IMAGE QUALITY CHALLENGES IN AUTONOMOUS DRIVING: A CONCEPTUAL FRAMEWORK FOR CAMERA LENS DEFECT DETECTION

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Abstract. Camera-based perception is fundamental for autonomous driving, yet its reliability is compromised by lens impairments. Temporary soiling (raindrops, mud, dust) and permanent defects (scratches, cracks) can obscure critical regions of the field of view, degrade detection accuracy, and create safety hazards. Although existing research addresses soiling detection, limited attention has been given to permanent lens damage and, more critically, to system-level safety responses when impairments occur.

This paper proposes a safety-aware conceptual framework for lens defect detection and response. The framework integrates: (i) boot-time self-checks with automated cleaning, (ii) real-time monitoring that characterizes severity, criticality, and recoverability of impairments, (iii) decision policies that map impairments to graded responses (from alerts to cautious driving or full stop), and (iv) optional temporal inpainting for non-critical regions. Safety monitoring ensures that fallback sensors (radar, ultrasonic, LiDAR) are prioritized when visual confidence is reduced.

The framework is dataset-agnostic, aligns with ISO 26262 and ISO 21448 standards, and is supported by example modules, state diagrams, and evaluation metrics. By linking lens defect detection with safety engineering, it provides both a theoretical foundation and a pathway toward practical deployment in autonomous vehicles.

Keywords— autonomous driving, camera soiling, lens defect detection, image quality, safety framework

Аннотация. Восприятие окружающей среды с помощью камер является фундаментальным для автономного вождения, однако его надежность снижается из-за повреждений объектива. Временные загрязнения (дождевые капли, грязь, пыль) и постоянные дефекты (царапины, трещины) могут закрывать критически важные области обзора, ухудшать точность распознавания и создавать угрозы безопасности. Несмотря на то, что существующие исследования уделяют внимание обнаружению загрязнений, мало внимания уделяется постоянным повреждениям объектива и, что еще

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важнее, системным мерам безопасности при возникновении таких нарушений.

В данной статье предлагается ориентированная на безопасность концептуальная структура для обнаружения дефектов объектива и реагирования на них. Структура включает: (i) самопроверку при запуске с автоматической очисткой, (ii) мониторинг в реальном времени, оценивающий степень, критичность и устранимость повреждений, (iii) политiku принятия решений, сопоставляющую дефекты с градуированными реакциями (от предупреждений до осторожного вождения или полной остановки), и (iv) опциональную временную реконструкцию изображений для некритичных областей. Система безопасности обеспечивает приоритетное использование резервных датчиков (радар, ультразвук, LiDAR), когда уверенность в визуальных данных снижена.

Структура является независимой от набора данных, соответствует стандартам ISO 26262 и ISO 21448 и поддерживается примерными модулями, диаграммами состояний и метриками оценки. Связывая обнаружение дефектов объектива с инженерией безопасности, она предоставляет как теоретическую основу, так и путь к практическому внедрению в автономные транспортные средства.

Ключевые слова — автономное вождение, загрязнение камеры, обнаружение дефектов объектива, качество изображения, система безопасности

Annotatsiya. Avtonom haydashda kamera orqali atrof-muhitni idrok etish muhim ahamiyatga ega, biroq linzaning nuqsonlari bu ishonchlilikni kamaytiradi. Vaqtinchalik ifloslanishlar (yomg‘ir tomchilari, loy, chang) va doimiy shikastlanishlar (tirnalishlar, yoriqlar) ko‘rish maydonining muhim qismlarini yopishi, aniqlikni pasaytirishi va xavfsizlikka tahdid tug‘dirishi mumkin. Mavjud tadqiqotlarda asosan ifloslanishni aniqlashga e’tibor qaratilgan bo‘lsa-da, linzaning doimiy shikastlanishlari va, bundan ham muhimrog‘i, nuqsonlar yuzaga kelganda tizimli xavfsizlik choralariga yetarlicha e’tibor berilmagan.

