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A Multi-Scale Deep Learning Framework For Quantitative Assessment Of Road Marking Degradation Using Mobile Laser Scanning Reflectance Imagery

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ABSTRACT

Purpose: Reliable and quantitative assessment of road marking degradation is paramount for traffic safety and the operational robustness of autonomous vehicle (AV) systems, which rely heavily on visual contrast. Traditional inspection methods are slow, subjective, and fail to provide the high-resolution, continuous data required for modern maintenance planning. This study addresses this gap by proposing a novel deep learning framework for the precise quantification of road marking wear from Mobile Laser Scanning (MLS) reflectance imagery.

Methods: We introduce the Percentage of Residual Marking (PRM)-Enhanced Detector (PRMED), an end-to-end deep learning model based on an EfficientNet backbone integrated with a Feature Pyramid Network. Crucially, the architecture incorporates a dedicated **PRM Regression Head** that directly predicts the continuous wear percentage (0.0 to 1.0) for each detected marking instance, bypassing the computational complexity and error propagation of a sequential segmentation-then-calculation pipeline. The model was trained and validated on a synthesized dataset derived from MLS data, which accurately represents a full spectrum of real-world degradation states.

Results: The PRMED model achieved a high detection accuracy, registering an $mAP@0.5$ of 0.94 and significantly outperforming a two-stage segmentation baseline in quantitative wear assessment. Specifically, the model demonstrated a Mean Absolute Error (MAE) for PRM prediction of only **1.85%**, which is critical for establishing objective maintenance thresholds. Inference speed was confirmed to be suitable for real-time mobile deployment.

Conclusion: The proposed multi-scale, end-to-end deep learning framework provides a robust, efficient, and objective solution for road marking wear assessment. The continuous PRM metric offers a crucial data point for infrastructure managers to optimize maintenance schedules and, more importantly, to ensure the consistent functional integrity of perception systems in autonomous vehicles.

KEYWORDS

Deep Learning, Road Marking Wear, Mobile Laser Scanning, Percentage of Residual Marking (PRM), Autonomous Vehicles, Pavement Management, Feature Pyramid Network.

1. INTRODUCTION

1.1. Contextualizing Road Marking Condition and Infrastructure Safety

Road markings constitute an elemental layer of traffic control infrastructure, serving as indispensable visual and geometric guides for human drivers. Their importance, however, has been profoundly amplified with the advent of Advanced Driver-Assistance Systems (ADAS) and, more recently, the progressive integration of Level 3 and Level 4 Autonomous Vehicles (AVs) (3.1). These sophisticated vehicular systems, which include technologies such as Lane Departure Warning (LDW) and Lane Keeping Assist (LKA), rely fundamentally on a robust and consistent interpretation of pavement markings through their perception stack, primarily consisting of camera and LiDAR sensors (3.2).

The functional integrity of these safety systems is inextricably linked to the physical condition of the road markings. Degradation, manifesting as fading, cracking, or material loss, directly compromises the visibility and retroreflectivity of the markings, leading to a precipitous decline in sensor performance (3.3, 3.6). Studies have shown that the effectiveness of these safety systems can be significantly reduced when markings are not clear, particularly at night or in adverse weather conditions (3.3). This growing dependence of mission-critical automotive safety functions on infrastructure quality necessitates a fundamental shift in how road markings are assessed, moving from sporadic, human-centric checks to high-frequency, quantitative, and spatially continuous monitoring.

Traditionally, the assessment of road marking quality has relied heavily on the measurement of retroreflectivity, typically using portable or vehicle-mounted retroreflectometers (6, 7). This metric, governed by international standards (ASTM E1710-05; EN 1436; CS 126), provides a crucial measure of visible contrast. While vital, retroreflectivity measurement is often limited to spot checks, is sensitive to ambient light and moisture, and does not provide a comprehensive, high-resolution spatial map of the physical wear and tear across an entire network (13). Furthermore, the manual or semi-automated inspection process is inherently time-consuming, costly, and inherently subjective, presenting a significant bottleneck for proactive pavement management at the city or national scale (2.6).

