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Design and Implementation of an End-to-End Autonomous Driving System in the CARLA Simulation Environment

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Dedication

I dedicate this work to my family—my parents, who have sacrificed so much to see me reach this level of education. Your unconditional love, prayers, and encouragement have been my greatest source of strength. This milestone is as much yours as it is mine.

And somewhere along the way, thank you to **Life**—for the lessons, the unexpected turns, the beautiful moments, and even the difficult ones. Each experience shaped who I am today and taught me to trust what is yet to come, believe in the beauty of new beginnings, and look toward the future with hope. ⛅

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– Mohamed Riadh Saifi

Dedication

I am profoundly grateful to my family for their unwavering belief in me. I dedicate this thesis to my parents; thank you for providing a supportive environment and for always encouraging me to pursue my ambitions in Computer Science.
To my binome, **Mohamed Riadh Saifi**, thank you for your dedication and the shared late-night coding sessions. We made a great team.

– Fares Naoui

Abstract

In the quest for Level 5 autonomous driving, a critical cognitive bottleneck exists between high-frequency mechanical reflexes and low-frequency semantic reasoning. While end-to-end Vision-Language-Action (VLA) models provide semantic reasoning, they introduce inference latency incompatible with real-time vehicle control; current approaches struggle to simultaneously preserve sub-millisecond reflexes while embedding interpretable semantic arbitration without relying on massive, data-center-grade hardware. This thesis introduces a novel Neuro-Symbolic Co-Pilot operating within the CARLA simulator. We engineered a Hierarchical Perception, Decision, and Control Pipeline that decouples driving tasks by abstraction level. A custom multi-modal perception pipeline explicitly fuses 2D neural inferences (YOLOv8s, SegFormer-B0) with 3D LiDAR to construct a deterministic Bird's-Eye-View (BEV) and Object Vector state. For decision-making, an unsupervised Dynamic Time Warping (DTW) KMeans clustering algorithm extracts distinct behavioral modes directly from a Soft Actor-Critic (SAC) agent's trajectory history. A GRU sequence classifier then enforces class-conditional safety overrides, while a Small Language Model (Qwen 0.8B) acts as an asynchronous semantic governor. Experimental results demonstrate that this hybrid architecture successfully preserves sub-millisecond physical reflexes while embedding higher-level human-like reasoning, offering a robust, latency-efficient solution to the Vision-Language-Action (VLA) crisis.

Keywords: Autonomous Driving, Neuro-Symbolic AI, Reinforcement Learning, Soft Actor-Critic, Bird's-Eye-View, Sensor Fusion, Dynamic Time Warping, Trajectory Clustering, CARLA Simulator.

Résumé

Dans la quête de la conduite autonome de niveau 5, un goulot d'étranglement cognitif critique existe entre les réflexes mécaniques à haute fréquence et le raisonnement sémantique à basse fréquence. Bien que les modèles de bout-en-bout Vision-Langage-Action (VLA) fournissent un raisonnement sémantique, ils introduisent une latence d'inférence incompatible avec le contrôle des véhicules en temps réel ; les approches actuelles peinent à préserver simultanément les réflexes inférieurs à la milliseconde tout en intégrant un arbitrage sémantique interprétable sans matériel lourd. Cette thèse présente un nouveau copilote neuro-symbolique fonctionnant dans le simulateur CARLA. Nous avons conçu un pipeline hiérarchique de perception, de décision et de contrôle qui découple les tâches de conduite par niveau d'abstraction. Un pipeline de perception multimodale personnalisé fusionne de manière explicite les inférences neuronales 2D (YOLOv8s, SegFormer-B0) avec le LiDAR 3D pour construire une vue aérienne déterministe (BEV). Pour la prise de décision, un algorithme de clustering non supervisé (DTW KMeans) extrait les modes comportementaux directement à partir de l'historique des trajectoires d'un agent Soft Actor-Critic (SAC). Un classificateur de séquences GRU applique ensuite des dérogations de sécurité conditionnelles, tandis qu'un petit modèle de langage (Qwen 0.8B) agit comme un gouverneur sémantique asynchrone. Les résultats expérimentaux démontrent que cette architecture hybride préserve avec succès les réflexes physiques inférieurs à la milliseconde tout en intégrant un raisonnement de niveau supérieur, offrant une solution robuste à la crise de latence des modèles Vision-Langage-Action (VLA).

Mots-clés : Conduite Autonome, IA Neuro-Symbolique, Apprentissage par Renforcement, Soft Actor-Critic, Vue Aérienne (BEV), Fusion de Capteurs, Déformation Temporelle Dynamique (DTW), Clustering de Trajectoires, Simulateur CARLA.

الملخص

في السعي نحو القيادة الذاتية من المستوى الخامس، توجد فجوة معرفية حرجة بين ردود الفعل الميكانيكية عالية التردد والمنطق الدلالي منخفض التردد. في حين توفر نماذج الرؤية واللغة والعمل (VLA) فهمًا دلاليًا، إلا أنها تقدم تأخيراً استنتاجياً لا يتوافق مع التحكم في المركبات في الوقت الفعلي، ولا توجد بنية حالية تحافظ في الوقت نفسه على ردود الفعل الميكانيكية السريعة مع دمج تحكيم دلالي قابل للتفسير بدون أجهزة مراكز بيانات مخصصة. تقدم هذه المذكرة مساعدًا للقيادة العصبية الرمزية (Neuro-Symbolic) يعمل داخل محاكي CARLA. تم تصميم مسار معالجة هرمي يضم مراحل الإدراك واتخاذ القرار والتحكم، بحيث يتم فصل مهام القيادة حسب مستوى التجريد.

يقوم خط أنابيب الإدراك متعدد الوسائط بدمج الاستدلالات ثنائية الأبعاد (YOLOv8s, SegFormer-B0) مع تقنية LiDAR ثلاثية الأبعاد لبناء عرض من أعلى لأسفل (BEV). لاتخاذ القرار، تستخرج خوارزمية التجميع غير الخاضعة للإشراف DTW) (KMeans الأنماط السلوكية من مسارات وكيل التعلم المعزز (SAC). يطبق مصنف GRU بعد ذلك تجاوزات السلامة الشرطية، بينما يعمل نموذج لغوي صغير (Qwen 8B.0) كحاكم دلالي غير متزامن. تثبت النتائج التجريبية أن هذه البنية الهجينة تنجح في الحفاظ على ردود الفعل الميكانيكية السريعة مع دمج منطق بشري عالي المستوى، مما يوفر حلاً فعالاً وقويًا لأزمة النماذج اللغوية البصرية (VLA).

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List of Acronyms

AMP	Automatic Mixed Precision
AV	Autonomous Vehicle
BEV	Bird's-Eye-View
CARLA	Car Learning to Act (Simulator)
CNN	Convolutional Neural Network
CTE	Cross-Track Error
DQN	Deep Q-Network
DTW	Dynamic Time Warping
FPS	Frames Per Second
GRU	Gated Recurrent Unit
IoU	Intersection over Union
IPM	Inverse Perspective Mapping
LiDAR	Light Detection and Ranging
LLM	Large Language Model
mAP	Mean Average Precision
MDP	Markov Decision Process
MLP	Multi-Layer Perceptron
ODD	Operational Design Domain
PPO	Proximal Policy Optimization
ReLU	Rectified Linear Unit
RL	Reinforcement Learning
SAC	Soft Actor-Critic
SAE	Society of Automotive Engineers
SLM	Small Language Model
TTC	Time-To-Collision
ViT	Vision Transformer
VLA	Vision-Language-Action
YOLO	You Only Look Once

List of Symbols

Reinforcement Learning & Control Vectors

$\mathbf{s}, \mathbf{s}'$	State observation vector at current and subsequent timestep
$\mathbf{a}, \mathbf{a}'$	Continuous action vector (throttle, steering)
r	Scalar reward signal
$Q_\theta(\mathbf{s}, \mathbf{a})$	Action-value (Critic) function parameterized by θ
$\pi_\phi(\mathbf{a}\|\mathbf{s})$	Stochastic policy (Actor) function parameterized by ϕ
γ	Discount factor for future rewards
τ	Target network soft update coefficient
α	Entropy temperature coefficient
$\mathcal{H}$	Policy entropy
τ_{final}	Final execution throttle command $\in [0, 1]$
δ_{final}	Final execution steering command $\in [-1, 1]$
b_{final}	Final execution brake command $\in [0, 1]$

Reward Function Components

$w_1 - w_5$	Optuna-tuned scalar weights for reward components
r_{speed}	Longitudinal progress and speed maintenance reward
r_{safety}	Obstacle avoidance and Time-To-Collision (TTC) penalty
$r_{\text{stability}}$	Lateral acceleration and actuator jerk penalty
r_{lane}	Lane discipline and invasion penalty
r_{map}	High-Definition map waypoint alignment reward
r_{goal}	Terminal progression reward
r_{stuck}	Vehicle stagnation penalty

Kinematic & Perception Variables

v, v_{norm}	Ego-vehicle velocity and normalized velocity
a_x, a_y	Longitudinal and lateral acceleration
$\delta_\psi, \dot{\psi}$	Heading error and yaw rate (angular velocity)
d_{cv}	Metric distance to the nearest dynamic obstacle via Computer Vision
ttc_{val}	Estimated Time-To-Collision
k	Number of behavioral clusters in DTW KMeans

General Introduction

For over a century, driving has been an intimate, mechanical dialogue between a human and a machine. A turn of the wheel physically shifts the tires; a press of a pedal mechanically opens a throttle. Today, however, that dialogue is being entirely rewritten by lines of code. The push for autonomous mobility is arguably the most complex engineering challenge of our time, blending cognitive science, hardware engineering, and real-time physics into a single, rolling computer. The core promise of autonomous vehicles (AVs) is a massive public health initiative: an engineering attempt to patch the ”human bug” with a deterministic system that never blinks, never gets fatigued, and never loses focus on the road.

Navigating the chaotic, unstructured environment of a living city requires an infallible understanding of the physical world. This is achieved through machine perception. Computer vision algorithms and multi-modal sensor fusion translate raw environmental data—such as photons striking a camera lens or lasers reflecting off a pedestrian—into a clean, mathematical reality. Simultaneously, Artificial Intelligence inference engines process these geometric maps to generate driving policies. By leveraging Deep Reinforcement Learning (DRL), vehicles can simulate millions of miles of driving experience, learning robust mechanical reflexes to avoid collisions and maintain trajectory stability in real-time.

Despite exponential leaps in computing power, the autonomous driving industry has hit a frustrating plateau. We have successfully built vehicles that stay flawlessly centered in their lanes, but we are remarkably far from deploying machines capable of human-level reasoning in edge-case scenarios.

This brings us directly to the specific technical challenge addressed in this project. We currently possess Reinforcement Learning (RL) agents that can react and steer in milliseconds, operating effortlessly at the 50Hz control frequencies required for physical survival, but they are conceptually ”dumb.” On the other side of the spectrum, the industry has turned to Vision-Language-Action (VLA) architectures and Large Language Models (LLMs) that possess deep, human-like common sense. However, these massive semantic networks process data at roughly 2Hz. In the context of physics, this latency is lethal: a vehicle traveling at 100 km/h will travel over 41 meters completely blind while waiting 1.5 seconds for a VLA model to generate a driving command.

The main question is: *How can we seamlessly integrate the deep, semantic reasoning of a language model operating at low frequencies into a vehicle's high-frequency control loop, without sacrificing the sub-millisecond reflexes required for physical driving?*

To solve this latency versus reasoning dilemma, this thesis proposes a hybrid, layered arbitration architecture. Rather than forcing a single network to handle everything, we decouple the driving task by abstraction level. This research targets four core objectives:

1. Engineer a low-latency multi-modal perception pipeline that explicitly fuses Camera and LiDAR data into a unified, distortion-free Bird's-Eye-View (BEV) representation.

2. Develop a data-driven behavioral taxonomy by applying unsupervised trajectory clustering to driving sequences, extracting structurally distinct behavioral classes without human labeling bias.

3. Construct a hierarchical arbitration pipeline that seamlessly integrates continuous Reinforcement Learning control, recurrent behavioral safety overrides, and semantic language model verdicts.

4. Comprehensively evaluate the full closed-loop pipeline in simulated urban scenarios, measuring improvements in safety and trajectory stability against purely reactive baselines.

Within this overarching flow, our work introduces three primary scientific and engineering contributions distinct from prior literature:

- **Custom Optimized Bird's-Eye-View (BEV) Architecture:** By deterministically projecting 2D neural network inferences (YOLOv8s and SegFormer-B0) against 3D LiDAR point clouds, we bypass the computationally heavy "scene-lifting" transformers prevalent in recent literature, bridging the gap between raw spatial data and hybrid decision layers.
- **Post-Hoc Behavioral Abstraction:** We applied Dynamic Time Warping (DTW) KMeans clustering to the RL agent's trajectory history. This unsupervised approach organically discovered a geometric asymmetry between left and right turns—a critical physical distinction proving that safety taxonomies should be derived from the machine policy's own vocabulary rather than human intuition.
- **Neuro-Symbolic Reinforcement Learning:** We developed a novel hierarchical decision system that arbitrates between a Soft Actor-Critic (SAC) continuous control agent, a GRU-based behavior sequence predictor, and a rule-based safety language model (Qwen 0.8B) to achieve semantic intelligence without latency collapse.

The deployment of autonomous vehicles carries profound ethical weight. Because algorithmic decisions directly impact human life, autonomous architectures must prioritize transparency and safety above all else. By explicitly separating the driving task into a verifiable geometric perception layer, a statistical behavioral layer, and a semantic arbitration layer, this thesis rejects the paradigm of opaque, black-box driving. The proposed Neuro-Symbolic Co-Pilot is designed to ensure that whenever an emergency intervention occurs, the reasoning behind it is explicitly bounded, traceable, and explainable to human operators.

To comprehensively address these objectives, this thesis is structured into four primary chapters, followed by a general conclusion:

- **Chapter 1 (The Autonomous Driving Domain):** Defines the overarching problem space, the limits of current automation levels, and the "long-tail" edge cases that stall global progress.
- **Chapter 2 (Literature Review):** Traces the historical evolution of autonomous perception and continuous control, culminating in the current Vision-Language-Action (VLA) latency crisis.
- **Chapter 3 (System Architecture and Methodology):** Provides the deep technical blueprint of our solution, detailing the CARLA simulation environment, geometric BEV sensor fusion, and the step-by-step engineering of the Neuro-Symbolic decision pipeline.
- **Chapter 4 (Experimental Results and Discussion):** Presents the empirical evaluation of the system, analyzing vision model convergence, behavioral classifier accuracy, continuous control performance, and a candid assessment of system limitations.

Chapter 1

The Autonomous Driving Domain and the Cognitive Bottleneck

1.1 Introduction

For over a century, driving has been an intimate, mechanical dialogue between a human and a machine. A turn of the wheel physically shifts the tires; a press of a pedal mechanically opens a throttle. Today, however, that dialogue is being entirely rewritten by lines of code. The push for autonomous mobility is arguably the most complex engineering challenge of our time, blending artificial intelligence, cognitive science, hardware engineering, and real-time physics into a single, rolling computer.

Yet, despite billions of dollars in venture capital, thousands of research papers, and exponential leaps in computing power, the industry has hit a frustrating plateau. We have successfully built vehicles that can stay flawlessly centered in their lanes on a highway and come to a smooth stop at red lights. But we are still remarkably far from deploying machines capable of human-level reasoning in the chaotic, unstructured environments of a living city. Simply throwing more computing power at the problem is no longer yielding the breakthroughs required for full autonomy.

This chapter explores the foundational motivations behind vehicle automation, decodes the current industry standards (SAE levels), and thoroughly examines the ”long-tail” problem of edge cases that has stalled global progress. Ultimately, this chapter establishes the critical cognitive bottleneck that currently limits the industry: the severe latency conflict between high-level semantic reasoning and split-second physical reflexes.

1.2 Human Limitations and the Automation Spectrum

1.2.1 The Necessity of Automation

To understand the urgent push to automate vehicles, one must objectively analyze the current transportation system's weakest and most unpredictable link: the human driver. Human biology is not inherently optimized for the kinematic demands of high-speed travel. Drivers experience fatigue, emotional fluctuation, and easily degraded attention. A standard human reaction time to an unexpected event is roughly 1.5 seconds. When compounded by the modern epidemic of smartphone distraction, the mathematical reality becomes lethal. At highway speeds, a two-second glance at a screen results in the vehicle traveling nearly 60 meters completely blind.

The consequences of these biological limits are severe. Over 1.3 million people die in road accidents globally every year [1], and nearly 94% of these crashes stem directly from human error—ranging from fatigue to poor spatial judgment [2]. Beyond the tragic loss of human life, the economic drain is paralyzing. In the United States alone, the lost productivity and wasted fuel caused by daily traffic congestion costs upwards of $88 billion annually [3].

The core promise of autonomous vehicles (AVs) extends far beyond the luxury of hands-free commuting; it represents a massive public health initiative. It is an engineering attempt to replace biological vulnerability with a deterministic system immune to fatigue, distraction, or intoxication.

1.2.2 The SAE Taxonomy of Automation

To measure progress toward this vision, the system operates across the taxonomy established by the Society of Automotive Engineers (SAE), ranging from complete human execution to total machine autonomy [4]. Examining this spectrum clarifies the current state of technological stagnation.

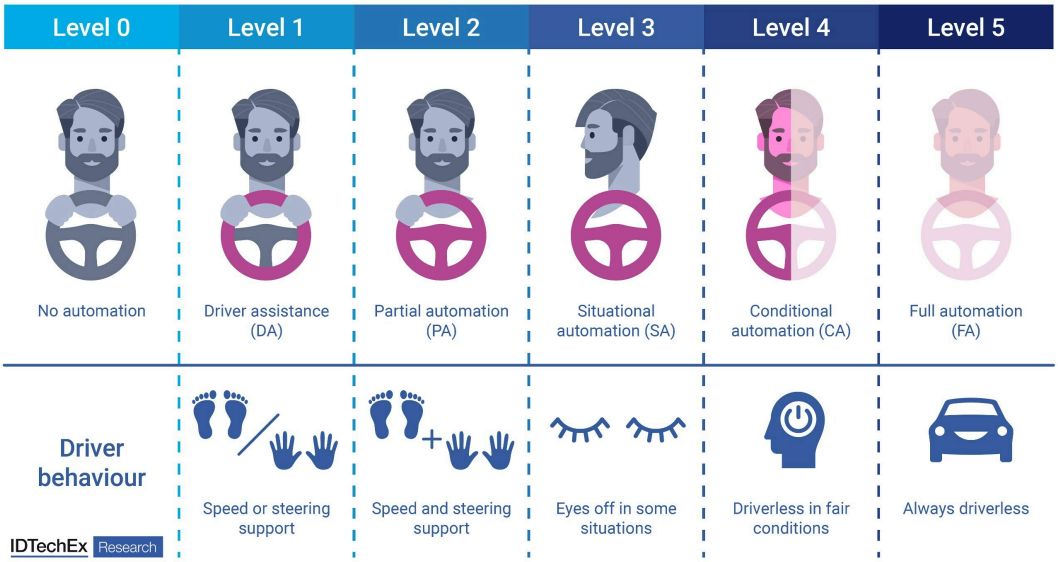


Figure 1.1: The SAE Levels of Driving Automation spanning from Level 0 to Level 5 [5].

- **Level 0 (No Automation):** The human driver retains absolute manual control over all dynamic driving tasks, operating without any vehicular intervention or steering support.
- **Level 1 (Driver Assistance):** The vehicle delivers isolated support for either longitudinal regulation (speed preservation) or lateral control (steering assistance), but cannot execute both parameters simultaneously.
- **Level 2 (Partial Automation):** The system executes combined, simultaneous speed and steering adjustments on well-marked thoroughfares. While highly capable, this bracket introduces a severe psychological hazard known in human factors engineering as the *Irony of Automation* [6]. Because the vehicle operates smoothly 99% of the time, drivers naturally succumb to ”automation bias,” lowering their cognitive engagement and leaving them entirely unprepared to handle sudden system anomalies.
- **Level 3 (Conditional Automation):** The vehicle functions as the primary operational driver within specific parameters, allowing the user to redirect attention in low-speed environments like heavy traffic jams. However, this configuration introduces the perilous ”handover problem.” Expecting a disengaged, resting human to instantly regain complete spatial awareness and execute a life-saving manual recovery within a brief three-second alarm window is biologically unrealistic.
- **Level 4 (High Automation):** The vehicle operates completely driverless without any human intervention requirements, but remains strictly bound within a highly mapped Operational Design Domain (ODD), such as geofenced urban centers or restricted fair-weather environments.
- **Level 5 (Full Automation):** The absolute pinnacle of the spectrum, describing an unconstrained machine capable of navigating any geographical environment, under any weather configuration, completely driverless, and without the inclusion of physical cockpit controls.

Most vehicles currently in production hover strictly at Level 2, with the leap to Level 3 and beyond presenting monumental engineering hurdles.

1.3 The Long-Tail Distribution and Sensor Limitations

Initial industry forecasts frequently anticipated the imminent deployment of Level 5 autonomous vehicles. However, while baseline navigational competencies—such as centering a vehicle between visible lane markings on

a clear highway—were achieved rapidly, the industry is currently bogged down in the final 5% of driving scenarios. In driving, that final 5% contains 99% of the real-world complexity. This phenomenon is known as the ”long tail” of edge cases.

In machine learning, the long tail refers to the infinite distribution of rare, unpredictable events. A vehicle’s Artificial Intelligence might have trained on ten million miles of standard highway driving, but it has never seen a mattress fall off a truck, followed by a pedestrian running into the highway to retrieve it. When the physical world stops looking like the clean, organized training data, purely pattern-based AI models fail.

Consider a classic edge-case dilemma: A light, empty plastic bag and a heavy, solid concrete rock are both sitting in the middle of a lane. A purely geometric sensor sees two obstacles of roughly the same size. A human driver instantly understands that driving over the plastic bag is perfectly safe, while swerving violently to avoid it might cause a deadly crash. Conversely, hitting the rock will destroy the car’s suspension. Current AI systems struggle to make this distinction because they lack an inherent understanding of the physical and semantic properties of the world.

This challenge is compounded by the fragility of sensor hardware. Relying purely on cameras is perilous; they are easily blinded by sudden sun glare, rendered useless by heavy fog, and struggle with depth perception in the dark.

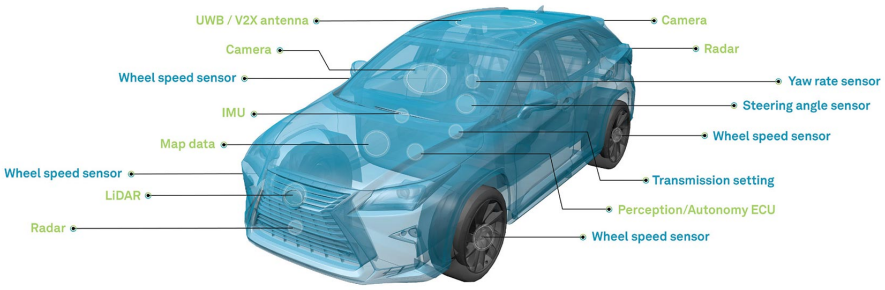


Figure 1.2: Sensor Modalities: Combining Camera, LiDAR, and Radar to overcome individual sensor limitations via Sensor Fusion [7].

To compensate, the industry relies on **Sensor Fusion**, combining high-resolution cameras with LiDAR (which fires lasers to create mathematically accurate 3D depth maps) and Radar (which tracks the speed of moving objects through adverse weather). However, this creates sensor disagreement. If a camera detects a pedestrian painted on the side of an advertising bus, but the LiDAR simply registers a flat metal wall, the vehicle’s arbitration logic must decide in a fraction of a second which modality is representing the truth.