Mazkur maqolada linza nuqsonlarini aniqlash va ularga javob berish uchun xavfsizlikka yo‘naltirilgan kontseptual yondashuv taklif etiladi. Ushbu yondashuv quyidagilarni o‘z ichiga oladi: (i) avtomatik tozalash bilan yuklanish vaqtida o‘z-o‘zini tekshirish, (ii) real vaqt rejimida kuzatuv orqali nuqsonlarning darajasi, muhimligi va bartaraf etilish imkoniyatini baholash, (iii) qaror qabul qilish siyosatlari yordamida nuqsonlarni turlicha javoblarga moslashtirish (ogohlantirishlardan ehtiyotkor haydash yoki to‘liq to‘xtashgacha), va (iv) katta bo‘lmagan nuqsonlarni ixtiyoriy vaqtinchalik tiklash (inpainting). Bundan tashqari

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xavfsizlik monitoringi vizual ishonchlilik pasayganda qo‘shimcha sensorlar (radar, ultratovush, LiDAR)ni ustuvor qiladi.

Taqdim etilgan yondashuv ma’lumotlar to‘plamidan mustaqil bo‘lib, ISO 26262 va ISO 21448 standartlariga mos keladi, shuningdek, modul misollari, holat diagrammalari va baholash mezonlari bilan qo‘llab-quvvatlanadi. Linza nuqsonlarini aniqlashni xavfsizlik muhandisligi bilan bog‘lash orqali, ushbu yondashuv nazariy asos va amaliy tatbiq yo‘lini taqdim etadi.

Kalit so‘zlar — avtonom haydash, kamera ifloslanishi, linza nuqsonlarini aniqlash, tasvir sifati, xavfsizlik tizimi

I. Introduction

Camera sensors are central to autonomous driving and Advanced Driver Assistance Systems (ADAS). They offer vital data for traffic sign recognition, lane keeping, and object detection. However, the resolution of camera inputs determines how reliable these features are. In practice, lenses are often exposed to adverse conditions such as rain, dust, mud, scratches, or cracks. These impairments reduce image quality and can create blind spots, leading to serious safety risks if not addressed.

Existing work has made progress in detecting soiling and, in some cases, attempting to restore affected regions [1]–[5]. While these methods provide valuable building blocks, most focus narrowly on transient artifacts such as raindrops. Less attention has been given to permanent lens defects (e.g., scratches, cracks) and, more importantly, to system-level decision-making when impairments occur. As a result, there remains a gap between soiling detection research and the safety requirements of real autonomous driving systems.

This paper addresses that gap by presenting a unified safety-aware framework for camera lens defect detection and response. The framework combines boot-time checks, real-time monitoring, severity-aware decision policies, and cautious fallback strategies. By aligning perception-level detection with system-level safety management, the framework ensures that vehicles can continue operating safely under mild impairments and stop gracefully under severe ones.

Contributions of this paper are as follows:

1. We design a boot-time self-check procedure that integrates automated cleaning and re-testing;
2. We define a severity–criticality–recoverability (S–C–R) model for characterizing lens impairments;
3. We propose decision policies that map impairments to graded responses, from alerts and cautious driving to full vehicle stop;

ISSN 3030-3907

4. We outline engineering templates, including state diagrams, decision tables, and evaluation metrics, to support future implementation and benchmarking.

Through this framework, we seek to bridge the gap between detection algorithms and safety engineering, laying the groundwork for both theoretical analysis and practical development in autonomous driving systems.

II. Background and Related Work

Lens Soiling Detection. Research in autonomous driving has increasingly addressed the issue of camera lens soiling. Uřičář et al. introduced SoilingNet [1], which provides pixel-level annotations of soiled regions and allows supervised learning for segmentation tasks. Building on this, Das et al. developed TiledSoilingNet [2], which divides the image into smaller tiles and performs classification per tile. This design enables efficient, real-time detection on embedded hardware, an important requirement for deployment in vehicles.

