



Research Article

Assessing the color status and daylight chromaticity of road signs through machine learning approaches

Roxan Saleh^{a,b,*}, Hasan Fleyeh^a, Moudud Alam^a, Arend Hintze^a

^a School of Information and Engineering, Dalarna University, Borlänge 781 70, Sweden

^b Swedish Transport Administration, Röda Vägen 1, Borlänge 781 89, Sweden

ARTICLE INFO

Article history:

Received 24 February 2023

Received in revised form 25 May 2023

Accepted 22 June 2023

Available online xxxx

Keywords:

Road signs

Daylight chromaticity

Regression

Classification

Prediction

Machine learning algorithms

ABSTRACT

The color of road signs is a critical aspect of road safety, as it helps drivers quickly and accurately identify and respond to these signs. Properly colored road signs improve visibility during the day and make it easier for drivers to make informed decisions while driving. In order to ensure the safety and efficiency of road traffic, it is essential to maintain the appropriate color level of road signs.

The objective of this study was to analyze the color status and daylight chromaticity of in-use road signs using supervised machine learning models, and to explore the correlation between road sign's age and daylight chromaticity. Three algorithms were employed: Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN). The data used in this study was collected from road signs that were in-use on roads in Sweden.

The study employed classification models to assess the color status (accepted or rejected) of the road signs based on minimum acceptable color levels according to standards, and regression models to predict the daylight chromaticity values. The correlation between road sign's age and daylight chromaticity was explored through regression analysis. Daylight chromaticity describes the color quality of road signs in daylight, that is expressed in terms of X and Y chromaticity coordinates.

The study revealed a linear relationship between the road sign's age and daylight chromaticity for blue, green, red, and white sheeting, but not for yellow. The lifespan of red signs was estimated to be around 12 years, much shorter than the estimated lifespans of yellow, green, blue, and white sheeting, which are 35, 42, 45, and 75 years, respectively.

The supervised machine learning models successfully assessed the color status of the road signs and predicted the daylight chromaticity values using the three algorithms. The results of this study showed that the ANN classification and ANN regression models achieved high accuracy of 81% and R^2 of 97%, respectively. The RF and SVM models also performed well, with accuracy values of 74% and 79% and R^2 ranging from 59% to 92%. The findings demonstrate the potential of machine learning to effectively predict the status and daylight chromaticity of road signs and their impact on road safety in the Swedish context.

© 2023 International Association of Traffic and Safety Sciences. Production and hosting by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

1. Introduction

Road signs play a crucial role in ensuring road safety and effective communication between drivers and the road infrastructure. Road signs serve as the primary medium for conveying information to road users, and it is imperative that they remain visible and easily readable both during the day and at night. The color of road signs is a crucial

factor in their visibility and legibility, especially in different lighting conditions. Different colors help drivers to identify and distinguish between signs [1], and as such, the chromaticity of the sign's color must meet the acceptable levels set by the relevant standards [2].

However, with time, the colors of road signs deteriorate, making them increasingly difficult to be seen, and as a result, the road authorities must replace these signs to maintain visibility and recognition [3]. In order to assess the condition of road signs, road authorities typically conduct in-suite inventory assessments using hand-held instruments. However, this process is time-consuming, labor-intensive, requires expensive tools, and can pose a risk to maintenance personnel [4].

The objective of this study is to explore the usefulness of purely predictive methods to evaluate the condition of road signs, as opposed to

* Corresponding author at: School of Information and Engineering, Dalarna University, Borlänge 781 70, Sweden.

E-mail addresses: roxan.saleh@trafikverket.se, rss@du.se (R. Saleh), hfl@du.se

(H. Fleyeh), maa@du.se (M. Alam), ahz@du.se (A. Hintze).

Peer review under responsibility of International Association of Traffic and Safety Sciences.

in-suite inventory assessment. Specifically, the study aims to determine the rate of deterioration of road sign color (daylight chromaticity) with a view to determining the time threshold when a sign needs to be replaced. Knowing the expected life of a road sign based on its color is crucial for informed decision-making about sign specifications and purchasing [5].

The study focuses on the use of machine learning to predict the condition of in-use road signs according to their daylight chromaticity and color status. The study employs classification models to predict if a road sign meets acceptable standards and nonlinear regression models to predict the sign's daylight chromaticity over time. By examining the application of machine learning in predicting the condition of road signs, the study highlights the cost-effective and reliable nature of this approach. The research compares various machine learning techniques and models using data from road signs in Sweden, demonstrating the potential benefits of this method in providing road authorities with an efficient and cost-effective way to evaluate the condition of road signs. Ultimately, these findings have the potential to improve road safety and communication between drivers and road infrastructure.

The research covers a broad range of topics, such as examining how different factors (such as age, class, color, direction, GPS positions, and retroreflectivity) affect the daylight chromaticity of road signs, evaluating the deterioration of their chromaticity over time, and gathering and offering significant data on road sign daylight chromaticity.

The findings from this research will provide road authorities with a better understanding of sign performance, help them make more accurate predictions about when to replace signs, and improve road safety and the effectiveness of road sign communication.

The remainder of this article is organized into several sections. A literature review is presented in Section 2, followed by research motivation and objectives in Section 3. In Section 4, the materials and methods, including data, algorithms, and models, are described. The results of the study and the performance of the proposed models for each algorithm are presented in Section 5. Section 6 provides a discussion of the findings, while Sections 7 and 8 offer conclusions and implications for practice. Finally, the limitations of the study and directions for future research are discussed in Section 9.

2. Literature review

The degradation of road signs has been widely studied in various environments, including isolated outdoor areas, actual roads (exposed

to weather, traffic, and vandalism), and indoor laboratory tests [5]. Despite the extensive research in this area, there remains a lack of understanding about color fading of road signs and its impact on retroreflectivity degradation. The purpose of this literature review is to provide a comprehensive overview of the current state of research in this area and to identify areas where further study is needed. Table 1 illustrates studies conducted by researchers investigating the degradation of road signs.

Previous research on the degradation of road signs has primarily focused on the expected lifespan of signs based on the deterioration of retroreflectivity [6–10]. Regression models have been developed to predict the coefficient of retroreflection (RA) and assess the rate of deterioration of retroreflectivity [1,11–14].

However, there has been limited research on the effect of color fading on retroreflectivity [15]. The deterioration of signs over time has been found to impact their performance in terms of both color chromaticity and retroreflectivity. Generally, signs that fail in chromaticity do so before those that fail in retroreflectivity [16].

A study performed in 2014 aimed to provide data on the life of road signs based on the degradation of retroreflectivity and color over time. The results showed that color, especially for red signs, may fall below adopted thresholds prior to retroreflectivity failure [17].

A study conducted in 2010 evaluated the performance of road signs in terms of retroreflectivity and color. Results from an experiment with 9 different sheeting products showed that aging affected both color chromaticity and retroreflectivity, with most products failing in color before retroreflectivity. Orange, red, and yellow sheeting were found to fail first under chromaticity, while white and green signs typically failed under retroreflectivity standards [18].

Prior research has examined the effect of color on the visibility and legibility of road signs [3], but there have been limited studies that have investigated the color and daylight chromaticity of these signs. Additionally, there have been no studies to predict the degradation of daylight chromaticity.

In conclusion, there is a clear need for further research to fill the gap in the field of road sign degradation. A comprehensive study is needed to understand the impact of color fading on retroreflectivity and to develop methods for predicting the degradation of daylight chromaticity. The findings from this literature review highlight the importance of studying the durability of road signs concerning color and the need for further investigation to ensure the continued safety of road users.

Table 1
Summary of the reviewed literature discussing road sign deterioration.

Author(s)	Year	Method	Aim
Saleh et al. [1]	2022	Supervised machine learning (ANN, SVM, RF)	Predict retroreflectivity
Black et al. [6]	1992	Statistical analysis	Study retroreflectivity deterioration with age
Rasdorf et al. [7]	2006	Night time inspection and field data	Evaluate nighttime performance of traffic signs considering retroreflectivity
Ré et al. [8]	2011	Linear regression	Predict retroreflectivity
Swargam [9]	2004	Neural network models and regression models	Predict retroreflectivity
Jamal et al. [10]	2022	Linear regression and neural network models	Predict retroreflectivity
Alkhulaifi et al. [11]	2021	Deep neural network, Regression: linear, polynomial	Predict retroreflectivity of signs
Babić et al. [12]	2017	Regression: linear, logarithmic, exponential	Predict retroreflectivity
Immaneni et al. [13]	2009	Regression	Examine relationships between retroreflectivity and age
Saleh et al. [14]	2022	Statistical analyses and regression	Predict retroreflectivity
Brimley et al. [15]	2013	Controlled long-term study	Evaluate the deterioration of traffic signs with respect to retroreflectivity
Hawkins [17]	2021	Literature review	Provide recommendations on the use of retroreflective sign sheeting based on prior research
Molino et al. [18]	2013	Spectroradiometric measurements	Compare instrument measurements with daytime perceptual judgments of color properties made by human observers in the field
Brimley et al. [19]	2010	Weathering simulation	Evaluate the performance of sign sheeting against retroreflectivity and color criteria using weathered samples.

