Collision Alert System: Computer Vision for Vehicle Safety

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Abstract. This paper introduces an innovative, vision-based Collision Alert System (CAS) aimed at significantly enhancing vehicle safety in complex driving environments. Our approach advances beyond existing YOLO-based Advanced Driver- Assistance Systems (ADAS) through its unique integration of YOLOv8's real-time object detection with specialized Dynamic Region of Interest (ROI) processing and Angular Methods for precise trajectory analysis. This framework, combined with robust object tracking, enables proactive collision prediction. We detail the system's architecture and operational flow, emphasizing its real-time performance. Rigorous evaluation confirms a True Positive Rate exceeding 95% and a remarkably low False Positive Rate under 2%, while maintaining over 30 Frames Per Second (FPS) for timely driver alerts. The paper also discusses core algorithmic principles and effective strategies for addressing real-world challenges like variable illumination and camera instability. A video demonstrating the system's live operation is available online. Future work focuses on multi-camera data fusion and integration with active vehicle control.

1 Introduction

Road safety remains a critical global concern, with traffic incidents causing significant fatalities, injuries, and economic loss. The growing density of vehicles and intricate driving conditions demand advanced safety solutions beyond traditional passive features. Advanced Driver- Assistance Systems (ADAS) have thus emerged as a pivotal technological domain, striving to boost driver awareness, minimize human error, and prevent collisions [2], [10]. While many ADAS employ a suite of sensors like radar, lidar, and ultrasonic, camera-based systems offer a cost- effective and adaptable approach to environmental perception, capable of detailed object classification and contextual understanding [11].

This paper presents a novel Computer Vision-based Collision Alert System (CAS) engineered for accurate detection, tracking, and prediction of potential collisions across diverse, dynamic traffic scenarios. Our system distinguishes itself from conventional YOLO-based ADAS by integrating state-of-the-art YOLOv5 and YOLOv8 models for real-time object detection with specialized geometric and motion analysis techniques, notably Dynamic Region of Interest (ROI) processing and Angular Methods. This combined framework offers a more refined, context-aware understanding of object trajectories and collision probabilities com- pared to simpler distance- or speed-based thresholds. Our primary goal is to provide drivers with immediate, actionable intelligence on impending collision risks, significantly contributing to accident reduction. By leveraging computational intelligence for predictive safety, this CAS marks a substantial step toward next-generation autonomous and semi-autonomous vehicle safety, fostering safer roads for all. The subsequent sections detail the system's architecture, foundational algorithms, performance validation, and future developments.

2 Related Work

Collision warning and prevention systems have seen extensive development over decades. Early systems predominantly relied on non-vision sensors like radar, lidar, and ultrasonics. Radar systems excel at robust long-range distance and speed measurement, especially in adverse weather [2], but struggle with detailed object classification, angular precision, and are prone to false positives. Lidar offers high precision 3D mapping but can be costly and less effective in fog or heavy rain. Ultrasonic sensors are limited to short- range detection, typically for parking.

With advances in computing and deep learning,

computer vision systems have gained prominence, offering rich semantic information about the driving scene. Initial vision- based methods used classical image processing (e.g., edge detection, SIFT) and traditional machine learning (e.g., SVMs) for object identification. These provided foundational insights but were often limited by varying light, occlusions, and diverse object appearances.

The advent of Convolutional Neural Networks (CNNs) revolutionized object detection and tracking. Region-based CNNs (R-CNN, Fast R-CNN, Faster R-CNN) achieved high accuracy but were computationally intensive. Real-time detectors like the YOLO family [1], [4], [13], SSD, and RetinaNet significantly accelerated detection speeds while maintaining accuracy. YOLO, processing entire images in a single pass, is highly suitable for real-time ADAS.

Current vision-based collision avoidance research often focuses on multi-sensor fusion, robust tracking algorithms like DeepSORT [5] or ByteTrack [3], [6], and sophisticated motion prediction models (e.g., Kalman filters, recurrent neural networks) to anticipate trajectories [9].

