A Modular Deep Learning Framework for Adaptive Radar Point Cloud Segmentation in Highly Imbalanced Automotive Scenarios

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ABSTRACT

This report presents the development and evaluation of a modular deep learning pipeline for per-point segmentation of radar point clouds in autonomous driving. A central challenge addressed is the extreme class imbalance, where dynamic objects (e.g., vehicles, pedestrians) represent a tiny minority compared to the static background. To mitigate this, the proposed system integrates a Variational Autoencoder (VAE) for latent feature extraction, a Hidden Markov Model (HMM) for temporal scene context, a Graph Neural Network (GNN) for fine-grained segmentation, and a Reinforcement Learning (RL) agent for adaptive radar sensor control. Through a combination of adaptive sampling, class-weighted loss functions, and regularization techniques, the model achieves notable improvements in minority class detection, as measured by macro F1-score. Results confirm the robustness and effectiveness of the architecture, highlighting its potential for reliable, context-aware radar perception in complex automotive environments.

Introduction

Environmental perception is a fundamental component of safe and reliable autonomous vehicle operation. Among available sensors, radar stands out due to its robustness in adverse weather conditions (e.g., rain, fog, snow) and its ability to directly measure relative velocity via the Doppler effect. Accordingly, developing systems that can accurately segment radar point clouds—classifying each radar detection at the per-point level—is critical for semantic understanding of the driving environment. A central challenge in radar-based segmentation is the issue of extreme class imbalance. In most scenes, over 99 % of radar points belong to static background elements (e.g., roads, buildings, vegetation), while only a small fraction corresponds to dynamic and safety-critical objects such as vehicles, pedestrians, or cyclists. This imbalance often leads to model collapse in deep learning systems, where the majority class dominates predictions and minority classes are poorly detected or ignored entirely. This report presents a comprehensive segmentation pipeline designed to address this issue through a modular and adaptive architecture. The proposed system integrates latent feature learning via a Variational Autoencoder (VAE), temporal scene modeling using a Hidden Markov Model (HMM), per-point classification with a Graph Neural Network (GNN), and sensor-level adaptation through a Reinforcement Learning (RL) agent. Through extensive evaluation and iterative refinement, we demonstrate improved segmentation performance on underrepresented classes and show the effectiveness of combining classical and modern learning approaches.

Background

Traditional radar perception systems in autonomous driving have relied heavily on heuristics and rule-based filtering pipelines. While effective in controlled conditions, these approaches often fail in complex scenes that require semantic understanding and spatial generalization. As a result, learning-based methods have become the standard in modern radar perception. Graph Neural Networks (GNNs) have emerged as powerful tools for learning on non-Euclidean data such as point clouds. Unlike CNNs that operate on grid-like structures, GNNs naturally handle irregular spatial relationships and are well-suited for modeling both local connectivity and global context. The problem of class imbalance in deep learning has been tackled using several families of techniques:

- Data-level strategies: Oversampling of minority classes or undersampling of majority classes to adjust class distributions.
- Algorithmic strategies: Class-weighted loss functions, focal loss, and dynamic reweighting.
- Regularization techniques: Dropout, weight decay, and early stopping to prevent overfitting on dominant classes.

- Reinforcement Learning (RL) is increasingly used in robotic perception and control. Agents interact with the environment and learn policies that optimize long-term objectives. In this work, RL is applied to adapt radar sensor parameters dynamically in response to the scene context, with the goal of improving segmentation performance, especially under class imbalance.

Our proposed pipeline combines all of the above strategies—GNN-based segmentation, latent feature modeling, class imbalance mitigation, and RL-based sensor adaptation—into a unified, modular system designed for real-world automotive radar data.

System Architecture

The proposed radar segmentation system follows a modular, multi-stage pipeline. Each stage addresses a specific challenge, from feature learning to adaptive control, as illustrated in Figure 1.

