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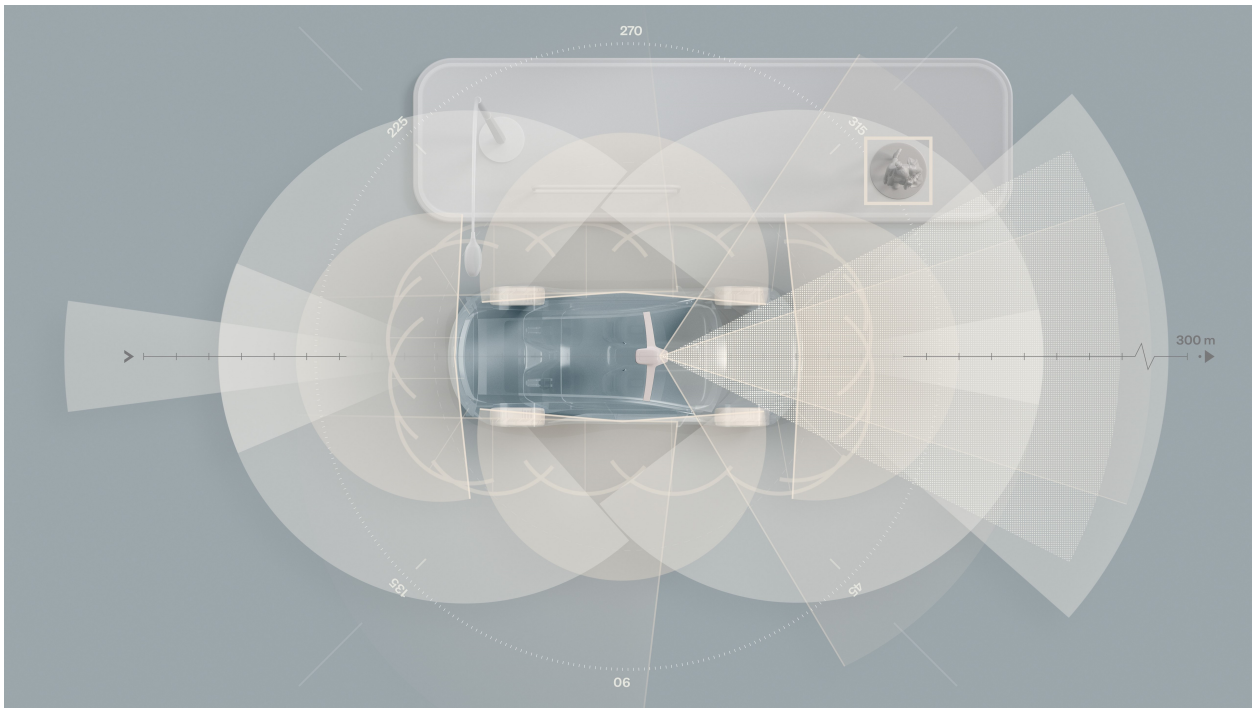

Enhancing Safety in AI-Based Object Detection for Autonomous Vehicles Through Out-of-Distribution Monitoring

Master's thesis in Systems, Control and Mechatronics

Yongzhao Chen, Luming Wang

DEPARTMENT OF ELECTRICAL ENGINEERING

CHALMERS UNIVERSITY OF TECHNOLOGY
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Abstract

The advent of Artificial Intelligence (AI) has revolutionized the automotive industry, introducing advanced functionalities such as object detection in autonomous vehicles. However, the inherent weaknesses of AI systems—including prediction uncertainties, limited interpretability, and susceptibility to adversarial attacks—pose significant safety risks. Existing safety standards like ISO 26262 and ISO 21448 are inadequate for addressing the non-deterministic and probabilistic nature of AI systems. This thesis addresses these challenges by developing and implementing a novel monitoring mechanism based on out-of-distribution (OOD) anomaly detection to enhance the reliability and safety of AI-based object detection systems in autonomous driving.

A comprehensive simulation platform was developed using the Carla software to generate street scene images, ensuring complete data autonomy and enabling future scenario simulations for robust validation. The methodology compared the direct use of training images with the extraction and analysis of feature values from hidden layers of deep learning models. Through iterative testing and scenario-based clustering, a feature distance method based on hidden layer outputs was identified as an effective metric for implementing the monitoring mechanism. This approach enhances the system's ability to detect anomalies and distributional shifts in real-time, addressing safety concerns associated with AI unpredictability.

Experimental results demonstrate a global negative correlation between model performance and feature distance, effectively identifying outliers—such as irrelevant animal images—that deviate significantly from the operational design domain data. The feature distance method improves the detection rate of out-of-distribution samples, proving its industrial applicability within the simulation environment. While real-world testing was not conducted in this study, future work will focus on validating the proposed mechanism in actual autonomous driving systems.

This thesis contributes to the research field by introducing a viable safety strategy for AI-implemented automotive functions, aligning with emerging safety standards tailored for AI systems. The proposed monitoring approach holds potential for patent development and future integration into Advanced Driver-Assistance Systems (ADAS) and Autonomous Driving (AD) products. Future research will extend this mechanism to other AI functionalities and explore its scalability and efficiency in real-world scenarios.

Keywords: AI safety, out-of-distribution detection, object detection, autonomous driving, CARLA Simulation, ISO 26262.

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Our sincere thanks also go to our industrial partner, Volvo Car Corporation, for providing the essential tools, funding, and guidance needed for this project. Their support was crucial to the completion of our work. Additionally, we extend our gratitude to Chalmers University of Technology for their invaluable guidance and support during this endeavor.

Lastly, we want to express our heartfelt appreciation to our family and friends. Their unwavering support and encouragement inspired us to persevere and reach this important milestone.

Yongzhao Chen & Luming Wang, Gothenburg, September 2024

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

AI	Artificial Intelligence
AD	Autonomous Driving
ADAS	Advanced Driver Assistance Systems
mAP	mean Average Precision
OOD	Out-of-Distribution
ODD	Operational Design Domain
OMS	Operational Model Scope
ISO	International Organization for Standardization

Contents

List of Figures

List of Tables

1
Introduction

1.1 Research Background

The rapid advancement of artificial intelligence (AI) has brought about significant benefits and applications across various fields. However, it also introduces several inherent risks and uncertainties, particularly concerning the reliability and trustworthiness of AI models. Ensuring that model inputs fall within the model's operational scope and that outputs can be trusted is a critical challenge. This challenge stems from the mathematical and theoretical uncertainties inherent in AI systems. Nguyen *et al.* discuss these uncertainties and the challenges they present in AI safety research [1]. Additionally, Zhang *et al.* provide a comprehensive survey on reliability and trustworthiness in AI models, highlighting the importance of addressing these issues in critical applications [2].

In the automotive industry, the application of AI has raised substantial safety concerns. The uncertainty in AI-based systems can lead to unpredictable behaviors, which is particularly concerning in safety-critical applications. Zhao *et al.* explore current techniques and open issues related to the safety testing of AI in autonomous vehicles [3]. Varshney and Wang also discuss the broader challenges and methods for ensuring AI safety in transportation systems [4]. Traditional methods to ensure safety, such as scenario-based testing, focus on defining OOD by limiting the environment and road conditions and conducting extensive testing within these constrained environments.

A crucial aspect of the research presented in this MSc thesis report is defining the model scope, including concepts like ODD, and OMS. Liang *et al.* present distance-based methods for OOD detection to help define the distribution of data encountered by AI models [5]. Similarly, Lin *et al.* propose advanced ensemble methods for detecting OOD data, contributing to the model's robustness in operational settings [6].

1.2 Research Questions

The key research questions addressed in this study are:

- Which system parameters are most effective for implementing successful OOD detection in an AI-based object detection system?
- To what extent does the OOD-based monitoring mechanism improve the performance and reliability of the object detection system in both controlled and real-world conditions?

- What are the potential applications of the OOD-based monitoring mechanism in industrial settings, and what factors influence its practical feasibility?
- What general design principles can guide the integration of OOD-based monitoring in AI systems to enhance reliability and robustness?

1.3 Research Objectives

The objectives of this research are:

- To explore effective OOD detection methods, focusing on suitable system parameters (e.g., feature distance metrics, confidence scores) that enable reliable monitoring within an AI-based object detection system.
- To implement and test the selected OOD-based monitoring approach, assessing its impact on system performance metrics such as detection accuracy, robustness, and reliability.
- To evaluate the degree of improvement in system performance attributable to the OOD-based monitoring mechanism.
- To assess the feasibility of the developed monitoring mechanism for industrial applications, considering scalability, integration challenges, and cost-effectiveness.
- To provide general design recommendations for implementing OOD-based monitoring in AI systems, aimed at enhancing reliability across various application contexts.

1.4 Thesis Structure

The structure of this thesis is outlined as follows:

- **Chapter 1: Introduction** - Provides the background, research questions, objectives, and an overview of the thesis structure.
- **Chapter 2: Literature Review** - Reviews relevant literature on AI safety, OOD methods, and monitoring mechanisms in the context of automotive applications.
- **Chapter 3: Methods** - Describes the methodologies used for data collection, model training, feature extraction, and the development of the monitoring mechanism.
- **Chapter 4: Results** - Presents the findings from the experiments and analyses conducted during the research.
- **Chapter 5: Discussion** - Discusses the implications of the results, the effectiveness of the monitoring mechanism, and the overall contributions to the research field.
- **Chapter 6: Conclusion and Future Work** - Summarizes the key conclusions and suggests directions for future research.