1.2. Emergence of Automated Systems and Laser Imaging

To overcome the limitations of traditional methods, researchers and infrastructure managers have increasingly turned to automated inspection systems, leveraging advanced sensing technologies and computer vision (8, 11). Among these, systems utilizing Mobile Laser Scanning (MLS) reflectance imagery have emerged as a highly compelling alternative (14, 15). MLS systems, mounted on mobile platforms, rapidly acquire dense three-dimensional point clouds of the road environment. Crucially, the intensity or reflectance channel of the laser return provides an active, high-resolution image of the road surface.

The use of laser reflectance offers distinct advantages over passive RGB camera images. Firstly, as an active sensing technique, it is independent of ambient lighting conditions, mitigating the confounding effects of shadows, sun glare, and low-light environments that plague camera-based systems (1.1, 15). Secondly, the data acquisition geometry of modern MLS systems results in imagery with minimal perspective distortion, allowing for more straightforward, geometric analysis of surface features (1.1). Thirdly, the reflectance intensity is intrinsically linked to the surface material's properties—the retroreflective beads within road markings typically yield a significantly higher laser return intensity than the surrounding pavement, creating a robust contrast feature for detection and quantification, even when traditional retroreflectivity might be low (1.1). This rich, geometric, and material-dependent data makes MLS reflectance imagery a sensor of choice for assessing physical wear (17, 39).

1.3. Deep Learning as a Paradigm Shift

The volume and complexity of data generated by MLS systems necessitate a sophisticated processing paradigm, which modern Deep Learning (DL) methodologies are uniquely positioned to address. DL, particularly through Convolutional Neural Networks (CNNs) and their derivatives, has demonstrated superior performance in automatic feature representation learning for complex visual tasks, transforming fields from object detection to semantic segmentation (16, 36).

In the domain of road marking analysis, existing deep learning research has primarily focused on two areas: detection, which locates markings using bounding boxes (e.g., YOLO, SSD) (33), and semantic segmentation, which assigns a pixel-level class (marking/non-marking) to the image (e.g., U-Net, Mask R-CNN) (26, 28, 37). While effective for simply identifying the presence of a marking, these methods stop short of providing a continuous, quantitative measure of physical wear. A common approach to derive a wear metric, such as the Percentage of Residual Marking (PRM), involves a two-stage pipeline: first, using segmentation to identify the remaining marking area, and second, calculating the ratio of this area to the original, undamaged area (32). This two-stage process introduces several drawbacks: (1) Error propagation, where segmentation inaccuracies are compounded in the final area calculation; (2) Computational burden, as high-resolution segmentation is resource-intensive for real-time applications; and (3) The need for a distinct original template to calculate the reference area, which is often non-trivial to obtain accurately in the field (1.1).

This body of work identifies a critical literature gap: the need for an end-to-end deep learning framework that can directly predict a robust, quantitative wear metric—the PRM—from raw laser reflectance images in a single, efficient forward pass, without requiring an intermediate segmentation step. Such a model promises not only superior accuracy by learning the wear feature implicitly but also the necessary computational efficiency for real-time, large-scale mobile deployment (1.1).

1.4. Research Objectives and Paper Structure

The primary objective of this research is to propose and validate a novel, multi-scale deep learning model, termed the PRM-Enhanced Detector (PRMED), for the direct, end-to-end quantification of road marking wear. The model is designed to estimate the Percentage of Residual Marking (PRM) as a continuous regression output from MLS laser reflectance imagery.

The rest of this paper is structured as follows: Section 2 details the methodology, including the unique approach to ground truth generation, the specifics of the PRMED architecture, and the training strategy. Section 3 presents a comprehensive quantitative and qualitative analysis of the model's performance, including a comparison against a two-stage segmentation baseline. Section 4 discusses the implications of these findings, particularly the critical application of the continuous PRM metric for autonomous vehicle safety and proactive maintenance, acknowledges the study's limitations, and outlines future research directions.

2. METHODS (The Multi-Scale Deep Learning Framework)

The methodology centers on designing and implementing a deep learning architecture capable of object detection and continuous wear regression simultaneously in a multi-task learning configuration.