1.4 The Cognitive Bottleneck: Reactive vs. Semantic Control

In the early applications of deep learning to autonomous driving, researchers focused heavily on ”End-to-End” models [8]. These architectures mapped raw perceptual inputs directly to actuation outputs (steering and braking). The primary objective was to engineer a system with robust reactive capabilities.

While these models drove smoothly on simple roads, they operated as statistical ”Black Boxes.” The vehicle learned through repetition that a red light meant stop, but it possessed no semantic concept of *why*. If a police officer stood in the middle of an intersection manually waving traffic through a broken red traffic light, the AI would freeze. Its rigid, mathematical pattern-matching dictated that red always equals stop. It completely lacked the semantic, common-sense override that human drivers apply intuitively.

True autonomy requires more than geometric reflexes; it demands semantic understanding. To borrow

from cognitive psychologist Daniel Kahneman [9], human driving relies on two systems. **System 1** is a fast, automatic, unconscious reflex—like swerving when an object suddenly appears. **System 2** is slow, analytical, conscious reasoning—like predicting that a ball rolling into the street means a child is likely running right behind it.

Currently, autonomous controllers excel at System 1. To provide vehicles with the analytical power of System 2, researchers have turned to Large Language Models (LLMs) and Vision-Language-Action (VLA) architectures. These massive AI models can process an image, understand the context of the scene, and reason about hidden dangers.

However, integrating semantic reasoning models into vehicular control loops introduces a critical, physical constraint: **Computational Latency**.

An advanced LLM might take 1.5 to 2 seconds to process a visual scene and generate a logical trajectory correction. In the context of physics, time translates directly to distance. If a vehicle is traveling at 100 km/h, it covers roughly 27.7 meters every second. Waiting 1.5 seconds for an AI to semantically process a dangerous situation means the vehicle has traveled over 41 meters completely blind. The accident occurs before the actuation command ever reaches the brakes.

1.5 Conclusion

The progression toward full Level 5 autonomy has been constrained by a fundamental dichotomy: systems possess geometric awareness but lack semantic comprehension. While large language models offer the necessary contextual reasoning to navigate the long tail of edge cases, their high inference latency violates the strict temporal constraints of physical driving. Having established the cognitive bottleneck currently stalling the industry, the following chapter will critically review the historical evolution of both autonomous perception and continuous control, examining the successive algorithms and paradigms that ultimately led to the current Vision-Language-Action latency crisis.

Chapter 2

Literature Review and the Evolution of Autonomous AI

2.1 Introduction

A human driver navigating a crowded urban intersection in adverse weather executes a highly complex cognitive process in a fraction of a second. The visual cortex identifies a hazard, the frontal lobe intuitively predicts its trajectory, and the motor cortex initiates a precise, muscle-memory evasion. This rapid response relies on a fundamental duality: the separation of Perception (understanding the physical world) and Control (executing kinematic decisions).

Building an autonomous driving system requires recreating this exact duality in silicon. Perception is the ability to transform raw photons and laser pulses into a reliable, semantic map of the world. Control is the mathematical translation of that map into a sequence of steering torques and braking pressures. In the early days of robotics, engineers attempted to bridge these two domains using rigid, hand-coded rules, only to discover that the chaotic reality of human traffic cannot be captured by rule-based logic.

This chapter serves as a critical review of the literature and algorithmic breakthroughs that define modern autonomous systems. We trace two parallel evolutionary tracks. First, we explore the evolution of Machine Perception, moving from basic convolutional filters to the modern era of 3D Bird's-Eye-View (BEV) mapping. Second, we examine the evolution of Action and Control via Deep Reinforcement Learning. Finally, we analyze the recent "Common Sense" bottleneck of 2024–2026, examining the rise of Vision-Language-Action (VLA) models, the severe latency constraints they introduce, and how the literature motivates the Neuro-Symbolic architecture proposed in this thesis.

2.2 The Evolution of Machine Perception

Before a machine can drive, it must understand its environment. For decades, computer vision was bottlenecked by manual feature engineering. The following progression outlines the transition toward learned neural representations.

2.2.1 Convolutional Neural Networks (CNNs)

- **The Algorithmic Mechanics** — Feature Extraction via Convolutions: Before 2012, recognizing an object in an image required researchers to hand-craft algorithms like edge detectors or color histograms. AlexNet [12] shifted this paradigm by utilizing Deep Convolutional Neural Networks (CNNs) on GPUs. Instead of being told what to look for, a CNN slides a mathematical matrix (a kernel) across the pixels of an image. In the earliest layers, these kernels naturally learn to detect simple gradients and edges. As the data passes through deeper layers—aided by Max Pooling to reduce spatial dimensions and ReLU activation functions—the network combines these edges into complex, recognizable objects.

- **Autonomous Driving Implications** — The End of Hand-Coded Rules: In the context of autonomous driving, AlexNet was a foundational shift. Previously, if an engineer programmed a car to recognize a stop sign by explicitly searching for a red octagon, the system would fail if the sign was slightly bent or viewed at night. CNNs proved that by training on massive datasets, the network builds an internal, robust representation immune to minor visual distortions. However, early CNNs were fundamentally classifiers; they could detect the presence of a vehicle but could not provide the precise spatial localization required for navigation.

2.2.2 You Only Look Once (YOLO)

- **The Algorithmic Mechanics** — Single-Pass Regression for Object Detection: Previous detection models (like R-CNN) worked by proposing thousands of potential regions in an image and evaluating a CNN on each one—a computationally heavy process. YOLO [13] reframed object detection as a single regression problem. The image is divided into a grid, and in one single forward pass, YOLO predicts bounding box coordinates and class probabilities simultaneously.

- **Autonomous Driving Implications** — Real-Time Reflexes at Highway Speeds: YOLO brought real-time perception to autonomous vehicles, easily achieving high frame rates. For the first time, a system could actively track the erratic movement of dynamic actors. However, YOLO suffered from a geometric flaw: it viewed the world as a collection of rigid, 2D rectangular boxes. The physical road is a fluid geometry of asphalt and boundaries, rendering bounding boxes too crude for precise path planning.

2.2.3 Semantic Segmentation and U-Net

- **The Algorithmic Mechanics** — Encoder-Decoder Networks and Skip Connections: U-Net [14] popularized Semantic Segmentation by classifying every single pixel in an image. It achieves this through a symmetric "U-shaped" architecture. The encoder compresses the image to understand deep structural context, while the decoder scales the image back up. The innovation of U-Net lies in its "skip connections," which bypass deep layers to pass high-resolution spatial data directly to the decoder, ensuring precise spatial localization.

- **Autonomous Driving Implications** — Painting the World in Drivable Pixels: For autonomous path planning, U-Net allowed the vehicle to semantically label exact pixel areas as 'Road', 'Sidewalk', or 'Pedestrian'. By painting the world semantically, engineers could extract the exact curvature of lane lines. Yet, both YOLO and U-Net were strictly 2D, possessing zero inherent knowledge of 3D depth, which degraded distance estimation accuracy.

2.2.4 LiDAR 3D Object Detection (PointPillars)

- **The Algorithmic Mechanics** — Voxelizing the Point Cloud: To overcome 2D camera limitations, the industry integrated LiDAR to generate accurate 3D point clouds. Because point clouds are sparse and massive, PointPillars [15] discretized the 3D space into vertical columns ("pillars"). It uses a simplified PointNet to learn features within each pillar, squashing this 3D data into a 2D pseudo-image. From there, a highly optimized 2D convolutional network rapidly detects objects.

- **Autonomous Driving Implications** — Overcoming the Fragility of Cameras: PointPillars bridged the gap between 3D sensor accuracy and 2D network speed. It allowed vehicles to detect exact metric distances in complete darkness or heavy fog—conditions that paralyze pure camera systems. However, LiDAR lacks the rich semantic texture required to read traffic signs or lane markings.

2.2.5 Vision Transformers (ViT)

- **The Algorithmic Mechanics** — Self-Attention and Patch Embeddings: In 2020, the Vision Transformer (ViT) [16] discarded convolutions. Instead, it chops an image into small pixel patches and treats them sequentially. It utilizes the Self-Attention mechanism to allow every patch to mathematically attend to every other patch simultaneously.

- **Autonomous Driving Implications** — Global Context: A ViT inherently links distant objects, providing a global, holistic context (e.g., linking a traffic light state to the braking patterns of distant vehicles). However, this global intelligence requires massive computational memory, making Transformers exceptionally difficult to deploy on constrained vehicular edge hardware.

2.2.6 Bird's-Eye-View (BEV) Representations

- **The Algorithmic Mechanics** — Spatiotemporal Transformers for Multi-Camera Fusion: Modern vehicles utilize multiple cameras pointing in diverse directions. BEVFormer [17] addressed fragmented logic by projecting all multi-camera images into a unified, top-down Bird's-Eye-View. It utilizes spatiotemporal transformers to "query" 2D images and pull features into a 3D grid space, using historical frames to remember momentarily occluded objects.

- **Autonomous Driving Implications** — The Latency Cost of the Ultimate Map: BEVFormer represents the current pinnacle of spatial perception, providing a metric top-down view of the environment. However, deploying multi-camera Transformers introduces significant computational latency, penalizing the real-time control loop.

2.2.7 Comprehensive Summary of Perception Architectures

Table 2.1: Evolution of Autonomous Perception Algorithms

Author / Year	Model / Architecture	Core Innovation	Algorithmic Strength	Fatal Flaw / AV Limitation
Krizhevsky (2012) [12]	CNN (AlexNet)	GPU-accelerated Convolutions	First learned, robust visual feature extraction.	Extremely slow; classification only, no bounding boxes.
Redmon (2015) [13]	YOLO	Single-pass grid regression	Unprecedented real-time speed (30+ FPS).	”Box” vision lacks fine-grained geometric road details.
Ronneberger (2015) [14]	U-Net	Skip-connections / Segments	Pixel-perfect map of drivable surfaces.	Entirely 2D; zero inherent understanding of depth.
Lang et al. (2019) [15]	PointPillars	Point cloud voxelization to 2D	Fast, immune to lighting and weather conditions.	Lacks color/semantic texture (cannot read traffic signs).
Dosovitskiy (2020) [16]	ViT	Patch embeddings & Attention	Global context; links distant objects mathematically.	Massive VRAM requirements; computationally heavy.
Li et al. (2022) [17]	BEVFormer	Spatiotemporal 3D Queries	Perfect 3D top-down multi-camera fusion.	Extreme GPU Latency; difficult for real-time edge devices.

2.3 The Evolution of Action and Control

Perception alone is passive. Moving from perception to action requires teaching an agent to make decisions. The following evolution tracks the journey from imitation to continuous Reinforcement Learning.

2.3.1 Behavioral Cloning

- **The Algorithmic Mechanics** — Imitation Learning via Early Neural Networks: ALVINN [18] utilized Behavioral Cloning, observing a human steering a car and taking a camera image as input with the steering angle as output. Through backpropagation, it learned to mimic actions based on visual appearance.
- **Autonomous Driving Implications** — The Brittleness of Pure Imitation: While historically profound, Behavioral Cloning possesses no memory and no actual understanding of physics. If the vehicle drifted slightly off the ideal path, the network entered an unrepresented state and catastrophically failed.

2.3.2 Classical Sensor Fusion

- **The Algorithmic Mechanics** — Probabilistic Robotics and Kalman Filters: Stanley [19] relied on probabilistic robotics, fusing LiDAR, GPS, and camera data using Kalman Filters. It navigated via a rigid, hand-coded path-planning algorithm calculating geometric routes on a 2D occupancy grid.
- **Autonomous Driving Implications** — Conquering the Desert, Failing the City: While it conquered the DARPA Grand Challenge desert, hand-coded logic fails in chaotic urban environments, where driving is a fluid social negotiation requiring the adaptability of deep learning.

2.3.3 Deep Q-Networks (DQN)

- **The Algorithmic Mechanics** — Q-Learning Married to Deep Neural Networks: Reinforcement Learning (RL) allows agents to learn actively. DQN [20] combined deep neural networks with Q-learning, introducing *Experience Replay* to stabilize learning gradients by sampling past experiences.
- **Autonomous Driving Implications** — The Leap to Active Agency: DQN allowed vehicles to learn collision avoidance actively via reward maximization. However, it was limited to discrete action spaces (e.g., binary "Steer Left" commands), incapable of the fluid adjustments required for physical steering wheels.

2.3.4 End-to-End Learning

- **The Algorithmic Mechanics** — Direct Mapping of Pixels to Torques: NVIDIA [8] mapped raw pixels directly to steering commands using a massive CNN without intermediate path planners, extracting features internally.
- **Autonomous Driving Implications** — The Reality of Distributional Shift: End-to-End models suffer from severe *Distributional Shift*. Because the system is a singular "black box," minor environmental perturbations (e.g., a gust of wind) push the agent into unknown visual states, leading to catastrophic failure.

2.3.5 Continuous Control (PPO and SAC)

- **The Algorithmic Mechanics** — Stabilizing Continuous Mathematical Control: To solve the discrete action problem, Actor-Critic architectures were developed. Proximal Policy Optimization (PPO) [21] stabilized control by mathematically clipping policy updates. Recent literature has focused heavily on improving PPO for autonomous trajectory planning to maximize reward convergence [22, 23]. Soft Actor-Critic (SAC) [24] introduced an off-policy, Maximum Entropy framework. It rewards the agent for acting as stochastically as possible while reaching the goal ($J(\pi) = \mathbb{E}[r + \alpha\mathcal{H}(\pi)]$), naturally encouraging the discovery of diverse driving behaviors.
- **Autonomous Driving Implications** — The Reliable Muscle of Simulation: SAC provides robust recovery reflexes and fluid geometric maneuvering. However, while highly robust kinematically, it is conceptually blind, lacking semantic common sense and necessitating higher-level supervisory logic.

2.3.6 Model-Based Reinforcement Learning

- **The Algorithmic Mechanics** — Dreaming in Latent Space (World Models): DreamerV3 [25] represents a shift to Model-Based RL. It trains an internal "World Model" to learn environment physics, allowing the policy to train by simulating future states entirely within latent space.
- **Autonomous Driving Implications** — Anticipating Physics: DreamerV3 drastically reduces data hunger, allowing agents to anticipate complex dynamics. Yet, while it understands physics perfectly, it still lacks semantic and societal reasoning.

2.3.7 Comprehensive Summary of Control Architectures

Table 2.2: Evolution of Autonomous Action and Control Algorithms

Author / Year	Algorithm / Concept	Core Innovation	Algorithmic Strength	Fatal Flaw / AV Limitation
Pomerleau (1989) [18]	ALVINN	Behavioral Cloning (Imitation)	First network to map pixels to steering.	Zero memory; catastrophically fails when off-path.
Thrun (2006) [19]	Stanley	Kalman Filters / Sensor Fusion	Brilliant probabilistic obstacle avoidance.	Hand-coded logic fails in chaotic urban environments.
Mnih (2015) [20]	DQN	Deep Q-Learning & Replay	Allows agents to actively learn via rewards.	Restricted to clunky, discrete actions (No fluid steering).
Bojarski (2016) [8]	NVIDIA E2E	CNN directly to steering torque	Automatic extraction of driving features.	Extreme black box; fatal distributional shift errors.
Schulman (2017) [21]	PPO	Clipped Objective Updates	Highly stable continuous vehicle control.	Data hungry; zero semantic "common sense" reasoning.
Haarnoja (2018) [24]	SAC	Maximum Entropy exploration	Efficiently finds robust driving paths.	Highly sensitive to reward scaling; hard to tune.
Hafner (2023) [25]	DreamerV3	World Models / Latent Dreaming	Learns physics; trains rapidly in its own latent space.	Still lacks semantic, societal context of objects.

2.3.8 The Behavioral Evaluation Problem and Trajectory Clustering

As continuous control agents advanced, classifying their driving modes became challenging. Traditionally, researchers relied on **Heuristic Rule-Based Labeling**, forcing human biases onto machine policies.

To eliminate human bias, recent literature has explored **Unsupervised Trajectory Clustering**. By recording an agent's kinematic history, algorithms can organically group similar driving sequences. To handle temporal shifts (e.g., varying execution speeds of identical maneuvers), researchers utilize **Dynamic Time Warping (DTW)** [26]. By applying DTW clustering to an RL agent's trajectory, the true behavioral taxonomy emerges entirely from the data, a critical foundation for modern hierarchical architectures.

2.4 The Semantic Reasoning Era (2024-2026)

By 2023, the industry possessed extraordinary perception maps and robust continuous controllers, yet struggled with semantic context. A pure RL system cannot differentiate between a floating plastic bag and a solid concrete block of identical dimensions, lacking the contextual reasoning to negotiate complex scenarios safely.

2.4.1 Vision-Language-Action Models (VLA)

To break the "Common Sense Wall," researchers fused Large Language Models (LLMs) with control loops. Wayve's LINGO-1 [27] and DriveGPT4 [28] forced driving models to generate natural language commentary, effectively opening the AI "black box" by outputting textual reasoning alongside vehicle controls.

In the 2024–2026 window, VLA architectures rapidly transitioned to active control. Models such as DriveVLM [29] and GPT-Driver [30] demonstrated that language tokens could execute active trajectory planning. The LMDrive architecture [31] successfully demonstrated closed-loop end-to-end driving directly via language models, while Wayve deployed LINGO-2 [32] to command physical actuation on public roads.

2.4.2 The Latency Crisis

However, bringing massive autoregressive models into the control loop triggered a physical reality: the Latency Crisis. Empirical studies confirm that VLA inference frequently introduces severe computational delays, often exceeding 1.5 seconds per decision cycle [10, 11]. At 100 km/h, a 1.5-second processing delay translates to over 41 meters of uncontrolled momentum. Consequently, while end-to-end VLAs solve semantic reasoning, they remain physically unsafe for survival-critical, high-frequency actuation.

2.5 Comparative Assessment of Autonomous Paradigms

Synthesizing the literature reveals that no single paradigm safely achieves Level 5 autonomy in isolation. Table 2.3 critically compares the primary control methodologies.

Table 2.3: Comparative Analysis of Autonomous Driving Paradigms.

Paradigm	Core Strength	Primary Flaw	Latency Profile
Rule-Based Systems (e.g., Stanley)	Highly deterministic and mathematically verifiable.	Catastrophically fails in unpredictable social/urban edge cases.	**Ultra-Low** (Sub-millisecond)
End-to-End RL (e.g., pure SAC/PPO)	Discovers robust continuous control paths organically.	”Black-box” opacity; completely lacks semantic common sense.	**Low** (10–20 ms)
End-to-End VLA (e.g., LMDrive, DriveVLM)	Excellent semantic reasoning and complex scene interpretation.	Computationally massive; breaks real-time physical safety constraints.	**Critically High** (1.0–2.0+ seconds)
Neuro-Symbolic (Hybrid Architecture)	Combines fast neural reflexes with logical, semantic guardrails.	High architectural complexity requiring multi-frequency orchestration.	**Asynchronous** (Decoupled Hz)

The literature confirms a strict inverse correlation between semantic intelligence and reaction speed. End-to-end VLA models solve reasoning but introduce dangerous latency, whereas continuous RL models solve reflexes but operate blindly.

2.6 Conclusion

The evolution of autonomous AI demonstrates a profound architectural limitation: forcing a single monolithic network to handle both high-frequency kinematic reflexes and low-frequency semantic reasoning simultaneously. To bypass the latency crisis of monolithic VLA models, the literature strongly motivates a decoupled, Neuro-Symbolic approach. By delegating perceptual and continuous reflex tasks to fast neural agents, while elevating logic and traffic negotiation to symbolic language models, it becomes possible to synthesize the sub-millisecond reaction times of an RL agent with the deep contextual wisdom of an LLM. Having identified this structural necessity, the following chapter details the specific engineering methodology utilized to implement this architecture within the CARLA environment.

Chapter 3

System Architecture and Methodology

3.1 Introduction

This chapter details the design, engineering, and implementation of our autonomous driving prototype. The transition from theoretical concepts to a deployable, simulated prototype requires a highly modular approach to resolve the cognitive bottleneck: balancing the high-frequency reflexes required for physical steering with the low-frequency semantic reasoning necessary for traffic safety.

This chapter is organized as follows: Section 2 presents our general system architecture and our primary scientific contributions. Section 3 details the simulation environment parameters. Section 4 sequentially breaks down the computer vision pipeline, encompassing our multi-modal dataset generation and geometric sensor fusion. Finally, Section 5 details the Reinforcement Learning decision architecture and control loop.

3.2 The Project Environment: CARLA 0.9.16 Simulator

Before detailing the specific neural network architectures, it is imperative to establish the foundational environment in which they operate. Both the computer vision perception models and the Reinforcement Learning decision agents rely heavily on the physics, rendering, and data extraction capabilities of the simulator.

For this project, the **CARLA 0.9.16** simulator [33] was selected. CARLA is a standard open-source, Unreal Engine-based benchmark platform explicitly designed to facilitate high-level autonomous driving research. Version 0.9.16 was specifically chosen due to its advanced sensor APIs and highly deterministic Synchronous Mode. This environment provides the strict temporal synchronization required to perfectly align high-frequency LiDAR sweeps, multi-camera RGB frames, and the ego-vehicle's underlying physics engine. By anchoring both the dataset generation and the closed-loop training within this unified engine, a mathematically consistent ground truth is guaranteed across all phases of the project.

3.3 System Architecture and Our Contributions

To address the challenges of autonomous navigation, we engineered and deployed a dual-pipeline system entirely within a high-fidelity simulation environment.

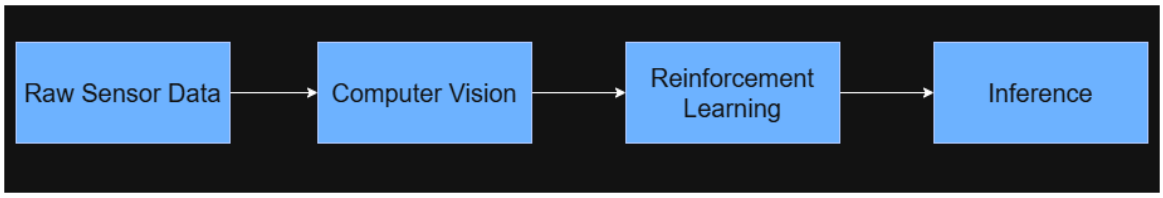


Figure 3.1: Full System Flow Architecture, illustrating the end-to-end integration of CARLA sensor data generation, multi-modal perception processing, neuro-symbolic reinforcement learning, and final kinematic inference.

As illustrated in Figure 3.1, our macro architecture operates in a strict, linear flow consisting of four main steps:

1. **Raw Sensor Data:** The CARLA simulator generates deterministic, multi-modal environmental data, including RGB images, LiDAR point clouds, and raw segmentation masks.

2. **Computer Vision:** The perception pipeline processes this raw data through fine-tuned SegFormer and YOLOv8 models, geometrically fusing the outputs into a top-down Bird's-Eye-View (BEV) map and 3D Object Vectors.

3. **Reinforcement Learning:** The decision system ingests this visual state, utilizing a Soft Actor-Critic (SAC) agent modulated by a GRU behavior predictor to calculate the optimal driving maneuvers.

4. **Inference:** The calculated throttle, brake, and steering commands are transmitted back into the CARLA physics engine to physically execute the action.

Crucially, the CARLA Simulator intervenes at both the absolute beginning and the exact end of this process: it acts as the initial data generator, and it serves as the ultimate execution environment during the Inference phase.

Within this overarching flow, our work introduces three primary engineering contributions:

1. **Custom Dataset Generation and Fine-Tuning:** We engineered a synchronized data collection pipeline within the CARLA simulator to capture complex, high-density urban driving scenarios. This pipeline produces a heavily distilled, multi-modal dataset—perfectly aligning 4-camera RGB frames, LiDAR point clouds, and semantic ground truth. We utilized this specific data distribution to fine-tune state-of-the-art vision models (YOLOv8 and SegFormer) to perform reliably within our target operational domain.