2

Literature Review

The application of artificial intelligence (AI) in various domains, particularly in safety-critical systems like autonomous driving, necessitates a thorough understanding of the underlying risks and methodologies to ensure reliable and trustworthy outputs. This literature review delves into several key areas to establish a foundational understanding of the current state of research and practice, emphasizing the latest developments in AI safety.

2.1 AI and Its Inherent Uncertainties

Artificial intelligence models, especially those based on deep learning, exhibit inherent uncertainties due to their complex and often opaque nature [7]. These uncertainties can be broadly categorized into two types: epistemic and aleatoric. Epistemic uncertainties, also known as model-related uncertainties, arise from the limitations of the model and its understanding of the data [8]. In contrast, aleatoric uncertainties are data-related and arise from the inherent noise and variability inherent to the data itself. These uncertainties have the potential to significantly impact the reliability of AI models, this is particularly the case in applications where safety is of paramount importance, such as autonomous driving. Recent studies have focused on reducing both types of uncertainties through methods like Bayesian deep learning, which integrates uncertainty estimates directly into the model [9, 10].

2.2 AI in the Automotive Industry

AI applications in the automotive industry, such as autonomous driving, bring significant safety challenges [11]. The deployment of AI in this field requires models that can function reliably under dynamic and unpredictable conditions. Ensuring the reliability of AI systems in these contexts is paramount. The use of neural networks, although powerful, introduces a layer of unpredictability due to their sensitivity to input data variations and the potential for out-of-distribution inputs. AI's role in autonomous vehicles also raises legal, ethical, and regulatory questions, as pointed out in recent literature [12, 13]. These issues underscore the need for robust methods to ensure that AI systems can operate safely and explainably in real-world environments.

2.3 OOD and Scenario-Based Testing

Scenario-based testing remains a cornerstone for validating autonomous driving systems by establishing predefined ODD that limit the operational scope to specific environmental conditions and driving scenarios [55, 15]. Recent advancements in scenario-based testing focus on improving the scalability and realism of test environments using synthetic and simulation-based platforms, which allow for the generation of a much wider range of test cases than traditional physical testing [16, 17]. These methods have highlighted the limitations of relying solely on ODD, as real-world variability is challenging to capture in predefined scenarios, particularly when considering edge cases and rare events [18].

2.4 OOD Detection

Detecting OOD inputs is a critical aspect of ensuring AI model reliability [19]. OOD inputs are those that differ significantly from the data that the model was trained on, potentially causing the model to behave unpredictably. In the context of autonomous driving, OOD detection ensures that the AI system can identify when it encounters a situation that falls outside its training distribution. Various OOD detection methods have been developed, such as distance-based techniques [20] and likelihood-based methods [21], both of which have shown promise in improving system robustness. Recent research has explored combining these techniques with uncertainty estimation to provide a more holistic approach to OOD detection [22, 23].

2.5 Operational Model Scope

The concept of OMS extends ODD by focusing specifically on the model's operational limits [24]. While ODD defines external environmental limits, OMS defines the internal limits of what the model can handle based on its training. Recent research has introduced methods to dynamically adapt OMS based on real-time data, allowing the model to adjust its operational limits as new information becomes available [25]. This ensures that the AI model continues to perform reliably even as it encounters new scenarios that may not have been explicitly covered during training.

2.6 Defining Data Distribution

Accurately defining the data distribution is essential for both OOD detection and OMS. Distance-based methods, such as Mahalanobis distance and Euclidean distance, have been commonly used to quantify deviations from the training data distribution [20, 26]. These methods help establish thresholds that can alert the system when it is operating outside of its normal range. In recent work, researchers have also looked into integrating feature-based distance metrics to enhance detection precision, especially in complex, high-dimensional input spaces [27, 28].

2.7 Monitoring Mechanisms in AI Systems

Effective monitoring mechanisms are crucial for maintaining AI system reliability, especially in real-time applications such as autonomous driving [29]. These mechanisms need to detect anomalies or OOD inputs and respond in a timely manner to ensure safe operation. Real-time monitoring systems have been developed to integrate OOD detection with uncertainty estimation, providing a more robust safety net for AI models in dynamic environments [30, 31]. The use of hybrid approaches combining traditional rule-based monitoring with AI-based anomaly detection has proven effective in enhancing system robustness and safety [32, 33].

2.8 Summary

This literature review highlights the critical aspects of AI safety in autonomous driving, including the inherent uncertainties of AI models, the limitations of scenario-based testing, and the importance of OOD detection and OMS. Recent advances in the field have focused on improving robustness through a combination of uncertainty estimation, real-time monitoring, and adaptive models that can adjust their operational limits dynamically. By exploring these areas, the review sets the stage for developing a robust monitoring mechanism that leverages distance-based methods and real-time anomaly detection to improve system performance and reliability in autonomous driving environments.

3
Methodology

This chapter delineates the methodological approach used in this study to address the research questions outlined in Chapter 1. The methodology encompasses five primary components: (1) the development of a robust monitoring mechanism, (2) the utilization of the Carla simulation platform for data generation, (3) data augmentation and preprocessing techniques, (4) the training and optimization of a YOLOv5 object detection model, and (5) the implementation of a distance-based OOD detection method. Each component is designed to contribute to the overarching goal of enhancing the reliability and safety of AI systems in autonomous driving applications.

3.1 Monitoring Mechanism

3.1.1 Theoretical Foundation

The monitoring mechanism developed in this study is grounded in the theoretical framework of anomaly detection in high-dimensional spaces [34]. This approach is particularly relevant to autonomous driving systems, where the detection of out-of-distribution data is crucial for maintaining system reliability and safety. The mechanism builds upon the concept of statistical distance measures in feature space [35], to identify anomalies in real-time data streams.

3.1.2 Principles and Design

The fundamental principle of the monitoring mechanism is to ascertain the validity and suitability of incoming data before it is processed by the AI system. This mechanism acts as an intermediary that scrutinizes data for potential anomalies or deviations from the expected distribution, thereby ensuring that the AI system operates within its defined scope. The design is inspired by the work of Hendrycks and Gimpel [36] on baseline approaches for detecting out-of-distribution examples in neural networks.

The design of the monitoring mechanism integrates seamlessly into the AI framework through a series of well-defined steps:

1. **Data Reception**: The mechanism initially captures incoming data from various sensors and inputs.
2. **Data Assessment**: Using advanced statistical techniques, the mechanism evaluates whether the data falls within OMS. This step involves the detection of OOD data, which the AI system may not be adequately trained to handle.

3. **Decision Making**: Based on the assessment results, the mechanism determines the suitability of the data for AI system processing. If deemed unsuitable, it triggers the generation of a failure data report.
4. **Failure Reporting**: When unsuitable data is identified, a comprehensive failure data report is generated and communicated to the user or logged for further analysis.

3.1.3 Implementation

The implementation involves a combination of software processes and algorithmic evaluations, structured as follows:

1. **Preprocessing**: Incoming data undergoes preprocessing to ensure standardization and quality, including normalization and cleaning steps. This process prepares the data for consistent evaluation in subsequent steps.
2. **Feature Extraction**: Multiple neural network architectures were evaluated for feature extraction, including ResNet-50 and ResNet-100 [51], as well as the feature extraction network within the YOLO object detection system itself [39]. Both the official YOLO pretrained parameters and custom parameters trained specifically for this project were considered.
3. **Threshold Determination**: A threshold for OOD detection was determined based on the feature distribution in the training data. This threshold acts as a reference point for distinguishing in-distribution data from potential OOD data.
4. **Distance-Based OOD Detection**: Using the established threshold, the monitoring mechanism applies a distance-based approach (e.g., Euclidean distance) to identify OOD samples. The mechanism calculates the distance between incoming data features and the feature space of the training data, flagging data points that exhibit significant deviations as potentially out-of-distribution.
5. **Continuous Monitoring**: The mechanism is designed for continuous, real-time monitoring of incoming data, offering ongoing assessments to ensure that only data within acceptable bounds is processed by the AI framework.

3.1.4 Integration with AI System Architecture

The monitoring mechanism is designed to seamlessly integrate with the architecture of the AI system. Figure 3.1 illustrates the flow of data through the monitoring mechanism and its interaction with other components of the system.