3. Research motivation and objectives

While previous research has highlighted the importance of retroreflectivity and color (daylight chromaticity) conditions for road sign visibility and legibility, there remains a lack of studies investigating the degradation of color and predicting daylight chromaticity of road signs.

This study addresses this gap in the field of road sign degradation by providing a comprehensive understanding of the impact of color fading on the age of road signs and developing methods for predicting the degradation of daylight chromaticity.

The aim of this study is to evaluate the efficacy of predictive methods in determining the rate of deterioration of road sign color (daylight chromaticity) and establish a time threshold for replacement. The objective is to provide decision-makers with crucial information about the expected life of road signs based on their color status. To achieve this, the study focuses on utilizing machine learning to predict the condition of in-use road signs based on their daylight chromaticity and color status.

4. Methods-material and experiments

4.1. Data description and pre-processing

This study focused on the collection and analysis of data from road signs in Sweden. In 2021, the lead author collected a new dataset by assessing 91 road signs randomly chosen in and around Stockholm (see Fig. 1). This dataset was combined with a dataset from 2018 that was previously collected by the Road and Transport Research Institute (VTI), which covered road signs from other regions of Sweden [19]. The two datasets were combined to broaden the geographical coverage, encompass a wider range of road sign categories and increased the number of observations. The combined dataset consisted of 695 records and the age of signs ranged from brand new to 44 years old, whereas the previous VTI dataset only included signs up to 35 years old [19]. The same measurement method and comparable measuring instruments were used in the two datasets.

The data analysis involved evaluating seven variables: age, class, color, direction, GPS positions, coefficient of retroreflection (RA), and daylight chromaticity.

The age of road signs was determined using the manufacturing year indicated on a sticker located at the back of each sign. However, some signs were missing this information due to illegible text or absent stickers. In order to ensure the accuracy of the dataset, all signs that did not have complete information were removed through a data cleaning process. As a result, approximately 8% of the total observations were eliminated and the cleaned data contained 636 records.

The retroreflective sheeting was categorized into three classes: Class 1 (most reflective), Class 2, and Class 3 (least reflective). The color of the signs was also noted, including blue, green, red, white, and yellow. The direction of the signs was recorded in degrees, providing the azimuth angle to which the sign was facing. North, East, South, and West were recorded as 0, 90, 180, and 270 degrees, respectively. The GPS position was included in the form of latitude and longitude coordinates. The coefficient of retroreflection (RA) was also included in the data, expressed as a ratio of the amount of light reflected back to the amount of light incident on the retroreflective material.

The daylight chromaticity of the road signs was measured and included in the data as well. The daylight chromaticity was measured using a Konica Minolta spectrometer CM-25cG system and was expressed in terms of X and Y chromaticity coordinates [20] (used to describe the color in a two-dimensional CIE color diagram).

These coordinates describe the color in terms of its position in a two-dimensional CIE color diagram and are used to describe the relative position of a color within the color box, Fig. 2. The color status of the road signs was evaluated according to acceptable minimum visibility

requirements set by the Swedish Transport Administration and European standards [2]. If the color of a sign passed the acceptable requirements, specifically the chromaticity boundaries, it was considered "Rejected." And the road sign should be replaced. Road signs with color located inside the designated area will be considered as "Accepted".

The color status of the road signs was evaluated according to the minimum visibility requirements set by the Swedish Transport Administration and European standards [2]. The European standards regulate the daylight chromaticity of road signs based on the coordinates in CIE color diagram and use color boxes to ensure that road signs have the correct color and are suitable for their intended purpose. The measured chromaticity was compared with the minimum retroreflectivity requirements in the European standards [2] and the signs were labeled "Accepted" or "Rejected", Fig. 3. If the color of a sign exceeded these chromaticity boundaries, it was considered "Rejected".

The dataset was imbalanced and had a severe class distribution skew with a ratio of 35:566, in the minority class compared to the majority class for color status. The Random Oversampling technique was used to create a balanced version of the dataset by generating new samples for the minority class. The data was cleaned, and any irrelevant variables were removed. The dataset (age, class, color, direction, GPS positions, Coefficient of retroreflection (RA), X, and Y) was scaled using normalization and standardization methods. Normalization scales variables to a range of 0 to 1 and is useful when the variables have vastly different ranges and no outliers [11], while standardization transforms the distribution of variables to have a mean of 0 and standard deviation of 1, making it suitable for data that follows a normal distribution [21,22].

4.2. Variable importance

According to state-of-the-art, there was no evidence that the previous studies examined the effect of factors such as road signs' age, class, color, direction, GPS positions, and Coefficient of retroreflection (RA) on daylight chromaticity. This study utilizes Random Forest (RF) to determine the relative importance of these variables and calculate the resulting importance scores to predict status, X, and Y. To improve the accuracy of the model, it is crucial to identify the key variables. By determining which variables are most crucial, the model can be streamlined, and its accuracy can be improved. Additionally, variable importance can provide insights into the relationships between features and target variables.

4.3. LOWESS regression analysis

In this study, Locally Weighted Scatterplot Smoothing (LOWESS) was utilized as an exploratory method to investigate the connection between age and daylight chromaticity degradation (X and Y). The aim was to determine the best fit. LOWESS is a non-parametric fitting method that doesn't rely on the assumption that the data follows a particular distribution. Unlike parametric fitting, it doesn't produce a universal equation to predict new data points.

The smoothing window size in LOWESS can be altered by specifying the fraction (0,1) of the data that the window should encompass. A fraction of 1.0 results in a straight line, whereas smaller fractions lead to a LOWESS curve that follows the data points more closely. In this study, a fraction of 0.3 was utilized to achieve a smoother LOWESS curve.

4.4. Algorithms

In this study, the color of the road sign, based on color status, was predicted using classification algorithms. Regression algorithms were used to predict the daylight chromaticity on CIE color coordinates of the road sign.

Three machine learning algorithms were employed in this study for both regression and classification models: Random Forest, Support Vector Machine, and Artificial Neural Network.



Fig. 1. The locations of the measured road signs. Red points represent the signs in the VTI data and those measured by the author are depicted in blue.

• Random Forest (RF)

Random Forest (RF) can be utilized for both categorical response variables (classification) and continuous response variables (regression). The predictor variables can also be either categorical or continuous [23].

The Random Forest Classifier (RFC) is used for classification, while the Random Forest Regressor (RFR) is utilized for regression. RFR performance can be improved by tuning its parameters [23–25]. In this

study, the RFR was trained with various tuned parameter values (such as `n_estimators`, `max_features`, `max_depth`, and `Random_state`) to find the highest-performing RFR model.

The mathematical equation of the RF architecture in regression is given in Eq. (1) and in classification is given in Eq. (2).

$$f(x) = \frac{1}{J} \sum_{j=1}^J h_j(x) \quad (1)$$

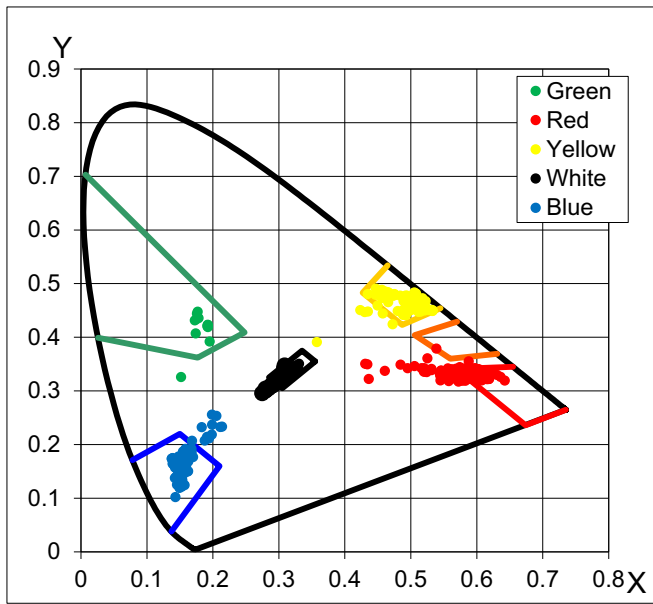


Fig. 2. Location of the measured road signs on CIE diagram (points falling outside the respective color box indicate rejected state).

$$f(x) = \arg \max_y \sum_{j=1}^J I(y = hj(x)). \quad (2)$$

Where $hj(x)$ is the prediction of the response variable at x using the j th tree.