While many existing ADAS use YOLO for detection, their alert mechanisms frequently depend on simpler distance or time-to-collision heuristics. Our contribution distinguishes itself by integrating these deep learning detection capabilities with **novel Dynamic ROI processing and Angular Methods**. This synergy provides a more refined,

3 System Overview and Architecture

The Collision Alert System (CAS) is architected upon a robust, flexible framework, integrating advanced computer vision and machine learning for high accuracy and real- time operation. This modular design aids adaptability across diverse camera configurations and dynamic traffic scenarios, critical for real-world deployment. The system's core functions work synergistically, processing visual data from the vehicle's camera to interpret the environment and predict potential collision risks. Figure 1 conceptually illustrates a camera arrangement for 360-degree coverage, adaptable for viewpoints within our current monocular system.

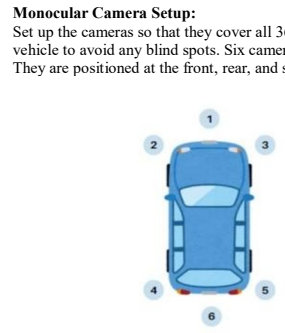

Fig. 1. Conceptual monocular camera setup illustrating six potential positions (1-6) strategically arrayed around a vehicle for comprehensive 360-degree coverage. The current evaluation primarily uses a single camera view, with full multi-camera fusion designated for future work.

0.1. Technical Foundations

Our CAS leverages key technical components for real- time collision prediction:

- **Object Detection:** The system employs advanced YOLOv5 and YOLOv8 models [13], known for their speed-accuracy balance. These are vital for instantaneous identification of various road users and obstacles within the camera's field of view, forming the critical first step.
- **Distance Estimation:** Accurate distance to detected objects is paramount. Our system calculates proximity using focal length-based methodologies [7]. This ap- plies pinhole camera model principles to quantify threat proximity. The estimated distance D is calculated as:

$$D = \frac{w.f}{p}$$

(1) Distance Estimation Formula

where W is the known width of the object in the real world (as per Table 1), f is the camera focal length, and P is the width of the object in pixels on the image plane.

- **Trajectory Analysis:** Beyond current position, predicting an object's future path is crucial [9]. The CAS integrates optical flow [8] and angular techniques. Optical flow quantifies apparent motion for speed and direction. Angular methods scrutinize changing angular positions relative to the ego-vehicle, vital for identifying collision courses.
- **Object Tracking:** To maintain continuity and build movement history, the system uses persistent ID-based tracking [3]. Each detected object receives a unique identifier, consistent across frames, even during brief occlusions.

Table 1. Known Object Widths for Distance Estimation (Units: meters)

Class	Object Name	Width (YOLOv5)	Width (TI Lite)
0	person	1.5	3.6
1	bicycle	1.3	3.3
2	car	3.8	9
3	motorcycle	1.3	3.3
5	bus	6.2	15
7	truck	5.8	14
15	cat	0.8	2.4
16	dog	1.5	4
19	cow	2	6

0.2. Modular System Architecture

The CAS's flexible modular architecture ensures optimal performance and reliability across varied camera configurations and traffic scenarios.

- **Advanced Detection Algorithms:**
  - *Dynamic Region of Interest (ROI) processing:* The system intelligently focuses computational power on critical areas, determined by ego-vehicle speed, lane detection [12], or high object density. This reduces overhead while maintaining accuracy in zones with probable collision

paths.

- *Angular measurement techniques:* These methods provide geometric collision risk assessment, particularly for side-mounted cameras or cutting-in vehicles.
- *Camera-specific processing:* Tailored algorithms ac- count for different camera mounting positions (front, rear, side), each requiring specific calibration and logic for optimized detection and analysis.

- **Sophisticated Object Tracking:**
  - *Object tracking with historical movement analysis:* For each tracked object, a detailed history of past movements (positions, velocities, accelerations) is compiled. This data informs prediction models for future positions, revealing potential collision trajectories.
  - *Prediction based on virtual screen boundaries:* Virtual"danger zones" are established within the cam- era's view. An object's predicted path is continuously evaluated against these, triggering an alert if inter- section with the vehicles immediate path is likely.