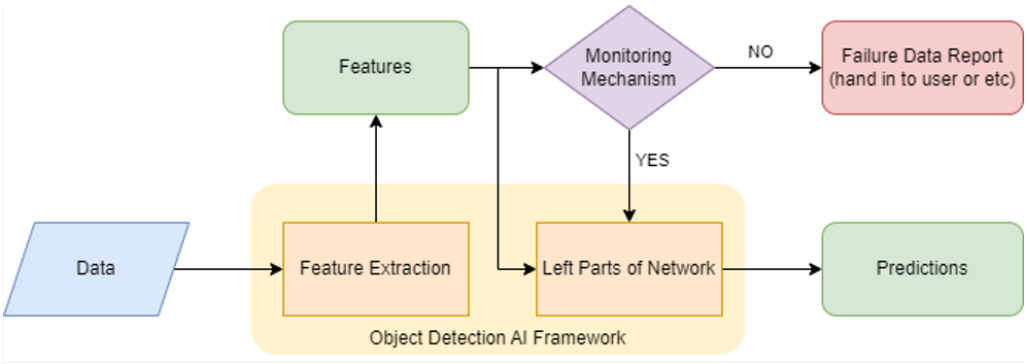

Figure 3.1: Conceptual Framework of the Monitoring Mechanism

This integration aims to minimize any additional latency or computational load on the system, which is essential to maintain the real-time performance required in autonomous driving applications. The main components involved in this integration are:

- **Data Input and Initial Processing**
  The framework initiates with image preprocessing following the idea of the YOLO methodology.
  The preprocessing pipeline includes image resizing to a fixed network input dimension, which ensures the later feature extraction has a universal output dimension, and normalization of pixel values to [0,1] range.
  These operations standardize the input format while enhancing the model's robustness to various image conditions.
- **Feature Extraction Module**
  The Feature Extraction module constitutes a fundamental component, characterized by the following attributes:
  - **Architectural Consistency**: Using unified network architecture and parameters in feature extraction as the original object-detection network, ensures coherent feature representations throughout the system.
  - **Computational Optimization**: Using extracted features for both monitoring and detection functionalities, minimizing computational redundancy and enhancing real-time processing capabilities.
- **Monitoring Mechanism**
  The monitoring system evaluates extracted features to determine the characteristics of the data distribution.
  - **Within-Distribution(ID) Processing**: For ID data identified, the system facilitates progression through subsequent network layers for object detection and prediction generation.
  - **Anomaly Detection**: Upon identification of the OOD data, the system initiates diversion protocols and generates comprehensive Failure Data Reports, incorporating relevant metadata for analysis.
- **Failure Data Management**
  The framework implements systematic protocols for the handling of OOD data, generating detailed analytical reports that facilitate user intervention, activation of the safety protocol, and optimization of the threshold during the

testing phases.

- **Prediction Generation and Output**
  For validated ID data, the system processes the extracted features through the prediction module, generating outputs for integration with AD/ADAS systems, enabling real-time operational decision making.

3.1.5 Characteristics Required for a Monitoring Mechanism

To ensure the effectiveness and efficiency of the monitoring mechanism, several key characteristics have been identified and implemented:

1. **Synchronization with AI Functional System**: The performance of the monitoring mechanism is designed to change synchronously with the AI functional system. This is achieved through a shared state management system, ensuring that the monitoring mechanism accurately reflects the system's current state and performance.
2. **Low Complexity and Performance Overhead**: The monitoring mechanism is designed to operate with lower complexity than the AI system, ensuring minimal computational burden.
3. **Universality and Adaptability**: The monitoring mechanism is designed to be universally applicable across different AI systems in the autonomous driving domain, requiring minimal adaptation to fit various models and architectures. This flexibility enhances its applicability and allows it to support a wide range of AI applications.

In summary, the monitoring mechanism plays a vital role in ensuring the AI system's reliability and safety by rigorously assessing incoming data and filtering out unsuitable inputs. This mechanism is particularly crucial in autonomous driving applications, where the consequences of processing erroneous data can be severe. The implementation described here represents a significant advancement in real-time monitoring of AI systems, combining theoretical rigor with practical considerations for deployment in safety-critical applications.

3.2 Platform

3.2.1 Carla Data Collection Platform

Carla is an open-source urban traffic simulator designed specifically for autonomous driving research [40]. It provides realistic urban and rural environments, supports various sensor configurations, and allows users to test and validate autonomous driving algorithms under different traffic conditions. The openness and high customizability of Carla make it an ideal choice for both academic research and industrial applications.

Platform Features

Based on the Carla platform, we have built a highly automated data collection platform. Its features include multi-car cooperative data collection, RGB cameras,

instance segmentation cameras, automated data labeling tools, and data quality inspection tools. These features enable the efficient generation of high-quality training data.

1. **Multi-Car Cooperative Data Collection**
   - Multiple cars drive synchronously to collect data on a selected map, covering a wider area and collecting richer data compared with only using one host vehicle to collect data within the same amount of time.
   - Supports offscreen rendering, which reduces the computational load on the system and enables smoother and more efficient data collection.
   - Supports loading settings from pre-defined parameters and automatic execution.
   - The platform can collect 2300 images under Epic graphic quality [41] in 40 minutes.
2. **One-Click Auto Data Collection**
   - Users can start the data collection process with a single click, greatly simplifying the operation.
   - This feature reduces human intervention, increasing the efficiency and consistency of data collection.
3. **Multi-Progress Label Tool**
   - Based on Carla's built-in instance segmentation camera and RGB camera, it achieves pixel-level accuracy in object contours without human intervention.
   - This tool can label 2300 images in two minutes, significantly speeding up data preparation.
   - Supports multiple label formats and can be customized according to needs.
4. **Data Inspect Tools**
   - Provides a human-machine interface that allows users to view and check the quality of each image.
   - Users can set the inspection interval to ensure that the data quality meets the training requirements.
5. **Label Inspect Tool**
   - Checks the match between label results and original data, and displays the results on the screen.
   - Allows users to set the number of images to be inspected at once (default is 8) and to set inspection intervals to improve efficiency.
   - This tool ensures the accuracy and consistency of data labeling.
6. **Training Set Format Tools**
   - The dataset was partitioned into training and validation sets using Scikit-learn's `train_test_split` function, which ensures a randomized yet stratified split to maintain class distribution balance. Additionally, a custom dataset remixing tool was used to harmonize data from diverse maps, achieving uniform mixing through iterative polling and mitigating potential data bias during the training process.

3.2.2 Data generation and augmentation

This section presents the data generation process and environmental settings used in our research. The choice of simulation environment and map characteristics is crucial for developing and validating the proposed OOD monitoring mechanism, as it allows us to test the system under various controlled yet realistic scenarios.

Data pattern analysis

Carla provides a variety of maps with different characteristics, as shown in Table 3.1. These official maps offer several advantages for our research: they are thoroughly tested for stability, feature realistic road designs, and present diverse driving scenarios ranging from urban to rural environments.

Table 3.1: Carla Map Characteristics

Map Name	Description
Town01	A small, simple town with a river and several bridges.
Town02	A small, simple town with a mixture of residential and commercial buildings.
Town03	A larger, urban map with a roundabout and large junctions.
Town04	A small town embedded in the mountains with a special "figure of 8" infinite highway.
Town05	Squared-grid town with cross junctions and a bridge. It has multiple lanes per direction. Useful to perform lane changes.
Town06	Long, multi-lane highways with many highway entrances and exits. It also has a Michigan left.
Town07	A rural environment with narrow roads, corn fields, barns, and hardly any traffic lights.
Town08	A secret "unseen" town used for the Leaderboard [42] challenge.
Town09	Another secret "unseen" town used for the Leaderboard challenge.
Town10	A downtown urban environment with skyscrapers, residential buildings, and an ocean promenade.
Town11	A large, undecorated map that serves as a proof of concept for the Large Maps feature.
Town12	A large map with numerous different regions, including high-rise, residential, and rural environments.

While these maps primarily represent US-American urban and road environments, this geographical specificity does not significantly impact our research objectives. The primary focus of this study is to evaluate the effectiveness of the OOD monitoring mechanism in improving object detection reliability, which is fundamentally independent of the specific geographic characteristics of the training data. The

underlying principles of our monitoring mechanism are designed to be generalizable, focusing on the structural aspects of feature distribution rather than the specific environmental contexts. The methodology can be readily applied to different geographical settings, provided appropriate training data is available.

Through our manual inspection and preliminary clustering analysis, these maps can be classified into two distinct categories:

- **Urban Mode**: Represented by Town10, it includes various urban roads, buildings, and traffic facilities.

Figure 3.2: Town 10 scene in Carla

- **Countryside Mode**: Represented by Town07, it encompasses rural roads, farmland, and natural scenery.

Figure 3.3: Town 7 scene in Carla

The data collection process was conducted across the seven compatible maps described above. For each map, we collected 40,000 images at a resolution of 640×640 pixels(hereafter referred to as the 40K dataset). Following a data cleaning process that removed invalid samples (defined as images containing no labelable instances), the final dataset comprised 32,608 valid street scene images. This filtering step was

necessary to ensure the quality and relevance of the training data, as images without detectable objects would not contribute meaningfully to the model's learning process.

Noise Datasets In-vehicle cameras often capture images with noise or even damage due to factors such as dust and stains, leading to a loss of critical information. Noise datasets incorporate Mosaic noise and Gaussian noise, applied to the images to mimic these conditions. Each town's original dataset contains 3 000 images. To simulate real-world conditions, over 20 levels of Gaussian and Mosaic noise are added to these images, generating noise datasets for testing. This approach helps in evaluating the model's performance under various noisy conditions.

Figure 3.4: Comparison of Original Image (left) with Gaussian Noise (center) and Mosaic Noise (right)

Figure 3.4 illustrates the impact of different noise types on an original image from our dataset. The left image (a) shows the original, unmodified scene. The center image (b) demonstrates the effect of applied Gaussian noise, which adds a granular texture across the entire image. The right image (c) shows the result of Mosaic noise, which creates a blocky, pixelated effect. These examples visually represent the range of distortions our model must contend with in our noise robustness tests.