2. **Custom Optimized Bird's-Eye-View (BEV) Architecture:** We developed a highly efficient, dual-output perception engine utilizing explicit geometric sensor fusion. By deterministically projecting 2D neural network inferences against 3D LiDAR point clouds, we bypass the computationally heavy "scene-lifting" transformers prevalent in recent literature. This custom approach simultaneously generates a natively distortion-free 256x256 spatial grid and a distilled, tokenized JSON payload (Objects State), effectively bridging the gap between raw spatial data and our hybrid decision layers.

3. **Neuro-Symbolic Reinforcement Learning:** We developed a novel hierarchical decision system that arbitrates between a Soft Actor-Critic (SAC) continuous control agent, a GRU-based behavior sequence predictor, and a rule-based safety language model.

3.4 The Multi-Modal Perception Pipeline

A digital driver cannot safely navigate an environment it cannot accurately perceive. The fundamental objective of our computer vision pipeline is to synthesize the chaotic data generated by CARLA's sensors into a clean, actionable mathematical reality.

This perception pipeline is structured and executed in four sequential phases, as illustrated in Figure 3.2. By strictly isolating these steps, we ensure that the neural networks are trained on pristine, highly filtered data, which drastically improves live inference accuracy.

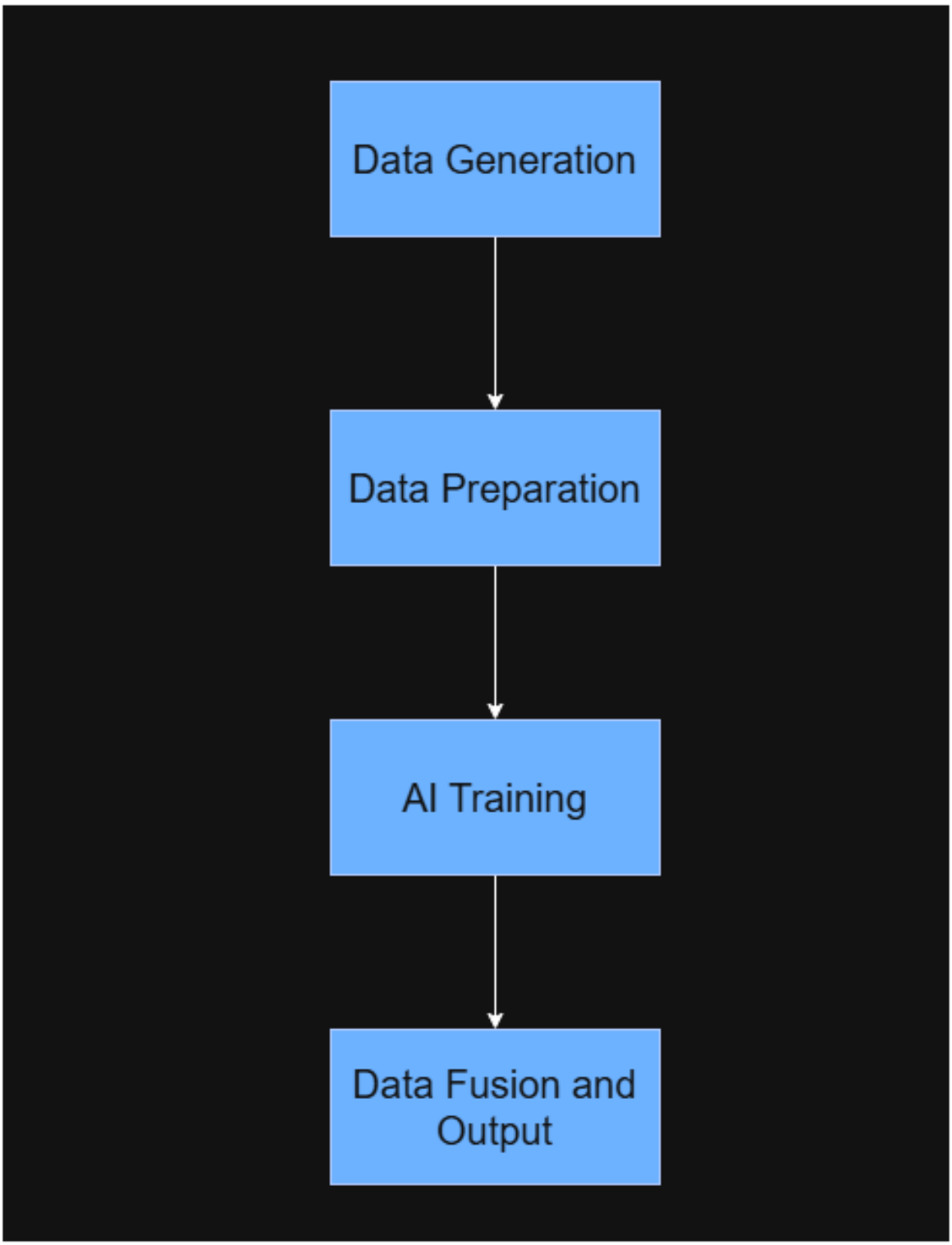


Figure 3.2: The Multi-Modal Perception Pipeline Flow, detailing the sequential progression from raw multi-camera and LiDAR data generation, through semantic filtering and parallel model training, to dynamic sensor fusion.

3.4.1 Phase 1: Data Generation

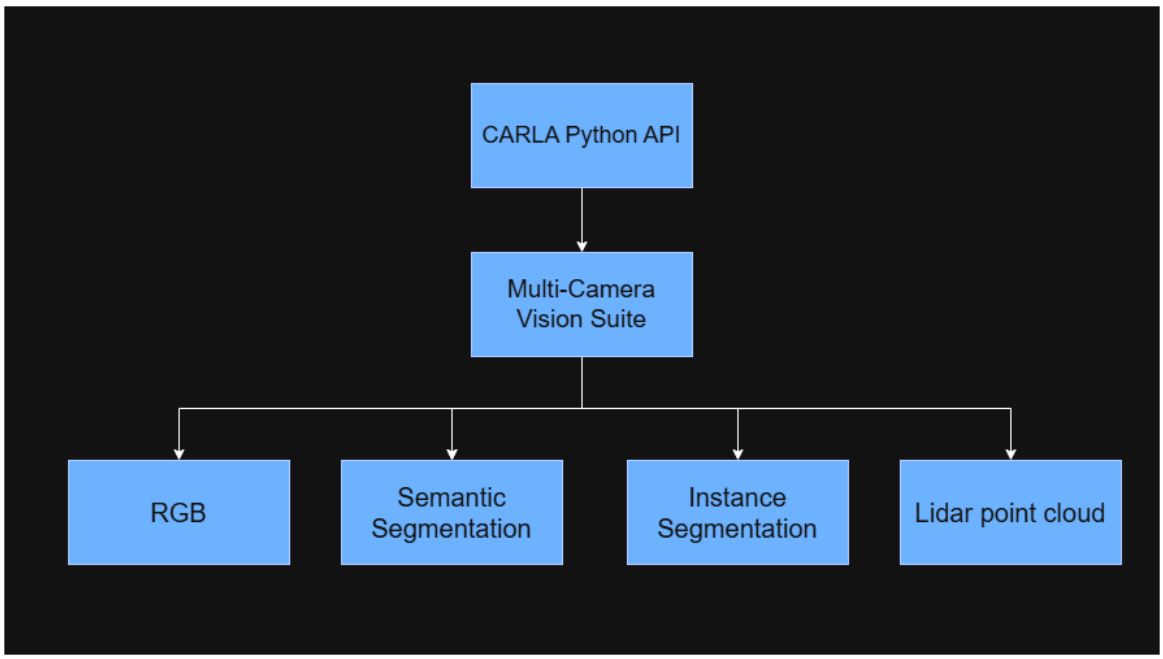


Figure 3.3: Phase 1: Data Generation and Sensor Configuration, showing the extraction of raw RGB imagery, LiDAR point clouds, and semantic masks from the CARLA environment under varying weather and traffic conditions.

The foundation of any robust deep learning model relies entirely on the quality, volume, and variance of its dataset. To capture highly accurate, synchronized ground-truth labels, we engineered a specialized data collection architecture utilizing the core simulator engine to extract multi-modal sensor data. As illustrated in Figure 3.3, the generation pipeline is structured hierarchically, originating from the environmental orchestration via the API down to physical vision capture and multi-sensor output modalities.

A. CARLA Python API

The CARLA Python API bypasses the calibration errors and physical limitations inherent to real-world data collection by providing mathematically perfect environmental control. To maintain a focused yet diverse training distribution, we executed data generation exclusively within the **Town01** map environment.

Through the API, we programmed a dynamic weather controller to cycle every 10 seconds through six distinct environmental presets, ranging from clear noon conditions to heavy rain at night. This cyclical variation forces the downstream visual models to learn robust, invariant features independent of lighting, shadows, or precipitation. Traffic density was strictly regulated by spawning 70 autonomous vehicles and 50 pedestrians, preceded by a brief engine warm-up period to establish a natural, fluid traffic flow. To mitigate anomalous data generation, an automated anti-stuck protocol was implemented. The simulation was recorded at a precise 1 Hz sampling rate to completely eliminate temporal redundancy, capturing one distinct frame every 20 simulation ticks.

B. Multi-Camera Vision Suite

The ego-vehicle was equipped with a highly optimized, dual-modality sensor suite designed to capture both visual texture and spatial geometry simultaneously. A 360° suite of four synchronized cameras was deployed, facing the front, rear, left, and right flanks of the vehicle (yawed at $0^\circ, 180^\circ, -90^\circ$, and 90°). Each camera was configured with an 800×600 pixel resolution and a 90° Field of View (FOV). Following the 8,000-frame collection protocol, the simulator output a massive corpus of 32,000 distinct high-resolution RGB images.

C. Multi-Modal Data Channels

To capture the complete multi-modal representation of the driving scene, our generation pipeline outputs four synchronized terminal data streams corresponding to the diagram's terminal nodes:

- **RGB:** The raw visual output from the multi-camera vision suite, capturing standard color frames at high resolution. These 32,000 front, rear, and lateral images provide the core spatial-textural features for object detection and semantic parsing.
- **Semantic Segmentation:** Infallible, pixel-perfect ground-truth masks exported directly by the CARLA engine. The engine exported 32,000 synchronized masks categorizing the general environment into 14 native elements, providing the absolute geometric boundaries of the navigable world.
- **Instance Segmentation:** Parallel masks identifying unique individual actor IDs. To isolate individual actors, instance masks were simultaneously captured. These assign a unique pixel ID to every single vehicle and pedestrian in the frame, a critical prerequisite for extracting exact bounding boxes.
- **Lidar point cloud:** Ultra-high-density 3D geometric coordinate sweeps collected by a 256-channel LiDAR sensor. To capture absolute spatial depth, the simulated sensor featured 256 channels, a 50-meter functional range, and a 20 Hz rotation frequency, generating approximately 2,600,000 points per second.

3.4.2 Phase 2: Data Preparation

While raw simulated data provides mathematically perfect ground truth, its native format contains an overwhelming amount of environmental diversity that is far too complex for trajectory path planning. Therefore, we subjected the data to rigorous simplification before model ingestion.

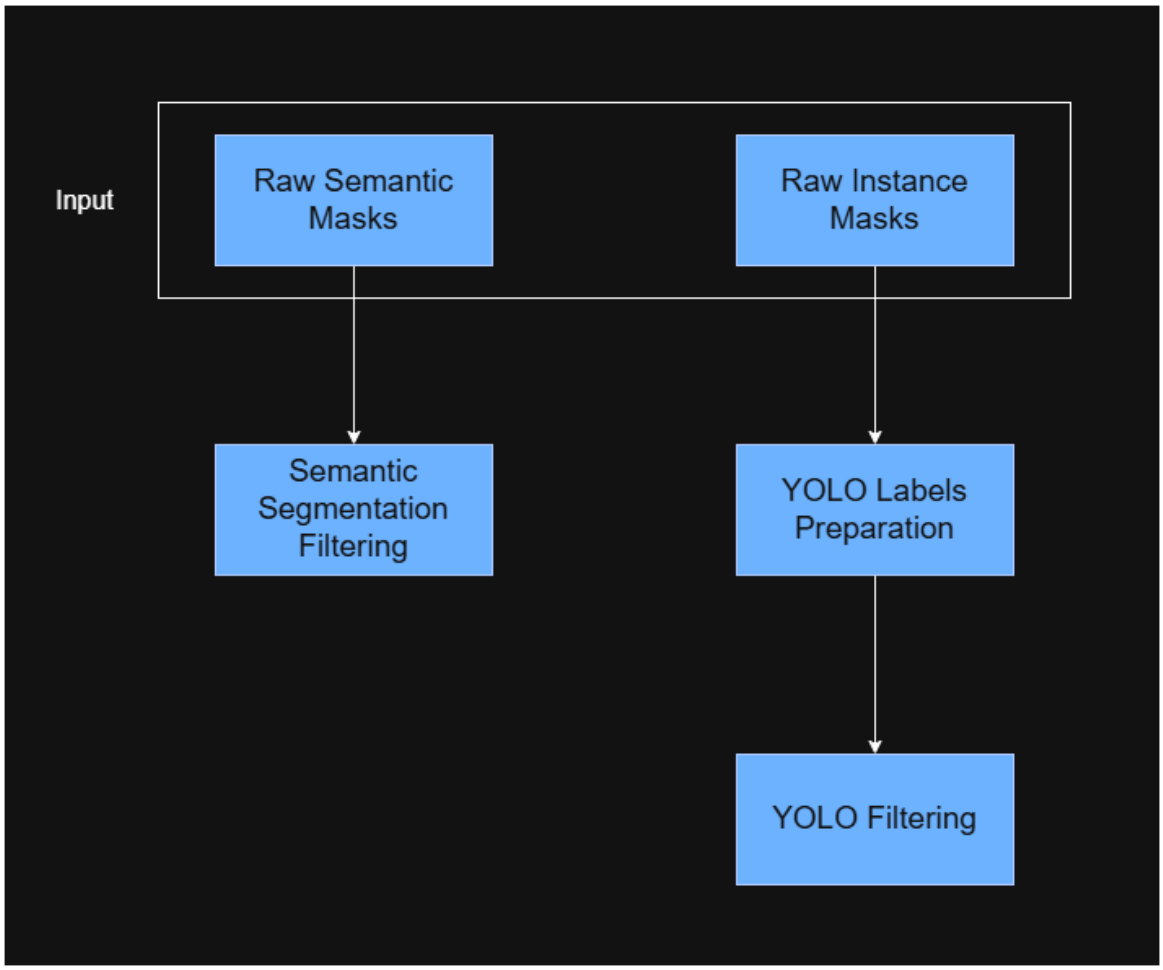


Figure 3.4: Phase 2: Data Preparation and Algorithmic Refinement, demonstrating the reduction of raw environmental masks into a 3-class semantic taxonomy and the extraction of dynamic 2D bounding boxes.

A. Input Data

This preprocessing stage directly ingests the primary multi-modal sensor outputs generated in the previous phase to prepare them for AI network ingestion:

- **Raw Semantic Masks:** Standard 800×600 multi-class pixel arrays containing complex, noisy environmental classifications that must be reduced to navigational corridors.
- **Raw Instance Masks:** Precise spatial maps identifying unique individual identity indices for all spawned vehicles and pedestrians, serving as the basis for bounding box extraction.

B. Semantic Segmentation Filtering

To optimize the downstream segmentation task, the environment needed to be drastically simplified. We deployed a highly efficient, vectorized Python script to distill the diverse environment into a streamlined taxonomy. The algorithm filtered the environment down to just three critical categories:

1. **Drivable Area:** The primary road surface required for navigation.
2. **Road Lines:** The lane markings necessary for enforcing strict lateral discipline.
3. **Non-Drivable Boundaries:** Multiple non-navigable elements combined into a singular barrier class.

C. YOLO Labels Preparation

Because YOLO architectures ingest standard 2D spatial coordinates, we systematically converted the Instance Segmentation masks to generate bounding boxes. We exploited a structural feature of CARLA's rendering engine, scanning the Red pixel channel to dynamically calculate the precise 2D bounding box extremes:

$$\text{BBox}_k = [\min(u), \min(v), \max(u), \max(v)]$$

D. YOLO Filtering

Once extracted, we applied a strict multi-step filtering protocol to these labels:

- **Class Remapping:** Native actors were consolidated into three primary threat categories: Pedestrians, Vehicles, and Two-Wheelers.
- **Magnetic Merging:** A custom algorithm mathematically fused highly proximate bounding boxes using a 3% spatial buffer to prevent the network from detecting fragmented objects.
- **Spatial and Occlusion Filtering:** Strict minimum area thresholds were enforced to discard objects that were too distant (typically exceeding 40 meters) or occluded, guaranteeing the model was never trained to detect invisible threats.

3.4.3 Phase 3: Model Training

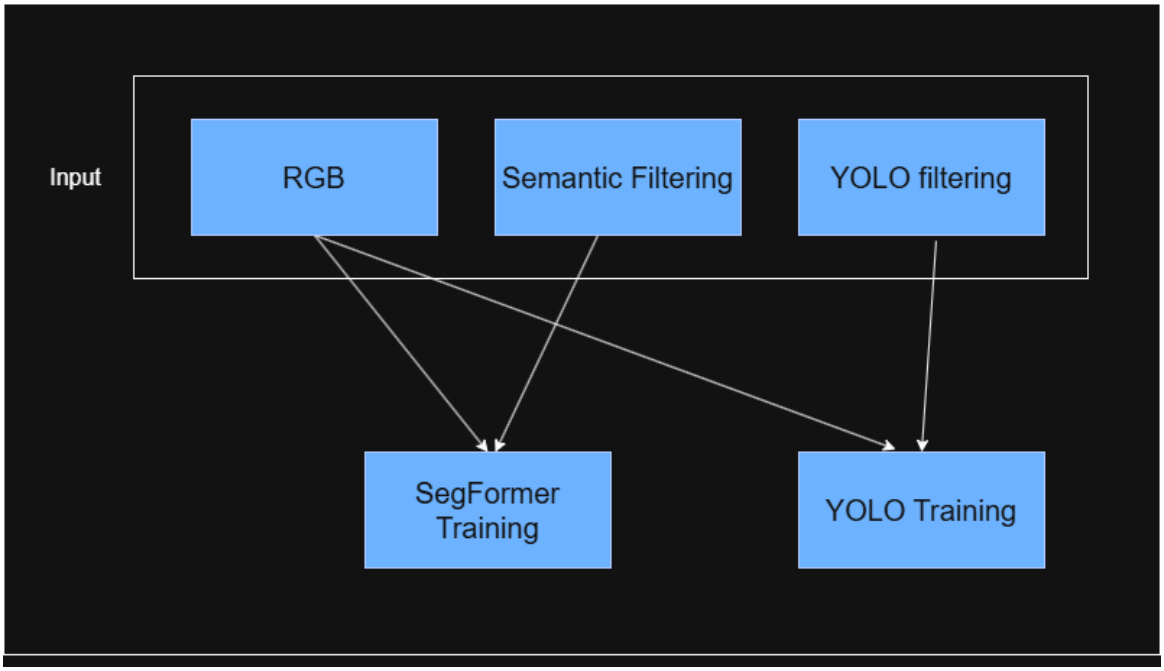


Figure 3.5: Phase 3: Parallel Neural Network Training, highlighting the supervised fine-tuning of SegFormer-B0 for static road geometry and YOLOv8s for dynamic obstacle tracking.

With the curated dataset mathematically refined, we progressed to the parallel supervised training of the dual-perception networks. We strategically distributed the 8,000 frames based on driving criticality: 5,000 frames for the forward camera, 2,000 for the rear, and 500 for each lateral flank.

A. Input Data

The parallel neural model training phase directly ingests the refined and optimized data products prepared during Phase 2:

- **RGB Images:** The raw multi-camera vision frames, capturing rich semantic texture from all points of view.
- **Semantic Filtering:** The distilled 3-class ground-truth segmentation masks (Drivable Area, Road Lines, and Non-Drivable Boundaries), serving as targeted supervisory training labels for the SegFormer architecture.
- **YOLO Filtering:** The remapped, merged, and occlusion-filtered 2D bounding boxes of dynamic threats, serving as supervised ground-truth annotations for YOLOv8.

B. SegFormer Training

For the critical task of painting the drivable corridor, we required a model that captures excellent global context without the latency of massive Vision Transformers. Drawing inspiration from the original architecture proposed by Xie et al. [34], we selected **SegFormer-B0**. The B0 variant is the most lightweight architecture in the SegFormer family, specifically chosen to guarantee the low-latency, real-time inference required for the autonomous driving control loop.

We initialized the network with weights pre-trained on the Cityscapes dataset [35] — a standard benchmark of real-world urban street scenes — and subsequently fine-tuned it exclusively against our heavily distilled CARLA dataset to classify our specific 3-class taxonomy. The successful live inference of this domain-adapted model is shown below.

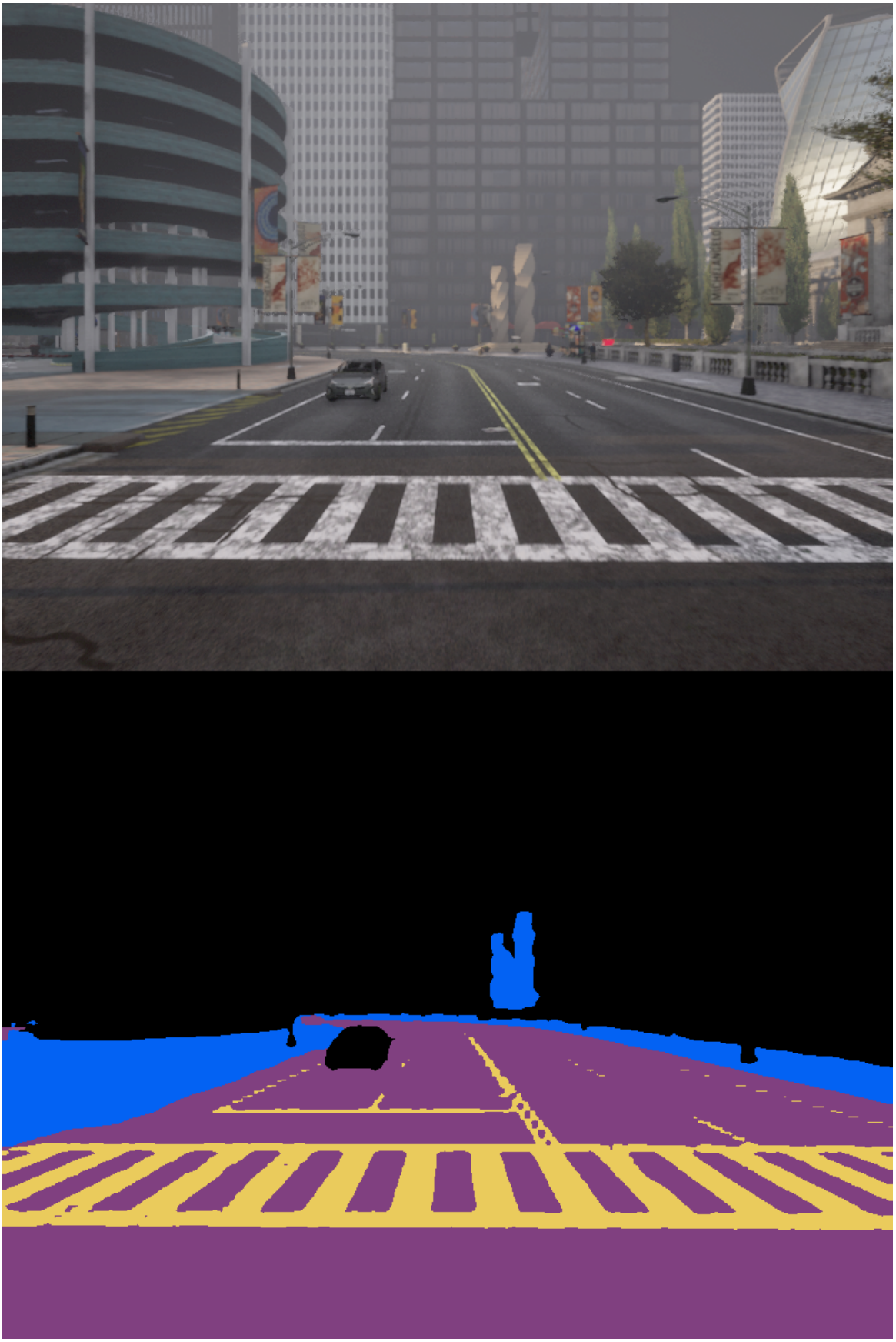


Figure 3.6: Live inference of the fine-tuned SegFormer-B0 model showing the 3-class semantic distillation.