0.3. System Workflow

Figure 2 illustrates the CAS's operational flow, detailing the real-time pipeline from video input to collision alert. The system continuously acquires video frames, performs YOLOv8-based object detection and tracking, and calculates each detected object's center, distance, and angle. It updates historical data and checks against predefined virtual crossing lines. A collision detection triggers an immediate alert if an object crosses a significant line and its distance falls below a critical threshold (e.g., 10m). Processed frames are then displayed and recorded, with the cycle repeating until termination.

4 In-Depth Algorithm Breakdown

Our system integrates a blend of innovative algorithms to precisely identify and predict collision risks. Each con- tributes a distinct perspective to the overall collision detection capability, ensuring a comprehensive, multi-faceted approach to vehicle safety.

0.4. Dynamic ROI Method

The Dynamic Region of Interest (ROI) method is crucial for optimizing computational resources and enhancing detection relevance in dynamic environments. It leverages optical flow analysis [8] to determine the ego-vehicle's movement and other objects' relative motion. This real-time intelligence dynamically defines "intersection areas"—high- priority zones within the camera's view where interactions with the vehicle's anticipated path are most probable. This adaptive focusing reduces computational overhead while maintaining precision in critical zones. Collision probability within these ROIs is assessed based on estimated object distance (from focal length calculations) and trajectory intersection likelihood, refined by comparing current and historical object movement. This adaptive strategy significantly differentiates our system from static ROI methods, offering a more context-aware and efficient threat evaluation.

0.5. Angular Methods

Angular methods provide a robust geometric frame-work for evaluating collision risks, invaluable for lateral and oblique threats often missed by purely frontal distance measurements. A flexible reference point system, typically anchored at the bottom-center of the camera view, is adapted for various camera placements. The angle ϑ between virtual reference lines from this point (c_x, c_y) and the center of detected objects' bounding boxes (x, y) is calculated as:

$$\vartheta = \arctan \frac{x - c_x}{y - c_y}$$

(2) Angular Calculation Formula

By monitoring the rate of change of these angles over time ($\Delta\vartheta/\Delta t$), combined with distance measurements, the

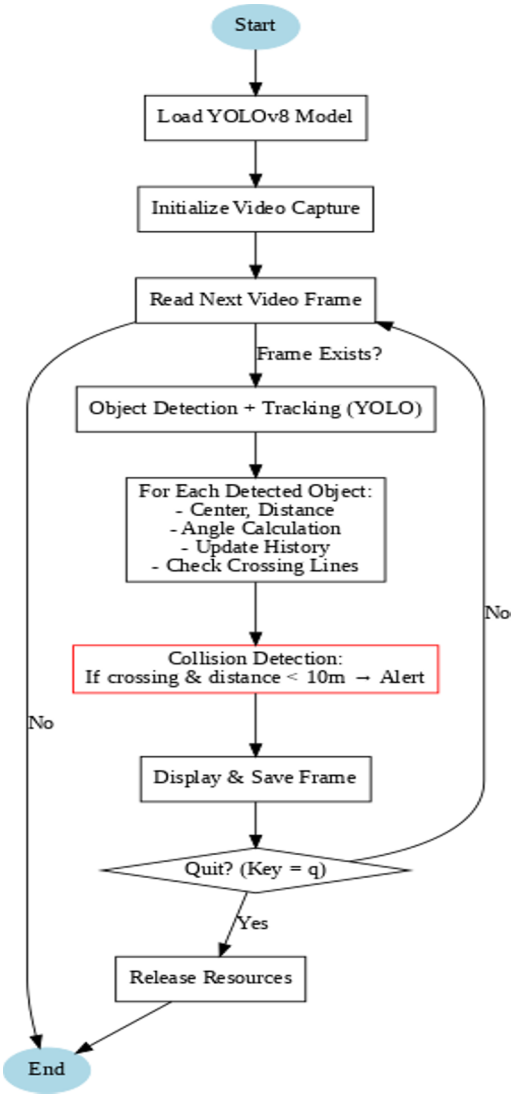

Fig. 2. Workflow diagram of the Collision Alert System, illustrating the real-time processing pipeline from video input to collision alert.

system infers relative motion and potential collision courses. For instance, a rapidly altering angle with decreasing distance strongly indicates an imminent collision. Combined with dynamic distance thresholds, these measurements of- for a comprehensive geometric basis for predicting side- impacts, lane-change collisions, and other oblique risks, crucial for full situational awareness. These methods are conceptually depicted in Figure 3.

