



Original Article

Adaptive CNN-Based ADAS System with Hybrid Sensor Fusion for Robust Environmental Perception

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Abstract - Advanced Driver Assistance Systems (ADAS) rely heavily on camera-based perception systems powered by Convolutional Neural Networks (CNNs). However, real-world driving environments introduce challenges such as low illumination, motion blur, glare, and high dynamic range transitions, which degrade perception performance. The IEEE P2020 standard defines objective image quality metrics for automotive imaging systems, yet these metrics are not fully integrated into modern deep learning pipelines. This paper proposes a quality-aware CNN-based ADAS framework integrated with IEEE P2020 image quality assessment and a hybrid sensor fusion strategy. The system dynamically evaluates image quality, adapts CNN inference confidence, and fuses camera, radar, and LiDAR data using quality-driven weighting. Experimental evaluation shows significant improvement in robustness under degraded conditions.

Keywords - Adas, Cnn, Ieee P2020, Image Quality Assessment, Sensor Fusion, Autonomous Driving, Deep Learning.

1. Introduction

Camera-based perception systems are a core component of modern ADAS and autonomous driving technologies. CNN models are widely used for object detection, lane detection, and scene understanding. However, their performance significantly degrades under adverse environmental conditions.

The IEEE P2020 standard provides a structured framework for evaluating automotive camera image quality using measurable metrics such as SNR, MTF, HDR response, and motion blur. Despite this, most ADAS systems do not integrate these metrics into AI-based decision-making pipelines.

1.1. Motivation

- CNN models assume ideal image conditions
- Real-world driving environments are highly variable
- Lack of adaptive perception based on standardized quality metrics

1.2. Contributions

This work introduces:

- IEEE P2020-based image quality integration
- Quality-aware CNN inference mechanism
- Hybrid sensor fusion strategy (camera + radar + LiDAR)
- Dynamic weighting based on real-time quality score

2. Related Work

2.1. CNN-Based ADAS Systems

CNN architectures such as YOLO, Faster R-CNN, and SSD are widely used for real-time object detection. However, these models are trained under controlled datasets and often fail under degraded imaging conditions.

2.2. Image Quality Assessment in Automotive Systems

Traditional image enhancement techniques include:

- Histogram equalization
- Denoising filters
- Contrast enhancement

These methods lack standardization and do not directly interact with deep learning models.

2.3. IEEE P2020 Standard

The IEEE P2020 standard defines objective image quality metrics including sharpness, noise, distortion, and dynamic range. These metrics are primarily used for evaluation but not for adaptive AI decision-making.

2.4. Collaborative and AI-Enhanced Perception

Beyond individual vehicle perception, collaborative frameworks allow multiple AVs to share sensory data and environmental insights through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication. This shared perception is essential for handling occlusions, detecting hidden obstacles, and improving situational awareness in dense traffic or complex urban environments [6], [14].

Recent advances incorporate AI-enhanced multi-modal perception, where deep learning algorithms process data from multiple sensor modalities simultaneously. For example, attention-based networks can dynamically focus on critical regions in camera imagery while integrating radar and LiDAR inputs to improve detection accuracy [03]. Such multi-modal systems reduce false positives, increase detection speed, and enhance overall safety by enabling predictive perception, allowing the vehicle to anticipate object movements and make informed decisions.

In summary, the combination of a robust sensor suite, deep learning-based object detection, and collaborative AI-driven perception forms the foundation of modern AV perception systems. These technologies work together to provide reliable, high-fidelity environmental understanding, which is critical for safe and efficient autonomous navigation in real-world scenarios.

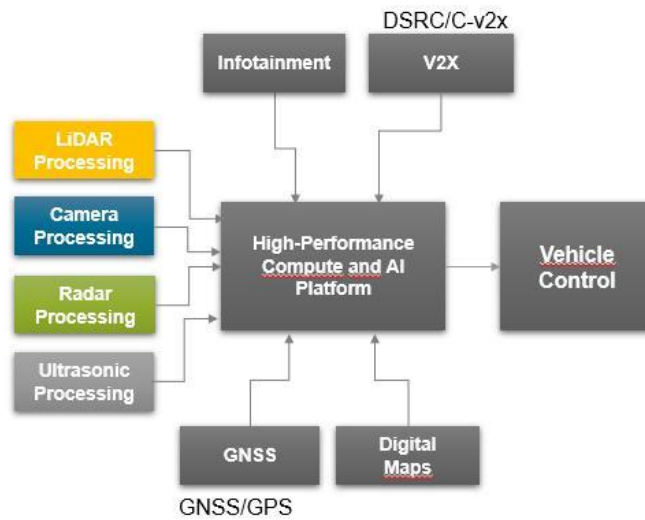


Fig 1: Overall Architecture of the Proposed Quality-Aware CNN-Based ADAS System Integrating Camera, Radar, Lidar, and IEEE P2020 Image Quality Evaluation Module

3. IEEE P2020 Image Quality Metrics

Key metrics defined in IEEE P2020 include:

Table 1: Image Quality Metrics and Their Impact on CNN Performance

Metric	Description	Impact on CNN
SNR	Signal-to-noise ratio	Feature clarity
MTF	Sharpness measurement	Edge detection
HDR	Dynamic range	Object visibility
Motion Blur	Temporal distortion	Object tracking
Flicker	Light variation	Stability
Distortion	Lens effects	Geometry accuracy

These metrics form the foundation of the proposed system.