Raindrop and Weather-Related Datasets. Several datasets and methods have focused on raindrops as a specific form of soiling. The "Raindrops on Windshield" dataset [3] provides lightweight annotations for raindrop detection, while WoodScape [4] includes multi-task fisheye images with some soiling conditions. These resources demonstrate community recognition of lens artifacts as a hazard, though they remain limited in scope.

Restoration and Inpainting. Beyond detection, some studies explore restoration of occluded areas. Uřičář et al. [5] proposed methods for restoring soiled fisheye camera inputs using inpainting techniques. While effective in non-critical areas, restoration poses risks if applied to safety-critical regions, as it may hallucinate false visual cues. Our framework therefore adopts a conservative stance, restricting inpainting to small, non-critical zones.

Safety Standards. Lens soiling and defects must also be seen through the lens of automotive safety standards. ISO 26262 [6] addresses functional safety when components fail, while ISO 21448 (SOTIF) [7] considers hazards from performance limitations, such as degraded sensor inputs. Any defect detection or correction method must therefore be coupled with safety-aware decision thresholds and fallback strategies.

Research Gap. Current work provides strong foundations in soiling detection and limited restoration. However, there is little focus on permanent defects (e.g., scratches, cracks) and on integrating detection with system-level safety responses. This gap motivates our contribution: a unified framework that combines detection, recovery, and safety-driven decision-making.

III. Problem Definition and Key Concepts

ISSN 3030-3907

Camera-based perception systems in autonomous driving can fail when the lens is obstructed or damaged. To reason systematically about these risks, we define key concepts used throughout this work:

- **Soiling (transient impairments).** Refers to temporary obstructions such as raindrops, mud, dust, or condensation on the lens or windshield. These artifacts typically vary over time and may be partially removed through cleaning or environmental changes;
- **Permanent defects.** Make reference to persistent lens damages like scratches, cracks, fading, or internal mist. In contrast to soiling, these impairments may increase with time and cannot be eliminated by cleaning;
- **Severity (S).** The proportion of the field of view (FOV) that is occluded or degraded. A higher severity indicates more extensive visual impairment;
- **Criticality (C).** Whether the impaired area overlaps with safety-critical regions of the scene, such as the drivable path, pedestrian crossings, or traffic-light zones. Small impairments in these areas may pose greater risk than larger impairments in peripheral regions;
- **Recoverability (R).** The potential to restore useful visual information. We classify impairments as: *cleanable* (removable by physical cleaning), *inpaintable* (recoverable using temporal evidence from past frames), or *not recoverable*.

This terminology enables a structured analysis of lens impairments and their impact on autonomous driving. In later sections, these dimensions (S, C, R) form the basis for our decision-making framework, ensuring that responses are proportional to the type and severity of the defect.

IV. Conceptual Framework for Lens Defect Detection

Our system integrates detection, temporal reasoning, and safety management through six modules (**Figure 1**):

1. **Soiling/Defect Detector** — Lightweight CNN applied to single frames or tiles, producing binary/segmentation masks. Output includes per-pixel impairment class (transparent dirt, opaque soiling, scratch, crack);
2. **Temporal Memory & Warper** — Stores recent clean frames and aligns them with the current view using optical flow or homography;
3. **Temporal Fuser / Inpainter** — For blocked pixels, checks past frames for consistent evidence. If valid, fills the pixel and outputs a confidence map; otherwise, leaves it masked;
4. **Decision & Policy Engine** — Evaluates impairment severity (blocked ratio), confidence of recovery, and position (critical vs. non-critical FOV). Maps conditions to driving modes: **Normal, Careful, or Stop;**

ISSN 3030-3907

5. **Cleaner Controller** — Manages cleaning mechanisms (wipers, air jets). If cleaning fails repeatedly, the defect is escalated as permanent;
6. **Sensor Fusion Supervisor** — When confidence is low, increases reliance on radar/LiDAR and lowers autonomy level.

Policy Examples:

- If <5% of FOV blocked → Normal mode;
- 5–25% blocked → Attempt cleaning; if unresolved, continue in Careful mode with alert;
- 25% or central FOV blocked → Stop vehicle, request maintenance.

