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Impact of Camera vs. Lidar Data on Road Attribute Identification Using Deep Learning: An Empirical Investigation

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Abstract

Road safety is a significant global issue, as approximately 1.19 million people die, and 20 to 50 million suffer injuries in road crashes each year. Existing proactive road infrastructure safety approaches depend on reliable identification of road safety attributes, including roadside hazards such as safety barriers, trees, poles, slopes, and drainage features. Recent advances in deep learning have enabled automated detection of these attributes using visual data; however, current studies have predominantly focused on either high-resolution camera imagery or Light Detection and Ranging (LiDAR) sensor data in isolation. While both modalities offer distinct advantages, their relative performance for roadside safety object detection has not been systematically compared, leaving practitioners without clear guidance on sensor selection for road safety assessment applications.

Camera-based imagery provides rich semantic information through colour and texture, enabling effective identification of features such as road markings, traffic signs, and material properties of roadside objects. However, camera performance degrades significantly under adverse environmental conditions such as low light, heavy rain, or fog. Furthermore, cameras may struggle with accurately detecting objects in shadowed areas or distinguishing between visually similar roadside features when colour and texture cues are limited.

In contrast, LiDAR-derived cross-sectional images preserve the geometric precision of the original 3D point cloud data in a 2D representation that is suitable for conventional computer vision pipelines. These orthographic projections maintain millimetre-level spatial accuracy and are invariant to lighting conditions, making them robust for detecting roadside features based on their geometric structure and shape. However, LiDAR intensity imagery lacks the rich semantic context provided by RGB colour information, potentially limiting classification accuracy for objects distinguished primarily by appearance or material properties rather than geometric structure.

This paper presents a comprehensive empirical comparison of RGB camera imagery versus LiDAR-derived cross-sectional images for automated roadside safety object detection using state-of-the-art (SOTA) YOLO-based deep learning models. Our methodology systematically evaluates both modalities across multiple dimensions**:** detection accuracy (precision, recall, mean Average Precision), per-class performance across 13 iRAP-defined roadside hazard categories, and detection robustness under varying scene complexities. We employ YOLOv8 and YOLOv11 architectures across multiple model scales (small, medium, large) to ensure our findings generalize across different complexity-performance trade-offs.

Our experimental dataset comprises camera images and LiDAR cross-sectional images collected from mobile mapping systems on Croatian highways, with ground-truth annotations for 13 roadside object classes such as safety barriers (metal and concrete), ditches, slopes, drainage features, trees, poles, etc. All objects are annotated with precise bounding boxes following COCO format, enabling direct comparison of detection performance between modalities.

The primary contributions of this research are: (1) a systematic, data-driven comparison quantifying the detection performance differences between camera and LiDAR imagery for roadside hazard identification across multiple SOTA deep learning architectures; (2) per-class performance analysis revealing which object types benefit most from each modality; (3) detection consistency analysis across different object sizes and

scene complexities. Our findings demonstrate that LiDAR-derived images provide more robust detection for geometrically-defined features such as slopes and drainage, and maintain consistent performance under varying lighting conditions.

The results of this study hold significant implications for the advancement of AI-driven road safety assessment. For transportation authorities and road safety practitioners, our findings provide evidence-based guidance for selecting appropriate sensor modalities when deploying automated road safety object detection systems. The comparative analysis enables cost-benefit evaluation of sensor investments, informs data collection strategies for road safety audits, and identifies which combinations of sensor types and deep learning architectures are most suitable for specific operational requirements. Furthermore, our work establishes baseline performance benchmarks for both modalities, facilitating future research in multi-modal sensor fusion and hybrid detection approaches.

Keywords: Road Safety; Deep Learning; Road Safety Attributes Identification; LiDar Data;