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Enhanced Scene Recognition and Object Detection for Autonomous Driving Environments Using Machine Learning ”Work in Progress” (WIP)

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Abstract

This work presents advancements in computer vision methodologies aimed at enhancing the safety and adaptability of autonomous vehicles in diverse driving environments. This study addresses key challenges such as real-time processing, environmental variability, and scene understanding by refining Mask R-CNN's object detection and segmentation capabilities and introducing a novel scene classifier. Mask R-CNN improvements enable precise identification of critical objects such as pedestrians, vehicles, and traffic signs. At the same time, the scene classifier dynamically adjusts detection parameters to optimize performance across urban, rural, and highway contexts under varying weather and lighting conditions.

The integration of these technologies improves real-time responsiveness and computational efficiency, which is crucial for dynamic autonomous driving applications. Evaluation metrics demonstrate significant gains in detection accuracy and processing speed, including mean Average Precision (mAP), Intersection over Union (IoU), and frame processing time. Preliminary results also highlight the effectiveness of data augmentation techniques and multimodal sensor data in mitigating challenges posed by adverse weather and ambiguous scenes.

This research contributes to developing robust, context-aware autonomous systems that enhance intelligent transportation networks' safety, reliability, and efficiency. Future directions include leveraging edge computing and advanced AI architectures to improve decision-making processes and achieve Level 5 autonomy.

Introduction

Autonomous vehicles rely ponderously on computer vision systems to interpret their environments and make real-time decisions. As these systems become more integrated into transportation, ensuring their accuracy and reliability is crucial [1]. A significant challenge in autonomous driving is detecting and segmenting objects such as pedestrians, vehicles, and traffic signs in complex environments [2]. Errors in object detection can undermine the safety and reliability of autonomous systems, potentially leading to accidents [3].

Mask R-CNN has emerged as a powerful tool for object detection and segmentation due to its high precision and adaptability in recognizing objects across varied environments [4]. Its ability to identify and segment objects within a scene makes it suitable for enhancing autonomous vehicle safety by improving environmental interpretation. However, despite its strengths, Mask R-CNN's performance can be limited in dynamic and complex driving scenarios, particularly where real-time response and computational efficiency are essential [5].

This study addresses these limitations by enhancing Mask R-CNN with a novel scene classifier to adapt detection parameters based on specific driving environments, such as urban, highway, and rural contexts, under varying conditions like day, night, and different weather patterns [6]. The classifier optimizes the model's efficiency and accuracy by adjusting settings based on context, ultimately improving real-time object detection in autonomous driving systems [7].

Lastly, this paper proposes a novel integration of scene classification and object detection, leveraging a scene-aware Mask R-CNN framework. Unlike prior works that rely solely on fixed detection parameters, our approach dynamically adjusts Mask R-CNN thresholds and feature extraction strategies based on real-time scene classification outputs. This leads to improved detection accuracy, lower false positives, and faster processing times. Our research answers key questions regarding environmental impact on object detection models and proposes solutions for improving robustness against fog, rain, nighttime conditions, and high-glare environments.

Literature Review

Advances in sensor technology and artificial intelligence (AI), including machine learning, are driving the rise of autonomous vehicles (AVs). These vehicles are equipped with sensors that allow them to detect the surrounding environment, make decisions, and navigate accordingly without human intervention. This literature review focuses on the key developments, challenges, and future directions of AVs.

Development of Autonomous Vehicles

Autonomous vehicles (AVs) are categorized into five levels of autonomy as defined by the Society of Automotive Engineers (SAE). Level 1 corresponds to basic driver assistance, while Level 5 represents full autonomy. Currently, most AVs operate at Level 2 or Level 3, where partial automation is supervised by humans. Achieving fully autonomous vehicles (Level 5) remains a significant challenge due to both technological and regulatory hurdles [25].

The evolution of AVs can be traced back to early advancements in robotics and sensor-based navigation systems. The first commonly used automated system, cruise control, marked an important initial step by enabling vehicles to maintain a constant speed without continuous driver input. Building on this foundation, modern AVs now integrate global positioning systems (GPS), sensors (e.g., LiDAR, radar, cameras), and advanced algorithms to detect objects, plan motion, and make real-time decisions [2]. Artificial intelligence-driven technologies, such as convolutional neural networks (CNNs), have further enhanced AVs' capabilities, allowing them to detect and classify objects in complex and dynamic environments [1].

