffic signs in each region, and thus affect the data collected on their age and retroreflectivity.

Figs. 9 and 10 show the lifespan of road traffic signs using the Kaplan-Meier estimator. These figures provide a survival analysis, offering a different perspective on the data compared to the logistic regression approach.

Table 3 compares the median survival times of road traffic signs in Sweden and Croatia using logistic regression and Kaplan-Meier estimator. Logistic regression generally predicts a longer lifespan for road traffic signs in both countries, particularly notable in the case of blue signs in Sweden. The percentage differences, calculated based on Kaplan-Meier estimates, show the greatest discrepancy in blue signs in Sweden, showing a 25% difference (equivalent to 7 years), and the least in yellow signs in Sweden (0% difference). This small difference, of 0 to 25%, and the high accuracy of the logistic regression models suggest that logistic regression is a reliable method for predicting the lifespan of road traffic signs.

These methodological differences significantly influence the maintenance strategies. Logistic regression, which can be influenced by the distribution of data across different age groups, offers insights into variables affecting sign durability but may not fully account for censored data (signs that have not yet failed or been replaced at the time of the study). Kaplan-Meier estimator, on the other hand, is used to estimate the survival function from lifetime data, providing a reliable estimate of survival probability over time, even with incomplete data.

Each method operates under different assumptions about the data. Logistic regression presupposes a specific form of relationship between the predictor (age) and the outcome (sign status), while Kaplan-Meier estimator is less assumptive about the survival distribution. The variations in results between these methods, particularly evident across different colors and regions, highlight the importance of considering regional and material-specific variables in the planning of road sign maintenance and replacement.

Logistic regression overestimates the lifespan of blue signs in Sweden (>35 years) compared to Kaplan-Meier's 28 years, while in Croatia, the results (20 years vs. 17 years) suggest more uniform aging. Red signs show a moderate discrepancy in Sweden (25 years vs. 21 years) and a closer estimate in Croatia (10 years vs. 12 years), indicating faster wear. White sign lifespans are similar in both countries, with a slight overestimation by logistic regression (Sweden: 16 versus 20 years; Croatia: 15 versus. 17 years). Yellow signs in Sweden consistently show a 20-year lifespan, with slightly shorter estimates in Croatia (14–16 years). These differences highlight the impact of regional variables and the variation in sign durability by color and location. The results indicate that blue signs are generally expected to be the most durable, while white and red signs have comparatively shorter lifespans.

4.3. Predicting retroreflectivity status

Three classification models, namely, RF, SVM, and ANN, were employed to predict the retroreflectivity status. Fig. 11 summarizes the performance of these models on randomly oversampled data. Overall, the accuracy of the three classification models was high for both the Swedish data (75 to 94%) as well as the Croatian data (80 to 90%). ANN performs the best followed by the RF models, while the SVM model had the lowest performance for both datasets.

One possible explanation for this high accuracy is that ANN models can learn and model non-linear and complex relationships between inputs and outputs. ANN models can capture more intricate patterns in the data that may not be easily identified using the other models. Additionally, ANN models can adjust their weights and biases during training, allowing them to adapt and improve their performance over time.

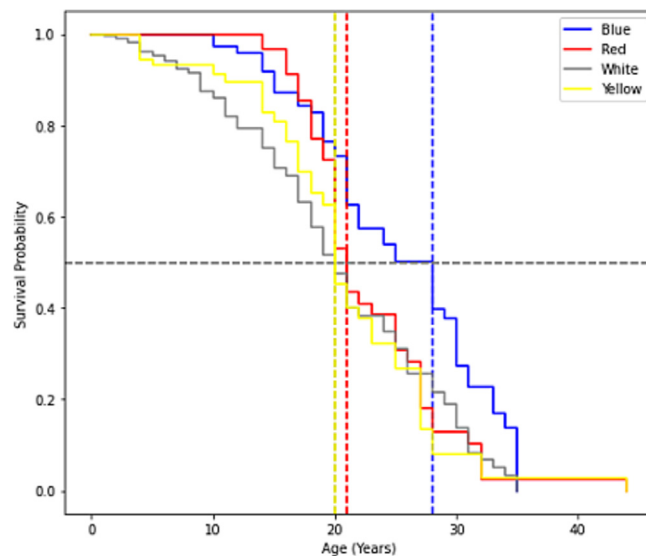


Fig. 9. Life Time Analysis of Road Traffic Signs in Sweden Using Kaplan-Meier estimator.