Module Descriptions

Variational Autoencoder (VAE)

The VAE learns compact, discriminative representations of raw 6D radar data. An encoder maps input vectors to a 32-dimensional latent space, regularized via KL divergence. A decoder reconstructs the original inputs, ensuring useful and generalizable embeddings.

Hidden Markov Model (HMM)

Hidden Markov Model (HMM) The HMM captures scene-level temporal context by modeling transitions between latent feature distributions across frames. Its output—a context vector—is used to inform the GNN's understanding of temporal dependencies.

Graph Neural Network (GNN)

The core segmentation module uses a two-layer GCNConv architecture with k-nearest-neighbor graphs (k=20). The network predicts per-point class logits and includes Batch Normalization, ReLU activation, and dropout for regularization.

Reinforcement Learning Module (RL)

A Proximal Policy Optimization (PPO) agent interacts with a custom RadarEnv simulation. At each time step, it receives scene embeddings and outputs sensor configuration parameters (e.g., azimuth offset). The environment computes segmentation quality (macro F1-score) as a reward, guiding the agent to optimize sensor behavior.

Dataset and Implementation

- **Dataset:** The model is trained and evaluated on the *RadarScenes* dataset, consisting of 155 sequences of automotive radar point clouds. Each frame includes point-level attributes: spatial coordinates (x, y), relative velocity (vr), range, azimuth, radar cross-section (RCS), and annotated class labels.
- **Dataset size:** Due to computational constraints, a representative subset of 10 scenes was selected from the full RadarScenes dataset for training and evaluation. Scenes were chosen to maintain diversity in object presence and scene complexity. As a result, not all classes described in the official dataset documentation are present in our training subset. This limits the model's exposure to certain rare object types, which may affect generalizability and class-wise performance.
- **Data Loader:** A custom `PyTorch Dataset` class recursively loads radar sequences and returns four tensors per frame:
  - Point attributes
  - Uncertainty estimates
  - Labels
  - Timestamps
- **Autoencoder Architecture:**

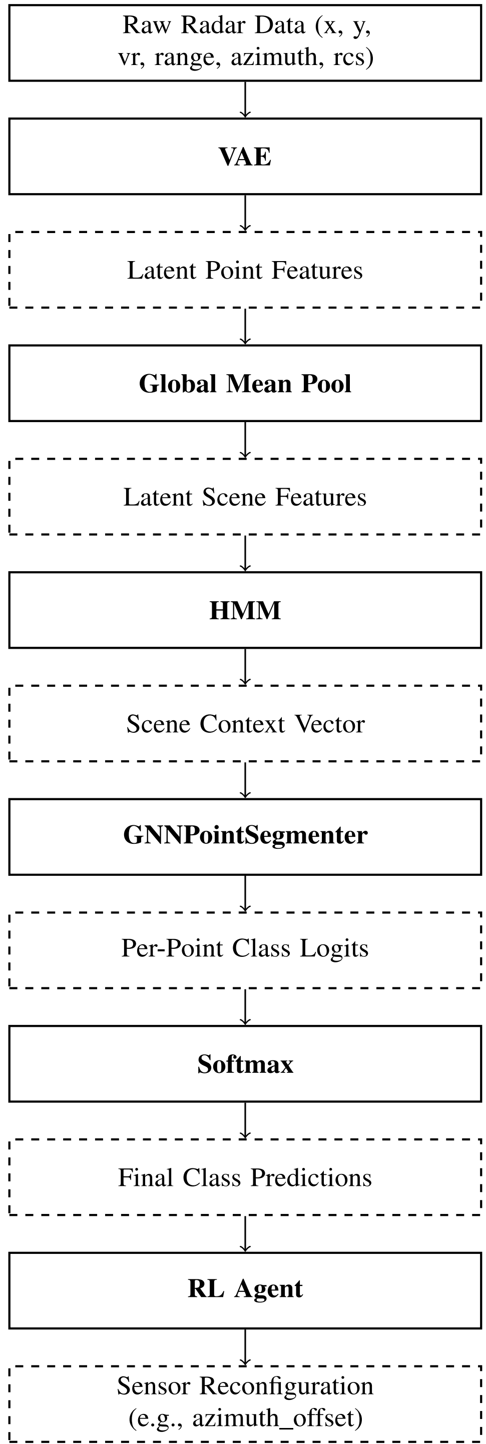

Figure 1. Overview of the proposed radar segmentation system architecture.