Object Detection and Scene Understanding

For AVs to be effective, they need to be able to detect and react to objects and obstacles in real-time. Object detection models like Faster R-CNN and YOLO (You Only Look Once) have significantly improved vehicle perception by identifying pedestrians, traffic signs, and vehicles more accurately and efficiently [3][8].

A complementary process called scene classification involves understanding the general environment (a city, a highway, a rural area) and adapting driving strategies accordingly. A widely used object segmentation tool, Mask R-CNN, helps navigate a safe environment by distinguishing relevant from irrelevant features [6].

Challenges in Autonomous Driving

Despite rapid progress, autonomous vehicles (AVs) face several critical challenges that hinder their widespread adoption and functionality. Urban areas with dense traffic, pedestrians, and cyclists present highly complex driving environments [5]. These scenarios demand AV systems to interpret dynamic and unpredictable behaviors accurately, a task that remains challenging due to the variability in human actions and congested surroundings. Navigating such environments while maintaining safety and efficiency is a persistent hurdle for AV development.

Adverse weather conditions, such as rain, snow, and fog, further complicate the functionality of AVs [11]. These conditions impair the accuracy of sensors like cameras and LiDAR, reducing the reliability of the perception systems. Limited visibility, reflections, and other environmental interferences can lead to erroneous object detection, increasing the likelihood of accidents. Addressing these weather-related challenges is crucial for enhancing the robustness of AV systems.

Real-time processing is another significant obstacle for AVs, as they require substantial computational resources to process vast amounts of data from multiple sensors simultaneously [24]. To ensure timely decision-making, AV systems must maintain low latency while handling complex computations. Achieving a balance between computational efficiency and high detection accuracy is critical for real-time performance in dynamic driving environments.

Additionally, AV deployment raises regulatory and ethical issues. In critical scenarios, AV systems may need to make moral decisions, such as choosing between two harmful outcomes, which introduces complex ethical dilemmas [25]. Furthermore, the lack of standardized regulations governing AV deployment across regions creates additional barriers to large-scale adoption.

Mask R-CNN

Mask R-CNN is a groundbreaking model in deep learning, designed to perform instance segmentation by identifying and segmenting individual objects at the pixel level. Introduced by He et al. (2017) [1], it extends the Faster R-CNN framework by incorporating an additional mask prediction branch, enabling it to simultaneously perform object detection, bounding box regression, and segmentation tasks. This multi-task capability has made Mask R-CNN a preferred choice for numerous computer vision applications, offering high accuracy and versatility. Its innovations, such as the use of Region Proposal Networks (RPN) and the RoIAlign technique, address challenges in spatial alignment and feature extraction, setting a new benchmark in segmentation tasks. The following sections delve into its architecture, applications, comparative performance, and the challenges it faces as researchers continue to refine its capabilities.

Introduction to Mask R-CNN

Mask R-CNN was introduced by He et al. (2017) [1], and represents one of the world's most advanced deep learning models for example segmentation. It is an extension of Faster R-CNN designed to segment pixels at the pixel-level. This model includes a branch for predicting object masks in addition to classification and bounding box regression. With this approach, a Fully Convolutional Network (FCN) is used for mask prediction and a Region Proposal Network (RPN) is used to identify regions of interest [1].

Architecture Overview

R-CNN Mask introduces a third segmentation branch based on the Faster R-CNN framework. An integrated multi-task loss is used in this model, combining bounding box regression, mask prediction, and classification. Specifically, He et al. (2017) [1] emphasized RoIAlign, which resolves misalignment issues associated with quantization in Region of Interest (RoI) pooling, increasing segmentation accuracy significantly. As a result of this innovation, feature maps and original images are spatially aligned.

Advancements and Applications

As a result of its introduction, Mask R-CNN has been applied to various fields, such as medical imaging, autonomous driving, and video analysis. Medical imaging researchers have adapted Mask R-CNN to segment organs in CT scans and detect anomalies in MRI scans [26]. Models for autonomous driving have been used for detecting pedestrians and vehicles, contributing to real-time object segmentation [27]. The Mask R-CNN architecture has also been transferred to video segmentation tasks, in which temporal consistency is guaranteed by incorporating optical flow into the model [28].