• Support Vector Machine (SVM)

Support Vector Classifier (SVC) was employed for classification and Support Vector Regressor (SVR) was used for regression models. The goal of SVC is to locate a hyperplane in an N -dimensional space that clearly separates the data points. The objective of SVR is to find the optimal hyperplane with the maximum number of points to assist in predicting a continuous value or target value.

The performance of SVM is affected by the choice of tuning parameters, such as kernel parameters and penalty or margin parameters [26,27].

This study used radial basis function (RBF) kernels in both classification and regression models to find the hyperplane in a higher dimensional space. Eq.(3) explains RBF mathematically.

$$f(x_1, x_2) = e^{-\frac{\|x_1 - x_2\|^2}{2\sigma^2}} \quad (3)$$

Where: ' σ ' is the variance (hyperparameter), $\|x_1 - x_2\|$ is the Euclidean Distance between two points x_1 and x_2 .

The Grid Search method was employed to determine the optimal combination of parameters (Gamma and C) that would result in superior prediction accuracy for the SVR models.

• Artificial Neural Networks (ANN)

In this study, a Multilayer Perceptron (MLP) classifier was utilized for classification, and a Multilayer Perceptron regressor was utilized for regression. The MLP Classifier was used to predict the status of the color of the road sign. On the other hand, the MLPRegressor was employed to predict daylight chromaticity.

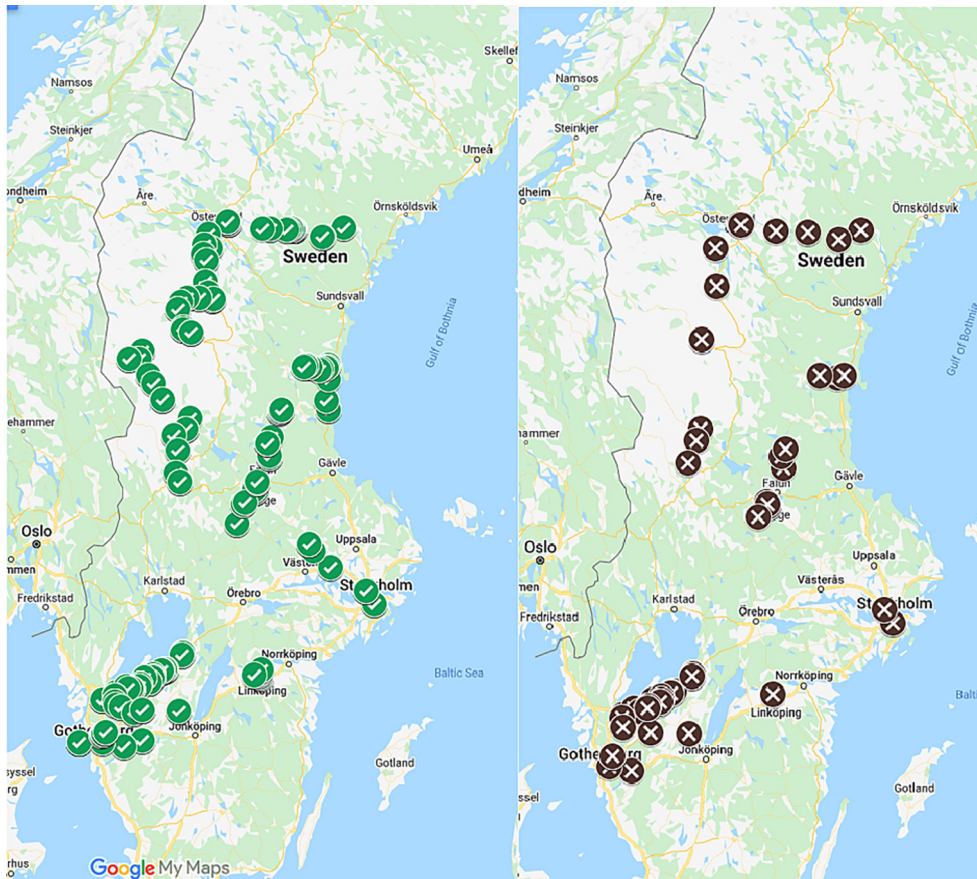


Fig. 3. The color status for the measured road signs (green accepted and black rejected).

Table 2
Summary of the models.

Input variables	Age, Class, Color, Direction, GPS	Age, Class, Color, Direction, GPS
Models	Classification	Regression
Algorithms	RFC SVC MLPClassifier	RFR SVR MLPRegressor
Splitting	3-fold Cross Validation (KCV)	train-test split with a 20% test set
Validation Using	Accuracy score, Precision, Recall, F1-Score	MAE, MSE, RMSE, R ²
Output	Color status (accepted/rejected)	Daylight chromaticity (X and Y)

The MLP Regressor models were configured using the following parameters: The number of layers and nodes were set to 150, 100, and 50. The number of epochs used for training the model was 300. The activation function used was 'relu', while the weight optimization algorithm across the nodes was set to 'adam'. A random state parameter was also included, which allows setting a seed for reproducing the same results. The mathematical equation of the ANN architecture is given in Eq. (4)

$$f(x) = (\sum xi \times wi) + b \quad (4)$$

4.5. Models

Table 2 summarizes the input and output variables, models, and algorithms used in this study. Two models were used in this study: classification models for predicting color status and regression models for predicting daylight chromaticity (X, Y).

Cross-validation is widely used to estimate the prediction error [28]. In this study, 3-fold cross-validation was applied to evaluate the classification models. For evaluating regression models, a train-test split was used, with 20% of the data assigned for testing.

Accuracy, precision, recall, and F1-Score were calculated to evaluate the classification models, with accuracy being the main metric used for comparison. Mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination (R²) were used to evaluate regression models, with RMSE and R² being the main metrics used to assess the fit of the regression model to the data. If the regression model fits the data perfectly, RMSE, MAE, and MSE have a value of zero, and R² has a value of one [8,29].

5. Results

5.1. Variable importance

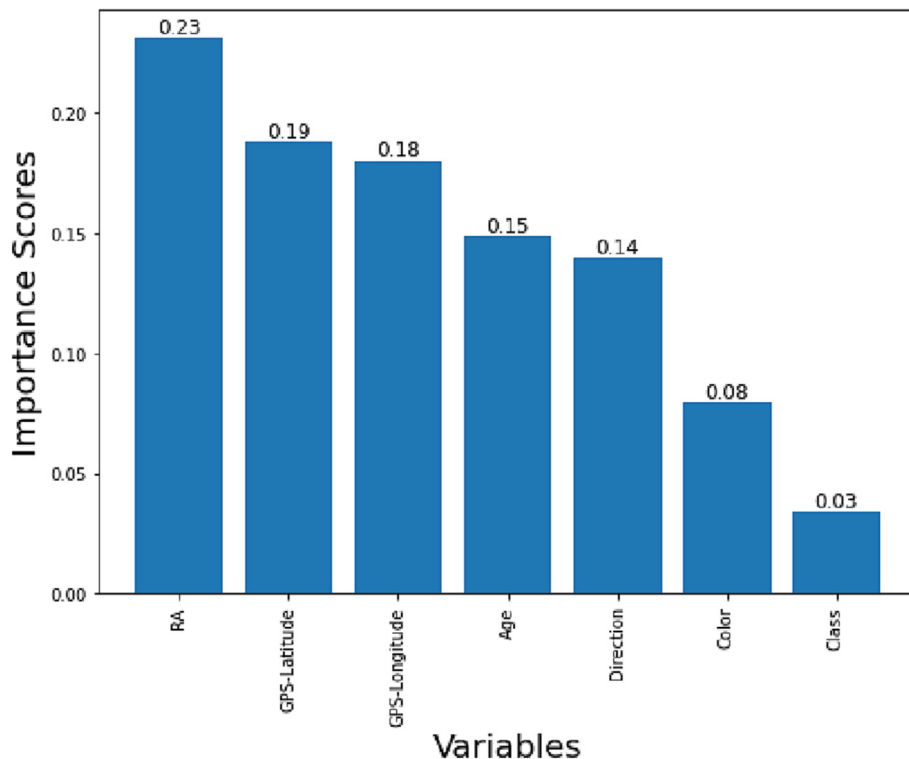
The impact of the input variables was analyzed using Random Forest (RF) models for both classification and regression. The results, presented in Figs. 4, 5, and 6, show the variables sorted in order of importance, with the most important variable to the color status and daylight chromaticity being the coefficient of retroreflection (RA).