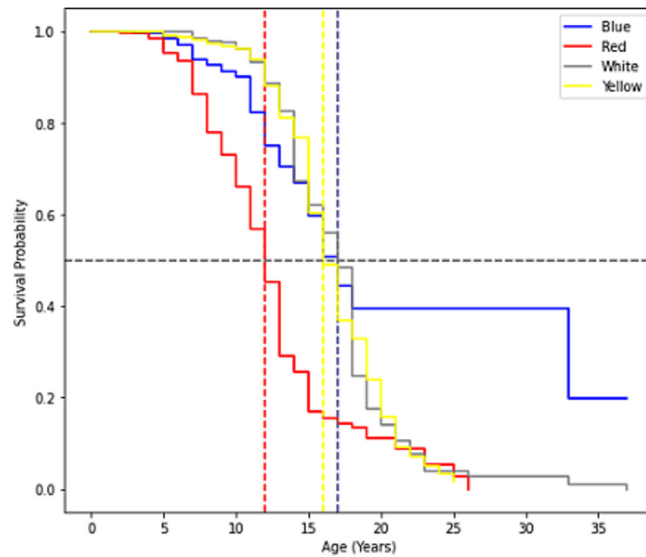


Fig. 10. Life Time Analysis of Road Traffic Signs in Croatia Using Kaplan–Meier estimator.

Table 3

Median Survival Time of Road Traffic Signs in Sweden and Croatia (in years).

Color	Swedish Road traffic signs		Croatian Road traffic signs	
	Logistic regression	Kaplan–Meier estimator	Logistic regression	Kaplan–Meier estimator
Blue	>35	28	20	17
Red	25	21	10	12
White	16	20	15	17
Yellow	20	20	14	16

On the other hand, RF and SVM models rely on different principles, utilizing decision trees and linear separation boundaries, respectively. While these models can be powerful for certain types of data and problems, they may struggle to accurately capture complex relationships between variables. Therefore, the accuracy of these models may be limited, especially when dealing with complex data.

The accuracy of the ANN classification models was higher for the Swedish dataset compared to the Croatian dataset, while RF and SVM showed higher accuracy using the Croatian dataset. This difference in the performance could be attributed to the difference in the sample sizes of the two datasets. The Swedish dataset had a smaller sample size, making it easier for the ANN to learn and generalize effectively. On the other hand, the larger sample size of the Croatian dataset may have given an advantage to RF and SVM, which are known for their ability to handle large datasets efficiently.

The adoption of classification models in our study for evaluating traffic sign acceptance is motivated by their capacity to navigate complex variables and manage the variability around retroreflectivity thresholds, without the need to compare each value for retroreflectivity with specific threshold values for each class and color in the applicable standard. This methodology streamlines decision-making processes by categorizing signs as 'accepted' or 'rejected', and it enhances comprehensive evaluation by incorporating a range of variables, including age, class, color, and location. This technique offers a detailed and practical assessment of traffic sign acceptability, moving beyond just the analysis of retroreflectivity measures.

4.4. Predicting the retroreflectivity of road traffic signs

Three regression models namely, RF, SVM, and ANN, are employed to forecast retroreflectivity. The performance estimations for these three models are demonstrated in Fig. 12. RF and SVM models exhibit similar performance, and this holds for both the Swedish and Croatian datasets. In contrast, the ANN regression model outperforms RF and SVM models in both datasets. RF and SVM models are based on linear models and are not as flexible as ANN. The flexibility of ANN enables it to capture more complex patterns in the data, resulting in superior performance for regression tasks.

When using the Swedish dataset, the ANN regression model achieves an R^2 value of 74%, compared to an R^2 of 94% using the Croatian dataset. ANN can effectively handle larger datasets, such as the Croatian dataset, which is often advantageous for regression tasks. On the other hand, SVM and RF did not perform as well (R^2 of 72%) with larger datasets like the Croatian dataset, due to their limitations in terms of model complexity and training time.