This ensures conservative, safety-first behavior.

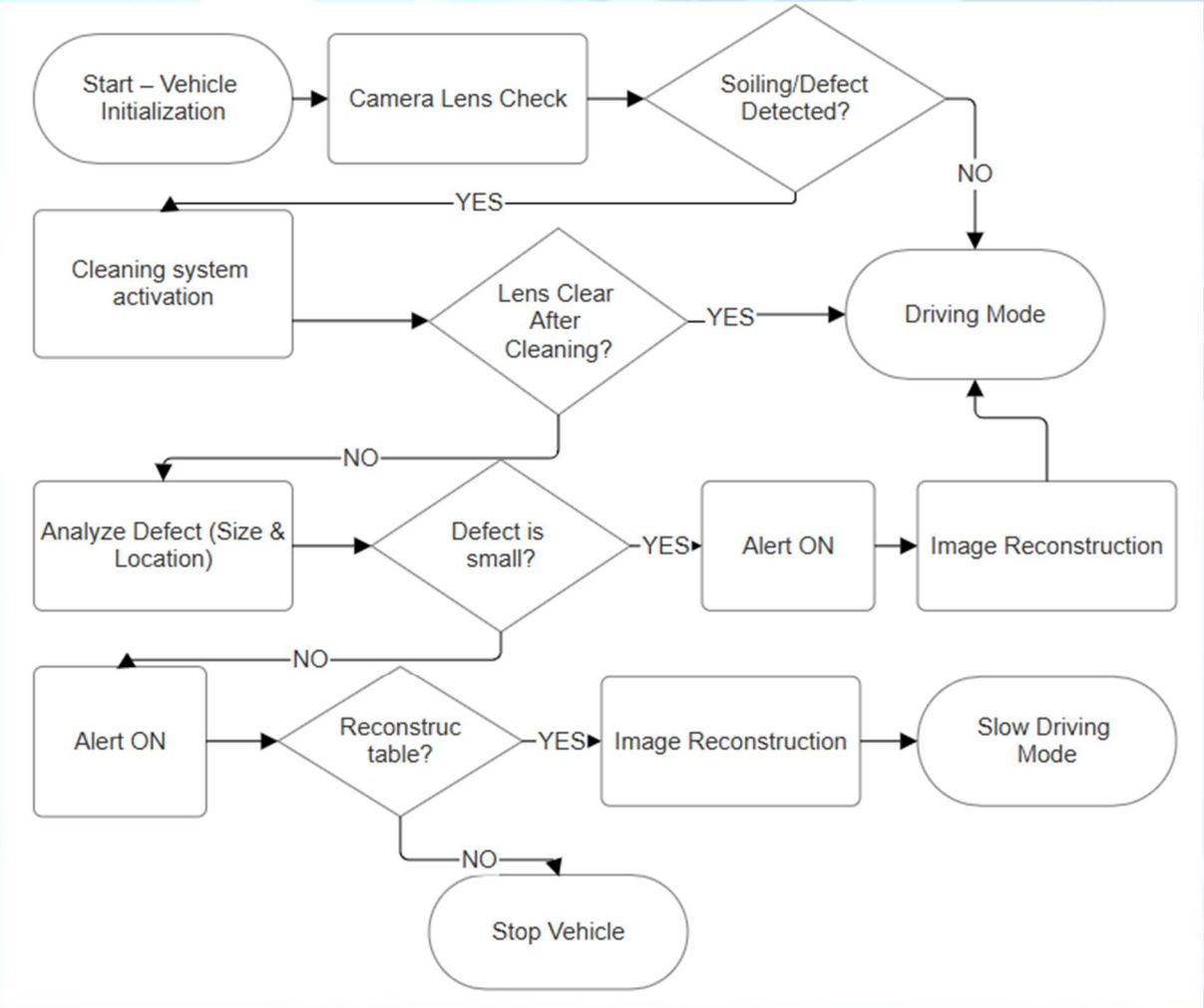


Figure 1 System Workflow Diagram: (Boot-Time State Machine) illustrates the self-check and cleaning loop.

