# Automated Evaluation of Pavement Marking Quality Based on Multi-Sensor Data

***Joanna Kulawik***
*Faculty of Computer Science and Artificial Intelligence, Czestochowa University of Technology*
*Czestochowa, Poland* *joanna.kulawik@icis.pcz.pl*

***Lukasz Karbowiak***
*Faculty of Computer Science and Artificial Intelligence, Czestochowa University of Technology*
*Czestochowa, Poland* *lkarbowiak@icis.pcz.pl*

**Abstract**

The primary objective of this work is the automatic analysis of road marking degradation, to support maintenance decision making. The evaluation is conducted in two main aspects: the visual condition, assessed using a camera, and the retroreflective quality, which ensures nighttime visibility and is evaluated using LiDAR data. We employ the latest YOLOv12 neural network for road marking detection, enabling real-time analysis during vehicle movement. Following detection, LiDAR data is recorded and used to analyze the quality of the reflected beams. The primary parameter considered in this analysis is the intensity of the reflected signal (ranging from 0 to 255). Based on this parameter, road markings are classified into two categories: good condition and those requiring maintenance. The proposed approach provides an automated and effective tool for road infrastructure monitoring within intelligent transportation systems.

**Keywords:** multi-modal, deep learning, YOLOv12, point cloud analysis, intelligent transportation systems.

## 1. Introduction

The growing demand for automated infrastructure monitoring in intelligent transportation systems has led to increased interest in multi-modal analysis of road markings. Road markings play a critical role in traffic safety, and their deterioration can compromise visibility and guidance, particularly under low-light conditions. This work focuses on the automatic assessment of road marking degradation to support maintenance decision-making processes. The analysis looks at two main aspects: how the markings look visually, checked with RGB camera data, and how well they reflect light, measured with LiDAR (Light Detection and Ranging) signal response [1]. Synchronization between sensors is realized by SDAS [4, 5]. For the detection of road markings, a deep learning-based approach is applied using the YOLOv12 [6] neural network, enabling real-time inference during vehicle movement. Once the markings are detected, LiDAR data is captured and analyzed with regard to the intensity of reflected signals, expressed on a scale from 0 to 255. Based on this parameter, markings are classified into two categories: those in excellent condition and those requiring maintenance. The proposed method demonstrates the potential of combining visual and LiDAR modalities in an efficient and scalable framework for monitoring the condition of road infrastructure.

## 2. Vision-based decision system

The application of the YOLOv12 model provided coordinates indicating the position of horizontal road markings within the image space. This model also returned information about the type of detected sign. The next stage of the work involved the development of a vision-based decision-making system. Initially, based on the data obtained from YOLOv12 for a given digital image, a fragment corresponding to a single object (road marking) was extracted. A single image analyzed by the YOLOv12 model may contain several different horizontal road markings. In these cases, we extracted as many image fragments as we detected and classified objects/signs. Each extracted fragment was subsequently processed independently as a separate image/sample. Although individual images can be analyzed by the vision-based decision system on their own, a dataset was prepared to evaluate the system's performance. For the purpose of testing, a set of images originating from video streams captured during test drives was developed. The dataset consisted of randomly selected frames taken from various recordings. A total of 2187 color images were obtained, all of which depicted a road surface with horizontal road markings. Using YOLOv12, both the coordinates and class affiliations of the detected signs were determined. In this way, a set of 3968 cropped color images was created, with each small image containing a single road marking.

The fundamental idea behind the vision-based decision system [3] relies on the observation that horizontal road markings exhibit a light gray color. In theory, a freshly painted sign is white, but in practice, due to wear and tear, its color tends to shift closer to light gray. These markings are applied directly onto the road surface, which is typically dark gray. The assumption behind the use of such signs is that they should remain clearly visible against the road background. Consequently, the essence of the decision system lies in the contrast between the painted sign (the object) and the road surface (the background). We developed the following methodology in response to these observations. First, the cropped image was converted to grayscale. In the next step, the image underwent a contrast enhancement transformation. We performed a simple operation for this purpose, multiplying each pixel's grayscale level by a factor of 1.1. This procedure caused the lighter pixels to shift closer toward white. The aim of the developed system was to determine whether a given road marking had degraded to the extent that repainting was required. Therefore, the contrast enhancement operation increased the visual distinction between a worn-out sign and the faded road surface, significantly facilitating further image analysis.