Irrelevant Datasets The irrelevant datasets are sourced from the COCO dataset [43], which includes over 80 different tags. For each tag, 500 images are extracted for testing. These datasets are used to test the AI system's ability to ignore irrelevant information and maintain focus on the relevant data for accurate decision-making.

3.3 YOLOv5 Model Implementation and Training

The YOLO family represents a significant milestone in object detection architectures, evolving through multiple iterations from YOLOv1 to YOLOv8. Each version has introduced architectural innovations and performance improvements.

3.3.1 The reason for choosing YOLOv5

In the development of the proposed OOD monitoring framework, we opted to use the YOLOv5 architecture as our primary object detection model. The selection of

YOLOv5 was predicated on several key factors:

- **Balanced Complexity** YOLOv5 offers a more moderate level of complexity compared to its successors (YOLOv6 and YOLOv7). While these later versions provide incremental improvements, YOLOv5 presents a more accessible architecture for in-depth analysis and interpretation.
- **Established Performance** YOLOv5 has demonstrated robust performance across various object detection benchmarks [44], providing a solid foundation for our research objectives.
- **Community Support** The extensive community support and documentation available for YOLOv5 facilitate easier implementation and troubleshooting throughout the research process.

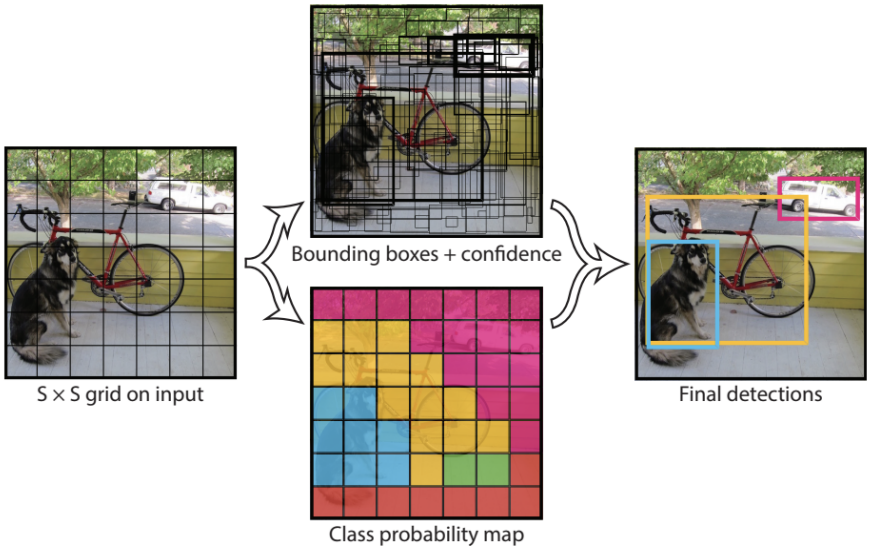

Figure 3.5: Basic Architecture of YOLO (You Only Look Once)

Figure 3.5 illustrates the basic architecture of YOLO. The model divides the input image into a grid and predicts bounding boxes and class probabilities for each grid cell, enabling fast and efficient object detection.

3.3.2 The reason for choosing Small version of YOLOv5

YOLOv5 provides several model variants that offer different trade-offs between computational efficiency and detection accuracy. These variants, denoted as YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x, are distinguished by their network architectures and parameter scales:

- **YOLOv5n (Nano)**: The most lightweight variant, designed for deployment on edge devices and resource-constrained environments. While sacrificing some detection accuracy, it achieves minimal inference time and memory footprint.
- **YOLOv5s (Small)**: A balanced model offering improved detection accuracy over the nano variant while maintaining reasonable computational requirements. This variant is suitable for applications with moderate computational resources.

- **YOLOv5m (Medium)**: Represents an intermediate solution with enhanced feature extraction capabilities. The medium variant achieves higher detection accuracy through increased network depth and width, while still maintaining acceptable inference speed.
- **YOLOv5l (Large)**: Incorporates a more sophisticated network architecture with significantly more parameters, resulting in superior detection performance. This variant is appropriate for scenarios where computational resources are not a primary constraint.
- **YOLOv5x (Extra Large)**: The most comprehensive variant, featuring the deepest and widest network architecture. While demanding substantial computational resources, it achieves the highest detection accuracy among all variants.

Each variant progressively increases network depth, width, and subsequently, the number of parameters, establishing a clear trade-off between computational complexity and detection performance. The selection of an appropriate variant depends on the specific requirements of the application, considering factors such as available computational resources, required inference speed, and target detection accuracy.

Within the YOLOv5 family, we adopted the YOLOv5s variant for our experimental framework. This selection was supported by comprehensive benchmarking results from both empirical studies and practical applications. Horvat et al. [45] conducted a thorough comparative analysis of YOLOv5 variants, demonstrating that YOLOv5s achieves an optimal balance between accuracy, computational cost, and inference speed.

According to their experimental results, YOLOv5s demonstrates significant performance advantages while maintaining computational efficiency. In terms of detection accuracy, it achieves a mAP@0.5 of 56.0% compared to YOLOv5n's 46.0%, where mAP (mean Average Precision) represents the model's average detection accuracy across all object classes with an IoU threshold of 0.5. This substantial improvement in accuracy comes with minimal computational overhead: YOLOv5s requires only marginally longer training time (6.4 versus 6.3 seconds per epoch) while actually achieving faster inference speed (7.5 ms versus 7.8 ms per image) compared to YOLOv5n.

While larger variants (YOLOv5m, YOLOv5l, and YOLOv5x) achieve higher accuracy, they demand significantly more computational resources. For instance, YOLOv5m improves mAP@0.5 to 63.9% but nearly doubles the training duration to 8.2 seconds per epoch. The largest variant, YOLOv5x, achieves the highest accuracy (68.9%) but requires substantially more resources, with training time exceeding 12 seconds per epoch and inference time increasing to 35.3 ms.

These empirical findings support our selection of YOLOv5s, as it provides an effective compromise between detection accuracy and computational efficiency, making it well-suited for the development and validation of our proposed monitoring mechanism where balanced performance characteristics are essential.

3.3.3 Training Process and Model Configuration

The training process of our YOLOv5 model was designed to align with the specific demands of the ODD monitoring mechanism while accommodating the hardware constraints of our NVIDIA RTX 4000 GPU (8GB VRAM). The model was trained on the 40K dataset described in Section 3.2.2 (Data generation and augmentation), which comprises 32,608 valid street scene images collected from seven CARLA maps. Below, we outline the key training configurations and the rationale behind each choice.

Image Size and Feature Consistency

The input image size was fixed at 640×640 pixels, deviating from YOLOv5's default adaptive scaling (which adjusts the longest side to 640 and the shorter side to the nearest multiple of 32). This fixed resolution ensures consistent feature map dimensions across all images, a critical requirement for the downstream feature extraction process in our monitoring mechanism.

Batch Size Optimization

The batch size was set to 28, determined through empirical testing to maximize GPU utilization without exceeding memory limits. Larger batch sizes enhance training efficiency by allowing more parallel computations, but in this case, our chosen size balanced hardware constraints with gradient stability.

Learning Rate Schedule

We maintained the default learning rate of 0.01, combined with cosine decay scheduling. This schedule, validated extensively by the YOLOv5 team across diverse datasets, allows for gradual learning rate reduction, promoting stable convergence during the later stages of training.

Epochs and Early Stopping

Training was conducted for up to 600 epochs, with early stopping triggered if validation loss did not improve over 10 consecutive epochs. This approach ensured comprehensive learning while minimizing overfitting.

Class Label Harmonization

We updated the class labels to align with object classes in the CARLA environment. Harmonizing labels across the CARLA, COCO, and YOLO frameworks ensured consistent classification and improved model accuracy. Table 3.2 illustrates the label mappings.

Table 3.2: Cross-Dataset Class Label Harmonization

Object Class	YOLO Label	CARLA Label	COCO Label
Traffic Light	0	7	10
Traffic Sign	1	8	13
Pedestrian	2	12	1
Rider	3	13	2
Car	4	14	3
Truck	5	15	8
Bus	6	16	6
Train	7	17	7
Motorcycle	8	18	4
Bicycle	9	19	5

In summary, our training configuration involved three main adaptations: (1) Class label harmonization specific to CARLA's annotation system, (2) Modified image resizing strategy to ensure consistent feature dimensions for the ODD monitoring mechanism, and (3) Hardware-appropriate parameter settings based on YOLOv5's official guidelines. While maintaining most of YOLOv5's well-validated default configurations, these targeted modifications enabled the model to effectively support our monitoring framework while operating within our computational constraints.

3.3.4 Performance Monitoring and Evaluation

To ensure rigorous tracking of the training process and model performance, we integrated several monitoring and evaluation mechanisms:

- **Real-time Metric Tracking** We utilized Weights & Biases (referred to as wandb), an experiment tracking tool widely adopted in the machine learning community, for continuous monitoring of key performance metrics. This platform provides real-time visualization and logging capabilities for tracking essential training metrics, including loss components, mean Average Precision (mAP), and per-class accuracies. This tool enabled us to dynamically monitor the training process, detect potential issues early, and maintain comprehensive records of our experimental results.
- **Validation Strategy** A stratified k-fold cross-validation approach ($k = 5$) was used to robustly assess the model's generalization capabilities across different subsets of our dataset.
- **Overfitting Prevention** We implemented early stopping with patience of 50 epochs, monitoring the validation loss to prevent overfitting while allowing for adequate model convergence.