V. Evaluation Framework and Metrics

Although this paper is primarily conceptual, it is essential to define how future implementations of the framework can be rigorously evaluated. A credible evaluation must consider not only detection accuracy but also runtime efficiency and safety relevance. We identify four key dimensions of evaluation:

ISSN 3030-3907

1. **Detection Accuracy.** Standard metrics such as Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) can be used to measure the ability to distinguish between clean and soiled images. For segmentation tasks, Intersection-over-Union (IoU) is appropriate for assessing mask quality;

2. **Real-Time Performance.** Since autonomous vehicles operate under strict latency constraints, evaluation should include runtime performance on embedded hardware. Latency per frame and throughput (frames per second) are critical indicators of deployability;

3. **Safety Impact.** Evaluation should extend beyond raw image quality metrics to capture how lens defects affect perception outcomes. For example, experiments may measure the drop in object detection accuracy or lane recognition quality under varying levels of occlusion. Safety Key Performance Indicators (KPIs), such as the number of alerts triggered per kilometer, provide a system-level perspective;

4. **Robustness and Generalization.** To avoid overfitting to a single dataset, models should be tested across multiple benchmarks (e.g., SoilingNet, TiledSoilingNet, Raindrops on Windshield). This ensures that the system can generalize to different types of soiling and defects.

Table 1.

Metrics for Evaluation

Metric	Purpose	Example
ROC/AUC	Distinguishing clean vs soiled images	Boot-time detection accuracy
IoU	Segmentation quality	Runtime soiling masks
Latency	Processing delay	Time per frame on embedded CPU
Safety KPI	Vehicle-level reliability	Alerts triggered per km

By combining these metrics, future studies can ensure that lens defect detection systems are not only technically sound but also safety-relevant and deployable in real-world driving conditions.

VI. Benchmark Datasets for Lens Soiling and Defect Analysis

A robust framework requires credible datasets for both development and evaluation. In the domain of autonomous driving, several benchmark datasets have been released to address lens soiling and related image quality challenges. These datasets differ in focus, scale, and annotation strategy.

ISSN 3030-3907

• **SoilingNet [1].** Provides pixel-level annotations of soiled vs. clean regions, enabling supervised training for segmentation tasks. It is widely used for boot-time and runtime detection benchmarking;

• **TiledSoilingNet [2].** Builds on SoilingNet by dividing images into smaller tiles, allowing efficient real-time detection and reducing computational load. Because of this, it is especially well-suited for embedded deployment;

• **Raindrops on Windshield [3].** A small dataset with an emphasis on segmenting and detecting raindrops. It highlights transient soiling but lacks broader coverage of mud, dust, or permanent damage;

• **WoodScape [4].** A multi-task fisheye dataset that includes various weather and lens conditions, providing a wider context for evaluating robustness across multiple perception tasks.

Table 2.

Representative Datasets for Lens Defect and Soiling Analysis

Dataset	Focus	Annotation	Strengths	Limitations
SoilingNet	Pixel-level soiling detection	Segmentation masks	High-quality annotations	Limited to specific soiling types
TiledSoilingNet	Tile-wise detection	Grid-based labels	Efficient, real-time capable	Reduced spatial precision
Raindrops on Windshield	Raindrop detection	Mask annotations	Lightweight, simple	Focused only on raindrops
WoodScape	Multi-task fisheye	Multi-label + segmentation	Covers wide driving scenarios	Not specific to lens defects

Despite their usefulness, existing datasets primarily focus on soiling (e.g., raindrops, mud, dust) and do not adequately represent permanent lens defects such as scratches, cracks, or delamination. This gap underscores the need for either dataset augmentation or synthetic data generation to evaluate systems designed for permanent impairments.

By situating our framework within this dataset landscape, we highlight both the available tools for benchmarking and the missing coverage that motivates future dataset development.