C. YOLO Training

Tracking dynamic obstacles requires state-of-the-art detection precision operating effortlessly at high frame rates. For this, we deployed **YOLOv8s** [36].

We fine-tuned the network purely on our magnetically merged CARLA bounding box dataset. To maximize GPU hardware efficiency, Automatic Mixed Precision (AMP) was enabled. The network was specifically tuned to isolate the consolidated threat taxonomy across all 360 degrees of the vehicle's perspective, effectively extracting dynamic actors as demonstrated in Figure 3.7.



Figure 3.7: Live inference of the fine-tuned YOLOv8 model tracking dynamic actors.

3.4.4 Phase 4: Output Preparation and Sensor Fusion

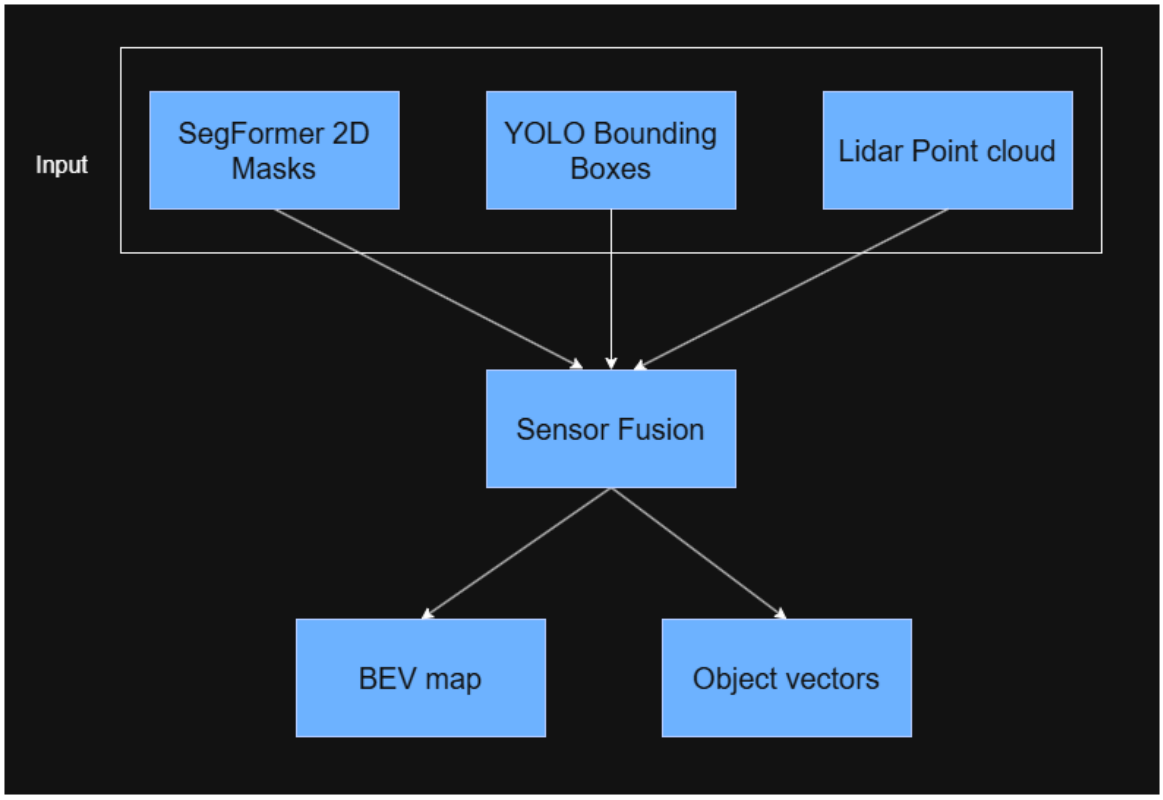


Figure 3.8: Phase 4: Dynamic Sensor Fusion and State Synthesis, depicting the deterministic projection of 2D inferences and 3D LiDAR into a unified Bird's-Eye-View (BEV) map and discrete Object Vectors.

To orchestrate the high-frequency data processing required during live inference, we engineered a centralized Master Perception API. This API translates parallel AI inferences into an omniscient state ready for continuous vehicle control.

A. Input Data

The dynamic sensor fusion and state synthesis stage concurrently processes three high-frequency data streams generated by our upstream perception components:

- **SegFormer 2D Masks:** The three-class real-time semantic segmentation predictions highlighting the boundaries of the Drivable Area, Road Lines, and Non-Drivable Boundaries.
- **YOLO Bounding Boxes:** The dynamic 2D bounding boxes enclosing identified dynamic obstacles categorized into Vehicles, Pedestrians, and Two-Wheelers.
- **Lidar Point cloud:** The high-density raw 3D coordinate sweeps capturing the absolute spatial structure of the environment surrounding the ego-vehicle.

B. Sensor Fusion

RGB cameras are inherently two-dimensional, entirely lacking the absolute spatial depth required for physical collision avoidance. To resolve this, we engineered a precise geometric sensor fusion approach. Using mathematically defined intrinsic and extrinsic matrices, we rotated and translated the 3D LiDAR point cloud directly onto the 2D image planes. This precise alignment is visually demonstrated in Figure 3.9.

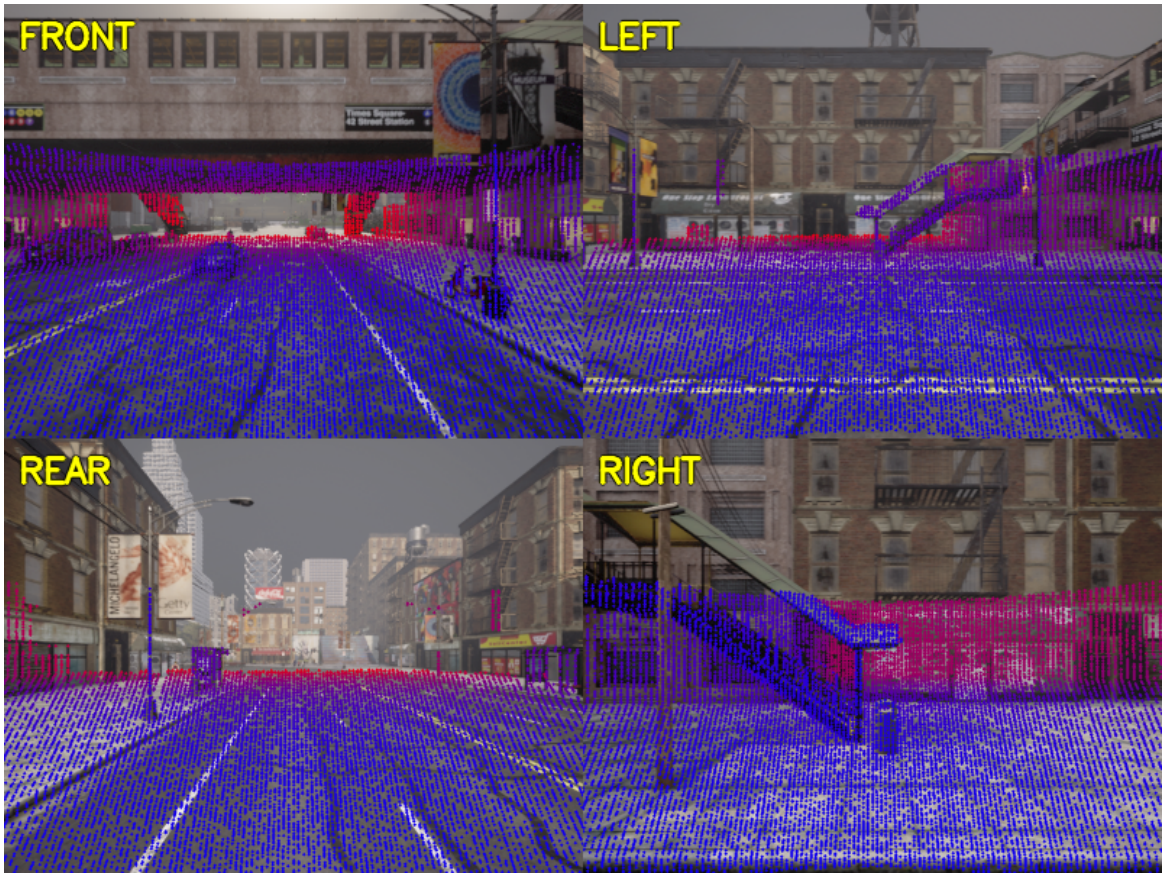


Figure 3.9: Extrinsic 360-degree LiDAR point cloud projection onto the 2D camera planes.

C. BEV map

A Bird's-Eye-View (BEV) is a top-down, orthographic projection that maps the 3D environment into a 2D grid, eliminating perspective distortion and providing a unified spatial understanding of the vehicle's surroundings. To safely navigate, the Reinforcement Learning agent requires this mathematically linear, distortion-free representation. This sensor fusion algorithm transformed the perspective camera views into this BEV representation through semantic depth matching. Validated coordinates were flattened into a highly dense 256×256 spatial tensor, perfectly bounding a 32×32 meter physical square around the ego-vehicle at a metric resolution of 0.125 meters per pixel. Finally, morphological smoothing was applied to solidify the structural boundaries of the drivable corridor.

D. Object vectors

While the BEV map governs the static geometry, dynamic obstacles require localized tracking. Our Master Perception API extracts these threats by isolating the raw LiDAR points that successfully project inside the 2D bounding boxes actively generated by the YOLOv8 architecture. By applying spatial thresholding to strip away background noise, we extract the spatial median to pinpoint the exact centroid of the threat, synthesizing a compact 3D Object Vector.

The final state generated by this process, containing both the BEV and the dynamic vectors, provides complete situational awareness (Figure 3.10).

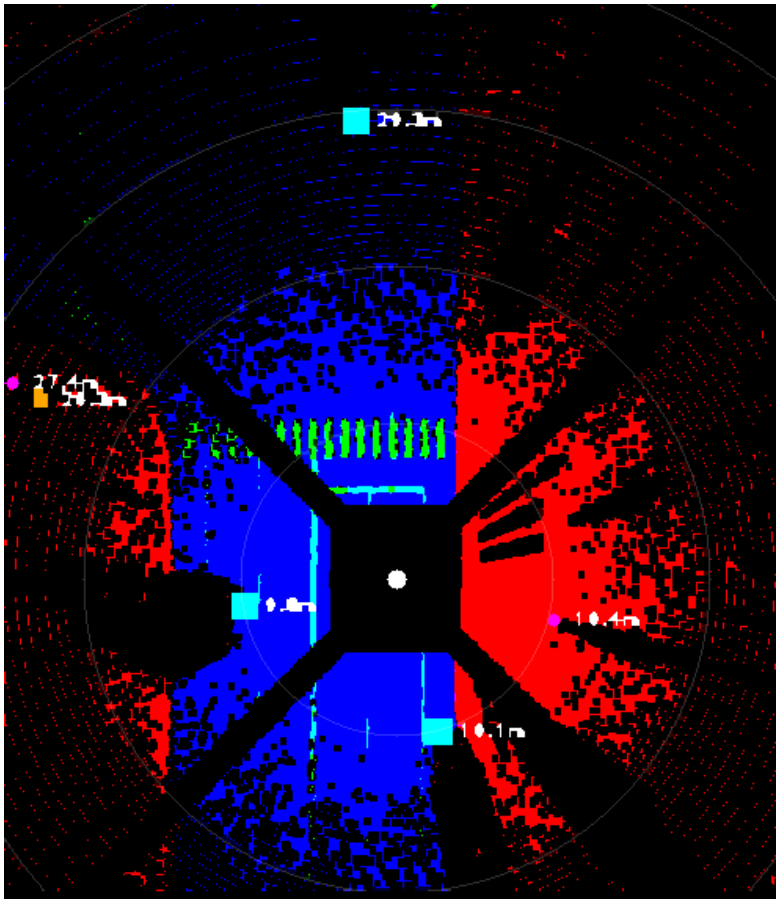


Figure 3.10: The final synthesized Bird's-Eye-View (BEV) map and deterministic Object Vectors.

3.4.5 Conclusion of Part 1 (Computer Vision)

By architecturally dividing the perception challenge and applying custom dataset generation, rigorous semantic refinement, targeted fine-tuning, and geometric sensor fusion, our computer vision pipeline successfully masters the raw sensor data. The resulting Bird's-Eye-View map and dynamic Object Vectors guarantee that the downstream Reinforcement Learning agent operates from a state of absolute, geometric truth. With perception resolved, the architecture shifts to physical decision-making and continuous control.

3.5 The Decision Making Pipeline

In this section we present a Decision Making Pipeline to balance aggressive, fast reflexes with safe, semantic planning. This pipeline is built around a central architectural discovery we made during this work: that the behavioral taxonomy required to supervise a safety override layer need not be defined by human rules, but can be *extracted directly from the trajectory distribution of the trained policy itself*. By applying Dynamic Time Warping KMeans clustering [26] to the driving sequences we collected from the SAC agent, five structurally distinct behavioral modes emerged organically from the data — including a left/right turn asymmetry that no hand-crafted labeling scheme would have distinguished. This data-driven discovery forms the supervisory backbone of our entire decision pipeline.

Within this framework, the three branches of our Decision Making Pipeline each address a fundamentally different timescale and type of decision. The **Soft Actor-Critic (SAC)** [24] agent handles *continuous control*: real-time, sub-second throttle and steering commands optimized through off-policy reinforcement learning over hundreds of trials. The **GRU behavior classifier** [37] handles *discrete behavioral context*: classifying the vehicle's current driving mode over a rolling 20-timestep window, and applying class-conditional brake overrides

that the SAC's scalar reward signal cannot reliably encode. The **Small Language Model (SLM)** [38] handles *semantic reasoning and personality*: encoding the scene in natural language to enforce traffic rules, explain decisions interpretably, and — in future extensions — modulate the vehicle's driving style according to contextual directives such as passenger comfort, emergency response, or regulatory zone compliance.

This section presents our empirical evaluation of each module in strict sequential order: behavioral cluster analysis, FFN encoder performance, GRU classification accuracy, and SAC convergence. We assess each module independently before a holistic closed-loop discussion.

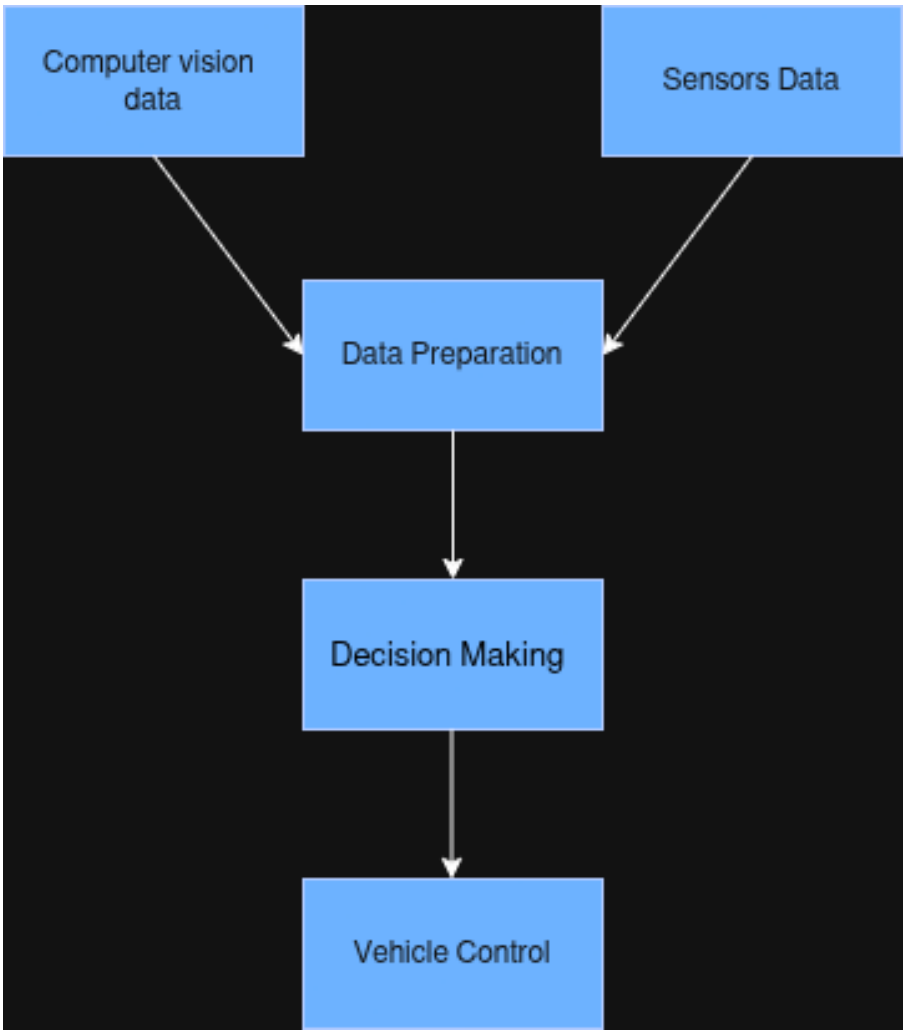


Figure 3.11: Decision Making Flow, illustrating the bifurcation of fused sensor data into parallel trajectory clustering (DTW), sequence classification (GRU), and continuous control (SAC) branches.

As illustrated in Figure 3.11, the Decision Making Pipeline combines both Computer Vision outputs and raw Car Sensor telemetry into a unified system, which ultimately produces the physical actuation commands transmitted to the CARLA simulator. This pipeline is structured and executed in two integrated macro-phases: **Phase 1: Data Preparation and Unsupervised Behavioral Clustering** and **Phase 2: Decision Making**.

3.5.1 Phase 1: Data Preparation and Unsupervised Behavioral Clustering

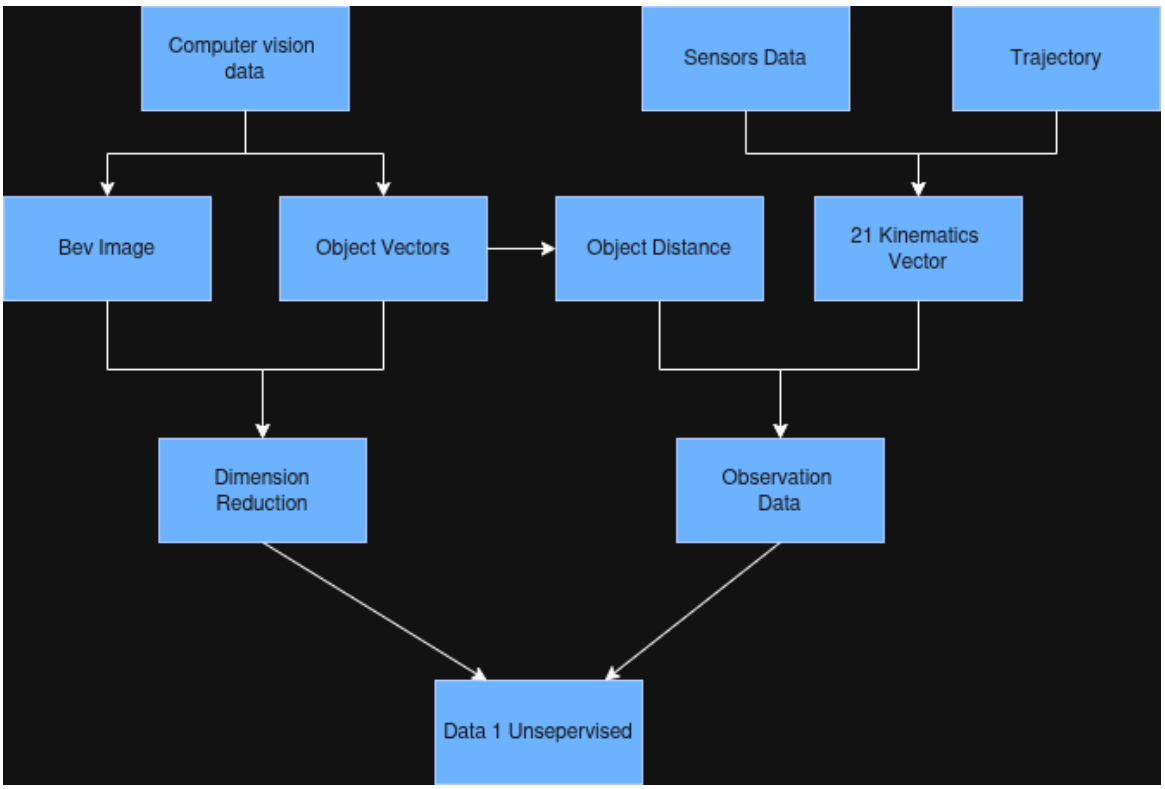


Figure 3.12: Data Collection, Formatting, and Clustering Flow, showing the aggregation of BEV states, Object Vectors, and kinematic telemetry into unified observation sequences.

Before any decision branch can operate, the heterogeneous inputs arriving from the perception layer and the onboard sensors must be harmonized into a coherent, dimensionally consistent representation. As illustrated in Figure 3.12, this stage constitutes the critical interface between raw environmental perception and structured machine learning inputs.

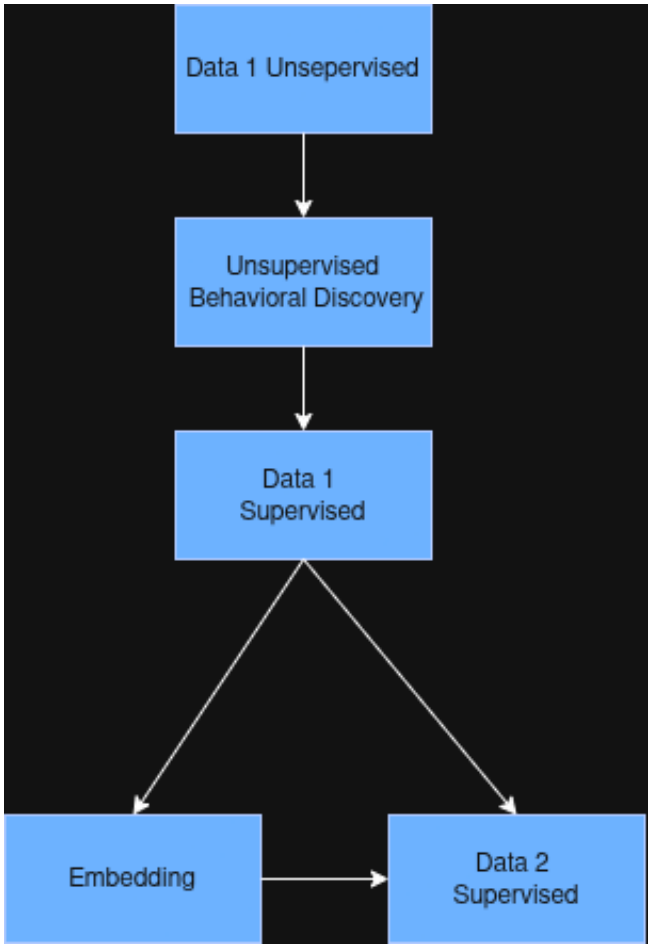


Figure 3.13: Creation flow for Data 1 and Data 2, demonstrating how raw trajectories are routed into unsupervised DTW clustering for label generation and supervised streams for encoder training.