Comparative Studies

A comparison of Mask R-CNN to U-Net and DeepLab has demonstrated its superior performance at handling overlapping instances and detailed object boundaries. The region-based approach of Mask R-CNN, as demonstrated by Lin et al. (2018) [29], outperformed U-Net for medical image segmentation tasks. In contrast to lightweight models like YOLO, Mask R-CNN has a high computational cost [8].

Challenges and Future Directions

Even though Mask R-CNN has been successful, its high computational requirements make it unsuitable for real-time applications. In recent studies, optimizations have been proposed to enhance efficiency, such as reducing the size of feature maps and pruning redundant layers [30]. For future research, transformer-based architectures may be integrated to improve global context understanding and lightweight Mask R-CNN variants may be developed.

Scene Classifier

Scene classification is fundamental to autonomous driving, enabling vehicles to understand and interpret their surroundings effectively. By categorizing environments into urban, rural, and highway settings, autonomous vehicles (AVs) can optimize their navigation strategies and allocate computational resources efficiently. This process involves the AV's perception system distinguishing between different driving environments, allowing it to focus on relevant elements within a scene. Accurate scene classification enhances the vehicle's ability to adapt to various driving conditions, ultimately contributing to safer and more reliable autonomous driving experiences.

Scene Classification in Autonomous Driving

Introduction to Scene Classification

The ability to categorize a space is crucial for autonomous vehicles (AVs) to understand their surroundings and to optimize their navigation strategies based on the type of driving environment in which they are operating. As part of the contextualization process, the AV's perception system is contextualized to distinguish between urban, rural, and highway settings. AV systems can thus allocate computational resources effectively, concentrating on relevant elements within a scene (Geiger et al., 2012) [5].

Integration of Object Detection in Scene Classification

The detection of objects is a critical part of scene classification. Vehicles, pedestrians, traffic signs, and lane markings can be identified by object detection, providing valuable input to scene classifiers. By combining fast R-CNN, YOLO, and Mask R-CNN models with scene classification, advanced models, such as Faster R-CNN, YOLO, and Mask R-CNN, enable precise object localization and segmentation [6][8].

As an example, in urban areas, object detection systems are designed to recognize pedestrians and traffic lights, while in rural areas, they are designed to recognize animals or debris. As a result of contextual information, the AV is able to adapt dynamically to the scene, improving its accuracy and reliability of scene classification [31].

Data Augmentation for Scene Classification

A wide range of conditions is captured in extensive datasets to ensure robust performance across diverse environments in scene classification and object detection models. To improve model generalization, data augmentation techniques play a crucial role. These techniques, such as image flipping, scaling, and brightness adjustment, introduce variability into the training data, enabling models to perform effectively under different lighting, weather, and viewpoint conditions.

Image flipping is a commonly used technique that helps the model generalize to symmetrical scenes[11]. This is particularly useful for scenarios like vehicles or road layouts that may be mirrored in different directions, enhancing the model's adaptability to various configurations. Scaling ensures that the model can detect objects and understand scenes at varying distances by accommodating different resolutions and perspectives, which is essential for detecting both nearby and faraway elements in dynamic environments[5]. Brightness adjustment simulates various lighting conditions, such as daylight, dusk, or artificial lighting, to improve the model's robustness in handling scenes with uneven illumination or challenging visibility[33].

By applying these data augmentation techniques, scene classifiers become more resilient to environmental changes, significantly enhancing their utility in real-world applications. This ensures that models trained on augmented datasets are better equipped to handle the complexities of diverse and dynamic driving environments.

Challenges and Future Directions in Combining Object Detection with Scene Classification

Integrating object detection and scene classification poses several unique challenges. One of the primary challenges is achieving real-time performance. Balancing computational efficiency and accuracy for both tasks is critical in time-sensitive scenarios, such as autonomous driving, where timely decision-making can significantly impact safety and functionality[32]. Ensuring that the system processes data with minimal latency while maintaining high detection and classification accuracy remains a significant hurdle.

Another challenge lies in dealing with ambiguous scenes. Environments where features overlap or lack distinct characteristics belonging to a specific scene type can confuse both object detection and scene classification models. For instance, in urban settings, objects like pedestrians, bicycles, and vehicles often appear closely clustered, making it difficult to differentiate them accurately. Such ambiguities require models capable of understanding nuanced contextual relationships.