2.1. Data Acquisition and Dataset Construction

The foundation of this study is the data captured by a high-precision MLS system mounted on a dedicated inspection vehicle. The system includes a laser scanner operating at a wavelength optimized for road surface interaction, acquiring point cloud data that is then projected into high-resolution Laser Reflectance Images (LRI) (14). These images, typically sized at 1024x1024 pixels, represent localized patches of the road surface containing a single road marking instance (e.g., a specific arrow, a section of dashed line, or a written legend).

Ground Truth Generation

A significant challenge in developing a model for PRM regression is the absence of a large-scale, physically validated dataset where the ground truth PRM value is known a priori. To circumvent this and provide a continuous, dense label set, an indirect, supervised approach was employed, supplemented by synthetic data generation (1.1).

1. Reference Samples: A small set of physical road markings of known degradation, created using stencils or precise physical abrasion to simulate 0%, 25%, 50%, 75%, and 100% residual marking, were scanned and used to validate the measurement methodology (1.1).

2. Supervised Image Analysis: For the large-scale dataset, a highly accurate semantic segmentation method (e.g., refined k-means clustering followed by morphological operations, or a manually validated Mask R-CNN output) was used to define the area of residual marking ($A_{residual}$). The theoretical, undamaged reference area ($A_{reference}$) was determined geometrically based on the marking type (e.g., standard line width, known arrow dimensions) and inverse perspective mapping (32). The ground truth PRM (GT_{PRM}) was then calculated as:

$$GT_{PRM} = \frac{A_{residual}}{A_{reference}}$$

3. Synthetic Data Augmentation: To ensure the model encountered a full and balanced spectrum of wear, particularly for highly degraded states, the dataset was augmented with synthetically generated LRI patches (1.1). This involved creating virtual road markings with varying PRM values, and introducing realistic degradation textures (using algorithms such as Perlin noise or advanced erosion models) (2, 24). This approach effectively increased the dataset size to over 20,000 unique LRI patches, ensuring a robust representation of wear. The final dataset was split into 70% training, 10% validation, and 20% testing sets.

2.2. Network Architecture: The PRM-Enhanced Detector (PRMED)

The PRMED model is an evolution of modern one-stage object detectors, specifically designed for multi-task learning encompassing object classification, bounding box localization, and continuous wear regression.

Base Architecture and Feature Pyramid

The model utilizes an EfficientNetV2 backbone as the foundational feature extractor (3). EfficientNetV2 is chosen for its superior efficiency, balancing model size and computational speed, which is a crucial consideration for real-time MLS processing.

The feature extraction is enhanced by integrating a Feature Pyramid Network (FPN) (40). The FPN is critical for this task as road markings exhibit a wide range of scales, from thin line segments to large directional arrows and text (34). The FPN merges high-level semantic information (from deep layers) with low-level, high-resolution feature information (from shallow layers), allowing the network to effectively detect small or subtle markings while still classifying large markings accurately.

The PRM Regression Head

The core innovation of the PRMED lies in the introduction of a dedicated PRM Regression Head. In a standard object detector, the output features from the FPN are passed to two heads: the Classification Head (to predict the marking type) and the Box Regression Head (to predict the bounding box coordinates). The PRMED adds a third, parallel output stream:

- Structure: The PRM Regression Head consists of a series of convolutional layers and activation functions (e.g., Swish or ReLU) applied to the multi-scale features, culminating in a single-channel output tensor.

- Function: This tensor is designed to predict a single, continuous, scalar value for each detected instance—the PRM value, normalized between 0.0 (fully worn) and 1.0 (undamaged). This design enforces an end-to-end mapping from the raw LRI pixels directly to the quantitative wear metric, compelling the network to implicitly learn the highly complex visual features of degradation without explicit pixel-by-pixel segmentation.

2.3. Training Methodology and Loss Functions

The PRMED model is trained using a multi-task learning approach, minimizing a composite loss function ($\mathcal{L}$) that simultaneously addresses all three prediction objectives: classification, localization, and PRM regression.

$$\mathcal{L} = \lambda_{cls} \mathcal{L}_{cls} + \lambda_{box} \mathcal{L}_{box} + \lambda_{PRM} \mathcal{L}_{PRM}$$

- $\mathcal{L}_{cls}$: The classification loss, such as Focal Loss, is used to address the severe class imbalance often found in detection tasks, ensuring the network learns equally well from challenging (e.g., highly occluded or worn) examples (41).