The most important variables affecting the color status were the RA and GPS position (Fig. 4), while RA and Age were found to be the most important variables affecting X and Y values (Figs. 5 and 6).

However, the class of the sheeting was found to be the least important in determining X and Y values (Figs. 5 and 6).

5.2. The relationship between age and daylight chromaticity (X, Y) degradation

As depicted in Section 4.1, age was found to be a very important variable in regard to daylight chromaticity (X, Y). As a result, further investigation into the degradation of color appearance (daylight

**Fig. 4.** Variable Importance Scores for color status.

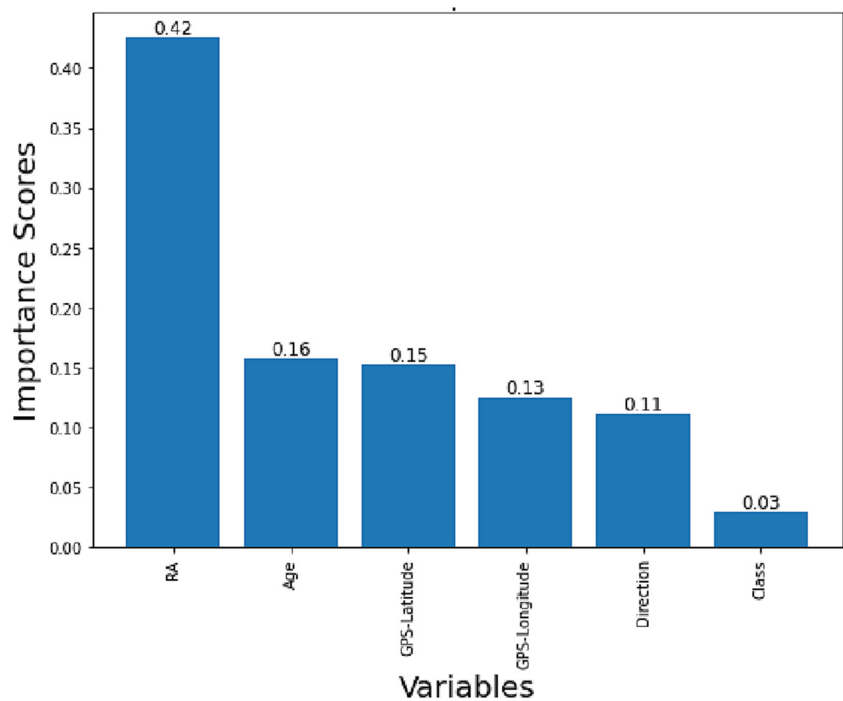


Fig. 5. Variable Importance Scores to X using Random Forest Regression.

chromaticity) was conducted to examine the relationship between age and daylight chromaticity.

To better understand this relationship, scatterplots were generated for each color along with LOWESS regression, as shown in Fig. 7. The purpose of this was to model the connection between X and Y with the age of the road sign. By studying the relationship between age and daylight chromaticity, we can gain deeper insight into the degradation of color appearance and how it can be prevented in the future.

According to the results of LOWESS regression, the relationship between X and Y with age was found to be approximately linear for the blue, red, and white colors. However, for the yellow color, the relationship was linear up to the age of 8 years, non-linear between 8 and 22 years, and finally linear after 22 years.

The changes in X and Y values over time were also observed for each color. The values of X and Y for blue and white sheeting increased with age, while X decreased, and Y increased for red sheeting. This explains

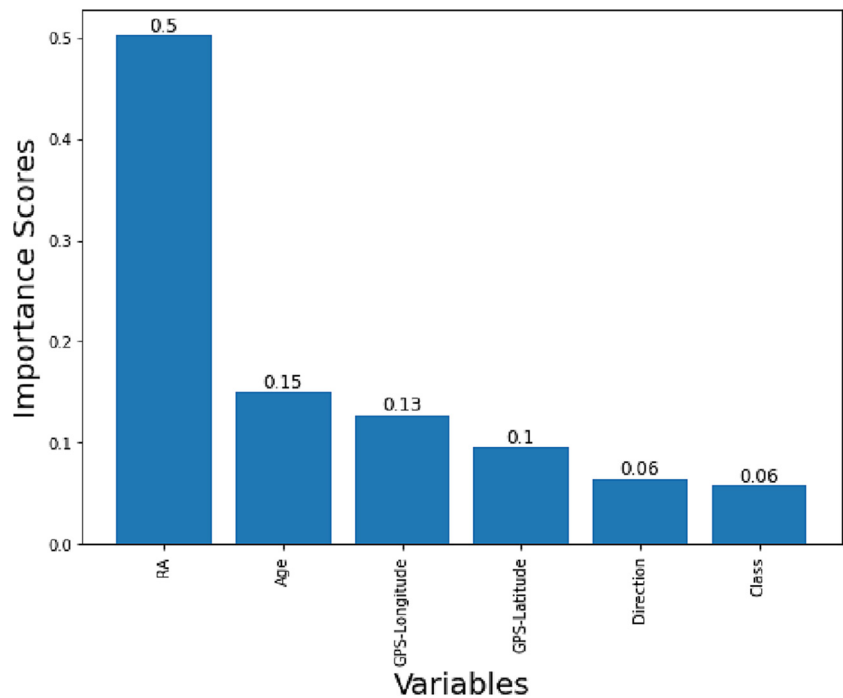


Fig. 6. Variable Importance Scores to Y using Random Forest Regression.

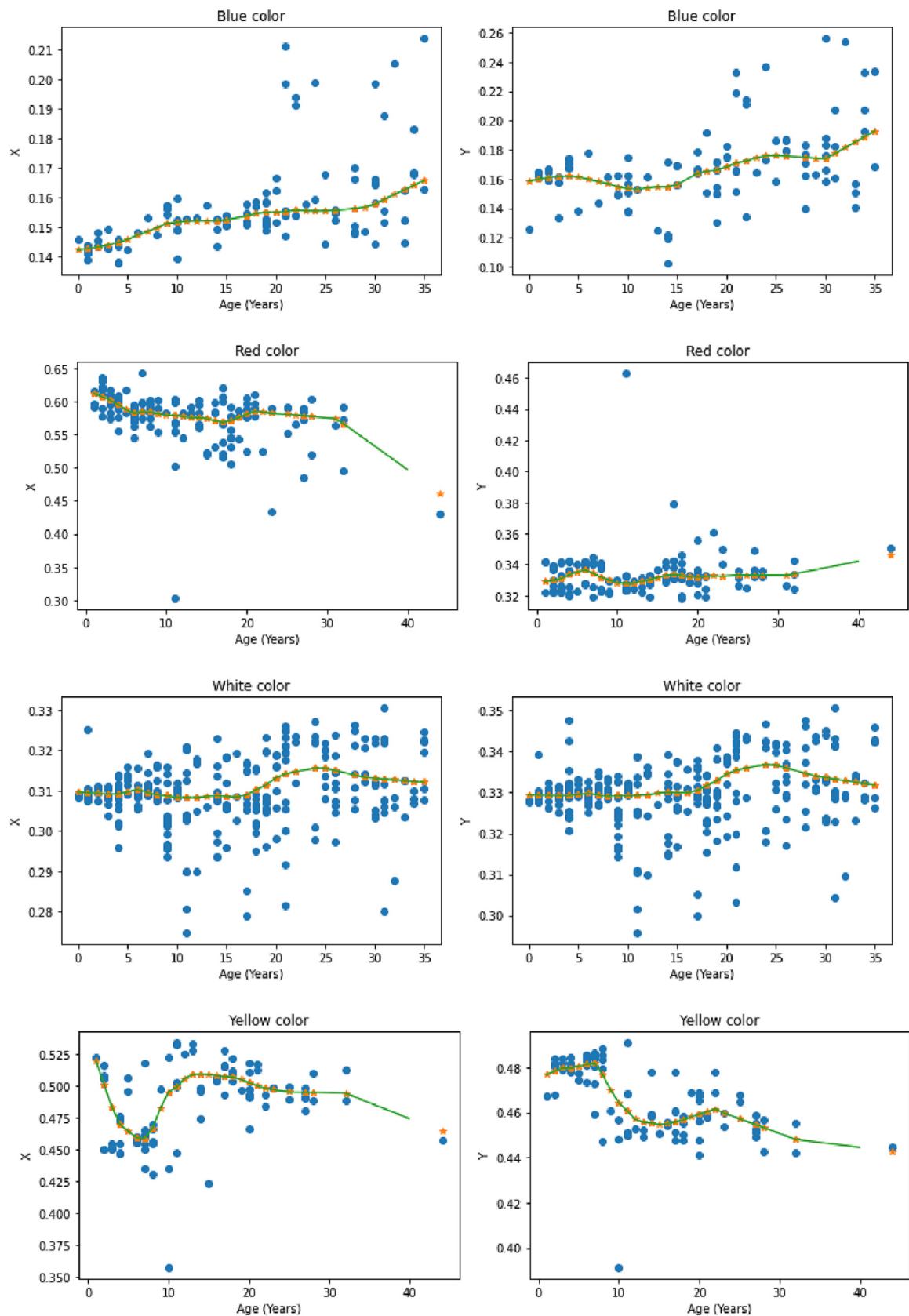


Fig. 7. LOWESS fit plots of the relationship between X and Y with age.