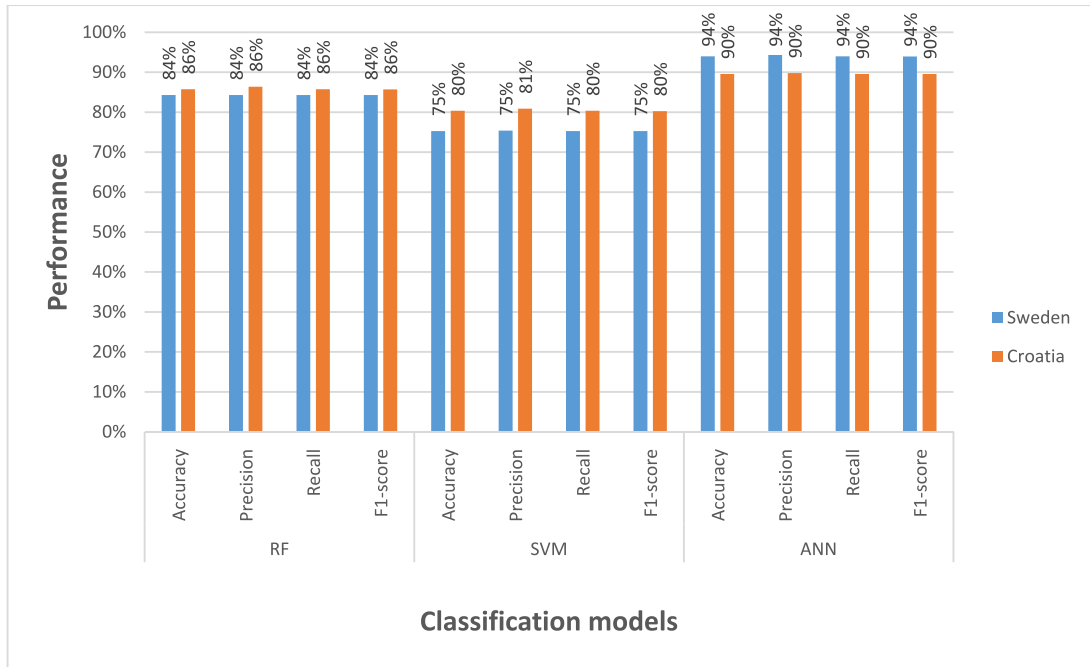


Fig. 11. Performance of classification models.