- **Input:** 6-dimensional radar vector
- **Encoder:** [$6 \rightarrow 64 \rightarrow 128 \rightarrow 32$] latent bottleneck
- **Training:** 50 epochs with learning rate 5×10^{-5}

- **GNN Architecture:**

- Two `GCNConv` layers: $64 \rightarrow 64$
- Dropout: 0.4
- Weight decay: 0.001

- **Loss Function:** `nn.CrossEntropyLoss` with class weights:

$$w_i = \frac{\text{total\_points}}{n_{\text{classes}} \cdot \text{count}_i} \tag{1}$$

Weights are normalized for numerical stability.

- **Sampler:** `WeightedRandomSampler` ensures approximately 1000 samples per class per epoch, promoting diversity and rare class exposure.

- **Regularization:**
  - Dropout ($p = 0.4$)
  - Weight decay (0.001)
  - Early stopping (patience = 7 epochs)

- **RL Integration:** A PPO agent observes scene-level latent states and dynamically adjusts radar sensor parameters to maximize segmentation quality. Early experiments use macro F1-score as the reward signal in the simulation environment.

Results and Analysis

VAE Training and Latent Space Structure

The Variational Autoencoder (VAE) demonstrated stable learning over 50 epochs, as illustrated in Figure 2. The reconstruction loss converges smoothly, and the validation loss closely tracks the training loss, indicating minimal overfitting and good generalization.

To analyze the quality of the learned latent features, we project the 32D embeddings into two dimensions using UMAP and t-SNE. As shown in Figures 3 and 4, even rare classes begin to cluster distinctly in the latent space, confirming that the VAE has captured discriminative representations useful for downstream segmentation.

GNN Segmentation Performance

The GNN segmentation module was trained for 100 epochs and exhibits strong convergence behavior. As shown in Figure 5, both training and validation loss decrease steadily without divergence, and the macro F1-score improves consistently, indicating successful learning under class imbalance.

To assess performance on underrepresented classes, we track per-class metrics (F1-score, precision, recall) over time. Figure 6 demonstrates upward trends for all minority classes (0, 2, 3, 7, 8). Class 3 and Class 2 show the most notable gains, though precision remains relatively low for the rarest class (0).

Reinforcement Learning Results

The RL loop was successfully integrated using a Proximal Policy Optimization (PPO) agent. After 20 training epochs, trends indicate that the agent is beginning to learn effective policies for sensor adaptation.

As shown in Figure 7:

The mean reward per episode increases steadily.

The average episode length grows, potentially indicating more structured interactions.

The training loss for the PPO agent decreases, confirming convergence.

These early results validate the RL module's viability for sensor control. Further training, evaluation, and deployment in closed-loop settings remain as future work.