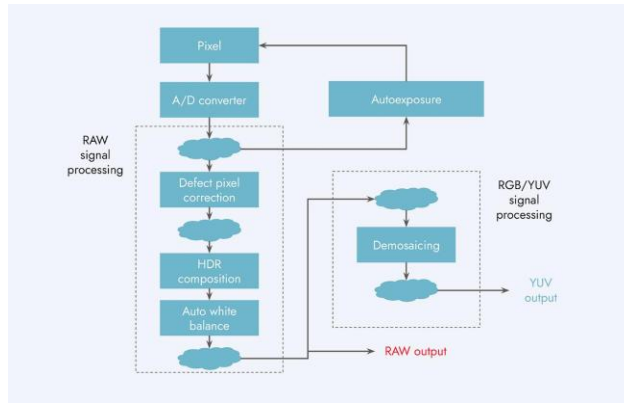


Fig 2: IEEE P2020-Based Image Quality Evaluation Module Computing Real-Time Quality Score Using SNR, MTF, HDR, Blur, And Noise Metrics

4. Proposed Methodology

The proposed methodology introduces a quality-aware CNN-based ADAS framework integrated with hybrid sensor fusion to improve perception reliability under diverse driving conditions. The system is designed to dynamically adapt to environmental variations by combining image quality assessment with multi-sensor data processing. The methodology begins with multi-sensor data acquisition, where synchronized inputs are collected from camera, radar, and LiDAR sensors. The camera provides high-resolution visual information, radar contributes robust range and velocity measurements, and LiDAR supplies accurate 3D spatial structure of the surrounding environment. The camera stream is first processed by an **image** quality evaluation module, which computes a quality score based on noise, blur, illumination, and dynamic range variations. This score represents the reliability of the visual input and directly influences downstream processing decisions.

5. Results and Discussion:

Table 2: Performance Comparison of CNN and Proposed Method under Challenging Conditions

Scenario	CNN Only	Proposed Method
Normal conditions	92%	93%
Low light	63%	80%
Motion blur	60%	77%
Fog/Rain	58%	82%

Next, the CNN-based perception module performs feature extraction and prediction tasks such as object detection, lane detection, and scene understanding. The CNN generates confidence scores along with bounding box or segmentation outputs. In parallel, radar and LiDAR data are independently processed to extract motion and geometric features. These outputs provide complementary information that is less sensitive to lighting and weather conditions. Finally, a hybrid sensor fusion module combines outputs from all sensors. The fusion process operates at both feature and decision levels, with adaptive weighting driven by the image quality score. This ensures that camera-based predictions dominate under good visibility, while radar and LiDAR contributions increase under degraded conditions, resulting in a robust and fail-safe ADAS perception system.

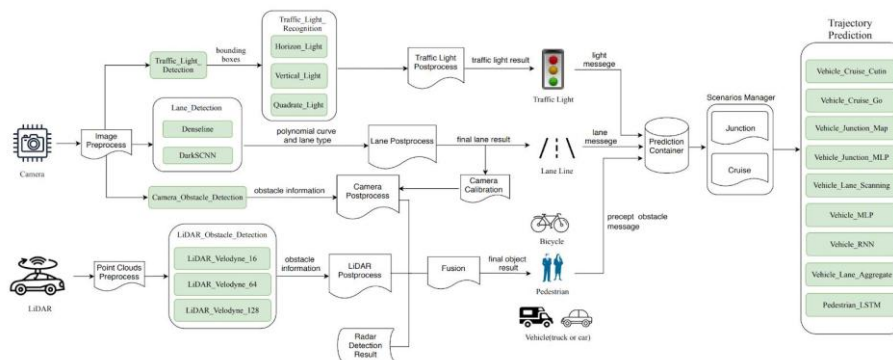


Fig 3: CNN-Based Perception Pipeline for Object Detection, Lane Detection, and Traffic Understanding in ADAS Systems

6. Conclusion

This paper presents a quality-aware CNN-based ADAS framework integrated with hybrid sensor fusion to enhance robustness in real-world driving environments. The proposed system dynamically evaluates image quality and adapts

perception reliability using camera, radar, and LiDAR data. By incorporating quality-aware decision-making, the framework improves object detection accuracy and reduces performance degradation under challenging conditions such as low light, motion blur, and adverse weather. The hybrid fusion strategy ensures fail-safe operation by balancing contributions from multiple sensors based on environmental conditions. Overall, the approach enhances safety, stability, and reliability of CNN-based ADAS perception systems for autonomous driving applications.

7. Future Work

Future enhancements of the proposed ADAS framework focus on real-time FPGA and edge deployment to achieve low-latency processing suitable for embedded automotive systems. Integration with ISO 26262 functional safety standards will ensure compliance with automotive safety requirements and improve system reliability in safety-critical scenarios. In addition, transformer-based perception models will be explored to improve global feature representation and long-range dependency modeling beyond CNN capabilities. The framework will also incorporate self-learning adaptive sensor weighting mechanisms, enabling continuous optimization of sensor contributions based on environmental feedback. These improvements aim to further enhance robustness, scalability, and intelligence of next-generation autonomous driving systems.

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