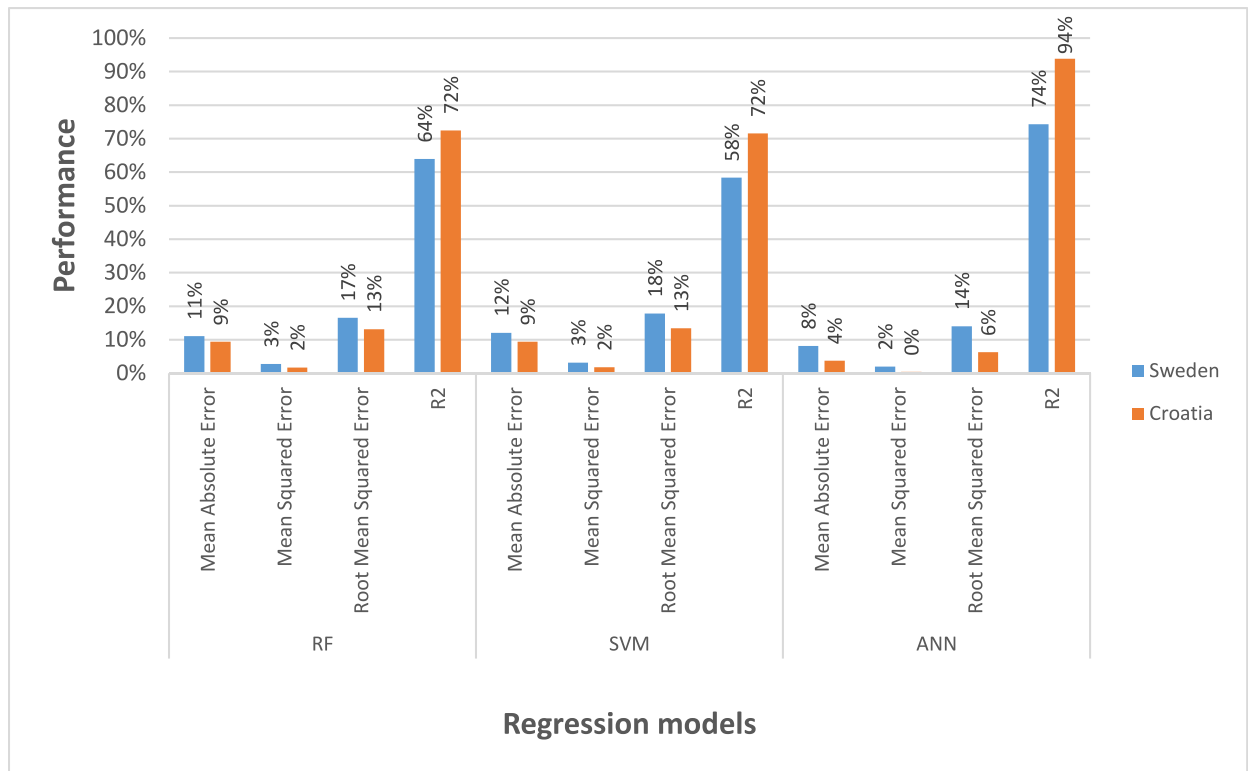


Fig. 12. Performance of the regression models.

Table 4

Models overview in prior literature and current study.

Year	Authors	models		Predicting		
		Regression R2 (%)	Classification Accuracy (%)	RA	Status	Service life
1992	Black et al. (Black et al., 1992)	50	–	Yes	–	–
2004	Swargam (Swargam, 2004)	62	–	Yes	–	–
2006	Rasdorf et al. (Rasdorf et al., 2006)	50	–	Yes	–	Yes
2009	Immaneni et al. (Immaneni et al., 2009)	52	–	Yes	–	Yes
2017	Babić et al. (Babić et al., 2017)	60	–	Yes	–	–
2021	Alkhulaifi et al. (Alkhulaifi et al., 2021)	97	–	Yes	–	Yes
2022	Saleh et al. (Saleh and Fleyeh, 2022)	–	98	–	Yes	–
2022	Saleh et al. (Saleh et al., 2022)	95	–	Yes	–	–
	Present study	74–94	90–94	Yes	Yes	Yes

4.5. Comparison with the state of the art

The current study stands out with significant distinctions in model performance compared to earlier research, as illustrated in Table 4. It demonstrates enhanced regression performance (up to 94% R^2) and attains high accuracy in classification models (up to 94%).

Furthermore, this study sets itself apart from prior research by effectively predicting retroreflectivity values, retroreflectivity status, and the service life of road traffic signs. These achievements reflect advancements in predictive capabilities and overall model effectiveness compared to the referenced earlier studies.

The importance of this study lies in its novel application of survival analysis, particularly the Kaplan-Meier estimator, to estimate the lifespan of road traffic signs. This approach represents an innovative use of a statistical tool traditionally reserved for medical and biological research, adapting it to address a significant challenge in transportation and infrastructure management. By employing survival analysis, this study provides a new perspective and methodology for predicting the durability and functional longevity of road traffic signs.

4.6. Limitations of the study

While this study has its strengths and promising aspects, it is important to acknowledge its limitations for potential improvement. The datasets used in this study is only collected in specific areas, so the models may not apply well to other places. To make the models more reliable, it would be helpful to gather data from other regions and countries. Another limitation is that the study only focused on machine learning algorithms and didn't consider other methods that could enhance accuracies, such as combining physical properties (light propagation and reflection) and domain knowledge about road traffic sign materials, weather conditions, and environmental factors.

Including these approaches could lead to better predictions. The study also only used certain variables and didn't take into account factors like environmental conditions and maintenance history, which could affect results. Considering additional variables could make the models more effective. Moreover, the study only tested a limited number of machine learning algorithms and didn't explore other potential models such as Gradient Boosting Machines or Deep Learning models. Trying out different approaches could improve accuracy. Lastly, the study focused mainly on predicting retroreflectivity but didn't investigate the causes of degradation or strategies for proactive maintenance. Understanding these factors and developing proactive models would be valuable for future research. By addressing these limitations, we can create better models for predicting the retroreflectivity of road traffic signs.