Subsequently, a histogram was generated for each analyzed image [2]. At this point, it is worth noting that during preliminary work involving the analysis of histogram plots across a relatively large set of images, a certain regularity was identified. Histograms of clearly visible signs consistently exhibited a concentration of light-colored pixels near the maximum grayscale value of 255. In contrast, images of poorly visible signs did not show this tendency. Based on this analysis, a threshold value of 225 was estimated to support the decision of whether a given sign should be categorized as requiring repainting. For the continuation of the analysis, it was assumed that the percentage ratio of pixels with grayscale values in the range <225:255> to the total number of pixels in a given image fragment would be calculated.equation 1). This computation provided information on the percentage of bright pixels relative to the entire image area.

$$BS = \frac{\sum hist[225:255]}{\sum hist[0:255]}, \quad (1)$$

where: $BS$ is the share of brightness; $\sum hist[225:255]$ is the sum of the histogram values from 225 to 255; $\sum hist[0:255]$ is the sum of all the histogram values from 0 to 255.

Establishing the percentage threshold to distinguish between a clearly visible sign and one that requires repainting was the next step. Furthermore, during the analysis, it was observed that pedestrian crossing signs typically contained a significantly higher number of white pixels compared to other types of signs, such as arrows. As a result, it was deemed necessary to define two separate thresholds: one for images containing pedestrian crossings and another for all other types of road markings. Ultimately, the following thresholds were estimated: $BS < 4\%$ for pedestrian crossings and $BS < 10\%$ for all remaining signs.Using the developed methodology and the estimated thresholds, tests were conducted to evaluate the accuracy of the decision-making system based on the previously prepared dataset of cropped images. As a result, it was determined that out of the entire set of 3968 tested images, 342 signs were identified as requiring repainting—of which 212 were pedestrian crossings, and 130 were other types of signs. A comparison of these results against the actual condition of the road markings demonstrated a high accuracy level of the developed system. On the right of the image Fig. 1, sample image containing road markings identified as requiring repainting are presented.

## 3. LiDAR-based approach

In addition to vision-based analysis, LiDAR sensor data was utilized to evaluate the retroreflective quality of road markings, an essential property to ensure nighttime visibility and overall road safety. The LiDAR device, mounted on the test vehicle, captured spatial and intensity data corresponding to the surface of the road, including detected horizontal markings. For each marking identified by the YOLOv12 model in the RGB image, the corresponding spatial region was mapped in the LiDAR point cloud using sensor calibration parameters (see Fig. 1)

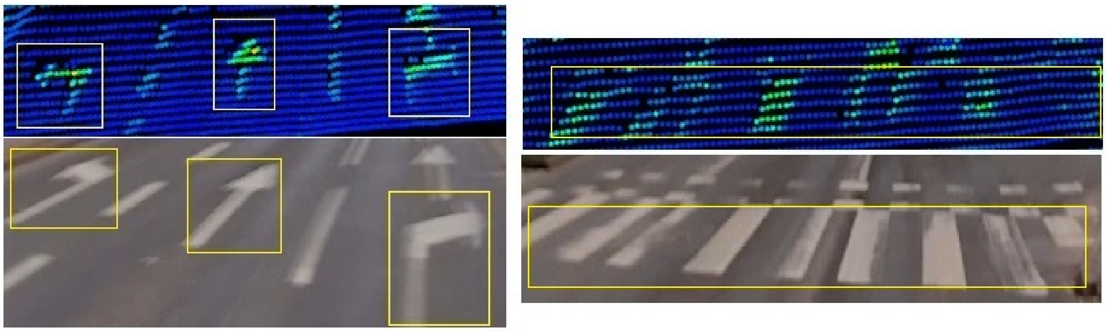

**Fig. 1.** Example data from the camera and LiDAR with detected objects.

The LiDAR system records intensity values in the range of 0 to 255, where higher values indicate stronger reflection. Freshly painted road markings, which include retroreflective materials, are expected to reflect significantly more LiDAR light than worn-out ones. The assumption in our methodology was that degraded markings exhibit noticeably reduced LiDAR reflectivity, and this feature can be leveraged for objective assessment.