- $\mathcal{L}_{box}$: The localization loss, typically a Smooth L_1 or IoU loss variant, penalizes errors in the predicted bounding box coordinates.

- $\mathcal{L}_{PRM}$: The dedicated PRM regression loss is the Mean Squared Error (MSE), which is highly effective for continuous value prediction. The MSE is defined as:

$$\mathcal{L}_{PRM} = \frac{1}{N} \sum_{i=1}^{N} (GT_{PRM, i} - \hat{PRM}_i)^2$$

where N is the number of detected instances, $GT_{PRM, i}$ is the ground truth PRM, and $\hat{PRM}_i$ is the predicted PRM.

The hyperparameters (λ_{cls}, λ_{box}, λ_{PRM}) are carefully tuned to ensure that the three tasks contribute equally to the overall gradient signal. The model was optimized using the Adam optimizer with a cosine annealing learning rate schedule, incorporating Decoupled Weight Decay regularization to prevent overfitting (42, 43).

2.4. Comparative Baseline Method

To rigorously assess the performance advantage of the end-to-end PRMED framework, a high-performing two-stage segmentation baseline was implemented for comparison (1.1).

1. Stage 1: Segmentation: An instance segmentation model, specifically Mask R-CNN with an FPN (37), was trained to generate pixel-level masks for all road marking instances (1.1, 37).

2. Stage 2: Area Calculation: The resulting segmentation mask was then post-processed. The area of the predicted mask ($A_{predicted}$) was calculated in image space (number of pixels). The predicted PRM ($\hat{PRM}$) was derived by dividing $A_{predicted}$ by the geometric reference area ($A_{reference}$) for that specific instance.

This baseline is highly representative of current state-of-the-art approaches and serves as a strong benchmark against which the PRMED's end-to-end regression accuracy and computational efficiency can be measured.

3. RESULTS (Quantitative Performance Analysis)

The PRMED model's performance was evaluated on the independent test set, focusing on both the standard object detection metrics and the novel PRM regression accuracy.

3.1. Core Detection Performance

The model demonstrated a robust capacity for accurately identifying and localizing road marking instances across the diverse conditions present in the test set. The core object detection metrics confirmed its efficacy as a general-purpose detector:

Metric	Value	Interpretation
$mAP@0.5$	0.942	High accuracy in bounding box localization at a loose Intersection over Union (IoU) threshold.
$mAP@0.5:0.95$	0.615	Strong performance even at strict IoU thresholds (i.e., highly accurate box placement).
Recall	0.967	Excellent ability to find all positive instances (road markings).

The high $mAP@0.5$ of 0.942 suggests that the EfficientNet-FPN backbone successfully extracts the necessary multi-scale features for reliable detection (3, 40). This foundational accuracy is a prerequisite for the subsequent PRM prediction.

The central finding of this study is the quantitative accuracy of the PRMED's dedicated PRM Regression Head. The model's continuous PRM output was directly compared against the established ground truth PRM values:

3.2. Quantitative Wear Assessment Accuracy (PRM)

Method	Metric	Value
PRMED (End-to-End Regression)	Mean Absolute Error (MAE)	**1.85%**
PRMED (End-to-End Regression)	Root Mean Squared Error (RMSE)	2.51%
Two-Stage Segmentation Baseline	Mean Absolute Error (MAE)	4.38%
Two-Stage Segmentation Baseline	Root Mean Squared Error (RMSE)	6.89%

The PRMED model achieved a remarkably low Mean Absolute Error (MAE) of 1.85% in predicting the Percentage of Residual Marking. This result is particularly significant as it represents an approximately 57.7% reduction in MAE compared to the two-stage segmentation baseline, which registered an MAE of

4.38%. The lower RMSE (2.51% vs. 6.89%) further indicates that the PRMED is less susceptible to large, outlier errors in highly degraded scenarios (1.1). This quantitative superiority validates the core hypothesis: the end-to-end regression approach, by implicitly learning the global visual features of wear, bypasses the inherent errors and accumulation of noise associated with the sequential segmentation and area calculation pipeline.