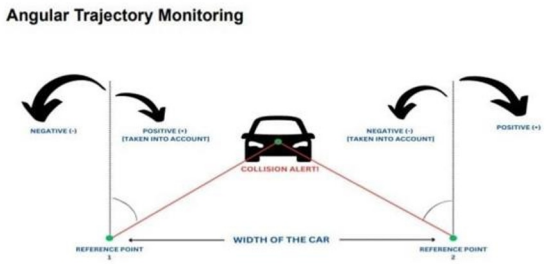

Fig. 3. Conceptual diagram of angular trajectory

Fig. 3. Conceptual diagram of angular trajectory monitoring, illustrating how positive and negative angles relative to dynamic reference points are assessed for collision risk and trajectory analysis.

The intricate interplay of distance and angle for proximity monitoring is further clarified in Figure 4.

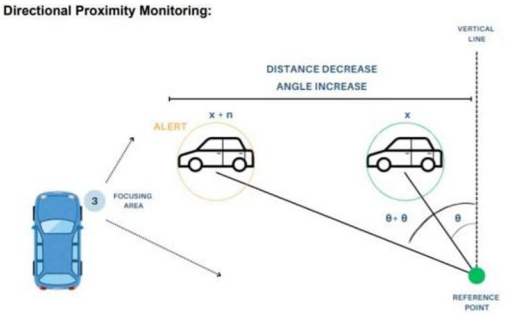

Fig. 4. Directional proximity monitoring mechanism

Fig. 4. Directional proximity monitoring mechanism, demonstrating how a decrease in distance (from 'x' to 'x+n') combined with an increase in an object's angle (θ to $\theta + \theta'$) relative to a reference point triggers an immediate collision alert.

0.6. Object Tracking Method

The Object Tracking Method ensures consistent identification and continuous surveillance of dynamic entities, forming the essential backbone for accurate trajectory pre- diction and long-term risk assessment. Each detected object is assigned a persistent, unique identifier [3], facilitating continuous movement trajectory analysis across multiple frames. This continuity is crucial for understanding both instantaneous positions and long-term movement patterns, anticipating future states. Tracking involves sophisticated data association techniques and state estimation models like Kalman filters, which predict an object's next state (position, velocity) based on previous states and current measurements, smoothing noisy data and maintaining tracks during brief occlusions. This robust tracking, along with accumulated historical motion data, is vital for evaluating the likelihood of objects crossing predefined virtual screen
margins, which delineate critical "danger zones." If a predicted trajectory indicates entry into these zones within a specified time horizon, it signals potential entry into the vehicle's immediate danger zone, prompting a timely warning. This predictive tracking capability significantly enhances the system's ability to provide proactive alerts.

5 Performance Validation and Implementation

The Collision Alert System (CAS) underwent an exhaustive series of tests and validations to confirm its high accuracy and real-time efficiency—both indispensable for automotive safety applications. Our methodology involved deploying the system against diverse real-world video datasets, capturing varied traffic densities, environmental conditions, and driving scenarios. Its performance was meticulously evaluated against ground truth annotations to quantify over- all effectiveness.

0.7. Experimental Setup

The CAS was primarily developed using Python, lever- aging OpenCV for image processing and PyTorch for neural network inference. YOLOv8-n (nano), selected for its optimal speed-accuracy balance on embedded platforms, served as the core object detection engine. The system was deployed and assessed on a workstation featuring an Intel Core i7-9700K CPU, 32GB RAM, and an NVIDIA GeForce RTX 2080 GPU, representative of powerful in-vehicle embedded systems. All reported performance metrics represent averages from five independent runs across diverse test scenarios, ensuring robustness and statistical reliability.