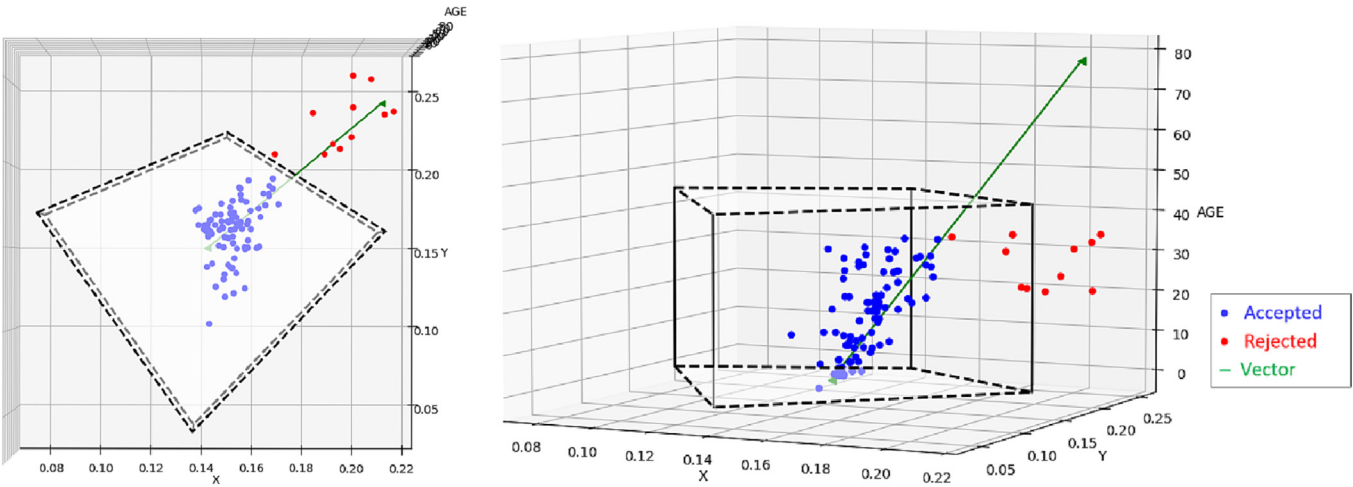


Fig. 8. The relationship between blue color and age.

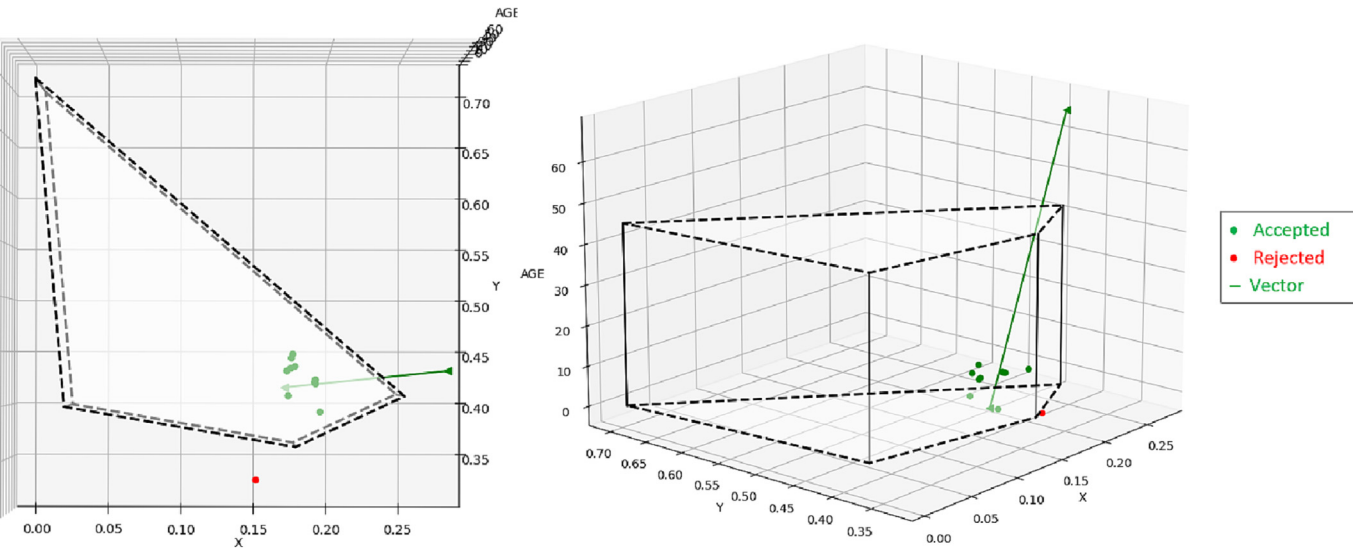


Fig. 9. The relationship between green color and age.

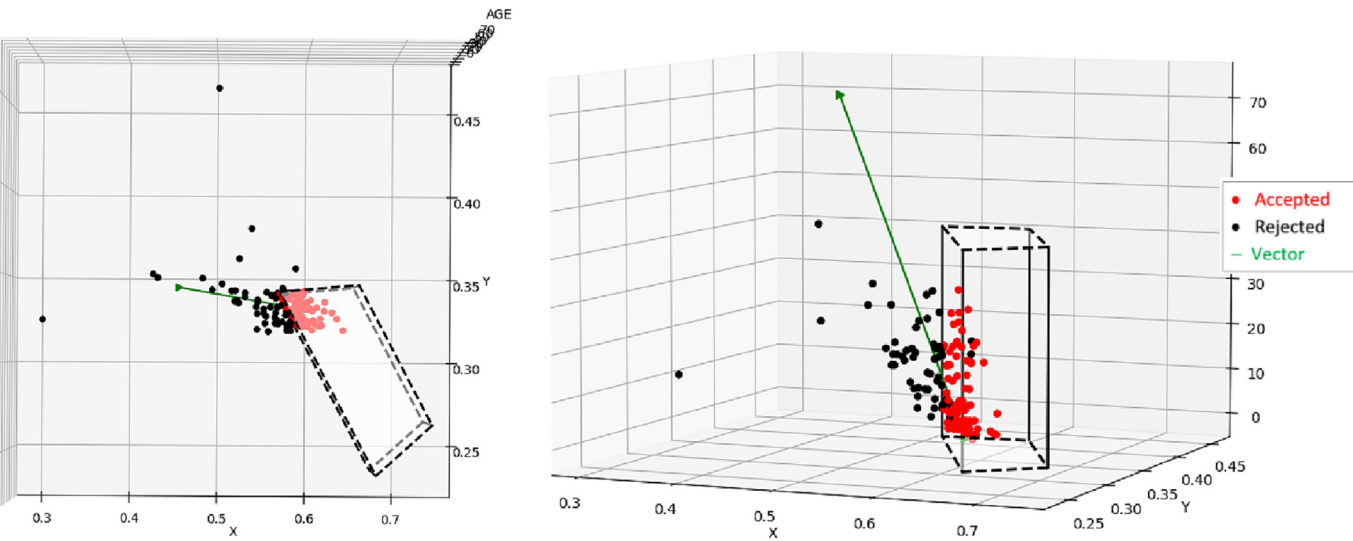


Fig. 10. The relationship between red color and age.