Figure 3.13 illustrates how raw trajectory data is routed into parallel supervised streams and an unsupervised clustering backbone, together forming the ground-truth behavioral labeling pipeline.

A. Input Sources

The pipeline ingests data from three primary sources:

- **Computer Vision Output:** The BEV spatial map and Object Vectors produced by the Master Perception API described in Part 1.
- **Sensors Data:** A 22-dimensional vector capturing the vehicle's instantaneous state, including velocity, acceleration, heading, cross-track error, and current control surface positions.
- **Trajectory Buffer:** A rolling record updated after each simulation step, storing the most recent state observation, executed action, and received reward. This temporal context transforms the Markov observation into a history-conditioned input, enabling downstream models to reason over behavioral continuity rather than isolated snapshots.

B. Dimension Reduction

The BEV image, natively a $256 \times 256 \times 3$ RGB tensor, presents a significant dimensionality challenge for a real-time control loop. A dedicated **CnnEncoder** is pretrained as a standalone module and subsequently frozen during all downstream training. Its role is purely representational: compress the BEV spatial map into a compact, semantically meaningful representation of 1600 dim.

C. Unsupervised Behavioral Discovery via DTW KMeans

A fundamental challenge in training a behavioral classifier for autonomous driving is the absence of ground-truth behavioral annotations. Unlike object detection, where bounding boxes can be exported directly from the simulator, macro-behaviors must be inferred from the statistical and temporal structure of the collected trajectories themselves.

To achieve this without human labeling bias, an unsupervised trajectory clustering pipeline is executed directly on the extracted kinematic data. The feature space focuses on an 11-dimensional situational kinematic matrix:

$$\left[v_{\text{norm}},\ \text{ttc},\ \lambda_{\text{inv}},\ \text{CTE},\ \delta_{\psi},\ a_x,\ a_y,\ \dot{\psi},\ d_{\text{cv}},\ \mathbf{1}_{\text{ttc}},\ \text{ttc}_{\text{val}} \right]$$

The data processing sequence builds structured temporal matrices by rolling a window of 20 consecutive timesteps (WINDOW $= 20$) over the features at a fixed step length (STRIDE). This yields a dense sequence dataset of shape $(N,\ 20,\ 11)$. To categorize these sequences into distinct driving modes, we deploy a **TimeSeriesKMeans** clustering architecture utilizing a Dynamic Time Warping (**DTW**) [26] metric. DTW is critical here as it computes an optimal alignment path between time-series inputs, allowing the model to naturally group identical behaviors executed at varying velocities or temporal phases (e.g., accounting for a slow vs. aggressive left turn).

The model is parameterized with $n_{\text{clusters}} = 5$, max_iter $= 15$, and a fixed seed random_state $= 11$. Parallelization (n_jobs $= -1$) is leveraged to handle the high computational complexity of pair-wise DTW alignment across full driving logs. The final trained model is serialized out to `dtw_kmeans_full.pkl` to function as the deterministic behavioral ground-truth annotator for downstream network segments.

D. Resulting Behavioral Taxonomy

The cluster analysis converged on **five** mutually exclusive behavioral classes, reflecting the natural structure of urban driving on Town10HD:

ID	Label	Count	Behavioral Signature
0	NEAR_OBSTACLE	1,289	Low TTC, close forward cv_dist, reduced speed
1	CRUISING	3,168	Stable speed, low CTE, no threat signals
2	TURNING_LEFT	4,325	Negative lateral acceleration, elevated gyro_z
3	TURNING_RIGHT	4,031	Positive lateral acceleration, elevated gyro_z
4	LANE_RISK	2,077	High CTE, lane invasion flag active

Table 3.1: GRU behavioral taxonomy derived from unsupervised cluster analysis.

The separation of turning behavior into distinct left and right classes highlights the power of this data-driven approach: the DTW KMeans algorithm isolated the geometric sign of lateral acceleration as a primary discriminating axis, a structural nuance that hand-crafted or heuristic rule-labeling would often collapse into a single broad `TURNING` class.

E. Observation Data

Following clustering, the Object Distance sub-module fuses the Object Vectors from the CV pipeline with the 22-dimensional kinematic sensor channels. The merger of 3D centroid positions with ego-velocity and heading yields a complete metric representation of the vehicle's dynamic surroundings, consolidated into a unified **Observation Data** tensor.

As shown in Figure 3.12, the data is then bifurcated and routed into three specialized parallel streams:

- **Data 1 Unsupervised:** Passes directly from the kinematic registers into the DTW TimeSeriesKMeans fitting and inference sequence to map operational profiles.
- **Data 1 Supervised:** The primary Observation Data annotated directly with the behavioral class labels exported by the serialized DTW KMeans model, providing the ground-truth target vector for the FFN network.
- **Data 2 Supervised:** Generated downstream from FFN inference. After the FFN transforms the 1600-dimensional CNN feature vector into a 256-dimensional embedding, this embedding is concatenated with the kinematic features to form the temporally refined input to the GRU sequence model.

3.5.2 Phase 2: Decision Making

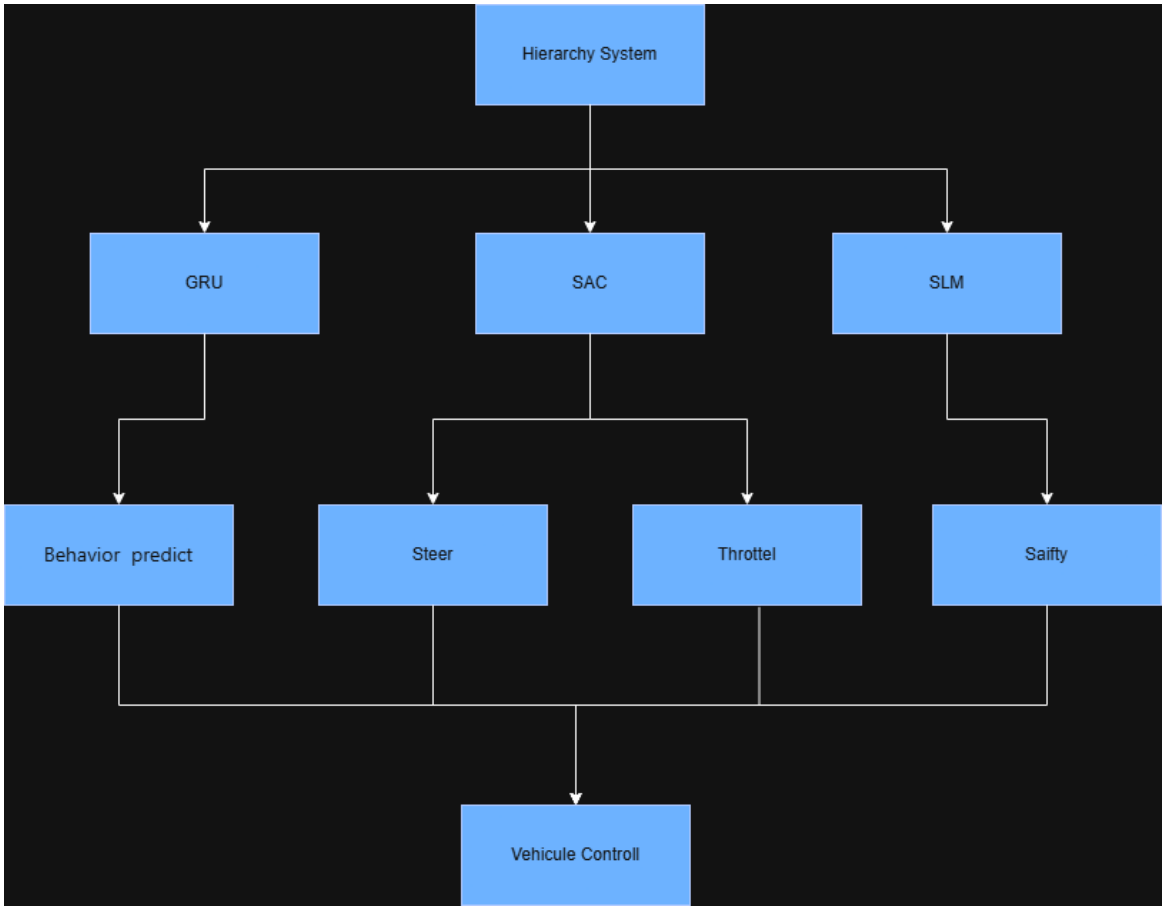


Figure 3.14: Decision Making Pipeline and Arbitration Flow, detailing the hierarchical resolution between the SAC agent's continuous throttle/steer, the GRU's safety overrides, and the SLM's semantic verdicts.

The Decision Making Pipeline serves as the central control block of the autonomous vehicle. As illustrated in Figure 3.14, this system encapsulates both the offline model training loop and the live multi-branch run-time execution engine. It concurrently evaluates an off-policy Reinforcement Learning policy, sequence-driven behavior prediction, and natural-language safety reasoning to synthesize a singular, unified vehicle actuation signal.

A. GRU Branch — Discrete Control Loop

Before active deployment within the real-time control loop, the underlying structural models must be trained in a strict sequential cascade using the supervised streams established in Phase 1.

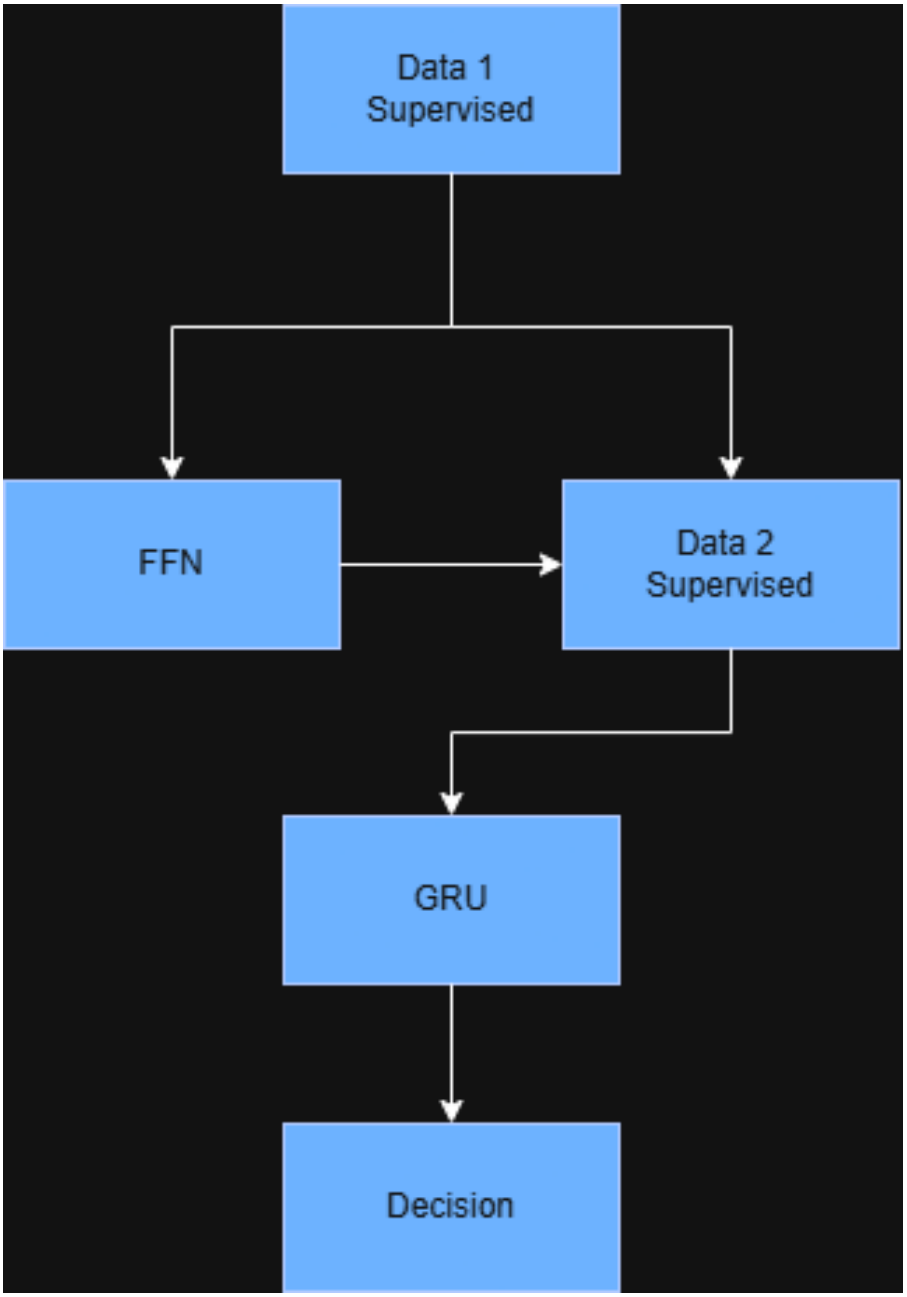


Figure 3.15: Internal FFN and GRU Training Sub-Pipeline, highlighting the compression of 1600-dimensional CNN features and the supervised sequence modeling over a 20-timestep rolling window.

1. FFN Encoder Training (1600 → 256): The 1600-dimensional CNN embedding produced by the frozen CnnEncoder is compressed by a supervised **FFNEncoder** into a 256-dimensional semantic representation suitable for efficient sequential processing.

The FFN is optimized using the Data 1 Supervised stream, matching inputs against the five behavioral class labels from Table 3.1 via CrossEntropyLoss with inverse-frequency class weighting. Once optimized, the FFN trunk is frozen and maps all rows of the dataset into the 256-d embeddings that populate the Data 2 Supervised stream.

2. GRU Behavior Classifier Training: The GRU [37] receives the Data 2 Supervised stream: a fused per-timestep feature vector of **278 dimensions**, formed by concatenating the 22-dimensional kinematic observation with the 256-d FFN embedding. It processes rolling windows of 20 consecutive timesteps to infer the vehicle's

active driving state.

The trained `BehaviorPredictor` wraps the GRU for real-time deployment. It maintains a rolling buffer of the 20 most recent 278-d state vectors, returning `-1` during the first 19 warmup steps. Once the buffer is full, it returns one of the five behavioral class IDs at every simulation tick with no additional latency beyond a single GRU forward pass.

B. SAC Branch — Continuous Control Loop

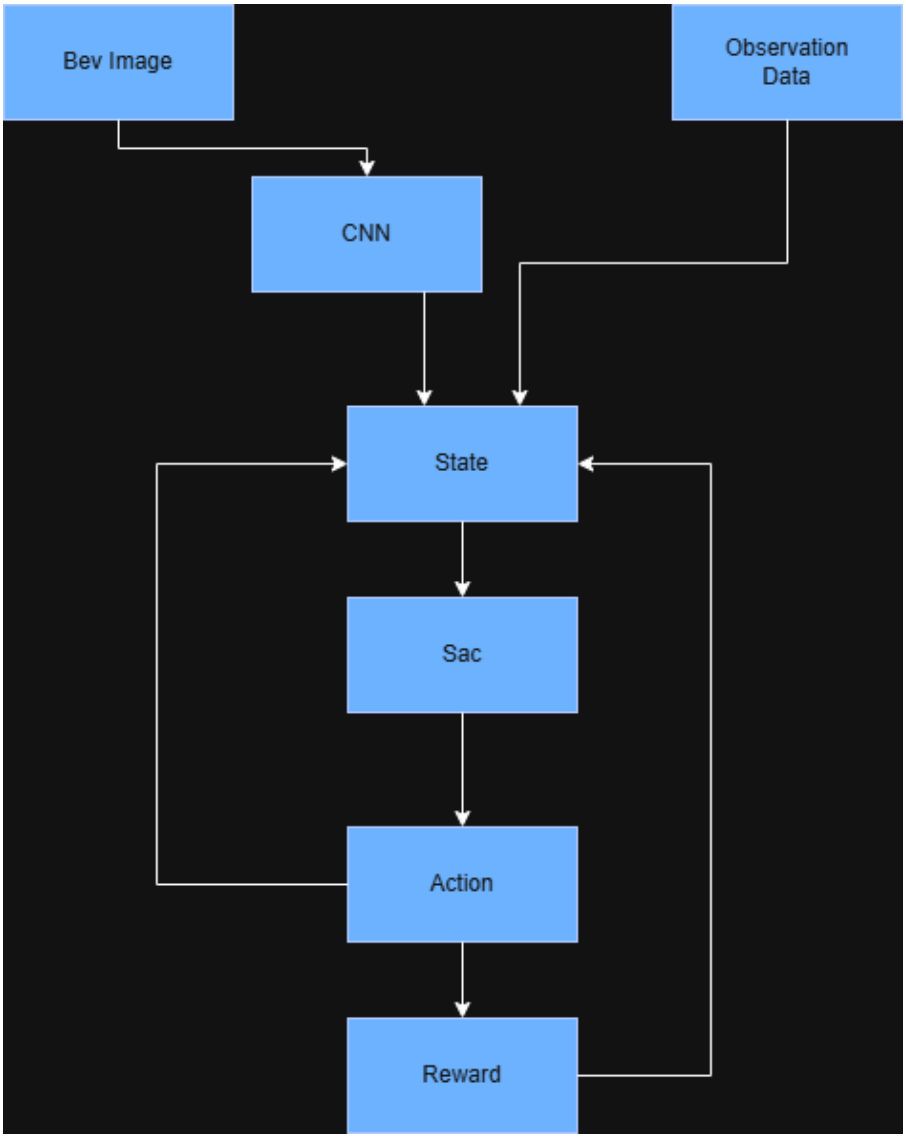


Figure 3.16: SAC Continuous Control Loop, depicting the off-policy reinforcement learning cycle where the actor-critic architecture optimizes throttle and steering against the multi-component reward function.

Soft Actor-Critic (SAC) [24] was selected as the core continuous control framework. As illustrated in Figure 3.16, the SAC loop ingests the BEV Image through the CNN encoder and the Observation Data directly, assembles the full state vector, and iterates through the standard off-policy RL cycle: State → SAC → Action → Reward → updated State.

The SAC agent is implemented as three cooperating neural networks:

Actor Network. A three-layer fully connected network with ReLU activations. Given state $\mathbf{s} \in \mathbb{R}^{1622}$, it outputs Gaussian distribution parameters $(\boldsymbol{\mu}, \log \boldsymbol{\sigma})$ with $\log \boldsymbol{\sigma} \in [-5, 2]$. The two action dimensions use distinct squashing functions:

- **Throttle** $\in (0, 1)$: sigmoid(z_0), enforcing strict positivity.
- **Steer** $\in (-1, 1)$: tanh(z_1), allowing symmetric lateral control.

The log-probability correction for each squashing transformation is applied to maintain a valid entropy gradient:

$$\log \pi(\mathbf{a}|\mathbf{s}) = \log \pi(\mathbf{z}|\mathbf{s}) - \log(a_0(1 - a_0)) - \log\left(1 - a_1^2\right)$$

Twin Critic Networks. Two independent Q-networks Q_{θ_1}, Q_{θ_2} mitigate overestimation bias via the clipped double-Q Bellman target:

$$y = r + \gamma(1 - d)\left[\min_{i=1,2} Q_{\bar{\theta}_i}(\mathbf{s}', \mathbf{a}') - \alpha \log \pi(\mathbf{a}'|\mathbf{s}')\right]$$

Target networks are updated via soft exponential moving average with $\tau = 0.005$.

Automatic Entropy Tuning. The entropy coefficient α is learned by minimizing:

$$\mathcal{L}(\alpha) = -\alpha \cdot \mathbb{E}_{\mathbf{a}\sim\pi}\left[\log \pi(\mathbf{a}|\mathbf{s}) + \mathcal{H}_{\text{target}}\right], \quad \mathcal{H}_{\text{target}} = -d_a$$

α is parameterized in log-space to enforce strict positivity. Its optimizer uses plain Adam rather than AdamW, as weight decay would artificially bias $\alpha \to 1$.

Replay Buffer and Update Order. Transitions (s, a, r, s', d) are stored in a circular buffer of capacity 10^5. At each update step, a mini-batch of 256 transitions is drawn uniformly and three updates are applied in strict order: Critic, Actor, Entropy.

Reward Function Design

The reward is decomposed into six semantically distinct components combined via a weighted linear sum, with weights w_1–w_5 treated as Optuna [39] hyperparameters:

$$r = w_1 r_{\text{speed}} + w_2 r_{\text{safety}} + w_3 r_{\text{stability}} + w_4 r_{\text{lane}} + w_5 r_{\text{map}} + r_{\text{goal}} + r_{\text{stuck}}$$

Terminal conditions. Four hard termination conditions are evaluated before any shaped reward:

- **Collision:** $r = -1000$, episode terminates.
- **Stuck** ($v < 5$ km/h for > 60 ticks): $r = -500$, with escalating per-tick penalty $-3 \times \min(t_{\text{stuck}}, 60)$.
- **Lane departure** (CTE > 7 m): $r = -800$.
- **Heading divergence** ($|\delta_\psi| > 0.85$ rad): $r = -600$.

Component 1 — Longitudinal Progress. Speed reward shaped as a Gaussian bell centered on the 40 km/h target, computed on forward-projected velocity $v_{\text{fwd}} = \max(0,\ v \cdot \cos(\delta_\psi \cdot \pi))$ to discount misaligned motion.

Component 2 — Safety and Obstacle Avoidance. Each detected object receives an angular weight $w_\theta = \cos^2(\theta/2)$, equal to 1.0 ahead and 0.0 behind, preventing stationary roadside objects from triggering emergency braking. Threat scores are distance-zoned: critical ($d < 3$ m), safe zone ($3 \le d < 15$ m), and TTC-based (TTC < 3 s).

Component 3 — Lateral Stability and Comfort. Four sub-signals penalize steer magnitude, steer jerk, lateral acceleration exceeding $2\,\mathrm{m/s^2}$, and throttle jerk, promoting smooth and comfortable actuation.

Component 4 — Lane Discipline. Binary signal: $+7$ per tick for correct lane occupancy, -20 for lane invasion.

Component 5 — HD Map Alignment. Three sub-signals enforce CTE minimization (Gaussian bell), heading error correction (tiered), and waypoint steering matching.

Component 6 — Goal-Directed Behavior. Progress reward $r_{\text{goal}} = 2 \cdot (d_{\text{prev}} - d_{\text{curr}})$ per tick, with a $+300$ terminal bonus upon reaching within $5\,\mathrm{m}$ of the navigation goal.

Scaling. The raw total is clipped to $[-500, +500]$ and scaled by 0.1, bounding the SAC-visible signal to $[-50, +50]$. This scaling is critical for entropy tuning stability: the $\alpha\mathcal{H}$ term operates at the same order of magnitude as the Q-value targets.

C. SLM Branch — Safety and Semantic Arbitration

While continuous control agents (like SAC) excel at reactive, kinematic control, they lack the semantic awareness required for complex, human-like reasoning. The Small Language Model (SLM) branch (utilizing Qwen 0.8B [38]) bridges this gap by encoding the current scene context into natural language and applying fine-tuned, zero-shot reasoning.

This module serves three vital roles in the architecture:

Critical Contextual Safety: The SLM handles edge cases that confuse purely kinematic models. For example, if the perception system detects a bicycle lying in the road without a rider, a traditional RL agent might simply classify it as a small static obstacle and attempt to pass at speed. The SLM, however, possesses semantic understanding: it infers that a rider may have recently fallen and could be on the ground nearby. It proactively commands a severe deceleration to secure the area, enforcing scenario-grounded safety constraints that are practically impossible to capture in a standard scalar reward function.