5. Conclusions and recommendations

Developing highly accurate regression models to predict the retroreflectivity of road traffic signs is challenging due to the nature of the degrading of the retroreflectivity and the complex and nonlinear relationship between retroreflectivity and other variables. To address this issue, classification models are used to estimate retroreflectivity status and predict whether a road traffic sign has an acceptable level of retroreflectivity.

This study marks a significant advancement in using machine learning classification models like Random Forest, Support Vector Machine, and Artificial Neural Network for predicting road sign retroreflectivity status. The novelty lies in effectively categorizing signs as 'accepted' or 'rejected', simplifying decision-making processes in maintenance and safety operations. These models consider a range of variables, enhancing decision accuracy in cases with retroreflectivity values near threshold limits. This aspect of the work is a notable contribution, offering a more detailed and precise approach to sign maintenance than previously available methods.

In this study, logistic regression has demonstrated high accuracy, establishing itself as a reliable method for predicting the lifespan of road signs. Its relative simplicity compared to survival analysis makes it more accessible, particularly for those

less versed in complex statistical modeling. This method is well-suited for binary outcomes, effectively modeling probabilities for scenarios like determining if a sign's condition is 'acceptable' or 'unacceptable'. A key advantage of logistic regression is its lesser dependency on precise time-to-event data, making it a valuable tool when such detailed data is either unavailable or unreliable.

The study also found that the sheeting class, color, and age of retroreflective sheeting have the most significant impact on retroreflectivity degradation, with age being the most critical factor in determining when the retroreflectivity status changes from accepted to rejected. Thus, using a higher sheeting class is essential to ensure the durability of visible and legible road traffic signs. By considering age, sheeting class, and color when predicting retroreflectivity status for road traffic signs, transportation agencies can ensure that signs are maintained and replaced as needed to maintain safe driving conditions.

This study concluded that about 62–94% of road traffic signs in Croatia acceptable after 10 years period (the warranty period) while in Sweden, it was about 71–95% of road traffic signs remained acceptable after 10 years. These differences in the predicted age of road traffic signs mounted in Sweden and in Croatia can be due to various factors including traffic volume, climate, geographic location, and maintenance frequency.

According to Croatian regulations, road traffic signs should undergo retroreflectivity coefficient checks within a 10-year timeframe. In contrast, this study suggests conducting the initial assessment of sign retroreflectivity after 15 years to evaluate their performance beyond the warranty period.

Finally, this study indicates that blue road signs are generally expected to have the longest lifespan, while red signs in Croatia and white signs in Sweden are predicted to have comparatively shorter lifespans due to faster degradation of retroreflectivity.

In future studies, it is recommended to exploring several techniques to enhance the performance of prediction models. These include investigating alternative scaling methods, considering the inclusion of additional variables such as weather conditions, and utilizing cross-validation. Exploring other class balancing techniques, like the Synthetic Minority Over-sampling Technique (SMOTE), can further improve model performance. Additionally, it is suggested to experiment with various kernel functions for SVM models.

Increasing the number of decision trees ($n_{\text{estimators}}$), fine-tuning hyperparameters, combining bagging and boosting techniques, and utilizing the Out-of-Bag (OOB) score can enhance the performance of Random Forest models. In the case of Artificial Neural Networks, investigating diverse architectures, implementing regularization techniques, employing learning rate scheduling methods, and exploring ensemble methods like bagging and boosting can all contribute to increased prediction accuracy.

These recommended areas of focus offer promising opportunities to enhance the predictive capabilities of SVM, RF, and ANN models and deepen the understanding of retroreflectivity degradation in road traffic signs.

For future research, other classification models can be used such as additional Survival analysis models and Bayesian models. These models can be used to estimate the probability of retroreflectivity status as a function of age. These models can be useful for incorporating prior knowledge into the analysis and for making more accurate and generalized probabilistic predictions.

CRedit authorship contribution statement

Roxan Saleh: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Hasan Fleyeh:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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