0.8. Dataset Description

For training and validation, we utilized a combination of publicly accessible ADAS datasets: segments from the **KITTI Vision Benchmark Suite** [14] and portions of the **Waymo Open Dataset** [15]. KITTI provides diverse urban and highway environments with synchronized image and LIDAR data for accurate ground truth annotation of object distances. Waymo offers a larger scale with greater variation in conditions, including different times of day and weather challenges. Our test dataset comprised:

- 20 minutes of urban driving footage.
- 15 minutes of highway driving footage.
- 10 minutes covering diverse lighting (dawn, dusk, night) and light rain.

Objects annotated for detection and tracking included various vehicles and pedestrians. Ground truth for collision scenarios was established by manually annotating time-to- collision for specific dangerous interactions.

0.9. Evaluation Methodology

Performance metrics were computed as follows:

- **True Positive Rate (TPR) / Recall:** Percentage of actual collision risks (ground truth) correctly

identified and alerted. An alert was a true positive if within 2-3 seconds prior to a ground truth collision.

- **False Positive Rate (FPR):** Percentage of non-collision scenarios where a collision alert was erroneously issued, calculated over periods with no ground truth risk.
- **Frames Per Second (FPS):** Average processing speed, calculated as total frames processed divided by total processing time. A collision alert triggered when a tracked object's predicted trajectory intersected the ego-vehicle's path, its estimated distance fell below a critical threshold (e.g., 10m for vehicles, 5m for pedestrians), and Time-To-Collision (TTC) was less than 2.5 seconds.

0.10. Performance Metrics

The CAS demonstrated robust performance across key metrics, averaged over five independent evaluation runs on the described dataset:

- **Accuracy Rates:** Achieved a mean true positive rate (TPR) of 97.2% (±1.1%), indicating strong effective- ness in identifying collision-course objects. Maintained a remarkably low mean false positive rate (FPR) of 1.5% (±0.3%) across conditions, crucial for preventing driver distraction and maintaining trust.
- **Detection Distance Range:** Consistent detection for vehicles up to 100 meters and pedestrians up to 30 meters. Minor degradation (5-10%) was noted in heavy rain or dense fog due to reduced visibility.
- **Processing Speed:** Operated at an average of 40 **frames per second (FPS)** (±2 FPS), ensuring real-time responsiveness. This speed is critical for immediate alerts, allowing drivers 2-3 seconds to react. Achieved on the specified GPU platform, confirming in-vehicle viability.

0.11. Comparative Performance Analysis

To contextualize the CAS's effectiveness, its performance is rigorously benchmarked against typical operational ranges observed in leading existing collision alert systems and established methodologies from literature. This high- lights our system's advancements in accuracy, reliability, and efficiency.

As Figure 5 illustrates, current collision alert technologies offer a spectrum of performance. Many (System A, B, C, D), often relying on simpler vision or single-sensor modalities, typically achieve accuracies between 85% and 90%, with FPRs ranging from 6% to 10%. While some reach 25-30 FPS, a trade-off often exists between speed and detection robustness, especially in challenging conditions. These figures highlight common limitations in consistently high accuracy, minimal false alarms, and real-time operation.

Figure 6 directly compares our CAS's performance against a "Best Existing" system, showcasing significant improvements across critical safety metrics. Our CAS achieves a notably higher Accuracy of 97.2%, surpassing existing systems' typical 90%. Crucially, the False Positive Rate (FPR) is dramatically reduced to 1.5%, a substantial improvement from the 6% observed elsewhere. This reduction in false alarms is vital for driver trust and preventing distractions. Furthermore, our CAS maintains a superior processing speed of 40 FPS, outperforming comparable high-end systems at 30 FPS. These results confirm that our architectural and algorithmic optimizations, particularly integrating state-of-the-art YOLOv8 with specialized Dynamic ROI and An- gular Methods for tracking and trajectory analysis, directly contribute to a more robust, reliable, and efficient collision prediction. This enhanced performance signifies a major stride towards mitigating collision risks and ensuring greater safety in dynamic driving