Final Model Performance

The culmination of our training process resulted in a model with the following characteristics:

- **Overall Precision** The final model achieved a mAP of 94% across all classes, calculated with an intersection over Union threshold of 0.5, which indicates

strong object detection and classification capabilities.

3.3.5 Performance Metric Selection: Accuracy vs. Likelihood

In evaluating object detection models such as YOLOv5, the choice of performance metrics is crucial. While confidence scores are widely used, this research prioritizes accuracy as the primary evaluation metric. This decision is grounded in both theoretical considerations and practical implications for autonomous driving applications.

Accuracy as a Primary Metric

Accuracy, defined as the ratio of correct predictions to the total number of cases evaluated, offers several advantages in the context of our research:

- **Direct Performance Indicator** Accuracy provides an unambiguous measure of the model's ability to correctly identify and classify objects, which is paramount in safety-critical applications like autonomous driving.
- **Statistical Robustness** As noted by Powers [47], accuracy offers a statistically meaningful criterion that reflects model performance across various object classes and environmental conditions.
- **Interpretability** In line with the findings of Doshi-Velez and Kim [48], accuracy is inherently more interpretable, especially for stakeholders without deep machine learning expertise, facilitating clearer communication of model performance.

Limitations of Likelihood-based Metrics

While likelihood-based metrics, including confidence scores, provide insights into model certainty, they present several limitations:

- **Calibration Sensitivity** As demonstrated by Guo et al. [38], neural networks can be poorly calibrated, leading to overconfident predictions that do not reflect true accuracy.
- **Context Dependency** Likelihood scores can vary significantly based on dataset characteristics and operational conditions, potentially obscuring true model performance [49].

Our approach aligns with recent trends in computer vision research, as exemplified by Ren et al. [50], who advocate for the use of accuracy-based metrics in safety-critical visual perception tasks.

Feature Extraction and Backbone Architecture Analysis

Feature extraction plays a critical role in the performance and generalization of object detection models. In this study, we conducted a comparative analysis of three configurations to determine the most suitable feature extraction approach for OOD detection in autonomous driving scenarios: (1) ResNet50 with pre-trained

weights, (2) YOLO backbone with pre-trained weights, and (3) YOLO backbone with project-specific weights.

Generalized Feature Extractors

The first two configurations, ResNet50 with pre-trained weights and YOLO backbone with pre-trained weights, were initially evaluated for their generalization potential in OOD detection.

- **ResNet50 with Pre-trained Weights**: ResNet50, introduced by He et al. [51], is a 50-layer deep convolutional neural network with residual connections. Its depth and residual structure mitigate the vanishing gradient problem, facilitating the training of deep networks. ResNet50's demonstrated success in various computer vision tasks made it a strong candidate for assessing general-purpose networks in OOD detection.
- **YOLO Backbone with Pre-trained Weights**: The YOLO backbone was also tested with pre-trained weights. Known for its computational efficiency, YOLO is optimized for real-time object detection tasks, making it suitable for high-speed applications like autonomous driving. The backbone's multi-scale feature extraction was expected to support OOD detection by capturing object features at various scales [52].

3.3.6 YOLO Backbone with Aligned AI Pipeline Parameters

To address the limitations observed with generalized feature extractors, we implemented the YOLO backbone using the same architecture and parameters as the AI pipeline itself. In the context of AD/ADAS systems, the AI pipeline refers to the sequence of processing stages responsible for analyzing sensor data, detecting objects, and making driving decisions. This pipeline is critical for ensuring the safety and reliability of autonomous systems [53]. The alignment of the YOLO backbone with the AI pipeline offered two main advantages:

- **Consistency in Feature Focus**: By aligning the YOLO backbone in the monitoring mechanism with the structure and parameters of the AI pipeline, we ensured that both systems were focused on the same feature space. This consistency enhances the monitoring mechanism's ability to detect OOD data in a way that closely aligns with the AI pipeline's internal representations.
- **Improved Efficiency through Shared Features**: Using an identical backbone architecture allows the AI pipeline to directly utilize the features extracted by the monitoring mechanism for data that passes the OOD check. This eliminates redundant feature extraction steps, thereby improving the overall processing speed and maintaining real-time performance.

3.4 OOD: Feature Distance-Based

3.4.1 Limitations of Scenario-based Approaches

Traditional approaches to ensuring AI system safety in autonomous driving have predominantly relied on scenario-based methods [54]. These methods attempt to define OOD through extensive testing of predefined scenarios and environmental conditions. However, this approach presents several fundamental limitations:

- **Combinatorial Explosion of Scenarios**
  - Scenario-based methods require an exhaustive enumeration of possible driving scenarios, which becomes impractical due to the combinatorial explosion of real-world conditions [55].
  - The increasing complexity of urban traffic environments further exacerbates this issue, making it challenging to achieve comprehensive testing [56].
- **Lack of Generalization**
  - Scenario-based methods often struggle to generalize to unforeseen situations, as they rely heavily on predefined test cases [54].
  - This limitation poses a significant safety risk, especially in scenarios involving rare or unexpected events that fall outside the predefined OOD [57].
- **High Costs and Time Requirements**
  - Developing and validating comprehensive scenario libraries is resource-intensive, requiring significant time and financial investments [55].
  - Physical testing of scenarios, such as on proving grounds or with simulation platforms, further adds to the cost and complexity [58].
- **Limited Adaptability to Dynamic Environments**
  - Scenario-based methods are inherently static and predefined, making them less adaptable to dynamic and evolving driving conditions [54].
  - Real-world environments often involve continuous changes, which scenario-based approaches struggle to accommodate effectively [56].

3.4.2 Feature-Based Monitoring Approaches

After examining the limitations of scenario-based approaches, we propose a feature-based methodology that leverages the inherent representational capabilities of neural networks. The fundamental premise of this approach rests on the hierarchical feature extraction capabilities of deep neural networks, particularly in their hidden layers.

Neural Network Feature Extraction

Deep neural networks, through their hierarchical architecture, progressively extract increasingly complex and abstract features from input images. This hierarchical feature extraction process has been extensively studied and validated in the literature [59, 60]. Research shows that lower layers of the network focus on capturing low-level visual features such as edges, textures, and colors, while deeper layers extract high-level semantic features, including object parts and categories [61]. These features, while potentially inscrutable to human interpretation, represent the fundamental patterns and characteristics that the network uses for object detection

and classification. The hidden layers of the network serve as feature extractors, transforming raw pixel data into increasingly sophisticated representational spaces that capture both low-level visual features and high-level semantic concepts [62].

Advantages of Feature-Based Approaches

This research, conducted as part of our work and presented in this thesis, leverages this characteristic by focusing on the feature representations learned by the network, rather than relying on human-defined scenarios. The approach is particularly advantageous because:

- It aligns naturally with the network's internal representation mechanisms;
- It captures nuanced patterns that might be overlooked in manually defined scenarios;
- It provides a continuous rather than discrete space for evaluating distribution shifts.

Different Distance Definitions and Their Prerequisites

There are several methods to define distance between data points, each with its unique characteristics and prerequisites:

1. **Euclidean Distance**
   Euclidean distance is the straight-line distance between two points in Euclidean space. It is defined as:

$$d(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}.$$

   where $x = (x_1, x_2, \ldots, x_n)$ and $y = (y_1, y_2, \ldots, y_n)$ are two points in n-dimensional space, and x_i and y_i represent the i-th coordinate of points x and y, respectively. Euclidean distance is simple to compute and interpret, making it suitable for most applications where the geometry of the data space is well-understood and roughly uniform.
2. **Mahalanobis Distance**
   Mahalanobis distance accounts for the correlations between variables and is defined as:

$$d(x, y) = \sqrt{(x - y)^T S^{-1}(x - y)},$$

   where S is the covariance matrix. This distance is useful in scenarios where the data distribution is known and significantly anisotropic.
3. **Cosine Similarity**
   Cosine similarity measures the cosine of the angle between two vectors:

$$\cos(\theta) = \frac{x \cdot y}{\|x\|\|y\|}.$$

3.4.3 Rationale for Choosing Euclidean Distance

Simplicity and Interpretability

Euclidean distance is one of the most fundamental and easily understood distance metrics. It measures the straight-line distance between two points in a Euclidean space, making it straightforward to calculate and interpret. This simplicity often

translates into ease of implementation and comprehension, which can be advantageous in practical applications. The geometric proximity provided by Euclidean distance offers a clear and intuitive measure of similarity, which is particularly beneficial in visualizing data and understanding the spatial relationships between data points.

Industry Relevance

In industries like automotive, healthcare, and finance, where OOD detection is critical for ensuring safety, reliability, and robustness, Euclidean distance has been demonstrated to be effective for anomaly detection in unsupervised settings [63, 64]. The automotive industry, for example, relies on continuous monitoring of sensor data to detect anomalies that could indicate malfunctions or hazardous situations. In such scenarios, Euclidean distance proves useful because it operates effectively without the need for supervised learning or labeled negative data (data outside the model's scope). This characteristic is particularly advantageous in real-world applications where acquiring labeled data—especially negative examples—can be challenging or infeasible. Its compatibility with unsupervised learning scenarios makes Euclidean distance an ideal choice for monitoring systems that must function reliably using only in-distribution data.