Additionally, sensor variability presents another obstacle. Autonomous systems rely on data from various sensors, such as cameras and LiDAR, each with unique characteristics and limitations [33]. Ensuring consistent performance across these modalities is essential for robust integration. Variability in sensor resolution, data quality, and environmental interference, such as rain or glare, can affect the accuracy of both object detection and scene classification.

Future advancements in deep learning, sensor fusion, and edge computing hold promise for addressing these challenges. Enhanced models that leverage multimodal data and real-time processing capabilities are expected to enable tighter integration of object detection and scene classification. These advancements will create systems capable of processing information rapidly and accurately in diverse driving conditions, paving the way for safer and more reliable autonomous driving technologies.

Research Questions

Considering the previous information, the researcher has developed the following questions:

1. How do different weather conditions (fog, rain, snow) affect the accuracy of Mask RCNN in autonomous vehicle applications?
2. What specific visual occlusions and distortions are introduced by fog and rain, and how do they impact object detection and segmentation performance?
3. How does low-light or nighttime conditions influence the illumination and image noise levels, and what is their effect on Mask R-CNN accuracy?
4. In what ways do glare and shadows caused by sunlight or reflective surfaces create high contrast or obscured regions, and how do these factors confuse segmentation models?
5. What are the most effective solutions or techniques to mitigate the adverse effects of weather and lighting conditions on Mask R-CNN performance in autonomous driving scenarios?
6. How can the robustness of Mask R-CNN be improved to handle challenging environmental conditions in real-time applications?

These questions aim to explore the extent of weather and lighting conditions' impact on Mask R-CNN and investigate potential solutions to enhance its performance in autonomous vehicle applications.

To address these challenges, it is essential to present data that illustrate Mask R-CNN's detection accuracy under various weather and lighting conditions using quantitative metrics such as mean Average Precision (mAP) and Intersection over Union (IoU). Visual examples of model outputs can further demonstrate specific challenges, such as occluded objects in foggy or lowlight environments. Comparative analysis across conditions can highlight the most affected object types, such as pedestrians or traffic signs, providing a detailed understanding of the model's limitations.

Several solutions can mitigate these effects, and their effectiveness should be demonstrated through data. Data augmentation techniques, such as adding synthetic fog, rain, or brightness adjustments during training, can be evaluated by comparing performance before and after augmentation. The integration of multimodal sensor data, such as combining camera inputs with LiDAR or radar, should be highlighted as a strategy to compensate for visual limitations and improve detection accuracy in adverse conditions. Preprocessing techniques, including dehazing, histogram equalization, and noise reduction, can also be analyzed for their impact on image quality and subsequent model accuracy.

In addition to these mitigation strategies, adaptive approaches can further enhance robustness. Dynamic parameter tuning, informed by scene classifiers, should be evaluated to demonstrate how it optimizes Mask R-CNN's performance for specific environmental contexts, such as urban versus rural or day versus night conditions. Likewise, the role of transformer architectures and attention mechanisms in improving global context understanding and resilience under adverse scenarios should be explored. Presenting results that compare these adaptive techniques across diverse driving contexts will provide valuable insights into their effectiveness.

Finally, the diversity of the training dataset plays a critical role in the model's ability to generalize across various conditions. Data should be presented to show the range of weather and lighting conditions represented in the dataset, along with an analysis of potential biases, such as an overrepresentation of urban scenarios. By addressing these research questions and presenting relevant data, this study can provide a comprehensive understanding of the challenges and solutions for improving Mask R-CNN's accuracy and reliability in real-world autonomous vehicle applications.

Methods

This study developed an advanced, adaptable perception system for autonomous driving that integrates scene classification and object detection to improve accuracy, efficiency, and real-time processing in complex driving environments. The research involved leveraging Mask R-CNN for object detection across varied driving contexts, including urban, highway, and rural settings under different weather conditions [1]. Additionally, a scene classifier was introduced to dynamically adjust system parameters based on driving context, further enhancing detection accuracy and computational performance [2].

System Design and Integration

The system integrates both scene classification and object detection as a cohesive framework for real-time autonomous driving applications. Mask R-CNN serves as the core object detection model, implemented to segment critical objects (e.g., pedestrians, vehicles, and traffic signs) across dynamic environments [8]. A scene classifier distinguishes between city, highway, and rural settings and identifies different times of day and weather conditions (e.g., sunny, cloudy, rainy) [9]. This classifier dynamically adjusts model parameters, enhancing detection accuracy and computational efficiency for each driving context [10].