VII. Safety Considerations and Systems Integration

Safety is central to the deployment of any perception module in autonomous driving. Camera lens soiling and defects fall under both functional safety (ISO 26262 [6]) and Safety of the Intended Functionality (SOTIF) (ISO 21448 [7]), as

ISSN 3030-3907

they represent hazards that can arise from degraded sensor performance rather than outright failure. Our framework incorporates safety in three complementary ways:

1. **Hazard Prevention through Early Detection.** Boot-time checks ensure that severe defects are identified before driving begins, preventing unsafe deployment of the perception system. Runtime monitoring extends this capability by detecting new occlusions that develop during driving;

2. **Severity-Driven Decision Policies.** Safety risks are not only a function of how much of the camera view is occluded but also where the impairment occurs. For example, a small crack in the image periphery may be tolerable, while an equally sized obstruction in the drivable corridor is unacceptable. Our system integrates severity, criticality, and recoverability into clear decision thresholds;

3. **Fallback and Graceful Degradation.** When impairments exceed safe limits, the system transitions into fallback states: activating Parktronics, radar, or ultrasonic sensors; restricting speed; and in severe cases, blocking vehicle motion. This ensures that failures degrade gracefully rather than producing unsafe behaviors.

Table 3.

Failure Modes and Responses

Failure Mode	Detection	Response
Full occlusion	Boot self-check	Block and request service
Partial occlusion in critical area	Runtime mask	Alert + slow mode
False alert	Low severity, stable KPIs	Continue; auto-clear
Risky inpainting	Detected use in critical region	Disable inpainting

By explicitly linking perception impairments to safety responses, the framework demonstrates compliance with established standards and provides a structured path toward real-world validation.

VIII. Practical Implementation Considerations

A key challenge in deploying lens defect detection on vehicles is balancing reliability with limited onboard resources. We outline several considerations for practical implementation:

1. **Model Selection.** Boot-time checks should use lightweight models that can run quickly on embedded hardware, ensuring minimal start-up delay. During runtime, more detailed segmentation models may be employed, provided they operate within real-time constraints [1], [2];

ISSN 3030-3907

2. **Critical Region Prioritization.** Region-of-interest (ROI) maps should be aligned with the perception stack so that occlusions in safety-critical areas (e.g., road center, pedestrian zones, traffic lights) are prioritized over less critical regions. This ensures that not all impairments are treated equally, avoiding unnecessary false alarms;

3. **Fallback Driving Policies.** When defects are detected, the driving policy should be adjusted: speed limits reduced, lane changes restricted, and reliance on non-visual sensors increased. This ensures graceful degradation rather than sudden failure;

4. **System Logging and Traceability.** All detected impairments, severity scores, and fallback states should be logged for post-analysis. Such records are essential for compliance with functional safety standards like ISO 26262 [6] and SOTIF [7].

Together, these considerations emphasize that defect detection is not only a perception problem but also a systems engineering problem.

IX. Conclusion

This paper presented a conceptual framework for detecting and managing camera lens impairments in autonomous driving. Unlike most prior studies that focus narrowly on soiling detection, our approach integrates both transient soiling (raindrops, mud, dust) and permanent defects (scratches, cracks) into a unified safety-aware model.

The framework introduces a structured process: boot-time self-check with automated cleaning, real-time monitoring using severity–criticality–recoverability (S–C–R) characterization, and graded decision policies ranging from alerts to cautious driving or full stop. Optional temporal inpainting is proposed for small, non-critical regions, while system-level safety monitoring ensures reliable fallback to radar, ultrasonic, or LiDAR sensors when visual confidence is low.

By combining detection methods with safety standards (ISO 26262, ISO 21448), the framework bridges the gap between perception algorithms and system-level reliability. It offers engineering templates—state diagrams, decision tables, and evaluation metrics—that can guide both theoretical analysis and practical deployment.

Future work will focus on extending available datasets to cover permanent defects, testing the framework with lightweight real-time models, and validating its impact on perception accuracy and driving safety. These steps will help transform the proposed framework from a conceptual contribution into a deployable solution for autonomous vehicles.

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