Computational Efficiency

Euclidean distance is computationally efficient, which is a significant advantage for real-time OOD detection. Its calculation involves basic arithmetic operations, allowing for quick computation even in large-scale datasets. This efficiency ensures that monitoring systems can operate in real-time, providing timely detection of out-of-distribution data without imposing a significant performance overhead on the system. This is particularly important in applications requiring immediate response to detected anomalies, such as autonomous driving systems or real-time financial fraud detection.

Versatility and Adaptability

Euclidean distance is versatile and can be adapted to various data types and structures. While primarily used for continuous numerical data, it can be extended or combined with other distance measures to handle categorical or mixed-type data. This adaptability ensures that Euclidean distance remains a valuable tool across diverse datasets and applications, further justifying its widespread use.

3.4.4 Hypothesized Monotonic Relationship with Model Performance

A fundamental hypothesis underlying our distance-based monitoring approach is the existence of a monotonic relationship between Euclidean distance in feature space and model performance metrics. The relationship is shown as below:

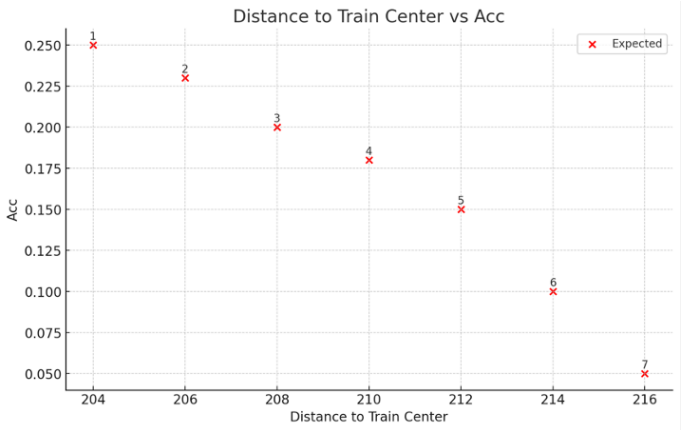

Figure 3.6: Hypothesized monotonic relationship between feature distance and model performance.

This hypothesized relationship serves as the cornerstone of our experimental framework and requires rigorous validation before implementation. The proposed relationship posits that as feature distance increases from the training distribution center, there should be a corresponding monotonic decrease in model performance metrics such as accuracy and Intersection over Union (IoU). This hypothesis is critical for several reasons:

- It forms the theoretical foundation for using distance measurements as a proxy for model reliability assessment;
- It provides the basis for establishing quantitative thresholds for acceptable model operation;
- It enables continuous rather than binary evaluation of model reliability;
- It potentially allows for predictive detection of performance degradation.

Given the centrality of this hypothesized relationship to our monitoring framework, its empirical validation constitutes a primary objective of our experimental design. The validation of this fundamental hypothesis represents a critical preliminary step in our research methodology. Subsequent chapters present results that test this hypothesized relationship, as it forms the theoretical basis for the entire monitoring framework. Should this relationship be empirically confirmed, it would provide substantial support for the viability of distance-based monitoring as an effective approach for assessing model reliability in autonomous driving applications.

4

Results

In this section, we present the outcomes and analyze the performance of the distance-based Out-of-Distribution (OOD) detection method developed and tested on the platform. The analysis covers the effectiveness of the distance-based method, the validation of our Intersection over Union (IoU) metric, and the impact of different noise types on the model's performance.

4.1 Validation of IoU Metric

To demonstrate the validity of our IoU metric, we compared three types of images: raw images, semantically segmented images with masks (original), and YOLO-detected images with bounding boxes and masks (detected). Figures 4.1, 4.2, and 4.3 illustrate this comparison.

Figure 4.1: Raw image from the dataset

Figure 4.2: Original semantically segmented image with masks

Figure 4.3: YOLO-detected image with bounding boxes and masks

The comparison across figures 4.1, 4.2, and 4.3 validates our IoU metric by showing the alignment between the raw input, the semantically segmented ground truth (original), and the YOLO-detected objects (detected). This alignment confirms that our IoU calculation accurately represents the model's detection performance. The progression from raw image to semantic segmentation to object detection with

bounding boxes demonstrates the effectiveness of our approach in identifying and localizing objects in the scene.

4.2 Distribution of Data Types

Figure 4.4 shows the distribution of different data types across the bias spectrum.

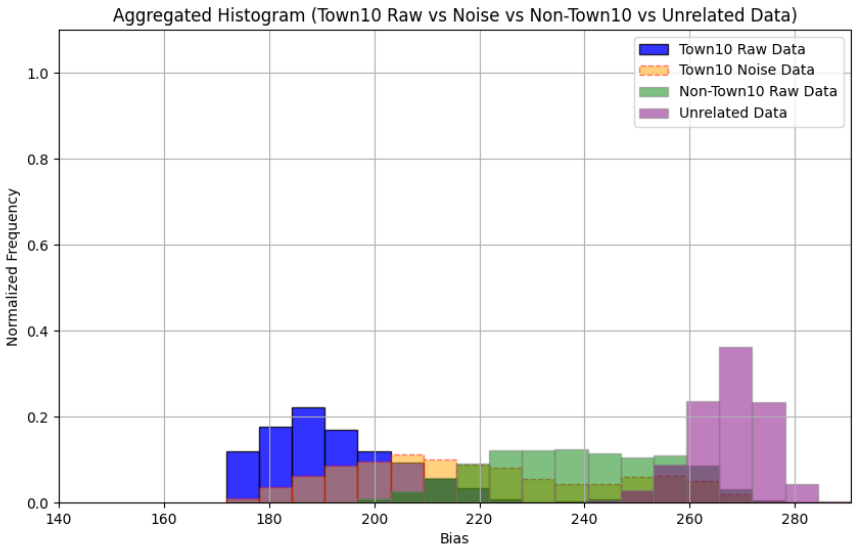

Figure 4.4: Aggregated Histogram: Town10 Raw vs Noise vs Non-Town10 vs Unrelated Data

This histogram provides valuable insights into the distribution of various data types:

- Town10 Raw Data (blue) represents a mini-batch from the original training set. It is concentrated in the lower bias range (180-200), indicating that it closely matches the overall training distribution.
- Town10 Noise Data (orange) is derived from the same training data as the blue segment, but with added noise. It shows a slight shift towards higher bias values, demonstrating the effect of the introduced perturbations.
- Non-Town10 Raw Data (green) consists of data from other cities within the same simulation environment as the training data. It is distributed across a wider range of bias values (220-260), suggesting varying degrees of similarity to the training data while maintaining some common characteristics.
- Irrelevant Data (purple) is composed of entirely dissimilar content. It is primarily concentrated at higher bias values (260-280), clearly distinguishing it from the in-distribution data.

This distribution supports the effectiveness of our distance-based method in separating different types of data based on their similarity to the training distribution.

4.3 Validation of Hypothesized Monotonic Relationship

The experimental results first validate our fundamental hypothesis regarding the monotonic relationship between feature distance and model performance, as proposed in Chapter 3. The comprehensive analysis of both Gaussian and Mosaic noise conditions across different town datasets demonstrates a clear, consistent inverse relationship between feature distance (bias) and model performance (IoU). This empirical validation provides the necessary foundation for the subsequent detailed analysis of our distance-based OOD detection method.

4.4 Distance-Based Method Performance and Effects of Noise

The distance-based approach demonstrated clear effectiveness in identifying out-of-distribution (OOD) data. We observed a monotonic relationship between the calculated Euclidean distance and the likelihood of the data being OOD.

To evaluate the robustness of our model and the effectiveness of the distance-based OOD detection method, we introduced two types of noise: Mosaic noise and Gaussian noise. Figure 4.5 illustrates the relationship between bias and Intersection over Union (IoU) for both Gaussian and Mosaic noise across different town datasets.

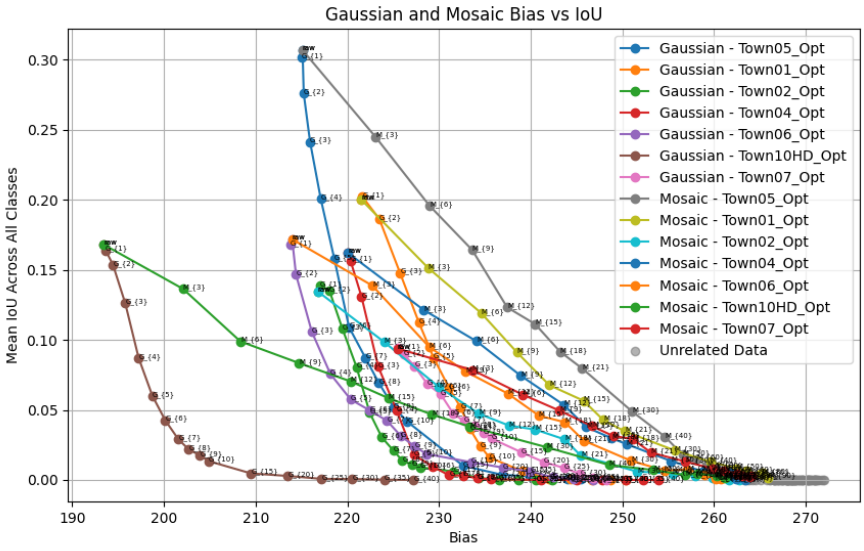

Figure 4.5: Gaussian and Mosaic Bias vs IoU for Different Town Datasets

To provide a more detailed analysis, we present separate plots for Gaussian noise (Figure 4.6) and Mosaic noise (Figure 4.7).