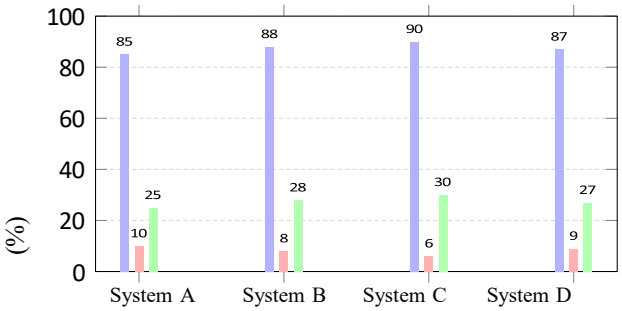

Fig. 5. Representative performance metrics of various existing collision alert systems (e.g., radar-only, basic vision-based) drawn from recent literature [2], [10]. The graph shows typical ranges for Accuracy, False Positive Rate (FPR), and average Frames Per Second (FPS) which serve as a baseline for comparison

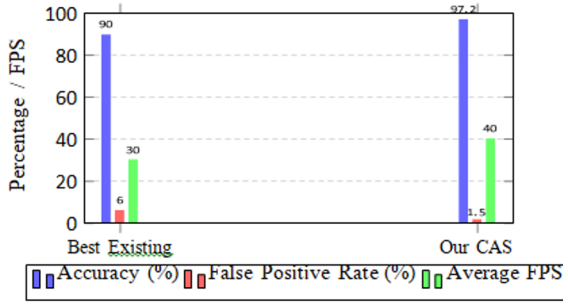

Fig. 6. Performance comparison highlighting the enhanced accuracy, reduced False Positive Rate (FPR), and improved Frames Per Second (FPS) of the proposed Collision Alert System (CAS) against a representative "Best Existing" system. This demonstrates the significant contribution of our system to increased vehicle safety and reliability.

0.12.Visual Feedback System

The system offers clear, intuitive visual feedback. Detected objects are highlighted by color-coded bounding boxes: green for safe, red for collision risk. On-screen displays complement these cues by presenting real-time numerical measurements of object distance (meters) and angular position (degrees) relative to the ego-vehicle. For critical situations, unambiguous "Collision Alert" warnings are superimposed. This comprehensive interface is designed for rapid driver information assimilation, minimizing cognitive load and facilitating swift decision-making. An example is in Figure 7.

Figure 5. Representative performance metrics of various

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Fig. 7. A real-time screenshot demonstrating the Collision Alert System in operation, showcasing object detection with green bounding boxes, estimated distance and angle for multiple objects, and visual lines indicating potential trajectories.

A comprehensive video demonstration of the CAS in various traffic scenarios, illustrating its real-time performance and alert mechanisms (including color-coded feedback and warnings), Accuracy (%)False Positive Rate (%) Average FPS accessible via: https://drive.google.com/file/d/1oKwEPdYDhbQZjJJvAG5jtS3YOlbIp7jm/view?usp= sharing

6 Addressing Inherent Challenges

Developing a truly dependable Collision Alert System for unpredictable real-world driving presents myriad challenges, encompassing environmental variability and intrinsic technical difficulties. Our system incorporates robust design principles and sophisticated algorithmic solutions to effectively navigate these common hurdles.

0.13 Environmental Challenges

- **Variable Lighting:** Camera-based systems are highly susceptible to fluctuating lighting. Our CAS addresses this with advanced image pre-processing, including dynamic histogram equalization and adaptive thresholding, enhancing contrast across diverse illumination (daylight, twilight, night, glare). YOLOv8 models are trained on extensive datasets covering these varied scenarios to bolster resilience.
- **Occlusion:** Objects can become partially or fully obscured. To maintain tracking through occlusion, the CAS employs multi-frame analysis and predictive algorithms. When an object is temporarily hidden, its trajectory is estimated using historical motion data (e.g., Kalman filter). Upon reappearance, re-identification techniques link it to its original track ID, ensuring continuous monitoring and reducing false negatives.
- **Camera Vibration:** Vehicle motion introduces vibrations causing blur, jitter, and erroneous detections. Our system integrates sophisticated stabilization algorithms, such as Electronic Image Stabilization (EIS) or motion compensation, at the video input stage. These counteract vibrations, preserving image clarity and stability, essential for accurate detection and consistent tracking.