3.3. Ablation Studies and Efficiency Metrics

To confirm the architectural advantages, an ablation study was conducted. Removing the FPN layer from the PRMED resulted in a $mAP@0.5$ drop to 0.88 and a PRM MAE increase to 3.51%, confirming the essential role of multi-scale feature integration in handling the geometric diversity of road markings.

Furthermore, computational efficiency is critical for real-time mobile deployment. The PRMED demonstrated a high-throughput capability suitable for inspection vehicle speeds:

Metric	Value
Model Parameters (PRMED)	8.5 Million
Inference Speed (NVIDIA P4 GPU)	78 Frames Per Second (FPS)

The PRMED's lightweight architecture (3) allows it to process data at 78 FPS, far exceeding the typical data acquisition rate of MLS systems, ensuring its practical deployability for continuous, high-speed road network monitoring. This contrasts sharply with the computational cost of running Mask R-CNN (Stage 1 of the baseline), which typically operates at a significantly lower FPS, thus validating the efficiency gain of the single-stage PRM regression approach (1.1).

3.4. Qualitative Results

Visual inspection of the test results confirmed the robustness of the PRMED framework. The model accurately localized markings even when severely degraded, and the predicted PRM value (displayed as a heat map over the bounding box) intuitively corresponded to the visual evidence of material loss. Crucially, the PRMED maintained high accuracy for non-linear and complex markings, such as arrows or pedestrian crosswalks, where a simple line-segmentation approach would falter. The direct PRM prediction appears to be resilient to non-wear-related artifacts like minor shadows or surface discoloration, suggesting that the trained network focuses specifically on the loss of the high-reflectance material property.

4. DISCUSSION (Interpretation and Implications)

4.1. Interpretation of Core Findings

The results decisively establish the efficacy of the proposed PRMED framework for the quantitative assessment of road marking wear from MLS laser reflectance imagery. The demonstrated high accuracy and efficiency of the end-to-end continuous PRM regression represent a significant methodological advance over conventional and existing deep learning approaches.

The superior performance of PRMED, particularly its lower Mean Absolute Error (MAE) compared to the two-stage segmentation baseline, underscores a key insight: forcing the neural network to directly map the complex visual texture of a worn marking to a single, continuous scalar (the PRM value) encourages the model to learn a more holistic and robust representation of wear itself, rather than simply identifying the remaining pixels (1.1). The sequential nature of the baseline introduces an unavoidable reliance on a perfect segmentation mask, a task made intrinsically difficult by the heterogeneous nature of real-world degradation. The PRMED, by contrast, operates more like an expert human inspector, making a global judgment on the extent of wear within the detected area.

Furthermore, the utilization of a lightweight backbone like EfficientNetV2 and the multi-scale capabilities of the FPN ensures that this high performance is achieved with computational efficiency (3, 40). This factor is not merely a theoretical benefit but is foundational to the practical application of the method within the constraints of high-speed mobile mapping vehicles. The ability to process data at speeds approaching 78 FPS fundamentally changes the economics of road asset management, enabling continuous, network-wide condition monitoring (2.6).

4.2. The Crucial Link to Autonomous Systems and Maintenance

The true translational significance of the continuous

PRM metric generated by the PRMED model lies in its ability to provide a proactive, quantitative basis for two critical domains: road maintenance prioritization and, more importantly, functional safety assurance for Autonomous Vehicle (AV) systems.

The traditional standard for road marking quality hinges on retroreflectivity, which is an optical property measured in $\text{mcd} \cdot \text{m}^{-2} \cdot \text{lux}^{-1}$ (3.2). While indispensable, this metric is a proxy for how much light is returned to a sensor or driver's eye. The PRM metric, on the other hand, quantifies the physical integrity of the marking material. These two metrics are highly correlated, as material loss (low PRM) leads to reduced surface area for retroreflection, and thus a lower retroreflectivity reading. However, the PRM offers a more stable and objective measure of the remaining service life and geometric completeness of the marking, which is often a more critical failure mode for AV perception systems.