To perform this analysis, each bounding box returned by YOLOv12 was used to define a spatial window in the 2D LiDAR projection plane. Within this window, the average intensity value was computed from all points classified as lying within the physical extent of the road marking. In cases where multiple markings appeared in one frame, each region was analyzed separately. Points falling outside the defined bounding box were ignored to avoid contamination from background surfaces such as asphalt or other objects.

A threshold-based classification was developed using statistical observations from a labeled dataset. During the training phase, it was noted that well-maintained markings consistently produced average LiDAR intensity values above 100, while worn-out signs usually scored below 60. Based on this empirical evidence, two thresholds were set: markings with an average intensity below 60 were labeled as requiring repainting, and those above were considered to be in good condition. Values in the intermediate range were considered borderline and subjected to further analysis based on the intensity distribution (e.g., the proportion of points above 200).

To validate the LiDAR-based approach, it was applied to the same set of 3968 cropped marks used in the vision-based experiment. Each region was evaluated on both an RGB and LiDAR-based basis. The results revealed a remarkable agreement between the two modalities: only three instances presented a mismatch between the classification results of the RGB and

LiDAR-based systems. Manual inspection of these outliers revealed that they involved complex lighting conditions, heavy shadowing, or partial occlusion by environmental elements such as leaves or dirt patches.

## 4. Results

The system was evaluated on a data set comprising 3,968 annotated road markings, including pedestrian crossings and directional signs. Interestingly, we observed only 3 discrepancies between the LiDAR- and vision-based decision modules. Each of these cases was manually reviewed and found to involve borderline conditions where contrast or reflectivity was ambiguous.

Across the entire dataset, the system recorded a total of 28 classification errors. Among these, 22 errors were due to overly conservative decisions, where the system classified a marking as needing repainting prematurely. The remaining 6 errors were underestimations, where the system failed to identify degraded markings that should have been flagged for maintenance. These results show that the detection system is very reliable and can apply what it learned well, especially when it comes to making safe choices that focus on repainting early.

## 5. Conclusion

The near-perfect alignment between the two independent systems reinforces the reliability of the proposed methodology. It also underscores the complementary nature of RGB and LiDAR sensing: while RGB is sensitive to visual degradation and paint wear, LiDAR directly reflects the physical retroreflective properties of the surface, which are often invisible to the naked eye. The fusion of both modalities offers a comprehensive assessment framework that can operate under various environmental conditions.

In addition, this redundancy enhances the robustness for real-world deployment. In scenarios where the data of one sensor is unreliable (e.g., low light conditions for cameras or reflective noise in LiDAR), the other can still provide valid insights. This bi-modal approach aligns with the goals of intelligent transportation systems, enabling continuous and autonomous monitoring of road infrastructure with minimal human intervention.

## References

[1] Aldoski, Z.N., Koren, C.: Assessment of traffic sign retroreflectivity for autonomous vehicles: a comparison between handheld retroreflectometer and lidar data. Archives of Transport 70(2), pp. 7–26 (2024)

[2] Dutta, M.K., Sarkar, R.K.: Application of retinex and histogram equalisation techniques for the restoration of faded and distorted artworks: A comparative analysis. Optik 272, pp. 170201 (2023)

[3] Kulawik, J., Kubanek, M., Garus, S.: The verification of the correct visibility of horizontal road signs using deep learning and computer vision. Applied Sciences 13(20) (2023)

[4] Piatkowski, J., Karbowiak, Ł., Depta, F.: Synchronized data acquisition system (sdas)-a software approach for synchronizing data recording from multiple sensors. In: International Conference on Information Systems Development (ISD). No. 32nd (2024)

[5] Piatkowski, J., Karbowiak, L., Depta, F.: A lightweight algorithm for synchronized multimodal data acquisition using temporal sample alignment. Scientific Reports 15, pp. 22711 (2025)

[6] Tian, Y., Ye, Q., Doermann, D.: Yolov12: Attention-centric real-time object detectors. arXiv preprint arXiv:2502.12524 (2025)