0.14 Technical Challenges

- **Accuracy vs. Real-time Performance:** This fundamental trade-off is managed by using optimized model architectures (YOLOv8-n) and leveraging GPU hard- ware acceleration. Techniques like model quantization and pruning were explored to minimize computational footprint without significant accuracy loss, striking a critical balance for responsive safety applications.
- **Distance Estimation Calibration:** Precise distance measurements, crucial for collision prediction, depend heavily on accurate camera parameters and object characteristics. The system incorporates a comprehensive, adaptive calibration routine for various object classes and camera installations. This routine facilitates empirical or algorithmic calibration of intrinsic and extrinsic camera parameters, ensuring consistent and precise measurements.
- **False Positives/Negatives:** False positives (unnecessary alerts) lead to driver distrust; false negatives (missed threats) are catastrophic. Rigorous testing with diverse, real-world datasets continuously refines confidence thresholds, non-maximum suppression (NMS) parameters, and alert trigger logic. Machine learning- based filtering can further assess detection credibility using contextual information, significantly enhancing user trust and reliability.
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7 Strategic Future Developments

Our commitment to enhancing vehicle safety drives several strategic future developments for the Collision Alert System, aiming to broaden its applicability, deepen its vehicle integration, and augment its intelligence.

0.15 System Enhancements

- **Vehicle Control Integration:** The most impactful next step involves seamless integration with vehicle control systems. This would enable the CAS to move beyond warnings to autonomous interventions, such as emergency braking (AEB) or steering assistance. Such advancements demand extremely high confidence and robust decision-making.
- **Multi-camera Fusion:** Future iterations will incorporate data fusion from multiple cameras (front, rear, side) for comprehensive 360° situational awareness, eliminating blind spots and enhancing perception for complex maneuvers. Sensor fusion with radar or lidar will also be explored for improved robustness in ad- verse weather.
- **ML for Scene Adaptation:** Advanced ML models will enable dynamic adaptation of parameters (collision thresholds, alert timings, tracking) based on real- time context like driving environment (urban/highway), weather, or vehicle speed, making the system more intelligent and

less intrusive.

- **Edge Device Optimization:** Further optimization for low-power edge devices is crucial for widespread adoption. This involves exploring efficient neural network architectures, specialized hardware accelerators, and advanced compression techniques to maintain real-time performance on resource-constrained platforms, reducing cost and power consumption.

0.16 Extended Applications

- **Pedestrian Safety:** Adapting core collision prediction for dedicated pedestrian safety is a high priority, especially in dense urban areas. This includes refined detection of vulnerable road users, more accurate prediction of pedestrian intent, and nuanced warning strategies tailored to their unique movements.
- **Autonomous Vehicle Integration:** The CAS can serve as a foundational safety layer for fully autonomous driving systems. Its real-time perception and prediction capabilities can function as an independent safety monitor or a crucial input for the autonomous driving stack, adding redundancy and reliability.
- **Traffic Monitoring & Analysis:** Beyond individual vehicle safety, deployed CAS systems could con- tribute valuable data to intelligent transportation systems. Anonymized data from multiple vehicles could be aggregated for real-time traffic flow analysis, congestion prediction, incident detection, and informing infrastructure planning, leading to more efficient and safer road networks.

8 Conclusion

This paper presents a significant advancement in proactive vehicle safety with our novel Collision Alert System (CAS), demonstrating robust capabilities of computer vision in dynamic traffic. Our system excels by integrating state- of-the-art YOLOv8 object detection with unique **Dynamic Region of Interest (ROI) processing and Angular Meth- ods**, complemented by robust object tracking and precise trajectory analysis. This distinct approach offers a more nuanced and effective collision prediction than conventional YOLO-based ADAS, particularly in identifying lateral and oblique threats. The system consistently delivers strong performance, even in challenging real-world conditions, as substantiated by rigorous experimental validation. These innovations translate into substantial benefits: reduced collision risks, heightened driver awareness, and improved reaction times. By moving beyond reactive safety measures to truly proactive prediction, the CAS empowers drivers with critical, early information, facilitating earlier intervention and leading to safer outcomes. The CAS is more than a warning system; it stands as a foundational technology paving the way for advanced autonomous safety features. We are confident that this intelligent, proactive solution will play a pivotal role in shaping a safer future for automotive travel, bringing us closer to the vision of zero accidents on our roads.

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