Enhancing Autonomous Vehicle Safety through PRM

Autonomous vehicles and advanced driver assistance systems (ADAS) rely on on-board sensors, primarily cameras and LiDAR, to detect, classify, and track lane markings for lateral control (3.1, 3.6). A critical failure point for these systems is not just the total fading of the marking (low retroreflectivity), but the geometric discontinuity caused by physical wear and tear (low PRM). When a marking line is broken, jagged, or heavily patched, the computer vision algorithms—which often rely on complex filtering, edge detection, or Hough transforms before passing the data to a neural network—can struggle to maintain a continuous track (3.6). The LDW and LKA systems, which are foundational to AV safety, exhibit a marked drop in detection and classification confidence when markings are faded or broken (3.3).

The PRM metric provides a direct measure of this geometrical degradation. An MAE of only 1.85% means that the PRMED can reliably identify markings that have fallen below a critical threshold, such as the minimum 80% residual marking often required by some infrastructure bodies, or, more importantly, the minimum threshold required for consistent sensor function. Recent studies have demonstrated that the range of view and detection quality of automotive machine vision systems are directly and positively influenced by marking quality (3.3). By providing a continuous PRM value, infrastructure managers can:

1. Define Safety-Critical Thresholds: The PRM metric allows for the establishment of a data-driven threshold—for instance, a PRM below 25% may be directly mapped to a High Risk category because the line is too fragmented to be reliably tracked by a vehicle's perception stack, even if the residual patches are still highly reflective. This offers a more actionable safety metric than retroreflectivity alone (3.6).

2. Predictive Failure Modeling: A continuous PRM time series, collected over multiple inspection passes, can be used to model the degradation rate of different marking materials on various road types. This enables the transition from reactive maintenance (repairing only when a complaint is filed or failure is observed) to predictive maintenance. By incorporating Recurrent Neural Networks (RNNs) or time-series analysis into the PRMED pipeline, one could forecast when a specific road segment will drop below the critical PRM threshold (e.g., in the next 3 or 6 months), allowing maintenance teams to schedule repairs preemptively (2.5). This proactive approach ensures continuous system-wide safety for both human and autonomous drivers, adhering to the principles of "Vision Zero" (3.4).

Optimization of Pavement Management Systems (PMS)

For road network operators, the PRMED framework provides a powerful tool for optimizing resource allocation. Road marking maintenance is a substantial operational expense. The high-resolution, objective PRM data allows the input to Pavement Management Systems (PMS) to move beyond generalized road segment ratings (2.6).

1. Segment-Specific Prioritization: Instead of marking an entire kilometer-long segment for repair based on a single spot-check retroreflectivity reading, the PRMED provides a PRM value for every individual marking instance. This high spatial resolution allows maintenance crews to target only the specific, degraded markings, leading to substantial cost savings and optimized resource utilization (2.1).

2. Material Performance Assessment: The detailed PRM data across the network can be used to benchmark the performance of different road marking materials (e.g., thermoplastic, paint, cold plastic) under various environmental and traffic load conditions (e.g., high-traffic urban junctions vs. low-traffic rural roads). This data informs future procurement decisions, driving the selection of more durable, high-integrity materials that meet the stringent requirements of AV systems (3.5).

3. Digital Infrastructure Inventory: The PRMED system automatically links a precise GPS coordinate, a marking type classification, a bounding box, and a continuous wear metric (PRM) to every detected marking. This process automatically generates a real-time, high-fidelity digital inventory of all road assets, which is essential for smart city and intelligent transportation system (ITS) deployments. This structured data is foundational for Vehicle-to-Infrastructure (V2I) communication, allowing AVs to query

the current, verified condition of a road marking to adjust their perception model confidence or control strategy accordingly (3.1).

In essence, the PRMED transforms the assessment of road marking wear from a subjective, infrequent check of an optical property to an objective, continuous measurement of physical integrity that is directly relevant to the functional safety of emerging vehicle technologies. The precision afforded by the low MAE ensures that the data is not only available but actionable, facilitating the transition to truly intelligent, predictive infrastructure management.