Model Training and Optimization

Mask R-CNN and the scene classifier were trained using Python libraries (TensorFlow and PyTorch) [14]. The training process was conducted in two stages: initial Mask R-CNN training for object detection, followed by the integration of the scene classifier for adaptive parameter adjustments. Optimization techniques, including hyperparameter tuning (e.g., learning rate, batch size) and regularization (e.g., dropout), helped prevent overfitting and enhance detection accuracy [15]. Various Mask R-CNN configurations were tested to balance computational efficiency with detection precision for each context [16]. Performance metrics, such as mean Average Precision (mAP) and Intersection over Union (IoU), were used to measure model accuracy, while processing time and memory usage were monitored to ensure real-time performance [17].

System Evaluation and Testing

The integrated system was tested across multiple driving scenarios (urban, highway, rural) and conditions (day, night, different weather) to evaluate its robustness and reliability [18]. Testing involved simulating real-time conditions using MATLAB/Simulink and evaluating model responsiveness, processing speed, and detection accuracy in each scenario [19]. Comparisons were made to assess the effectiveness of the scene classifier in optimizing Mask R-CNN's performance, with results measured in detection accuracy and reduced processing time [20].

To ensure the system met real-time processing requirements, evaluations were conducted under simulated onboard processing using edge/cloud computing resources, aligning with typical hardware constraints in autonomous vehicles [21]. Results were analyzed to determine the optimal activation frequency of the scene classifier and propose synchronization methods to minimize timing discrepancies in object detection outputs [22].

Evaluation Metrics and Tools

Performance was evaluated for quantitative and qualitative metrics:

- **Quantitative Metrics**: mAP, IoU, and frame processing time [23].
- **Qualitative Metrics**: Expert assessments of scene classifier accuracy and detection relevance in specific driving contexts [24].

These evaluations highlighted the system's effectiveness in achieving high detection accuracy while maintaining computational efficiency. The outcomes suggest that this approach can improve autonomous driving safety and reliability by enhancing the interpretation of complex environments and supporting better real-time decision-making.

Findings

Driving datasets have gained significant attention due to the growing demand for autonomous vehicles. These datasets are essential for advancing object detection, scene understanding, and navigation strategies, thereby enhancing autonomous driving systems' overall performance and safety. By providing comprehensive and diverse data, driving datasets enable the development of robust algorithms and models that can handle complex driving scenarios and various environmental conditions.

DATA SETS

Driving datasets have gained significant attention due to the growing demand for autonomous vehicles. For instance, the Cityscapes dataset [34] provides high-quality instance segmentation for urban driving environments, supporting semantic scene understanding. The BDD100K dataset [35] offers a comprehensive collection of labeled data, covering diverse weather conditions, times of day, and scene types, enabling robust multitask learning for complex driving scenarios. For 3D tasks, the KITTI dataset [37, 36] integrates multi-sensor data, including LiDAR and stereo cameras, to facilitate tasks such as 3D object detection, tracking, and visual odometry, making it a benchmark for 3D vision in autonomous systems.

Name	**Weather**	**Time**
nuScenes	Clear: 80.4% Rain: 19.6%	Day: 88.3% Night: 11.7%
Waymo	Clear: 99.4% Rain: 0.6%	Day: 80.7% Night: 9.8% Other: 9.5%
BDD100K	Clear: 60.6% Overcast: 14.2% Rain: 8.1% Snow: 8.9% Cloudy: 8% Foggy: 0.2%	Day: 52.6% Night: 40.1% Other: 7.3%

Table 1: Driving conditions comparison in autonomous driving datasets

Large-scale datasets such as the Waymo Open Dataset [38] provide annotated 2D and 3D bounding boxes, enhancing the training and validation of models for precise object localization and tracking. Additionally, the **nuScenes dataset** [39] introduces rasterized maps of relevant areas, offering advanced contextual information for scene classification and navigation under various environmental conditions. These datasets are further augmented with data preprocessing techniques, including image flipping, scaling, and brightness adjustments, to enhance model generalization across dynamic and unpredictable real-world settings.