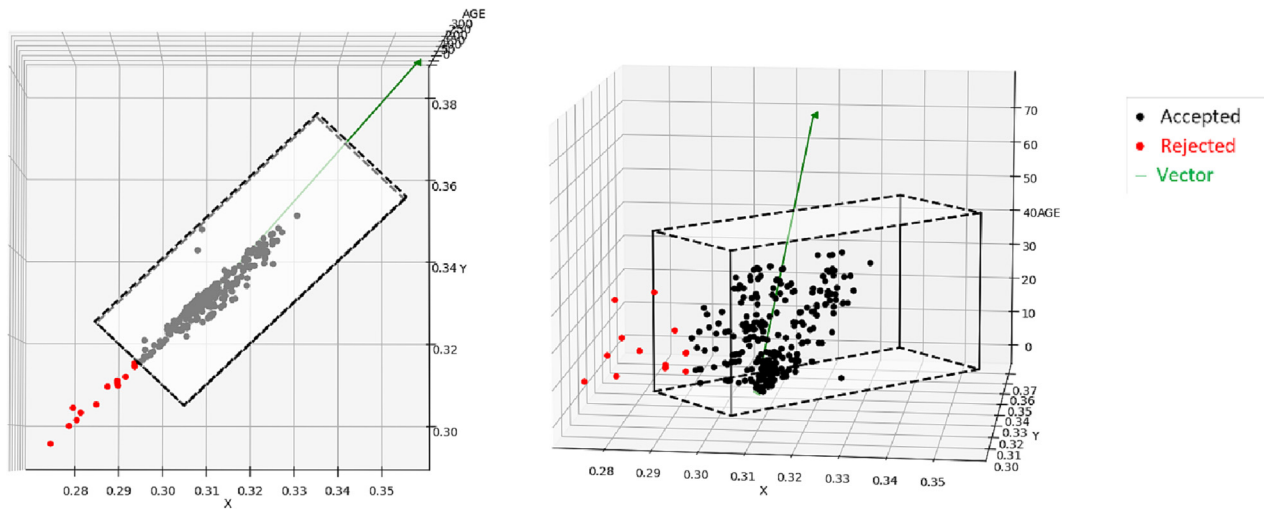


Fig. 11. The relationship between green color and age.

why blue and red sheeting tends to bleach and move towards a white color over time.

In contrast, the X value for yellow sheeting decreased during the first 8 years, then changed direction twice between the ages of 15 and 22 years. After that, both X and Y decreased with age. As a result, the yellow color moves inside the yellow color box during degradation, leading to a longer lifespan for this color.

5.3. Predicting the age of road signs according to colors

As proven in section 4.1, the passing of time has an impact on the color of road signs. The color pigments used in the printing process can be affected by different conditions that cause fading of the colors by aging. Additionally, it was found that the relationship between age and daylight chromaticity (X, Y) was linear, section 4.2.

The impact of age on daylight chromaticity (X, Y) was further investigated through the use of 3D plots, as seen in Figs. 8–12, to find the expected service life of each color of road sign.

A matrix was created from the 3D points, where each row represents a point, and each column represents a dimension. The matrix was centered by subtracting the mean value of each column from each data point. Finally, Singular Value Decomposition (SVD) was applied to the centered matrix to find the principal components of the data. The first

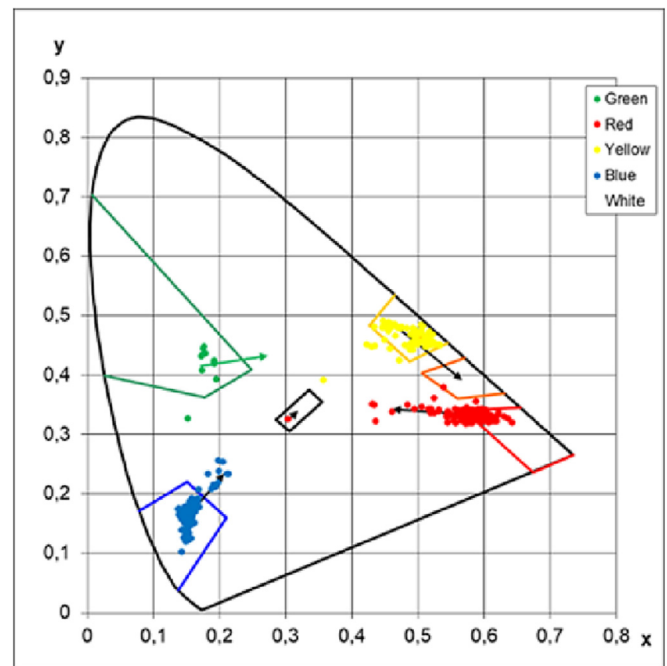


Fig. 13. Directions of color changes with age using PCA.

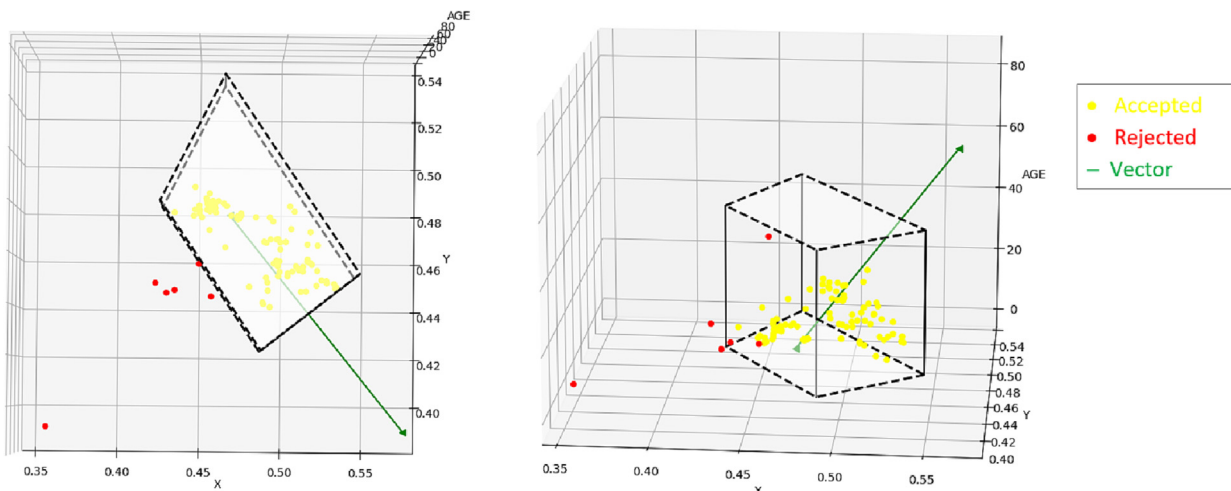


Fig. 12. The relationship between yellow color and age.

Table 3
Accuracy of classification models.

Scale		Accuracy	Precision	Recall	F1-Score
RF	Stand/Norm	0.79	0.80	0.86	0.83
SVM	Stand/Norm	0.74	0.63	0.67	0.64
ANN	Stand	0.76	0.82	0.86	0.83
	Norm	0.81	0.83	0.89	0.86

principal component that explains the most variance in the data represents the direction in which the points vary the most. This vector indicates the direction of degradation of X and Y with respect to age, and the intersection point of this vector with the color box gives the age when the road sign should be replaced.

The relationship between age and daylight chromaticity (X, Y) for each road sign color was visualized in 2D CIE diagram (Fig. 13) by projecting the vectors representing the mean degradation of X and Y with age. It was observed that the blue and red colors move towards the white color box located in the center of the CIE diagram. The green color is expected to lighten and turn yellow with aging. On the

other hand, the yellow color is anticipated to exit the color box after 35 years. These findings provide insight into the expected changes in color appearance of the road signs over time.

The blue, green, red, and white road signs were expected to have ages of approximately 45, 42, 12, and 75 years, respectively. However, due to a limited number of green road signs in the data, the expected age of green color could not be concluded.

The red color was found to move out of the color box rapidly, with an expected age of only 12 years. It is anticipated that white road signs will have a lifespan of over 75 years.

The yellow road signs were predicted to have an age of 35 years because of the nonlinear relationship between age and X, Y.

5.4. Predicting the color status of road signs

The performance of the models was evaluated on oversampled and scaled data, and the results are summarized in Table 3. The classification models achieved high accuracy rates ranging from 74% to 81%.