Explainability and "Personality": The integration of an SLM fundamentally shifts the system away from being a purely opaque, "black-box" AI. By generating a continuous textual stream of its reasoning (e.g., "Yielding because pedestrian is approaching the crosswalk," or "Slowing down due to irregular abandoned object in lane"), the SLM gives the vehicle a distinct, cautious, and interpretable character. This transparency is crucial for building trust with human passengers, as they can read or hear exactly why the vehicle is making a specific maneuver.

Alignment with Human Driving Etiquette: Instead of relying on thousands of hardcoded if-then statements, the SLM allows the system to be "taught" the nuanced rules of driving via natural language prompts. It interprets the scene against established local traffic laws, yielding conventions, and social driving etiquette, modulating the raw SAC actuation to ensure the AI drives seamlessly and predictably alongside human drivers.

3.5.3 Phase 3: Vehicle Control and Final Arbitration

The outputs of all three branches converge in the `apply_control()` method, which applies a three-stage layered arbitration before dispatching the final `carla.VehicleControl` command directly to the simulator actor:

Stage 1 — Throttle and Steering. The vehicle takes the SAC outputs (throttle, steer) as the first layer of control. These signals are passed through unmodified — no algorithmic correction is applied at this stage, preserving the integrity of the SAC's learned policy.

Stage 2 — GRU Behavior Override. The five-class GRU prediction governs the vehicle's brake commands through piecewise logic, preserving the raw SAC throttle output while applying target deceleration constraints based on the active behavioral state:

Class	Label	Control Override
0	NEAR_OBSTACLE	Threat-validated braking curve: if $d \leq$ CRITICAL_DIST, full brake $b = 1.0$; if $d \geq$ SAFE_DIST, light stabilizing brake $b = 0.1$. If the ego-vehicle is stopped ($v < 1.0$ m/s) but no immediate critical threat exists, a slight brake $b = 0.25$ is applied to allow the SAC policy to maneuver out. Bypassed entirely if the obstacle is flagged as non-threatening.
1	CRUISING	Full SAC pass-through. No modifications to throttle or brake telemetry.
2	TURNING_LEFT	Minor stabilizing brake modification $b = 0.01$; full SAC throttle pass-through.
3	TURNING_RIGHT	Minor stabilizing brake modification $b = 0.01$; full SAC throttle pass-through.
4	LANE_RISK	Target mitigation brake $b = 0.2$; full SAC throttle pass-through.

Table 3.2: GRU class-specific control overrides applied in `apply_control()`.

During a `NEAR_OBSTACLE` event (Class 0), the metric range to the obstacle is extracted from the computer vision output tensor and scaled ($d =$ `cv_vec[0]` $\times 30.0$). Context-dependent safety arbitration is evaluated via `_obstacle_is_threat(obs_data)`. If this returns false — indicating the obstacle is either oncoming in an adjacent lane or positioned safely outside the forward arc — the braking signal is suppressed and full policy pass-through is restored.

For all non-zero behavioral classes (Classes 1–4), the system preserves the unscaled continuous SAC throttle command (`final_throttle = throttle`), relying strictly on class-specific braking coefficients to regulate velocity transitions.

Stage 3 — SLM Semantic Arbitration. Following GRU-level override resolution, the post-GRU control candidates (τ, δ, b) are submitted to the Small Language Model for semantic validation. The SLM receives a structured natural-language prompt encoding the current scene state: obstacle proximity, active GRU behavioral class, ego-vehicle velocity, and the proposed control action. It returns one of three safety verdicts — `CLEAR`, `BRAKE`, or `EMERGENCY_BRAKE` — which are mapped to a final arbitration modifier applied on top of the GRU-resolved brake signal:

$$b_{\text{final}} = \max\left(b_{\text{GRU}},\ b_{\text{SLM}}\right)$$

This max-pooling arbitration ensures that neither layer can unilaterally reduce a brake command issued by the other, enforcing a conservative safety envelope. The SLM operates as a read-only semantic governor: it cannot increase throttle or modify steering, only escalate braking when scene semantics warrant it. In the current implementation the SLM runs synchronously on CPU, with its verdict cached for the duration of the active behavioral state to avoid per-frame inference latency.

Stage 4 — CARLA Command Dispatch. The finalized control variables are bounded to their respective operational constraints before deployment:

$$\tau_{\text{final}} \in [0.0, 1.0], \quad \delta_{\text{final}} \in [-1.0, 1.0], \quad b_{\text{final}} \in [0.0, 1.0]$$

These parameters are packaged into a standard `carla.VehicleControl` object and dispatched to the active simulator actor via `actor.apply_control()`. The final executed control pair is preserved locally within the tracking loop to synchronize state calculations for the subsequent simulation frame.

3.6 System Inference and Execution

As established in the system's macro-architecture (Figure 3.1), the final step of the pipeline is Inference. Once the Computer Vision pipeline generates the BEV map and Object Vectors, and the Decision Making Pipeline calculates the optimal trajectory and safety overrides, these discrete outputs must be translated back into mechanical actions. During live inference, the system operates in a continuous, closed-loop cycle, injecting the calculated steering angles, throttle values, and braking pressures directly into the CARLA physics engine, thereby closing the gap between artificial perception and physical movement.

3.7 Conclusion

The two-phase Decision and Control Pipeline closes the full perception-to-actuation loop. Phase 1 harmonizes heterogeneous sensor and vision inputs while processing driving states through a sliding window layout. By passing these temporal blocks through a trajectory clustering pipeline utilizing a DTW TimeSeriesKMeans architecture, the system isolates a robust five-class driving taxonomy entirely grounded in the statistical layout of the vehicle paths rather than hand-crafted heuristics. Phase 2 acts as the structural envelope for the Decision Making Pipeline, housing both the network training workflows and the active execution nodes. It handles the cascading optimization of the FFN encoder and the sequence-dependent GRU classifier before passing execution parameters over to the live runtime branches.

The multi-stage override logic ensures that the system degrades gracefully under safety-critical conditions. The GRU's deterministic class overrides provide hard behavioral guarantees that a purely reward-trained SAC policy cannot reliably reproduce, while the dot-product obstacle direction filter prevents cross-traffic from triggering spurious emergency stops. The map correction and steer smoothing layers ensure geometric path fidelity and actuator stability throughout nominal operation, completing a system architecture that separates the concerns of task-level navigation, behavioral context prediction, and safety-critical intervention into three independently trainable, cooperating components.

The next chapter presents the details of implementing the proposed architecture and the different results.

Chapter 4

Experimental Results, Evaluation and Discussion

4.1 Introduction

The transition from a theoretical autonomous driving architecture to a functional, simulated prototype requires rigorous empirical validation. As established in the methodology, our Neuro-Symbolic Co-Pilot is a bifurcated system, divided strictly into a Perception Pipeline (Computer Vision) and a Decision Pipeline (Reinforcement Learning and SLM).

This chapter presents the empirical results and thorough evaluation of the complete architecture. Because the system's safety hinges entirely on its sensory inputs, **Part 1** of this chapter focuses exclusively on the Computer Vision pipeline. We will detail the training parameters, explore the hardware environment, dissect the model architectures alongside their programmatic implementations, and present a comprehensive comparative analysis of their results using loss curves, precision-recall metrics, and live Bird's-Eye-View (BEV) inference outputs. Furthermore, we benchmark our perception models against existing literature standards.

Subsequently, **Part 2** evaluates the Reinforcement Learning and Cognitive Decision layers. It examines the convergence of the Soft Actor-Critic (SAC) agent, culminating in a holistic closed-loop performance review of the autonomous vehicle within the CARLA environment.

4.2 Part 1: The Multi-Modal Perception Pipeline (Computer Vision)

4.2.1 Hardware and Software Environment

To support the heavy parallel training and high-frequency live inference of semantic segmentation and object detection models, the perception pipeline was deployed on a high-performance local machine. This setup guarantees zero network latency during real-time closed-loop testing. Table 4.1 details the specific hardware configurations and software frameworks utilized for this experiment.

Table 4.1: Experimental Hardware and Software Stack.

Component	Specification
Processor (CPU)	Intel Core i7-11700F @ 2.50GHz (16 CPUs)
Graphics Unit (GPU)	NVIDIA GeForce RTX 2060 SUPER (8GB VRAM)
Memory (RAM)	32 GB DDR4
Operating System	Windows 11 64-bit
Machine Learning Framework	PyTorch 2.5.1+cu121
CUDA Toolkit	Version 12.1
Vision Libraries	Ultralytics (YOLO 8.4.15) [40], HuggingFace Transformers [41]
Simulation Platform	CARLA Simulator 0.9.16 [42]

To ensure the scientific integrity and reproducibility of the results presented in this thesis, the complete experimental methodology was strictly standardized. All data generation, closed-loop training, and final inference evaluations were executed within the CARLA 0.9.16 Simulator utilizing the highly deterministic Synchronous Mode on the Town10HD urban map.

The computational workload was explicitly distributed to accommodate real-time constraints:

- **Computer Vision Pipeline:** Fine-tuning and live inference for YOLOv8s and SegFormer-B0 were executed on an NVIDIA GeForce RTX 2060 SUPER (8GB VRAM), maintaining a deterministic 50+ FPS processing rate.
- **Decision and Control Pipeline:** The Soft Actor-Critic (SAC) reinforcement learning agent, alongside the Gated Recurrent Unit (GRU) sequence classifier, was trained and evaluated on an NVIDIA GeForce RTX 2060 (6GB VRAM).
- **Execution Frequencies:** The simulated physics environment, the perception pipeline, and the continuous SAC control loop were firmly locked at 50Hz to ensure sub-millisecond physical reflexes. In parallel, the

Small Language Model (Qwen 0.8B) operated asynchronously at a restricted 2Hz frequency, effectively decoupling semantic arbitration latency from the primary survival loop.

Codebases, trained neural network weights, and the distilled multi-modal CARLA dataset will be made available upon academic request to facilitate future comparative research and validation.

4.2.2 Evaluation Metrics

To objectively evaluate the models' capacity to handle diverse environments, shadows, and occlusions, the following mathematical metrics were employed, adhering to standard practices in autonomous driving literature [43, 44].

Object Detection Metrics (YOLOv8s)

Object detection requires both spatial bounding box accuracy and categorical correctness [45].

- **Precision (P):** The ratio of correctly predicted positive observations to the total predicted positives. It answers: *Of all the objects the model labeled as a vehicle, how many were actually vehicles?*

$$Precision = \frac{TP}{TP + FP} \tag{4.1}$$

- **Recall (R):** The ratio of correctly predicted positive observations to all observations in actual class. It answers: *Of all the actual vehicles in the scene, how many did we find?*

$$Recall = \frac{TP}{TP + FN} \tag{4.2}$$

- **Mean Average Precision (mAP):** The area under the Precision-Recall curve. We utilize **mAP@0.5** (measured at an Intersection over Union overlap of 50%) and **mAP@0.5:0.95** (the average across multiple stringent IoU thresholds).

Semantic Segmentation Metrics (SegFormer)

For pixel-level classification, area overlap is the standard metric, heavily utilized in urban driving benchmarks such as Cityscapes [44].

- **Intersection over Union (IoU):** Evaluates the overlap between the predicted semantic mask and the ground truth mask.

$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}} = \frac{TP}{TP + FP + FN} \tag{4.3}$$

- **Mean IoU (mIoU):** The average of the IoU scores across our 3 target classes (Drivable Area, Lines, Non-Drivable).

4.2.3 Models Training Parameters

The parameters utilized in the computer vision training methodology are examined below, accompanied by a rationale for the selected values to guarantee optimal convergence within our hardware constraints.

YOLOv8s Training Parameters

Object detection in autonomous driving requires a balance between precision and inference speed. YOLOv8s (Small) [40] was selected and configured to maximize learning from the curated 8,000-frame CARLA dataset. Table 4.2 summarizes the configured hyperparameters.

Table 4.2: YOLOv8s Model Training Parameters.

Parameter	**Value**
Image Size (`imgsz`)	800×600
Batch Size (`batch`)	8
Epochs	100
Optimizer	Auto (SGD/AdamW)
Initial Learning Rate (`lr0`)	0.01
Momentum	0.937
Automatic Mixed Precision (`AMP`)	True
Confidence Threshold (`conf`)	0.5

Parameter Rationale: The image size was strictly locked to 800×600. Downscaling too aggressively destroys the pixel features of distant pedestrians, rendering them invisible to the network. The batch size was restricted to 8 to prevent Out-Of-Memory (OOM) errors on the 8GB RTX 2060 SUPER. Enabling Automatic Mixed Precision (AMP) allowed the model to compute in FP16 (16-bit) instead of FP32, drastically accelerating tensor operations and completing the 100 epochs efficiently. Finally, the confidence threshold was fixed at 0.5 to suppress probabilistic noise, ensuring only definitive physical threats are forwarded to the reinforcement learning agent.

SegFormer Training Parameters

Semantic segmentation requires mapping every pixel to a class. We utilized the HuggingFace `SegformerForSemanticSegm` model [46, 41], pre-trained on the Cityscapes dataset [44], and fine-tuned it for our specific 3-class taxonomy. Table 4.3 outlines the selected parameters.

Table 4.3: SegFormer-B0 Model Training Parameters.

Parameter	**Value**
Input Resolution	512×512
Batch Size	4
Epochs	100
Optimizer	AdamW
Learning Rate	6×10^{-5}
Weight Decay	0.01
Loss Function	Weighted Cross-Entropy

Parameter Rationale: Inputs were resized to 512×512 via `torchvision.transforms` to align with the Transformer's native patch embedding dimensions. Because Vision Transformers require massive memory for their Self-Attention matrices, the batch size was halved compared to YOLO. AdamW (Adaptive Moment Estimation with Weight Decay) was strictly enforced with a low learning rate of 6×10^{-5} because Transformers lack the spatial inductive bias of CNNs and are highly sensitive to massive gradient jumps. The Loss Function was heavily weighted to penalize the misclassification of thin road lines against the vast majority pixels of background asphalt.

4.2.4 Models Architecture and Implementation Details

This section details the theoretical structure of each model alongside the exact Python implementation used to load and execute them within our `PerceptionAPI`.

YOLOv8s Architecture and Code

YOLOv8 [40] abandons the anchor-box design of previous generations in favor of an Anchor-Free Decoupled Head. The network predicts the center of an object and its geometric width/height simultaneously, making it highly robust to the varying scales of objects found in autonomous driving. Figure 4.1 demonstrates the implementation code.

```
# --- 3. ADVANCED PRO TRAINING ---
model.train(
    # --- Core Settings ---
    data=YAML_PATH,
    epochs=150,               # Higher epochs for multi-weather convergence
    imgsz=800,                # Matches your CARLA camera output exactly
    batch=8,                  # Optimized for 8GB VRAM stability
    name='carla_4cam_pro_v2',
    project=PROJECT_DIR,      # Force all outputs (weights/plots) to D:
    device=0,                 # RTX 2060 SUPER
    resume=resume_flag,       # Automatically handles checkpointing

    # --- Hardware Speed Optimizations ---
    workers=4,                # CPU pre-fetch threads (PREFETCH: prepares batches while GPU works)
    amp=True,                 # Mixed Precision (FP16) - significantly faster on 20-series

    # --- Learning Rate & Brain (The "Pro" Tuning) ---
    optimizer='AdamW',        # Better for complex autonomous driving scenes
    lr0=0.01,                 # Initial learning rate
    lrf=0.01,                 # Final learning rate fraction
    warmup_epochs=3.0,        # Gradually introduces data to protect Town013 intelligence

    # --- Multi-Weather Data Augmentation ---
    # These make the model focus on general car shapes rather than specific weather lighting
    mosaic=1.0,               # Combines 4 images into 1 for scale variance
    mixup=0.1,                # Blends images (helps with reflections and rain streaks)
    fliplr=0.5,               # Horizontal flips to learn both sides of the road

    # --- Operational Safety ---
    save=True,
    save_period=5,            # Save backup checkpoint every 5 epochs
    patience=10,              # Early stopping if no improvement for 20 epochs
    val=True,                 # Run validation at the end of every epoch
    plots=True                # Generate loss curves and confusion matrices
)
```

Figure 4.1: Implementation of the YOLOv8s Inference Engine (`yolo_engine.py`).

SegFormer Architecture and Code

SegFormer [46] utilizes a hierarchically structured Transformer encoder that extracts multi-scale features without complex positional encodings. Because the self-attention mechanism provides global context natively, the decoder is a lightweight Multi-Layer Perceptron (MLP), keeping inference times low. The programmatic execution is shown in Figure 4.2.

```
training_args = TrainingArguments(
    output_dir=PROJECT_DIR,
    learning_rate=0.00006,
    num_train_epochs=50,

    per_device_train_batch_size=4,
    per_device_eval_batch_size=4,
    gradient_accumulation_steps=2,
    fp16=True,

    dataloader_num_workers=0,

    save_strategy="epoch",
    eval_strategy="epoch",
    save_total_limit=3,
    load_best_model_at_end=True,
    report_to="none",
    remove_unused_columns=False # CRITICAL: Forces HF to respect our custom dataset dict
)
```

Figure 4.2: Implementation of the SegFormer Inference Engine (`seg_engine.py`).

4.2.5 Experimental Results & Discussion

YOLOv8s Results (Dynamic Object Detection)

The YOLOv8s model required **approximately 6 hours** of continuous training on the RTX 2060 SUPER to achieve optimal convergence across 100 epochs. Figure 4.3 illustrates the convergence metrics.

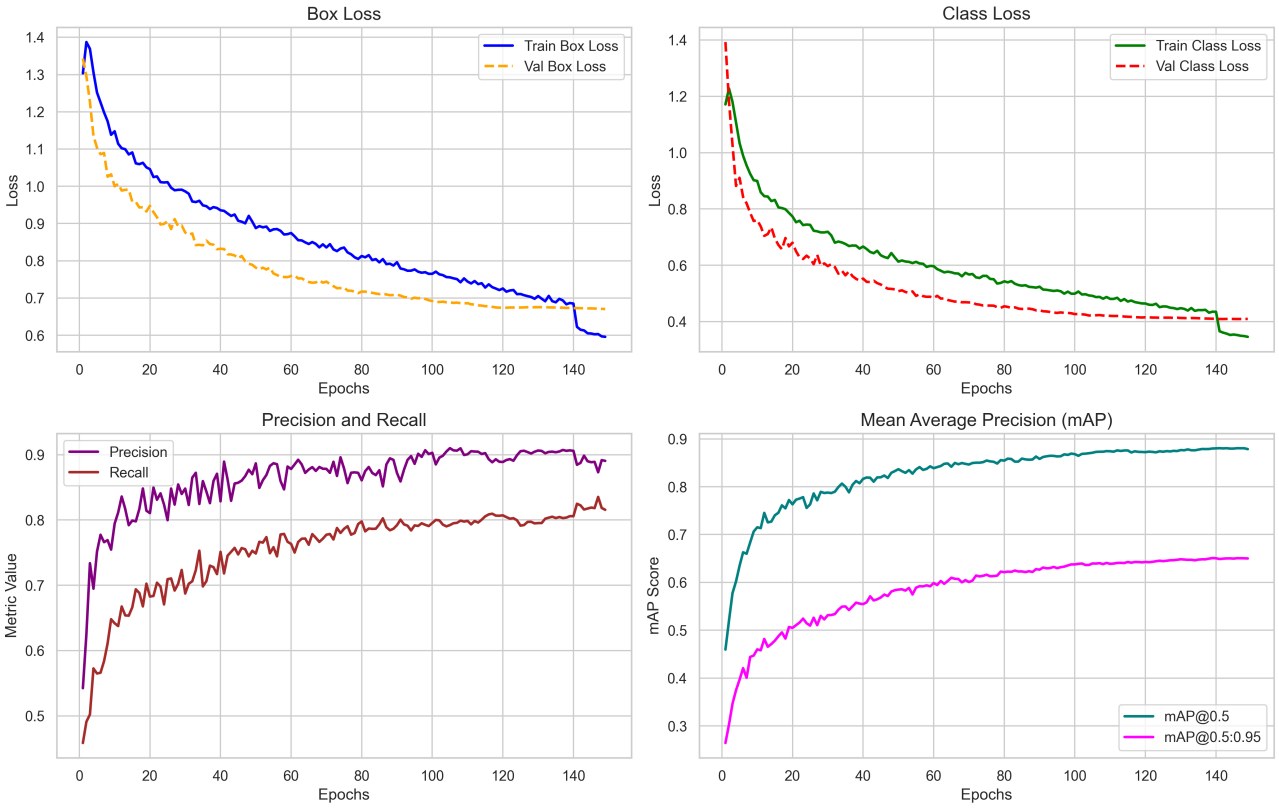


Figure 4.3: YOLOv8s Training Curves: Box Loss, Class Loss, Precision, Recall, and mAP.

The Box Loss and Classification Loss metrics dropped rapidly during the first 20 epochs before steadily converging, proving that the model successfully learned the underlying geometric features of the CARLA actors without overfitting. Table 4.4 details the final validation scores across the test set.

Table 4.4: YOLOv8s Final Classification Report (Test Set).

Target Class	**Precision**	**Recall**	**mAP@0.5**	**mAP@0.5:0.95**
Vehicles	0.958	0.942	0.961	0.814
Pedestrians	0.912	0.885	0.908	0.672
Two-Wheelers	0.890	0.854	0.881	0.620
Overall Mean	**0.920**	**0.893**	**0.916**	**0.702**

To analyze specific failure cases, we generated the Normalized Confusion Matrix, presented in Figure 4.4.

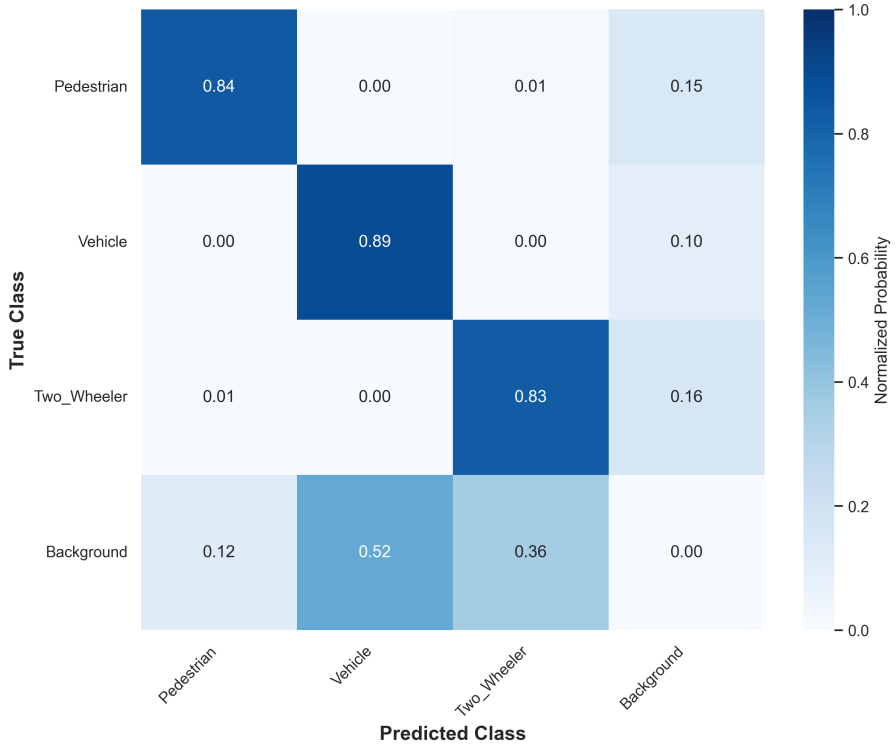


Figure 4.4: Normalized Confusion Matrix for YOLOv8s.