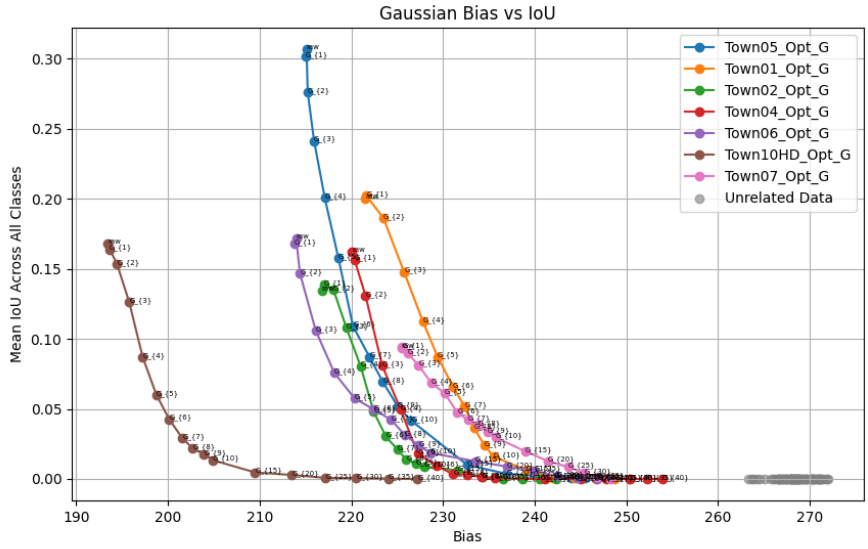

Figure 4.6: Gaussian Bias vs IoU for Different Town Datasets

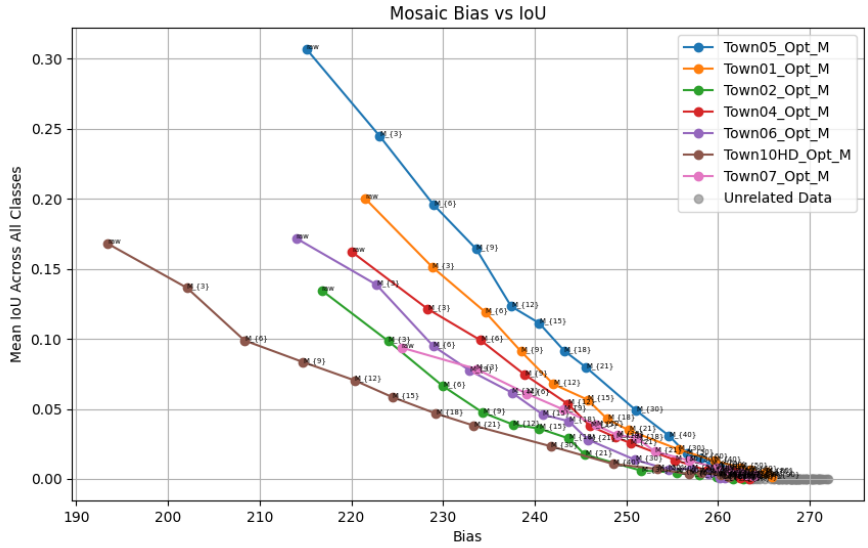

Figure 4.7: Mosaic Bias vs IoU for Different Town Datasets

Key observations from these plots include:

- Both Gaussian and Mosaic noise show a clear inverse relationship between bias and IoU, confirming that increased distance from the training data center correlates with decreased model performance.
- The impact of noise varies across different town datasets, as evidenced by the varying slopes and patterns of the curves.
- Gaussian noise generally shows a more pronounced effect on model performance compared to Mosaic noise, particularly in the lower bias ranges.

- The unrelated data points (grey) consistently show very low IoU values, validating the method's ability to identify completely out-of-distribution samples.
- The method produced a clear separation between in-distribution and out-of-distribution data under both noise conditions, confirming that distance is a reliable metric for OOD detection.
- The monotonic nature of the curves shows a strong correlation between distance (bias) and model performance (IoU), making it an effective tool for unsupervised anomaly detection.
- The approach highlights the limitations of human-defined criteria in determining data quality, as the distance method offers a more continuous, objective, and scalable evaluation of OOD data.
- At the leftmost point of the curves, both noise types converge because the amount of noise added to the images is minimal. This means the images remain nearly identical to the original data, preserving their key features and distributions. As a result, the model's ability to recognize objects is not significantly affected, leading to equivalent performance metrics.

4.5 Optimal OOD Threshold

Based on the aggregated histogram (Figure 4.4), we can observe that an optimal threshold for OOD detection appears to be around a bias value of 240. This threshold effectively separates the majority of in-distribution data (Town10 Raw and Noise Data) from out-of-distribution data (Non-Town10 and Unrelated Data).

Implementing a monitoring system with this threshold would effectively filter out data that does not meet the expected distribution, thereby improving the overall reliability and performance of the AI system.

4.6 Validation of OOD Detection Method

To evaluate the effectiveness of our OOD detection method, we conducted a validation experiment focusing on data points with bias values between 235 and 245. This range was chosen based on the distribution observed in Figure 4.8, where it represents a transition zone between in-distribution and out-of-distribution data.

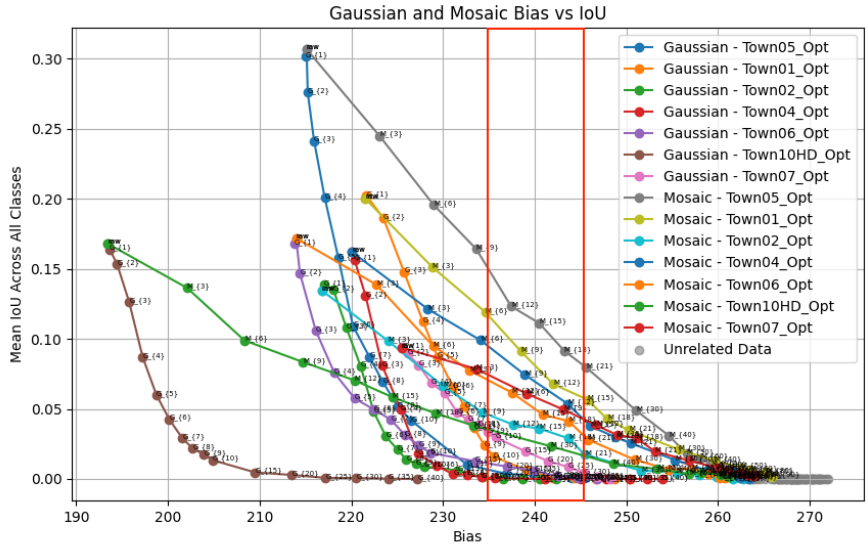

Figure 4.8: Gaussian and Mosaic Bias vs IoU for Different Town Datasets

We selected all noise image folders within this bias range for our validation experiment. The results demonstrate a significant improvement in model performance after applying the OOD detection method:

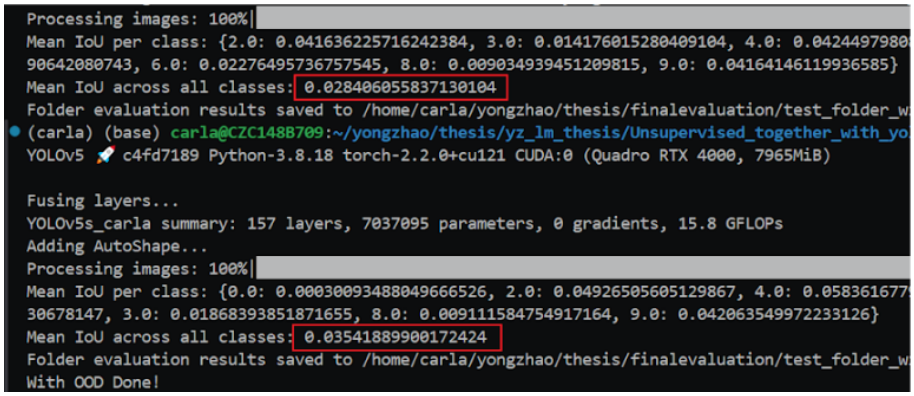

Figure 4.9: Comparison of Mean IoU Before and After OOD Detection

As shown in Figure 4.9:

- Before OOD detection, the mean IoU across all classes was 0.0284.
- After applying OOD detection and removing identified outliers, the mean IoU increased to 0.0354.