The three classification models (RF, SVM, and ANN) used the same variables (age, color, class, GPS coordinates, and direction) in their

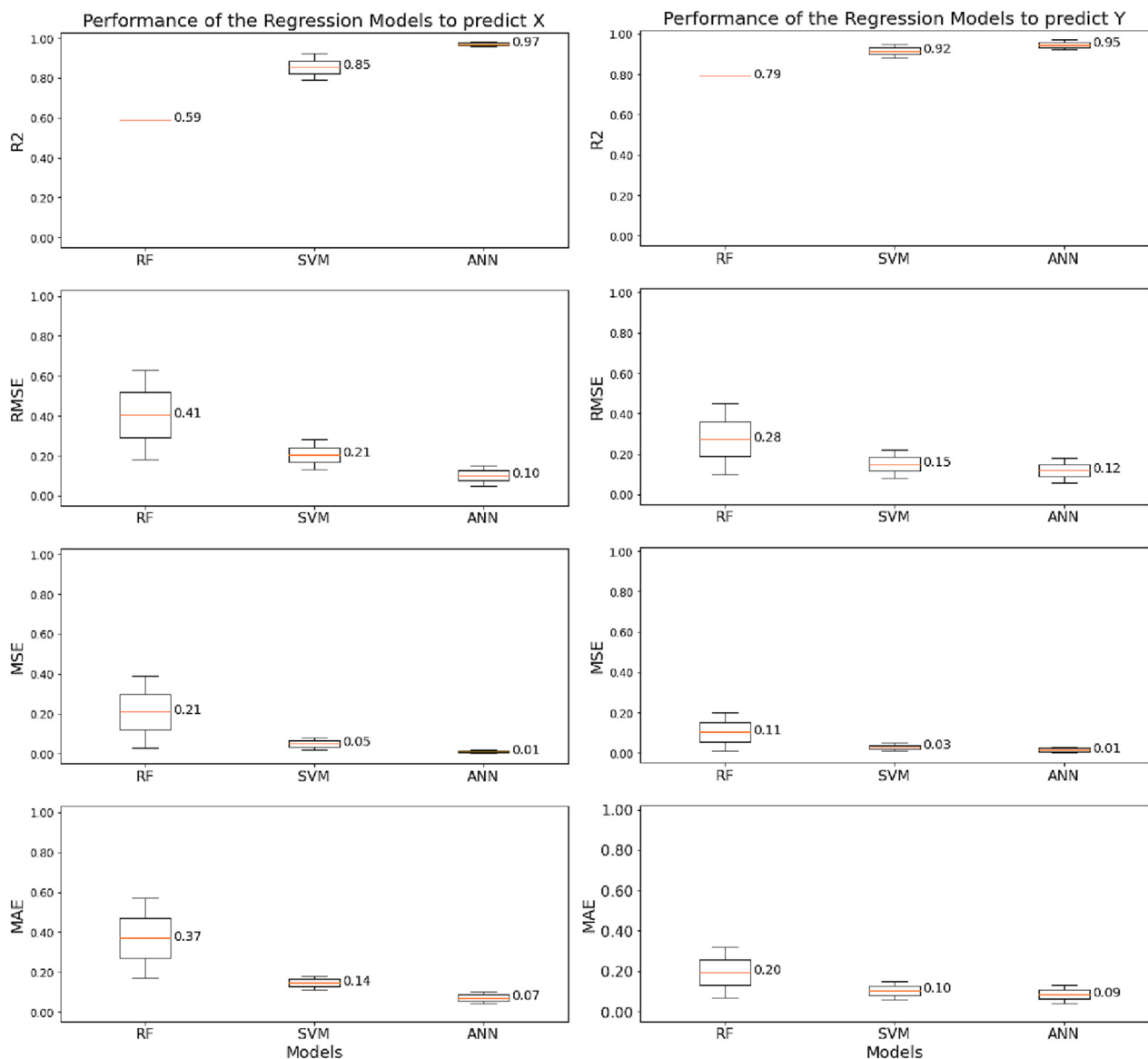


Fig. 14. Box plot representing a summary of performance metrics (R2, RMSE, MSE and MAE) for regression models.

predictions, as these variables were found to be important for the RF model. Despite some variables potentially being less important for SVM and ANN models, they were still included for comparative purposes.

Among the three models, ANN was found to have the highest accuracy (81%) in predicting the color status, likely due to its ability to learn and model complex non-linear relationships between inputs and outputs [30]. The other two models, RF and SVM, also performed well, with accuracy values ranging from 74% to 79%.

5.5. Predicting the daylight chromaticity (X and Y)

The results of the regression models for predicting daylight chromaticity (X and Y) using RF, SVM, and ANN are summarized in Fig. 14. The accuracy (R^2) of these models ranges from 59 to 97% and RMSE ranges from 10 to 41%.

The ANN model performs the best with the highest R^2 values (97%, and 95% for predicting X and Y, respectively) and the lowest RMSE (10%, and 12% for predicting X and Y, respectively).

6. Discussion

Previous studies on the degradation of road signs have mostly focused on the expected lifespan of signs based on the deterioration of retroreflectivity. However, this study proves that color fading is also an important factor that affects the expected age of road signs and their visibility and legibility. By focusing on the color status and daylight chromaticity of road signs, this study provides valuable insights into improving the regulation of road signs, reducing maintenance costs, and ensuring road safety.

The study found that the coefficient of retroreflection (RA) was the most important variable that affects color status (degradation of color) and daylight chromaticity. This relationship can be explained by the fact that both daylight chromaticity and RA are influenced by the same factors. Over time, exposure to different factors such as UV light, temperature fluctuations, and chemical exposure can cause the retroreflective layer to degrade, leading to a decrease in its ability to reflect light. At the same time, exposure to these factors can also cause the color pigments used in the printing process to fade or deteriorate.

The class of retroreflective sheeting used for road signs does not have a big impact on the degradation of the color of the signs. The class of sheeting refers to the level of retroreflectivity, or the ability of the material to reflect light back to its source, such as a vehicle's headlights.

All classes of retroreflective sheeting are typically printed in the same way. The process of printing involves applying a layer of ink or pigments onto the surface of the sheeting to create the desired text or image. This printing process is done using specialized equipment that is designed to work with the specific properties of the retroreflective material. The main difference between the classes of retroreflective sheeting lies in the quality and durability of the retroreflective layer, not in the printing process or printing quality. Regardless of the class of retroreflective sheeting used, appropriate printing equipment and materials must be used to ensure that the printed color has a high-quality and long-lasting result.

The red color was found to move out of the color box more rapidly than other colors. It tends to fade more quickly than other colors for several reasons, such as red pigments are often more sensitive to UV light than other colors. Red pigments absorb more light energy than other colors, which can cause them to degrade more quickly.

In the printing process, some red pigments are less chemically stable than other colors. This makes them more susceptible to fading or deterioration when exposed to environmental factors such as humidity, temperature fluctuations, or chemical pollutants.

Among the classification models used in this study, ANN was found to have the highest accuracy in comparison to SVM and RF models. ANN

has a flexible training process and its ability to be fine-tuned to improve performance.

Even ANN regression model performs the best for predicting X and Y. The superior performance of the ANN model is likely due to its ability to learn and model complex relationships between inputs and outputs, leading to accurate predictions.

Low prediction accuracy (R^2 of 59%) in RF regression models can be attributed to factors such as overfitting, limited model complexity, sensitivity to outliers, missing data, and limited feature selection. To improve the performance of RF regression models, it is important to carefully preprocess the data and tune the hyperparameters.

7. Conclusions

This study fills the gap in research by analyzing the impact of several factors that affect the color fade of road signs with respect to their age and daylight chromaticity. The study analyzed the impact of various factors on the color fade of road signs such as....

- The study concluded that color, sheeting? class, GPS coordinates, direction, and coefficient of retroreflection are important to color status and daylight chromaticity.
- It is also conclude that the relationship between the age of the sign and its daylight chromaticity is linear for blue, green, red, and white colors, but not for yellow at the age of up to 22 years.
- Predicted age for blue, green, red, white, and yellow sheeting was 45, 42, 12, 75, and 35 years, respectively.
- Red pigment used in road signs is more susceptible to fade and deteriorate due to its location near the edge of the designated CIE color box.
- To extend the lifespan of red signs, it is suggested to use red pigments located closer to the center of the CIE color box.
- The regulation of color (daylight chromaticity) of road signs is crucial to improve visibility and legibility, ensuring road safety and reducing maintenance and replacement costs.
- Machine learning models, including RF, SVM, and ANN, were used to predict the color status and daylight chromaticity of road signs with high accuracy.
- The models achieved an accuracy ranging from 74to 81% for classification and R^2 ranging from 59 to 97% for regression.