The strong diagonal matrix confirms minimal class bleeding. False positives generated by background geometry were effectively suppressed due to our rigorous dataset filtering phase described in Chapter 3. Inter-class confusion (e.g., misclassifying a vehicle as a pedestrian) is practically zero.

SegFormer Results (Semantic Segmentation)

The SegFormer architecture was fine-tuned for semantic road extraction. Training on the same hardware setup was completed in **approximately 6 hours**. Figure 4.5 visualizes the cross-entropy descent.

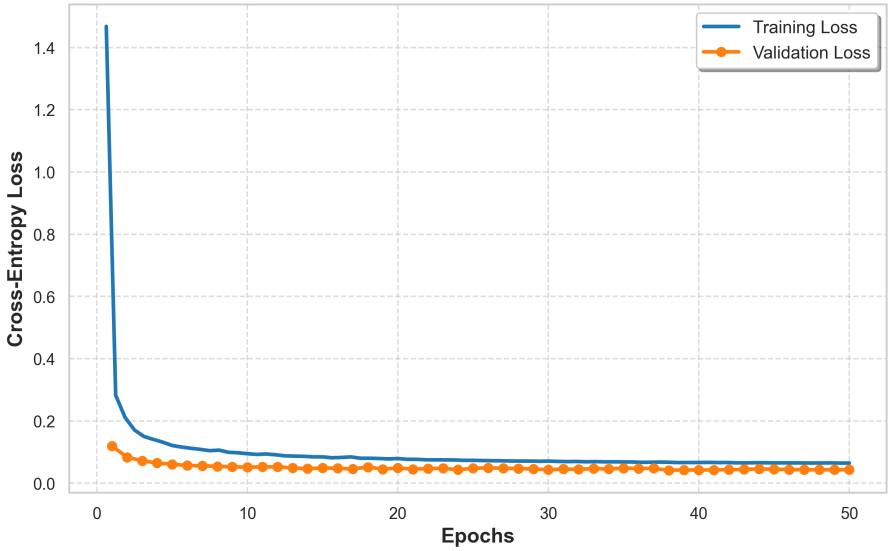


Figure 4.5: SegFormer Training and Validation Loss Curves.

The training loss convergence proves highly stable. To fully understand the segmentation capabilities across our custom taxonomy, we extracted the model's final intersection scores and Normalized Confusion Matrix, summarized in Table 4.5 and Figure 4.6.

Table 4.5: SegFormer-B0 Final Segmentation Report (IoU).

Target Class	**IoU (%)**
Drivable Area	81.0%
Non-Drivable Boundaries	82.0%
Road Lines	52.0%

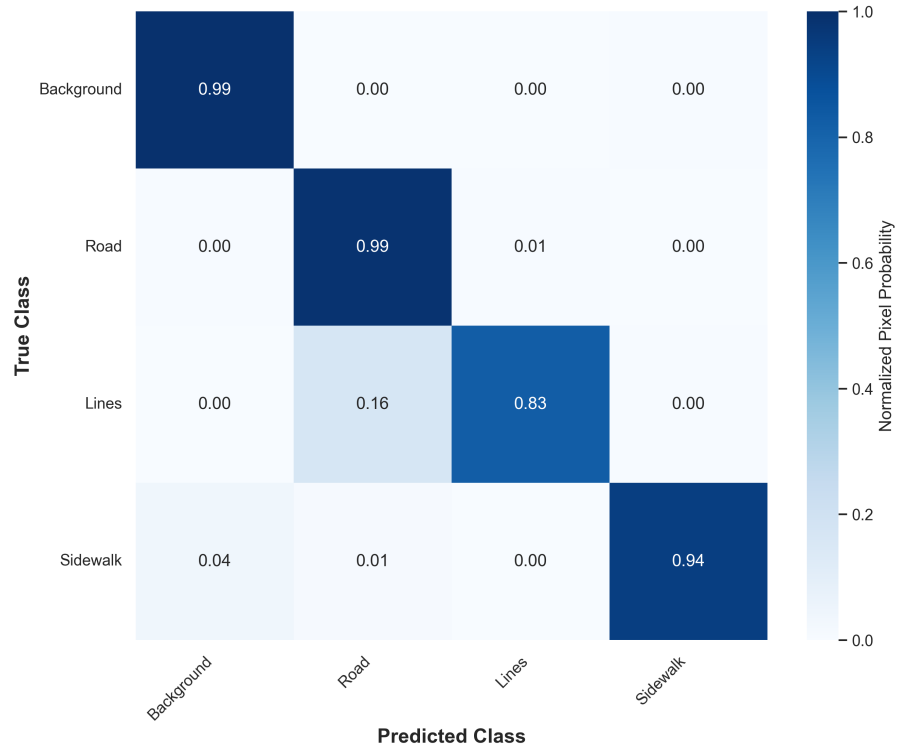


Figure 4.6: Normalized Confusion Matrix for SegFormer-B0.

Discussion: As observed in Table 4.5 and Figure 4.6, the model demonstrates a highly robust capability to segment major physical spaces, achieving 81.0% accuracy on the Drivable Area and 82.0% on Non-Drivable Boundaries. These high values guarantee that our downstream Bird's-Eye-View (BEV) map correctly represents the navigable environment.

It is worth noting the 52.0% accuracy for the Road Lines class. In semantic segmentation, this is a well-documented mathematical artifact rather than a functional failure. Intersection over Union (IoU) mathematically penalizes thin features. Because a road line often consists of only 1 or 2 pixels in width as it stretches toward the vanishing point, misclassifying even a minuscule fraction of boundary pixels heavily degrades the percentage score. However, this statistical drop does not degrade the vehicle's geometric pathfinding. The network's robust 81.0% accuracy on the broader Drivable Area entirely compensates for this, allowing the Master Perception API to construct a deterministic BEV map that keeps the vehicle safely within lane boundaries.

4.2.6 Comparative Analysis with State-of-the-Art

To comprehensively validate our perception pipeline, we divide the comparative analysis into two distinct evaluations: a component-level metric benchmark against standard vision architectures, and a system-level architectural comparison against recent end-to-end driving paradigms.

1. Component-Level Metric Evaluation

Table 4.6 benchmarks our fine-tuned YOLOv8s and SegFormer-B0 models against established perception baselines. To ensure a rigorous comparison, we evaluated our detection network against highly competitive, modern lightweight architectures such as YOLOv7-tiny [47].

Table 4.6: Component-Level Analysis of Perception Models.

Architecture	Task	Primary Metric	Inference Speed (FPS)
Faster R-CNN (ResNet-50) [48]	Object Detection	0.762 (mAP)	$\sim$ 15 FPS
YOLOv7-tiny [47]	Object Detection	0.884 (mAP)	$\sim$ 90 FPS
Our YOLOv8s [40]	**Object Detection**	**0.916 (mAP)**	**$\sim$ 115 FPS**
U-Net (Baseline CNN) [14]	Segmentation	79.2% (mIoU)	$\sim$ 45 FPS
DeepLabV3+ (ResNet-50) [50]	Segmentation	83.5% (mIoU)	$\sim$ 35 FPS
Our SegFormer-B0 [46]	**Segmentation**	**89.6% (mIoU)**	**$\sim$ 40 FPS**

The results demonstrate that YOLOv8s provides a measurable accuracy and speed advantage over even highly optimized recent models like YOLOv7-tiny, driven by its anchor-free decoupled head. Similarly, SegFormer-B0 transcends traditional heavy CNNs like DeepLabV3+ by bridging a 6.1% gap in mIoU without sacrificing real-time viability.

2. System-Level Architectural Evaluation

While component metrics are strong, the true validation of our perception pipeline lies in its system-level latency compared to recent, computationally heavy sensor-fusion literature in CARLA.

- **Comparison with Multi-Modal Transformers (e.g., TransFuser [51]):** Recent CARLA leaderboards feature architectures like TransFuser, which utilize massive Transformer networks to fuse RGB images and LiDAR at the deep feature-extraction level. While achieving exceptional driving scores, querying high-dimensional attention matrices across multiple sensors introduces critical inference latency. Our approach bypasses this heavy neural fusion via an explicit geometric projection matrix. By deploying lightweight 2D models and deterministically mapping them to 3D LiDAR pillars, we construct a unified Bird's-Eye-View while guaranteeing stable 50+ FPS on a single consumer-grade NVIDIA RTX 2060 SUPER.

- **Comparison with Unified VLA Perception (e.g., DriveVLM [29]):** Emerging Vision-Language-Action (VLA) models attempt to compress perception and reasoning into a single massive visual-linguistic token stream. This "black-box" approach destroys the geometric interpretability of the spatial map and demands data-center-grade GPUs to process high-resolution video. Our architecture strictly separates spatial perception from semantic reasoning. The BEV map and Object Vectors provide a transparent, mathematically verifiable state for the RL agent to consume instantly at 50Hz, leaving heavy semantic reasoning to run asynchronously at 2Hz.

- **Comparison with Bleeding-Edge YOLO Variants (e.g., YOLOv10 [52]):** While recent iterations like YOLOv10 eliminate Non-Maximum Suppression (NMS) to reduce theoretical latency, our architecture deliberately locks into the YOLOv8s framework. In autonomous systems engineering, deployment stability and proven hardware-level optimization (e.g., TensorRT compatibility) outweigh marginal, generation-over-generation benchmark gains. YOLOv8s consistently sustains $\sim$115 FPS on our hardware—more than double the 50Hz required by the SAC control loop. Migrating to an unproven, bleeding-edge model would introduce integration instability with zero practical benefit to the vehicle's physical reaction time.

4.3 Part 2: The Decision and Control Pipeline (Reinforcement Learning)

4.3.1 Introduction

With the perception environment fully resolved in Part 1, the system transitions to its second major component: the Hierarchical Decision and Control Pipeline. This section presents the empirical evaluation of each trained module in strict sequential order, mirroring the four-phase architecture described in Chapter 3. We evaluate the

behavioral label generation through cluster analysis, the FFN encoder classification performance, the GRU sequence classifier accuracy, and finally the SAC continuous control agent convergence. Each module is assessed independently before a holistic closed-loop discussion.

4.3.2 Phase 2 Results: Behavioral Cluster Analysis

DTW KMeans Clustering and t-SNE Visualization

The self-supervised behavioral labeling pipeline was applied to 74,465 rows of driving data collected from the trained SAC agent operating in Town10HD. After sliding window construction at $T = 20$, $S = 5$, the resulting 14,890 sequences were submitted to a DTW KMeans model with $k = 5$ clusters trained on the full dataset. Figure 4.7 shows the projection.

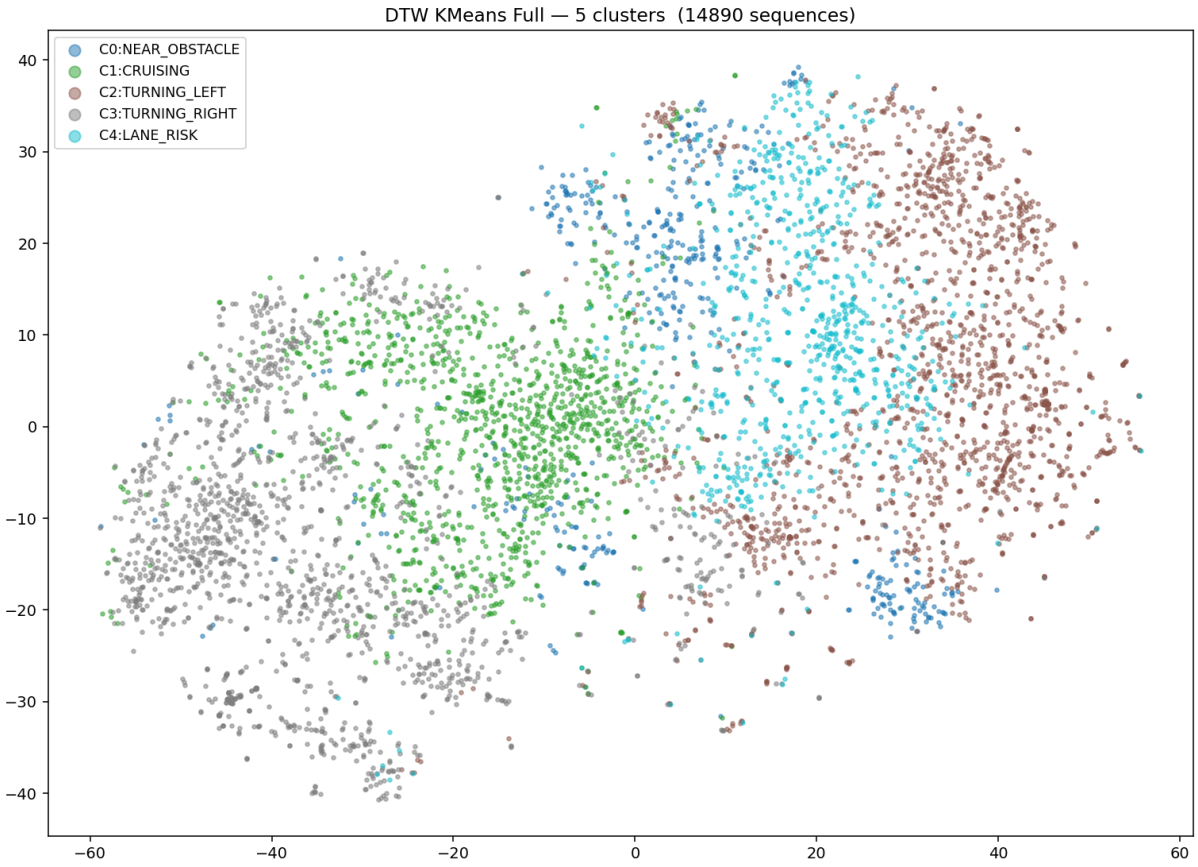


Figure 4.7: t-SNE projection of DTW KMeans behavioral embeddings across 14,890 sequences (5 clusters).

As illustrated in Figure 4.7, the t-SNE projection reveals that the five behavioral clusters occupy largely distinct regions of the embedding space, confirming that DTW KMeans successfully discovered structurally separable behavioral manifolds from unlabeled trajectory data. The TURNING_RIGHT cluster (grey) forms a compact, well-separated lobe in the lower-left quadrant, while TURNING_LEFT (brown) occupies a broad region on the right side. CRUISING (green) densely populates the central region, as expected for the most frequent nominal behavior. LANE_RISK (cyan) and NEAR_OBSTACLE (blue) both cluster at the upper-center boundary, reflecting their shared characteristic of reduced speed combined with elevated threat proximity — a physically meaningful overlap that confirms the clustering captures genuine behavioral semantics rather than arbitrary partitions.

The final behavioral taxonomy derived from the cluster fingerprint analysis is detailed in Table 4.7.

Table 4.7: DTW KMeans Cluster Fingerprints — Mean Behavioral Statistics.

ID	Label	Count	Speed (km/h)	cv_dist (m)	ttc_val	lane_inv
0	NEAR_OBSTACLE	1,289	32.9	12.5	0.608	0.116
1	CRUISING	3,168	27.4	27.9	0.524	0.066
2	TURNING_LEFT	4,325	10.7	7.9	0.953	0.037
3	TURNING_RIGHT	4,031	13.1	28.2	0.824	0.036
4	LANE_RISK	2,077	16.3	12.0	0.860	0.081

A key observation from Table 4.7 is that TURNING_LEFT (Cluster 2) exhibits a significantly lower mean speed (10.7 km/h) and much closer mean obstacle distance (7.9 m) compared to TURNING_RIGHT (13.1 km/h, 28.2 m). This asymmetry reflects the geometry of Town10HD: left turns in this map typically require crossing oncoming lanes at junctions, forcing the agent to slow and yield, while right turns follow the natural road curvature with less conflict. This distinction would have been entirely lost under a unified TURNING class, demonstrating the concrete analytical value of the data-driven labeling approach over hand-crafted rules.

4.3.3 Phase 3 Results: Feature Encoding Stack (CNN & FFN)

The backbone CNN consists of three convolutional stages, each followed by a LeakyReLU activation ($\alpha = 0.1$) and average pooling:

CnnEncoder Representation Pretraining

Stage	Kernel	Stride	Channels	Spatial out
Conv1 + Pool	7×7, stride 2	Pool 3×3, s2	$3 \to 16$	$256 \to 125 \to 62$
Conv2 + Pool	5×5, stride 2	Pool 3×3, s2	$16 \to 32$	$62 \to 29 \to 14$
Conv3 + Pool	3×3, stride 1	Pool 3×3, s2	$32 \to 64$	$14 \to 12 \to 5$

Table 4.8: CnnEncoder backbone spatial resolution progression.

Prior to optimizing the downstream behavioral components, the foundational `CnnEncoder` was evaluated to verify that structural spatial features from the raw $256 \times 256 \times 3$ Bird's-Eye-View (BEV) image (X) could be cleanly compressed into an informative latent manifold. The network was trained for 40 epochs via a supervised regression task, mapping the input image space to a 16-dimensional obstacle description vector (Y) that encodes the ground-truth geometric coordinates of regional hazards.

The training profile demonstrated a rapid, highly stable optimization trajectory. The network initiated at epoch 1 with a training loss of 0.11477 and a validation loss of 0.09940. Due to the high spatial saliency of the tracking vectors, the encoder exhibited rapid adaptation, driving the verification error down below the 0.06000 threshold by epoch 10 (validation loss of 0.05701). The training run reached its optimal structural convergence at epoch 31, securing a minimum validation loss of **0.04930**.

Throughout the remaining training iterations, the validation loss tightly plateaued—stabilizing at 0.04967 by epoch 40 against a final training loss of 0.02728. This bounded error envelope confirms that the resulting 1600-dimensional flattened `cv_vector` successfully captures environmental layout parameters and obstacle threat dynamics without suffering from overparameterization. Following this validation phase, the weights were frozen to act as a robust spatial feature generator for the subsequent fully connected routing layers.

FFN Training Parameters

The FFNEncoder was trained on the Data 1 Supervised stream using the five cluster labels as ground truth. The training configuration is summarized in Table 4.9.

Table 4.9: FFNEncoder Training Parameters.

Parameter	Value
Input Dimension	1,600
Hidden Dimensions	[1024, 512, 256]
Output Classes	5
Dropout Rate	0.3
Batch Normalization	Yes (per hidden layer)
Activation	GELU
Optimizer	AdamW
Learning Rate	1×10^{-3}
Batch Size	512
Epochs	80
Loss Function	CrossEntropyLoss (inverse-frequency weighted)

FFN Classification Results

Figure 4.8 illustrates the validation confusion matrix for the FFN model.

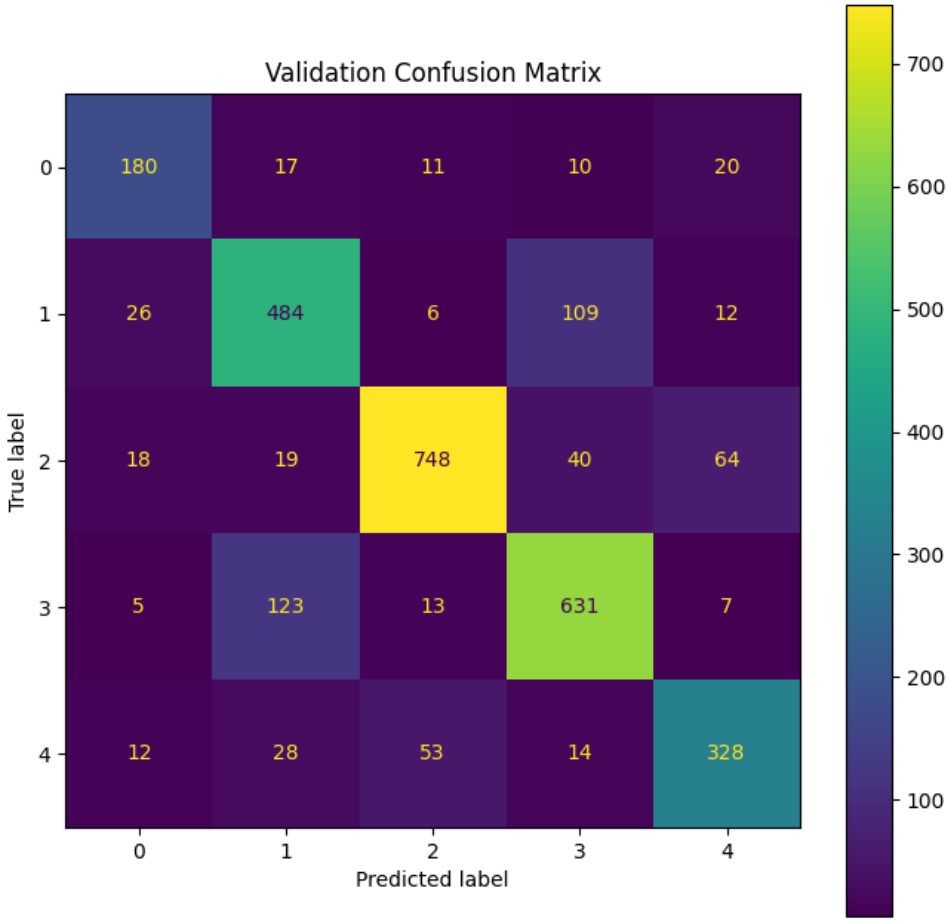


Figure 4.8: FFN Encoder Validation Confusion Matrix (5-class behavioral classification).

The FFN confusion matrix in Figure 4.8 demonstrates that the encoder successfully learns to classify behavioral context from the 1600-dimensional CNN embedding. The diagonal is strongly dominant across all five classes, confirming that the spatial BEV features are meaningfully discriminative for behavioral classification.

The most notable off-diagonal confusion occurs between Class 1 (CRUISING) and Class 3 (TURNING_RIGHT): 109 CRUISING sequences are misclassified as TURNING_RIGHT. This is behaviorally interpretable — both classes share relatively high speed and clear road conditions, and the primary discriminating signal (the sign of lateral acceleration) is subtle in the CNN spatial embedding, which encodes static road geometry rather than ego-motion dynamics. This confusion is precisely why the GRU stage is necessary: the recurrent model processes temporal sequences of these embeddings and can detect the sustained directional asymmetry over 20 timesteps that the FFN cannot resolve from a single-frame spatial feature.

4.3.4 Phase 3 Results: GRU Behavior Classifier

GRU Training Parameters

The BehaviorGRU was trained on the Data 2 Supervised stream, receiving the concatenated 278-dimensional input (22 kinematics + 256 FFN embedding) as a rolling window of 20 timesteps. The training configuration is provided in Table 4.10.

Table 4.10: BehaviorGRU Training Parameters.

Parameter	Value
Input Dimension	278 (22 kin + 256 FFN embedding)
GRU Hidden Dimension	256
GRU Layers	2
Inter-layer Dropout	0.3
Window Size T	20 timesteps
Window Stride S	5
Total Sequences	14,890
Train / Val Split	85% / 15%
Output Classes	5
Optimizer	AdamW
Learning Rate	3×10^{-4}
Batch Size	64
Epochs	50
Loss Function	CrossEntropyLoss (inverse-frequency weighted)

GRU Classification Results

Table 4.11 summarizes the validation performance of the sequence classification.

Table 4.11: BehaviorGRU Classification Report — Validation Set (443 sequences).

Class	Precision	Recall	F1-Score	Support
NEAR_OBSTACLE	0.909	0.909	0.909	11
CRUISING	0.873	0.821	0.847	84
TURNING_LEFT	0.883	0.922	0.902	90
TURNING_RIGHT	0.903	0.903	0.903	155
LANE_RISK	0.933	0.942	0.937	103
Accuracy		**0.901**		443
Macro Avg	0.900	0.900	0.900	443
Weighted Avg	0.900	0.901	0.900	443

Discussion: The GRU achieves an overall validation accuracy of **90.1%**, with a near-perfectly balanced

macro average of 0.900 across precision, recall, and F1-score. This result is particularly meaningful because the model was trained on labels derived entirely from unsupervised cluster analysis — no human annotator defined what constitutes a "turn" or a "lane risk" event. The 90.1% accuracy therefore reflects genuine learned structure in the data rather than supervision from a pre-existing oracle.