This improvement represents a 24.6% increase in IoU, indicating that our OOD detection method effectively identified and removed problematic data points, leading to enhanced model performance. It is worth noting that for bias values larger than this range, the results would likely be even more pronounced, as the distinction between in-distribution and out-of-distribution data becomes more apparent. This validation experiment provides strong evidence for the efficacy of our OOD detection method in improving the overall performance of the object detection model in

autonomous driving scenarios. By successfully filtering out data points that deviate significantly from the expected distribution, the method enhances the model's ability to accurately detect and localize objects in the scene.

4.7 Comparative Analysis of Noise Types

Comparing the effects of Mosaic and Gaussian noise:

- Mosaic noise appears to have a more gradual impact on model performance compared to Gaussian noise, as evidenced by the generally shallower slopes in the Mosaic curves of Figure 4.5.
- Gaussian noise shows a more pronounced effect on model performance, with steeper declines in IoU as bias increases.
- Both noise types demonstrate the effectiveness of the distance-based method in identifying OOD data, as the relationship between bias and IoU remains consistent across different town datasets.

These results validate the robustness of our distance-based OOD detection method and highlight its potential for real-world applications in autonomous driving systems, where varying environmental conditions and noise are common challenges.

5
Conclusion

This research aimed to develop and evaluate a distance-based Out-of-Distribution (OOD) detection method for enhancing the reliability and safety of AI systems in autonomous driving applications. The study used a YOLO-based object detection model trained on the CARLA simulator data and employed various data augmentation techniques to simulate real-world scenarios.

5.1 Key Findings

5.1.1 Effectiveness of Distance-Based OOD Detection

The experimental results strongly support the efficacy of the distance-based approach for OOD detection. The monotonic relationship observed between the Euclidean distance (bias) and the model's performance (IoU) demonstrates that this method can effectively identify data points that deviate from the training distribution. This relationship held true across different town datasets and under various noise conditions, highlighting the robustness of the approach.

The clear separation between in-distribution and out-of-distribution data, as evidenced by the aggregated histogram and the combined bias vs. IoU plot, further validates the method's discriminative power. The optimal OOD threshold identified at a bias value of around 240 provides a practical guideline for implementing this method in real-world systems.

5.1.2 Impact on Model Performance

The implementation of the OOD detection method resulted in a significant improvement in model performance. The 24.6% increase in mean IoU after removing identified outliers demonstrates the tangible benefits of this approach. By filtering out data points that do not align with the expected distribution, the method effectively enhances the overall reliability and accuracy of the AI system.

5.1.3 Robustness to Different Noise Types

The comparative analysis of Mosaic and Gaussian noise effects provides valuable insights into the method's robustness. While both noise types showed a clear inverse relationship between bias and IoU, the varying impacts observed (with Gaussian noise generally having a more pronounced effect) highlight the importance of considering different types of data perturbations in OOD detection systems.

5.2 Limitations and Future Improvements

While this study has demonstrated promising results, it is important to acknowledge several limitations that provide opportunities for future research and improvement.

5.2.1 Limitations of the CARLA Simulator

The use of the CARLA simulator, while providing a controlled environment for our experiments, introduces certain limitations:

- Environmental Fidelity: CARLA's ability to simulate complex environmental factors such as weather conditions, lighting variations, and seasonal changes is limited compared to the real world. This may affect the robustness of our model when applied to actual driving scenarios.
- Vehicle Diversity: The range of vehicle models available in CARLA is finite and may not fully represent the diversity of vehicles encountered in real-world driving situations. This limitation could impact the model's ability to generalize to a broader range of vehicle types and designs.
- Sensor Simulation: While CARLA provides simulated sensor data, the fidelity of this data may not perfectly match that of real-world sensors, potentially affecting the applicability of our findings to physical autonomous driving systems.

5.2.2 Metric Limitations

The current implementation of IoU as a performance metric, while effective in demonstrating the benefits of our OOD detection method, has its limitations:

- Simplicity: Using IoU as the sole metric may be considered reductive, as it may not capture all aspects of model performance relevant to autonomous driving scenarios.
- Context Insensitivity: IoU does not account for the relative importance of different objects in a driving scene or the potential consequences of misclassification.

5.2.3 Limitations on OOD threshold

The use of OOD threshold is often tricky, as it mitigates the risk of filtering out critical inputs which could represent "reality", here "reality" refers to real-world data or inputs that slightly deviate from the training data distribution. For example, if a strict OOD threshold is chosen, which leads to filtering out too much "reality" data, the model may lose its ability to adapt to real-world conditions, making it unable to handle slightly OOD data that is common in practical scenarios, and vice versa. So, this threshold should balance between rejecting genuinely OOD data and retaining in-distribution or slightly outlier data but still remains relevant to OMS.

5.2.4 Future Improvements

To address these limitations and further advance this research, we propose the following future improvements:

1. Real-world Validation: Conduct experiments using real-world driving data to validate the effectiveness of our OOD detection method beyond simulated environments. This would help address the limitations of the CARLA simulator and provide more robust evidence for the method's practical applicability.
2. Enhanced Environmental Simulation: Collaborate with simulator developers to improve the fidelity of environmental simulations, including more diverse weather conditions, lighting scenarios, and seasonal variations. This would help create a more challenging and realistic testbed for our OOD detection method.
3. Expanded Vehicle Dataset: Incorporate a wider range of vehicle models and types into the simulation to better represent the diversity of real-world traffic. This could include various makes and models of cars, as well as other vehicle types such as motorcycles, buses, and emergency vehicles.
4. Comprehensive Evaluation Metrics: Develop and implement a more nuanced set of performance metrics that can provide a holistic view of model performance. This could include:
    - Object-specific metrics tailored to different types of road users (e.g., vehicles, pedestrians, cyclists).
    - Temporal consistency measures to evaluate performance over sequences of frames.
    - Safety-oriented metrics that specifically address critical aspects of autonomous driving, such as collision prediction and avoidance.
5. Sensor Fusion: Explore the integration of multiple simulated sensor types (e.g., LiDAR, radar) to enhance the robustness of the OOD detection method and more closely mirror real-world autonomous driving systems.
6. Adaptive Thresholding: Develop methods for dynamically adjusting OOD detection thresholds based on real-time environmental conditions and system performance, enhancing the adaptability of the system to varying driving scenarios.
7. Explainable AI Integration: Incorporate explainable AI techniques to provide insights into the decision-making process of both the object detection model and the OOD detection method, enhancing transparency and trust in the system.

By addressing these limitations and pursuing these future improvements, we would like to enhance the robustness, reliability, and real-world applicability of our OOD detection method for autonomous driving systems. This continued research will contribute to the development of safer and more capable AI-driven vehicles, bridging the gap between simulated environments and the complexities of real-world driving scenarios.

5.3 Implications for Autonomous Driving Systems

The success of this distance-based OOD detection method has significant implications for the development and deployment of autonomous driving systems:

1. Enhanced safety: By effectively identifying and filtering out OOD data, this method can help prevent AI systems from making decisions based on unreliable or unfamiliar inputs, thereby enhancing overall system safety.
2. Improved reliability: The ability to continuously monitor and evaluate input data against the expected distribution can lead to more reliable and consistent performance of autonomous driving systems across various environmental conditions.
3. Adaptive learning: This approach opens up possibilities for adaptive learning systems that can dynamically adjust their operational boundaries based on encountered data distributions.
4. Explainability: The clear relationship between distance metrics and model performance contributes to the explainability of AI decision-making processes, which is crucial for building trust in autonomous systems.

5.4 Future Research Directions

Based on the findings of this study, several promising avenues for future research emerge:

1. Integration with other techniques: Exploring the combination of this distance-based method with other OOD detection techniques, such as generative models or ensemble methods, could potentially yield even more robust systems.
2. Computational efficiency: As autonomous driving systems require real-time processing, future research should focus on optimizing the computational efficiency of the OOD detection method to ensure its viability in resource-constrained environments.
3. Comparative analysis of OOD detection methods: Conduct a comprehensive comparison of the distance-based method with other state-of-the-art OOD detection techniques, including:
    - Density estimation-based methods (e.g., kernel density estimation)
    - Deep generative models (e.g., variational autoencoders, generative adversarial networks)
    - Ensemble-based approaches combining multiple OOD detection strategies
4. Multi-modal OOD detection: Investigate the integration of data from multiple sensor modalities (e.g., camera, LiDAR, radar) to develop a more robust OOD detection system that can handle sensor failures or inconsistencies.
5. Temporal OOD detection: Extend the current frame-by-frame analysis to incorporate temporal information, developing methods that can detect OOD scenarios based on sequences of frames or sensor readings over time.
6. Edge case generation: Develop techniques to systematically generate and analyze edge cases and rare events that may not be well-represented in standard

datasets, to further evaluate and improve the OOD detection method's performance in unusual situations.

7. Transfer learning for OOD detection: Explore the use of transfer learning techniques to adapt the OOD detection model to new environments or vehicle types with minimal retraining, enhancing the scalability and adaptability of the approach.

In conclusion, this research has demonstrated the potential of distance-based OOD detection methods to significantly enhance the reliability and safety of AI systems in autonomous driving applications. By providing a robust framework for identifying and handling out-of-distribution data, this approach contributes to the development of more trustworthy and capable autonomous vehicles. As the field continues to evolve, further refinement and validation of these methods will be crucial in realizing the full potential of AI-driven autonomous transportation systems.

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