8. Implications for practice

The studys' results have significant implications on the transportation industry in terms of road sign maintenance, placement, and design. The study found that different colored road signs have different lifespans ranging from 12 to 75 years based on the signs' colors., As a result, transportation authorities should prioritize the production and maintenance of red road signs due to their shorter lifespan and chromaticity placement near the edges of the CIE red box.

To reduce the impact of color fade caused by environmental factors, such as sunlight, rain, and snow, it is crucial to use high-quality red pigments that are resistant to fading and deterioration and properly maintain the signs. Using red pigments that are closer to the center of the CIE color box for red can help reduce the risk of color fading and ensure the red color on the sign remains consistent and vibrant over a more extended period.

Regulating the colors of road signs is crucial for maintaining traffic safety, and it's essential to pay attention to more than just retroreflectivity. In fact, some road signs may fade in color before losing their retroreflectivity, which can significantly impact their effectiveness. This is especially true for red road signs, which are crucial for ensuring safety on the road.

Regulating the daylight chromaticity of road signs is also important for color consistency and high visibility, which is essential for road safety. This regulation can minimize the need for frequent repairs or

replacements of signs due to color fade or degradation, ultimately reducing replacement costs. However, some white road signs have been discovered to have various problems, such as dirt, grime, mildew, mold, cracking, and peeling, despite having a long lifespan of over 75 years. This discrepancy can be attributed to harsh environmental conditions such as tree sap, which can penetrate the surface and cause cracking and peeling. Additionally, being located outside of the color box means that the signs are subjected to extreme weather conditions, further shortening their lifespan.

In summary, road sign color regulation is an essential factor in maintaining traffic safety, and it should not be overlooked in favour of retroreflectivity alone. Red road signs are crucial for ensuring safety on the road and must be visible in daylight and at night. By paying attention to both retroreflectivity and color regulation, transportation authorities can ensure that road signs remain effective and that drivers can accurately and easily identify them, promoting road safety for all.

9. Limitations and future research

Limitations of the study include the relatively low R^2 values of the regression models used to predict the daylight chromaticity of road signs, indicating the need for further research to improve the accuracy of predicting the expected service lifespan of road signs.

Future research should consider additional factors such as sign size, location, weather conditions, and air pollution, which may affect the deterioration rate of road sign color. Furthermore, expanding the dataset to include road signs from different regions and countries can increase the generalizability and applicability of the models.

Declarations of Competing Interest

None.

References

- [1] R. Saleh, H. Fleyeh, Using supervised machine learning to predict the status of traffic signs, *Transport. Res. Proced.* 62 (2022) 221–228.
- [2] European Committee for Standardization, EN 12899–1. Fixed, Vertical Road Traffic Signs—Part 1: Fixed Sign, European Committee for Standardization, Brussels, Belgium, 2007 57p.
- [3] R.G. Mantovani, A.L. Rossi, J. Vanschoren, B. Bischl, A.C. De Carvalho, Effectiveness of random search in SVM hyper-parameter tuning, 2015 International Joint Conference on Neural Networks (IJCNN), Ieee 2015, July, pp. 1–8.
- [4] P. Siegmann, S. Lafuente-Arroyo, S. Maldonado-Bascón, P. Gil-Jiménez, H. Gómez-Moreno, Automatic evaluation of traffic sign visibility using SVM recognition methods, *Proc. 5th WSEAS Int. Conf. on Signal Processing, Computational Geometry & Artificial Vision* 2005, September, pp. 170–175.
- [5] E.A. Harris, W. Rasdorf, J.E. Hummer, A control sign facility design to meet the new FHWA minimum sign retroreflectivity standards, *Public Works Manag. Policy* 14 (2) (2009) 174–194.
- [6] K.L. Black, S.F. Hussain, J.F. Paniati, Deterioration of retroreflective traffic signs, *ITE J.* 62 (7) (1992) 16–22.
- [7] W.J. Rasdorf, J.E. Hummer, E.A. Harris, V.P.K. Immaneni, C. Yeom, Designing an Efficient Nighttime Sign Inspection Procedure to Ensure Motorist Safety, Raleigh, NC, 2006.
- [8] J.M. Ré, J.D. Miles, P.J. Carlson, Analysis of in-service traffic sign retroreflectivity and deterioration rates in Texas, *Transp. Res. Rec.* 2258 (1) (2011) 88–94.
- [9] N. Swargam, Development of a Neural Network Approach for the Assessment of the Performance of Traffic Sign Retroreflectivity, 2004.
- [10] A. Jamal, I. Reza, M. Shafuallah, Modeling retroreflectivity degradation of traffic signs using artificial neural networks, *IATSS Res.* 46 (4) (2022) 499–514.
- [11] A. Alkhulaifi, A. Jamal, I. Ahmad, Predicting traffic sign retro-reflectivity degradation using deep neural networks, *Appl. Sci.* 11 (24) (2021) 11595.
- [12] D. Babić, D. Babić, D. Macura, Model for predicting traffic signs functional service life—the republic of croatia case study, *Promet-Traffic&Transportation* 29 (3) (2017) 343–349.
- [13] V.P. Immaneni, J.E. Hummer, W.J. Rasdorf, E.A. Harris, C. Yeom, Synthesis of sign deterioration rates across the United States, *J. Transp. Eng.* 135 (3) (2009) 94–103.
- [14] R. Saleh, H. Fleyeh, M. Alam, An analysis of the factors influencing the Retroreflectivity performance of in-service road traffic signs, *Appl. Sci.* 12 (5) (2022) 2413.
- [15] B. Brimley, P.J. Carlson, The current state of research on the long-term deterioration of traffic signs, *Transportation Research Board 92nd Annual Meeting*, Vol. 2, No. 3, 2013, January.
- [16] H. Hawkins Jr., Research on Traffic Sign Retroreflective Sheeting Performance: A Synthesis of Practice, vol. No. TRS2101, Dept. of Transportation. Office of Policy Analysis, Research & Innovation, Minnesota, 2021.
- [17] J.A. Molino, J.F. Kennedy, P.A. Beuse, C.C. Miller, W. Davis, C.K. Andersen, Daytime Color Appearance of Retroreflective Traffic Control Sign Materials, vols. No. FHWA-HRT-13-018, United States, Federal Highway Administration, 2013.
- [18] B.K. Brimley, C. Senior, H.G. Hawkins Jr., P.J. Carlson, Analysis of retroreflectivity and color degradation in sign sheeting, *Compendium of Student Papers: 2010 Undergraduate Transportation Scholars Program* 2010, p. 81.
- [19] Erik Kjellman, Carina Fors, S. Lundkvist, Analysis of life-cycle costs for traffic signs with focus on retroreflective sheeting materials, *Swedish National Road and Transport Research Institute, VTI*, 2018.
- [20] H. Preston, K.C. Atkins, M. Lebens, M. Jensen, Traffic Sign Life Expectancy (No. MN/RC 2014-20), 2014.
- [21] P.J.M. Ali, R.H. Faraj, E. Koya, P.J.M. Ali, R.H. Faraj, Data normalization and standardization: a technical report, *Mach. Learn. Tech. Rep.* 1 (1) (2014) 1–6.
- [22] A. Ambarwari, Q.J. Adrian, Y. Herdiyeni, Analisis Pengaruh Data Scaling Terhadap Performa Algoritme Machine Learning untuk Identifikasi Tanaman, *J. Rekayasa Sist. dan Teknol. Inf.* 4 (1) (2020) 117–112.
- [23] A. Cutler, D.R. Cutler, J.R. Stevens, *Random forests*, Ensemble Machine Learning, Springer, Boston, MA 2012, pp. 157–175.
- [24] L. Breiman, *Random forests*, *Mach. Learn.* 45 (1) (2001) 5–32.
- [25] E. Scornet, Tuning parameters in random forests, *ESAIM: Proceed. Surv.* 60 (2017) 144–162.
- [26] P.V.S. Machado, Traffic Sign Replacement Strategy, North Carolina State University, 2019.
- [27] V. Solo, Selection of tuning parameters for support vector machines, *Proceedings. (ICASSP'05). IEEE International Conference on Acoustics, Speech, and Signal Processing*, 2005, vol. 5, IEEE 2005, March, pp. v–237.
- [28] T. Fushiki, Estimation of prediction error by using K-fold cross-validation, *Stat. Comput.* 21 (2) (2011) 137–146.
- [29] D. Chicco, M.J. Warrens, G. Jurman, The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation, *PeerJ Comp. Sci.* 7 (2021), e623.
- [30] M. Rocha, P. Cortez, J. Neves, Evolution of neural networks for classification and regression, *Neurocomputing* 70 (16–18) (2007) 2809–2816.