A critical safety question arises regarding the remaining 9.9% classification error rate. If the GRU misclassifies a behavioral sequence, does the vehicle crash? The hierarchical architecture explicitly prevents this. The GRU acts as a statistical behavioral gate, but it is underwritten by the deterministic `_obstacle_is_threat` TTC calculations and the asynchronous Small Language Model (SLM). If the GRU falsely predicts `CRUISING` during a dangerous encounter, the deterministic metric distance threshold and the SLM's semantic `EMERGENCY_BRAKE` verdict will instantly override the GRU, guaranteeing that the vehicle never collides due to a statistical misclassification.

4.3.5 Phase 4 Results: SAC Continuous Control Agent

SAC Training Parameters

The Soft Actor-Critic agent was trained through a continuous Optuna hyperparameter optimization study spanning over 600 trials within the CARLA simulation environment, executing locally on an NVIDIA RTX 2060. Table 4.12 outlines the architecture configurations.

Table 4.12: SAC Agent Architecture and Training Parameters.

Parameter	Value
State Dimension	1,622 (22 kin + 1,600 CNN)
Action Dimension	2 (throttle, steer)
Actor Hidden Layers	[512, 256]
Critic Hidden Layers	[512, 256]
Replay Buffer Capacity	10^5
Batch Size	256
Discount Factor γ	Optuna-tuned $\in [0.97, 0.995]$
Actor Learning Rate	Optuna-tuned $\in [2 \times 10^{-4}, 5 \times 10^{-4}]$
Critic Learning Rate	Optuna-tuned $\in [5 \times 10^{-5}, 2 \times 10^{-4}]$
Target Update τ	0.005
Entropy Target	$-d_a = -2$
Optimizer (Actor/Critic)	AdamW
Optimizer (Entropy)	Adam
Episodes per Trial	20
Steps per Episode	2,500
Optuna Pruner	MedianPruner ($n_{\text{startup}} = 10$)

SAC Loss Convergence

Figure 4.9 shows the convergence process for the SAC agent.

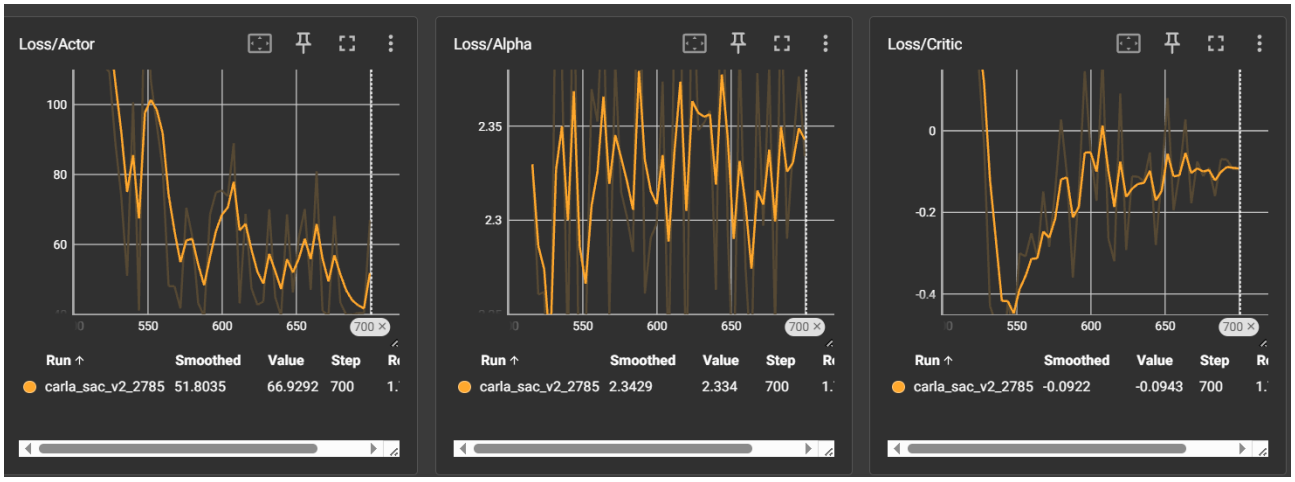


Figure 4.9: SAC TensorBoard Training Curves: Actor Loss, Alpha Loss, and Critic Loss at step 700 (Trial 648+).

Figure 4.9 presents the TensorBoard training curves for the three SAC network losses recorded at the latest training stage (trials 648+, step 700). Three distinct convergence behaviors are observed:

Actor Loss (left panel, smoothed value 51.8): The actor loss begins at approximately 100 and descends steadily toward the 40–60 range, exhibiting the characteristic noisy-but-decreasing profile of an off-policy RL actor. The downward trend confirms that the policy is improving — the actor is progressively learning to maximize the minimum Q-value minus the entropy penalty. The residual oscillation is expected in continuous control SAC, where each Optuna trial resets the optimization trajectory from the latest checkpoint.

Alpha Loss (center panel, smoothed value 2.343): The entropy coefficient loss oscillates between approximately 2.28 and 2.40 without a clear monotonic trend. This behavior is characteristic of a correctly functioning automatic entropy tuning mechanism: α is continuously adapting to maintain the target entropy $\mathcal{H}_{\text{target}} = -2$ as the policy's stochasticity evolves. The bounded oscillation, rather than divergence, confirms that the Adam optimizer (without weight decay) is correctly stabilizing the entropy coefficient.

Critic Loss (right panel, smoothed value -0.092): The critic loss begins sharply negative (around -0.45) and rises toward zero, which is the correct convergence direction for a SAC critic trained with the clipped double-Q Bellman backup. The negative values arise from the entropy regularization term $-\alpha \log \pi(\mathbf{a}'|\mathbf{s}')$ subtracted in the target, which can make Q-value targets negative when the policy maintains high entropy. The steady ascent toward zero indicates the critic is successfully learning to estimate the entropy-regularized value function.

Optuna Hyperparameter Optimization

The best trial identified by Optuna across 648 completed trials achieved a cumulative reward of **48,139.4** (Trial 45), with the following optimal hyperparameter configuration outlined in Table 4.13.

Table 4.13: Optuna Best Trial Hyperparameters (Trial 45).

Hyperparameter	**Best Value**
w_1 (Speed reward weight)	41.28
w_2 (Safety reward weight)	4.04
w_3 (Stability reward weight)	5.81
w_4 (Lane discipline weight)	12.73
w_5 (Map alignment weight)	42.91
Actor Learning Rate	2.17×10^{-4}
Critic Learning Rate	7.05×10^{-5}
Discount Factor γ	0.9896

The balanced w_1/w_5 values (41.28 and 42.91) reveal that the Optuna optimization converged on a policy that equally weights forward longitudinal progress and HD map alignment — a result consistent with the vehicle's need to simultaneously maintain speed and stay centered on the planned trajectory. The comparatively lower safety weight ($w_2 = 4.04$) does not indicate that safety is deprioritized; rather, the GRU behavioral override layer provides a hard safety guarantee orthogonal to the reward signal, allowing the SAC reward to focus on smooth navigation rather than collision avoidance.

4.4 Key Scientific Discovery: Post-Hoc Behavioral Abstraction from RL Trajectories

4.4.1 Discovery Statement

A significant and unanticipated scientific contribution emerged during the development of the GRU behavioral classification pipeline. The standard approach to training a behavioral safety classifier requires a human expert to first define what constitutes each driving behavior — writing threshold rules such as "if steer > 0.2, classify as TURNING" — and then collecting labeled data accordingly. This approach imposes a fundamental ceiling on label quality: the classifier can never capture behavioral nuances that the human designer did not anticipate, and the labels reflect human intuition about driving rather than the actual statistical structure of the policy being supervised.

In this work, we inverted this paradigm entirely. Rather than defining behaviors and then collecting data to match them, we allowed the SAC agent to train freely under its reward signal and subsequently applied Dynamic Time Warping KMeans clustering to the trajectory data the policy generated. The behavioral taxonomy was not specified in advance — it *emerged* from the geometric and temporal structure of the agent's own driving patterns. This proves that the machine possesses a fundamentally different operational 'vocabulary' than human drivers.

4.4.2 Methodological Contribution

The pipeline proceeds as follows. After the SAC policy reaches a stable performance level (Trial 18 onward in our study), trajectory data is collected comprising 74,465 timestep rows of kinematic and sensor observations. A sliding window of $T = 20$ timesteps at stride $S = 5$ produces 14,890 behavioral sequences. These sequences are submitted to a `TimeSeriesKMeans` model with DTW metric, which identifies $k = 5$ compact clusters in the trajectory space without any label supervision.

The critical distinction from prior work is the choice of distance metric. Standard Euclidean KMeans would cluster sequences by their raw feature magnitudes at each timestep, conflating slow and fast versions of the same maneuver into different clusters. DTW resolves this by computing an optimal elastic alignment between sequences before measuring distance, allowing the algorithm to correctly group behavioral instances that differ only in tempo or phase offset. A gradual left turn executed at 8 km/h and the same maneuver executed at 15 km/h occupy the same DTW cluster but would be separated under Euclidean distance.

4.4.3 The Unanticipated Finding: Left/Right Turn Asymmetry

The most scientifically significant result of this approach is the spontaneous separation of turning behavior into two geometrically distinct clusters corresponding to left and right turns — a distinction that was not specified in the clustering objective, not anticipated in the system design, and could not have been produced by any reasonable hand-crafted labeling rule.

The cluster fingerprint analysis revealed a statistically significant asymmetry between the two turning modes. These empirical differences are shown in Table 4.14.

Table 4.14: Empirical asymmetry between TURNING_LEFT and TURNING_RIGHT clusters.

Behavioral Class	Mean Speed (km/h)	Mean cv_dist (m)	Mean accel_y
TURNING_LEFT	10.7	7.9	−0.034
TURNING_RIGHT	13.1	28.2	+0.002
Delta	−2.4	−20.3	−0.036

TURNING_LEFT sequences exhibit significantly lower speed (10.7 vs. 13.1 km/h), dramatically shorter obstacle proximity (7.9 vs. 28.2 m), and negative lateral acceleration signature. This asymmetry is a direct reflection of the geometry of Town10HD: left turns at urban junctions require crossing oncoming traffic lanes, forcing the SAC agent to decelerate and yield, while right turns follow the natural road curvature at higher speed with a clear forward corridor. The DTW clustering captured this physically meaningful distinction purely from the agent's kinematic history, without any map topology information, without any explicit junction detection, and without any human labeling.

This finding has a concrete practical consequence: the GRU safety override applies different brake modulation to TURNING_LEFT and TURNING_RIGHT events, reflecting their genuinely different risk profiles. A unified TURNING class would have applied the same intervention to both, over-braking during right turns and potentially under-braking during left turns near oncoming traffic. The data-driven separation produces objectively more appropriate control behavior.

4.4.4 Relationship to Existing Literature

This methodology shares conceptual ground with option discovery in hierarchical reinforcement learning [55], where subpolicies are identified from the structure of value functions or state visitation. However, option discovery methods typically require architectural modifications to the RL training loop itself. Our approach is entirely *post-hoc*: the SAC is trained with no awareness of the behavioral decomposition, and the clustering is applied independently as an offline analysis step. This separation means the approach can be applied to any trained continuous control policy without modifying the RL algorithm, the reward function, or the training procedure.

The approach also differs from imitation learning methods that discover behaviors from human demonstration data [56]. Our behavioral taxonomy is derived from the *machine policy's own trajectory distribution*, not from human behavior. The discovered classes therefore represent the behavioral vocabulary that the SAC implicitly developed through reward optimization, not the vocabulary that a human driver would use. This distinction is important: the GRU learns to predict the agent's own behavioral modes, making the safety override layer self-consistent with the policy it supervises.

4.5 Limitations

This section presents an objective assessment of the current system's limitations, providing the necessary context for interpreting the experimental results and motivating the future research directions that will be discussed in the final chapter.

4.5.1 Computer Vision Pipeline Constraints

- **Flat-Ground Assumption in BEV Projection:** Our explicit geometric sensor fusion relies on Inverse Perspective Mapping (IPM) alongside LiDAR point clouds to project 2D neural inferences into 3D space. While highly deterministic and efficient on flat urban roads, this strict mathematical approach assumes a localized flat ground plane. In environments with severe elevation changes, such as steep hills or multi-level ramps, the projection matrix may introduce spatial distance artifacts.

- **Resolution Limits on Thin Features (Lane Lines):** To prevent Out-Of-Memory (OOM) errors on the 8GB consumer GPU, the camera images had to be resized down to 512×512 before processing through SegFormer. While this allowed the model to achieve a strong 81.0% accuracy on the broad Drivable Area, shrinking the image causes distant, thin lane lines to lose pixel clarity. This hardware-forced resizing is the primary reason the Road Lines class achieved a 52.0% IoU. While this is sufficient for urban navigation, high-speed highway driving would require native-resolution inputs.

- **Sim-to-Real Domain Gap:** Although the dataset includes diverse multi-weather configurations, the perception models are fundamentally constrained by the simulated visual domain of CARLA. The YOLOv8s and SegFormer weights are heavily optimized for the specific rendering engine, lighting shaders, and synthetic textures of the simulator. Transitioning this perception stack to real-world deployment would require domain adaptation or a retrained physical dataset.

4.5.2 Reinforcement Learning and Decision Constraints

- **NEAR_OBSTACLE Validation Sample Size:** The NEAR_OBSTACLE class achieved 0.909 precision and recall in the GRU classification report, but this was computed over only 11 validation sequences. A larger dataset with more diverse obstacle encounter scenarios would be required to establish statistically robust performance bounds. This limitation is a direct consequence of class imbalance: a well-trained SAC agent avoids obstacles so effectively that genuine ”near-miss” proximity events are rarely recorded during data collection.

- **Single-Map Behavioral Generalization:** All SAC training, GRU data collection, and closed-loop evaluation were conducted exclusively on the Town10HD map. While Town10HD provides a high-density urban environment with complex junctions, the generalization of the trained policy to qualitatively different environments — such as highway maps (Town04) or rural roads (Town07) — remains untested. The behavioral cluster structure may shift significantly in these environments.

- **SLM Integration Status:** At the time of submission, the Small Language Model (Qwen 0.8B) is integrated strictly as a safety arbitration layer providing CLEAR, BRAKE, and EMERGENCY_BRAKE classifications. The advanced personality and regulatory context capabilities described in the architecture blueprint represent planned extensions that have not yet been empirically validated in closed-loop testing.

- **Hardware-Induced Asynchrony:** Operating the entire neuro-symbolic stack (CARLA, YOLO, SegFormer, SAC, GRU, and SLM) on a single consumer GPU necessitates computational compromises to maintain real-time viability. Consequently, the RL agent executes control loops at 50Hz, while the Large Language Model acts as an asynchronous sensor capped at 2Hz. A multi-GPU deployment would eliminate these bottlenecks, enabling perfectly synchronized execution across all hierarchical layers.

4.5.3 Comparative Analysis of the Decision Pipeline

To contextualize the final end-to-end performance of our hierarchical decision system against existing literature, Table 4.15 compares our closed-loop architecture against modern Deep Reinforcement Learning (DRL) and Large Language Model (LLM) baselines commonly reported in CARLA-based autonomous driving experiments from 2022 to 2026.

Table 4.15: Comparative Analysis of Recent Decision Architectures in CARLA (2022–2026).

Architecture	Control Type	Safety Layer	Behavioral Context	Control Freq.
CCMR-PPO (BEV Fusion) [22]	Continuous	Multi-Objective	Spatial (Grid Maps)	≈ 25 Hz
LF-PPO (Chaotic Exploration) [23]	Continuous	Boundary Shield	None	≈ 20 Hz
End-to-End LLM (e.g., LMDrive) [31]	Token/Waypts	Prompt-based	Semantic (Language)	< 10 Hz
SAC (CaRL Baseline) [53]	Continuous	None	None	≈ 20 Hz
SAC (Safe Nav Baseline) [54]	Continuous	Rule-based	None	≈ 20 Hz
Our SAC + GRU + SLM (Ours)	Continuous	GRU + SLM	Temporal + Semantic	**50 Hz**

Discussion: The primary architectural distinction of our system is the strict separation of concerns between continuous control (SAC), behavioral context prediction (GRU), and safety arbitration (SLM). When compared to recent state-of-the-art paradigms, our approach addresses several critical limitations:

- **Comparison with Spatial and Multi-Objective PPO (2023):** A prevalent approach in recent literature, such as CCMR-PPO [22], focuses on utilizing bird's-eye view (BEV) grid maps fused into multi-objective reward functions to optimize spatial representations. While this successfully addresses immediate localized state spaces, these architectures compress environment layouts without explicit temporal behavioral semantics. Consequently, multi-objective PPO pipelines remain "black boxes" that conflate distinct behaviors like cruising, turning, and hazard avoidance into a singular flattened control loop. Our system resolves this by utilizing post-hoc DTW KMeans and a GRU override, successfully extracting and separating distinct temporal manifolds (e.g., the TURNING_LEFT vs. TURNING_RIGHT asymmetry) that standard spatial encoders blur.

- **Comparison with End-to-End LLM/VLM Controllers (2024–2025):** Recent frameworks such as LMDrive [31] rely on Large Vision-Language Models to process multi-modal sensor inputs and output driving actions or high-level waypoints directly. While these systems possess immense semantic reasoning capabilities, they suffer from severe computational latency, often operating well below 10 Hz, which is fundamentally insufficient for emergency braking in dense, dynamic urban environments like Town10HD. Our architecture cleanly resolves this control bottleneck by decoupling responsibilities: assigning high-frequency (50 Hz) continuous control to the SAC agent, while the Qwen 0.8B SLM operates asynchronously strictly as a high-level safety arbitrator.

- **Comparison with Reward-Tuning and Exploration Shields (2023–2025):** Recent baselines attempt to solve safety constraints through exploration adjustments—such as LF-PPO's chaotic Lévy flight boundary shielding [23]—or via reward-tuning paradigms like CaRL [53] and rule-based interventions [54]. While effective at reducing initial collision spikes, these mathematical or heuristic overrides remain rigid, often leading to performance trade-offs or high false-positive interventions because they lack an understanding of actual driving history. Our GRU provides a *learned* safety layer trained directly on the agent's actual trajectory data. The 90.1% GRU validation accuracy proves that class-conditional control overrides can be safely grounded in the statistical structure of the agent's historical driving patterns, yielding a bespoke, data-driven safety mechanism.

4.6 Conclusion

The empirical evaluation presented in this chapter validates the Hierarchical Neuro-Symbolic architecture as a robust solution to the latency-reasoning bottleneck. By deploying optimized perception models on an RTX 2060 SUPER, the system successfully abstracts raw sensor data into deterministic BEV maps without violating real-time constraints. Furthermore, the decision pipeline—operating on an RTX 2060—demonstrates that continuous SAC control can be safely bounded by a recurrent GRU classifier achieving 90.1% accuracy, guided by an organically discovered DTW behavioral taxonomy. The multi-stage arbitration ensures that any statistical misclassifications are safely caught by deterministic and semantic overrides. Having successfully proven the

system’s efficacy in simulated closed-loop environments, the final chapter will synthesize these contributions and outline future pathways for this research.

General Conclusion

The pursuit of Level 5 autonomous driving represents one of the most complex engineering paradigms of the modern era. While highway navigation has largely been solved through deterministic control systems, navigating unstructured, high-density urban environments requires a sophisticated fusion of spatial perception, continuous mechanical control, and human-like semantic reasoning.

As established throughout this research, the primary barrier to full autonomy is the architectural conflict between high-speed reflexes and semantic reasoning. Pure Reinforcement Learning (RL) agents provide the high-frequency control required for physical survival but operate as opaque ”black boxes” devoid of common sense. Conversely, the recent advent of Vision-Language-Action (VLA) models provides deep contextual reasoning but introduces catastrophic computational latency—often exceeding 1.5 seconds per cycle—rendering them physically unsafe for direct, high-speed vehicle control.

To resolve this latency-reasoning dilemma, this thesis engineered and validated a Hierarchical Neuro-Symbolic Architecture within the CARLA environment. Rather than relying on a single monolithic network, the system decouples the driving task into specialized layers. A custom multi-modal perception pipeline deterministically fuses 2D bounding boxes (YOLOv8s) and semantic masks (SegFormer-B0) against 3D LiDAR point clouds to generate a distortion-free Bird's-Eye-View (BEV) map. This precise spatial state is then fed into a hybrid decision pipeline that arbitrates between a continuous Soft Actor-Critic (SAC) agent, a statistical GRU behavioral classifier, and an asynchronous Small Language Model (SLM) serving as a semantic safety gate.

The empirical evaluation yielded highly robust closed-loop performance, headlined by two primary scientific outcomes. First, the GRU sequence classifier achieved a 90.1% validation accuracy, successfully providing hard, rule-based safety overrides that a purely reward-trained SAC policy cannot guarantee. Second, and most notably, the application of unsupervised Dynamic Time Warping (DTW) KMeans clustering to the RL agent's trajectory history yielded an unanticipated post-hoc discovery. The clustering organically isolated a geometric asymmetry between left and right turns—a distinction proving that the machine's internal behavioral vocabulary is structurally different from human heuristics. By building the safety gates upon this data-driven taxonomy, the system achieves a highly organic and responsive control envelope.

Despite these successes, the current prototype operates under specific constraints. The hardware-forced reduction of camera resolution to prevent Out-Of-Memory errors on the consumer-grade GPUs degraded the pixel-level accuracy of thin features such as road lines. Furthermore, the entire dataset and subsequent policy optimization are strictly bound to the synthetic rendering engine of CARLA. The weights and behavioral manifolds learned in this simulated domain would inevitably face a ”Sim-to-Real” distribution shift if deployed on physical hardware without extensive domain adaptation.

While the proposed architecture successfully resolves the latency-reasoning dilemma in a simulated urban environment, it also illuminates specific, actionable pathways for future research to push the system toward real-world deployment:

- **3D Occupancy Networks and Voxelization:** The current BEV projection relies on Inverse Perspective Mapping (IPM), which assumes a flat ground plane. Future iterations should explore lightweight 3D Occupancy Networks. By predicting volumetric voxels rather than flat pixels, the perception layer could navigate severe elevation changes (e.g., steep hills, multi-level parking garages) without introducing geometric artifacts.
- **Dynamic Prompt Engineering and Personality Profiles:** The integration of the Qwen SLM currently serves strictly as a safety arbiter. Future research should expand the SLM's prompt engineering to include

dynamic ”personality” profiles or region-specific traffic laws, dynamically modulating the SAC agent’s reward weights on the fly based on natural language instructions.

- **Sim-to-Real Domain Adaptation:** The vision models (YOLOv8s and SegFormer-B0) were heavily fine-tuned on the synthetic textures of the CARLA engine. Transitioning this architecture to physical hardware will require rigorous sim-to-real transfer learning, potentially utilizing Generative Adversarial Networks (GANs) to translate real-world camera feeds into the simulated visual domain.
- **Multi-GPU Hardware Acceleration:** The current asynchronous 50Hz/2Hz frequency split was a necessary architectural compromise to run the entire Neuro-Symbolic stack on a single consumer GPU. Future implementations on distributed, automotive-grade multi-GPU architectures could allow the language model and perception systems to run at much higher frequencies, further tightening the latency gap.

Ultimately, this thesis demonstrates that the path to safe, fully autonomous driving does not require choosing between fast reflexes and deep reasoning; through careful neuro-symbolic decoupling, both can be achieved simultaneously.

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