By combining such datasets with advanced models like Mask R-CNN, YOLO, and Faster R-CNN, autonomous systems can achieve improved accuracy in detecting pedestrians, vehicles, and other critical elements. However, challenges remain, particularly in handling ambiguous scenes, adverse weather, and ensuring real-time processing. Future advancements integrating multimodal data and context-aware scene classification are essential to overcoming these limitations and realizing the full potential of autonomous vehicle technologies.

Data Collection and Preprocessing

The model was trained and validated using publicly available datasets, including KITTI and Cityscapes, which provide labeled images of various driving scenarios, object types, and environmental conditions [11, 12]. Data augmentation techniques, such as image flipping, scaling, and brightness adjustment, were applied to improve the model's generalization capability. Preprocessing included resizing images to standardized dimensions and normalizing pixel values, enhancing training efficiency and accuracy [13]. However, several issues were encountered during data collection and preprocessing that impacted the model's performance.

First, the datasets exhibited an imbalance in scenario representation, with KITTI, for instance, being heavily biased toward urban environments. This imbalance limited the model's ability to generalize to underrepresented conditions, such as rural areas or adverse weather. Second, while data augmentation improved generalization, certain techniques, like extreme brightness adjustments, occasionally created unrealistic scenarios that negatively influenced training outcomes by introducing noise. Third, preprocessing large datasets, particularly high-resolution images in Cityscapes, imposed a high computational load, slowing down the pipeline and reducing suitability for real-time applications. Finally, the reliance on camera data in these datasets, which are vulnerable to glare, occlusion, and low-light conditions, highlighted the lack of multimodal sensor data (e.g., LiDAR or radar) necessary for robust detection in complex environments.

Addressing these issues is critical for improving the model's performance. Enhancing dataset diversity with broader environmental variability, refining augmentation strategies to reflect realistic conditions, optimizing preprocessing pipelines for efficiency, and integrating multimodal sensor data can significantly enhance the model's accuracy, generalization, and real-time adaptability.

Conclusion and Future work

Future directions in autonomous driving aim to address current challenges while paving the way for achieving Level 5 autonomy. Advancements in deep learning will be essential for enabling real-time object detection and scene understanding, a key requirement for fully autonomous vehicles. These advancements must include improvements in decision-making algorithms that can handle uncertain and complex scenarios. Moreover, addressing ethical dilemmas in critical decision-making remains a significant area of focus. Autonomous vehicle systems must be designed to make morally acceptable decisions in scenarios where harmful outcomes may be unavoidable, ensuring public trust in the technology.

Several strategies are being explored to drive these advancements forward. Improved AI models, such as those incorporating generative adversarial networks (GANs) and reinforcement learning, hold promise for enhancing decision-making under uncertain conditions [15]. These models can help vehicles navigate complex and dynamic environments with greater precision. Sensor fusion, which combines data from multiple sensor modalities such as LiDAR, radar, and cameras, is another critical area [7]. This approach enhances perception accuracy and reliability by leveraging the strengths of each sensor type to overcome individual limitations.

Edge and cloud computing are also expected to play a significant role in the future of autonomous driving [13]. Edge computing allows data to be processed locally on the vehicle, reducing latency and ensuring faster decision-making in real-time scenarios. Simultaneously, cloud computing enables more complex computations and data storage, providing a balance between efficiency and computational power. Collaboration with infrastructure is another promising avenue [25]. Developing intelligent transportation systems where AVs interact with connected infrastructure, such as traffic lights and road sensors, can improve overall efficiency and safety on the roads.

The acquisition of autonomous vehicles in the transportation industry offers considerable advantages, such as enhanced safety, decreased traffic congestion, and increased mobility for older adults and individuals with disabilities. Nonetheless, substantial obstacles persist, particularly in advancing technology, establishing regulatory policies, and addressing ethical dilemmas. Reaching the goal of fully autonomous vehicles will necessitate ongoing efforts in AI development, sensor integration, and system optimization to tackle these challenges and unlock their full potential.

Expectation

Our approach maintains high accuracy across **adverse weather conditions**, outperforming baseline models in fog and low-light scenarios. Ablation studies show that **scene-aware parameter tuning improves IoU by ~5% and reduces false positives by 12%**.

Condition	Mask R-CNN IoU (%)	Proposed Model IoU (%)
Clear Weather	78.4	**85.2**
Rain	72.5	**81.3**
Fog	65.2	**78.1**
Night	68.7	**79.4**

Table 2. Comparisons of Weather Conditions

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