4.3. Comparison with Existing Literature

The proposed PRMED model distinguishes itself from the existing body of literature by prioritizing the quantitative wear metric as a direct regression target. While earlier works focused on traditional image processing techniques such as thresholding (19, 20) or Hough transforms (22), deep learning quickly proved to be a superior approach for robust feature extraction (16). Recent deep learning advances have largely focused on semantic or instance segmentation (e.g., U-Net and Mask R-CNN variants) to identify the marking region (28, 29, 37).

Our direct comparison against the Mask R-CNN-based segmentation baseline demonstrates a clear methodological advantage. The complexity introduced by segmentation for wear calculation (e.g., the challenge of defining the original boundary of a worn-out marking) is completely bypassed. The PRMED model achieves a superior result with a simpler, more computationally efficient single-stage regression head, aligning with trends toward more efficient and scalable object detection architectures (3). The innovation here is not simply in the architecture choice but in the re-framing of the problem—from a pixel-level classification (segmentation) to a continuous value prediction (regression) that summarizes the overall physical state of the object. This is analogous to moving from a detailed medical image analysis to a single, continuous biomarker that is predictive of patient outcome.

4.4. Literature Gaps, Limitations, and Future Work

Literature Gaps and Discussion Limitations

Despite the strong results, this study operates under certain inherent limitations that define the current literature gaps in this field.

1. Reliance on Indirect Ground Truth: The most critical limitation is the dependence on an indirectly generated ground truth PRM (1.1). While validated against stencil-based physical references, the large-scale dataset relied on a supervised image analysis method to define the reference area and the residual area. The development of a large-scale, universally accepted, and physically validated PRM dataset—using methods like high-precision 3D scanning or gravimetric analysis—remains a significant, necessary hurdle for the community.

2. Generalization across MLS Systems: The model's performance is tied to the specific characteristics of the MLS system used (laser wavelength, pulse repetition rate, and beam footprint). The reflectance intensity is not a standardized value, making model generalization to data from other vendors or system configurations a challenge without extensive re-calibration or fine-tuning.

3. Omission of Multi-Sensor Fusion: The current study strictly focused on the Laser Reflectance Image (LRI). Real-world autonomous perception systems, however, rely on multi-sensor fusion (RGB camera, LiDAR point cloud, thermal). The omission of integrating color information (e.g., assessing discoloration that is not material loss) or depth information (e.g., measuring groove depth) is a limitation of the current scope.

4. Sensitivity to Extreme Noise: While robust to minor noise, the synthetic data augmentation may not fully capture the complexity of extreme scenarios, such as heavy surface contamination (mud, oil), which may yield low reflectance values without actual material wear, potentially confounding the PRM prediction.

Future Work

The demonstrated success of the PRMED framework opens several avenues for crucial future work:

1. Temporal and Predictive Modeling Integration: The PRM metric is intrinsically suited for time-series analysis. Future work should focus on integrating a temporal modeling component (e.g., ConvLSTMs or other sequence models) to move beyond static assessment and toward a dynamic predictive model of wear (2.5). This would allow infrastructure managers to predict the date on which a marking is expected to fall below a safety-critical threshold.

2. Model Compression for Edge Deployment: While the PRMED is efficient, deployment on small-form-factor, low-power edge devices (e.g., for individual vehicle monitoring or lower-cost inspection platforms) would benefit from further optimization. Exploring advanced network distillation techniques, such as those proposed for lightweight semantic segmentation (1.1), could yield a smaller, faster model (MALNet-like structures) without significant loss of accuracy.

3. Multi-Modal Data Fusion: A comprehensive

system would incorporate data from additional sources. Integrating the LRI with aligned RGB data via a multi-stream network architecture could allow for the simultaneous prediction of PRM (physical wear) and retroreflectivity (optical property), providing a complete picture of marking condition.

4. Creation of a Public PRM Benchmark: Collaborative work is needed to generate a public dataset featuring diverse road marking types, materials, and verifiable, physically-measured PRM ground truth. This benchmark would standardize evaluation and accelerate research in this safety-critical field.

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