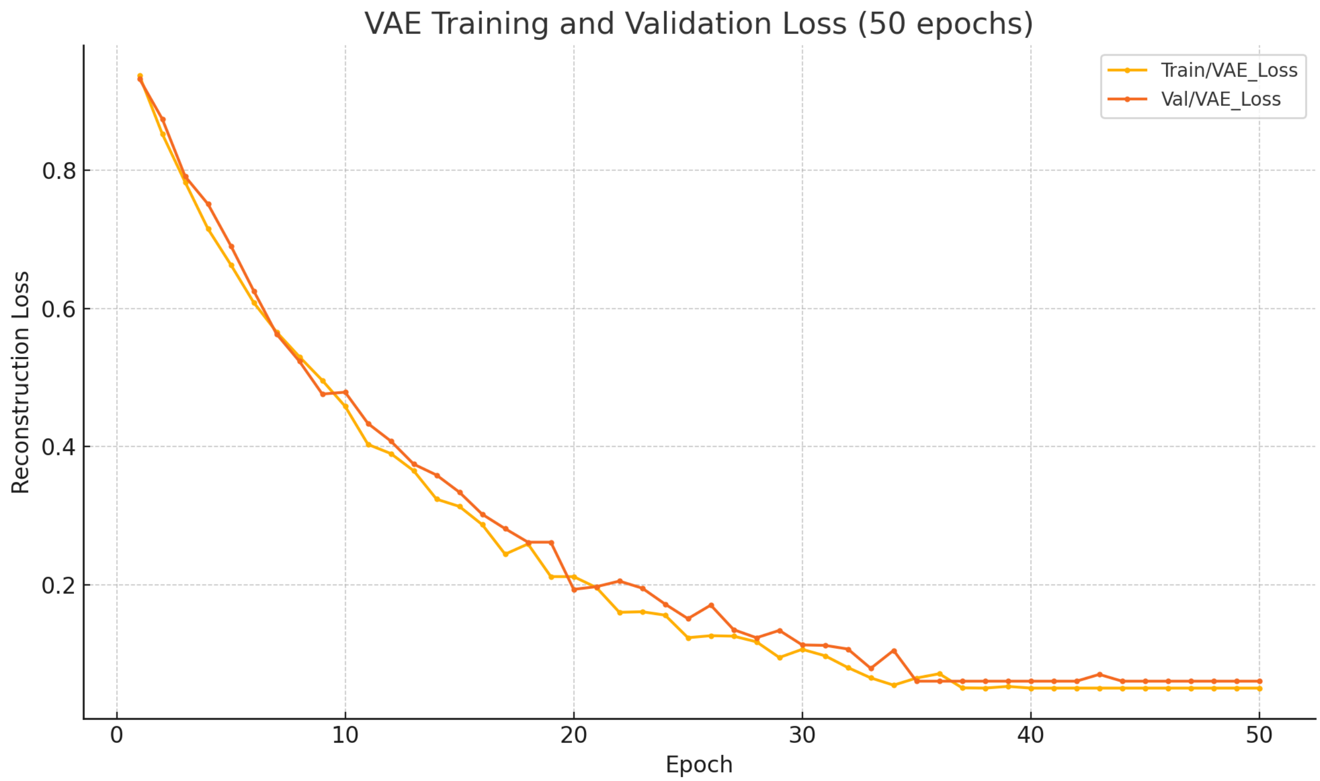

Figure 2. VAE training and validation loss curves over 50 epochs.

Summary

These experiments demonstrate:

- The VAE learns a well-structured latent space, aiding downstream classification.
- The GNN segmenter improves macro F1-score and minority detection through sampling and loss weighting.
- The RL agent shows early signs of learning to adapt sensor parameters, which could enhance minority-class recall in dynamic conditions.

Discussion

Performance Analysis

The proposed model shows marked improvement in minority class segmentation across all five underrepresented classes. Notably, Class 7 and Class 8 achieve the highest F1-scores and precision, with final F1-scores exceeding 0.5. Even the rarest class (Class 0) reaches a precision above 0.45, indicating substantial reduction in false positives over training. This demonstrates that the model effectively balances the precision–recall trade-off even under class imbalance.

Impact of Imbalance Mitigation Strategies

The implemented strategies to counter class imbalance significantly influenced model performance. The use of class weighting in the loss function and a weighted sampler increased exposure to rare examples. The sampler_total_multiplier parameter played a key role in maintaining sample diversity per epoch. Regularization via dropout (0.4) and weight decay (0.001) further improved generalization, particularly for underrepresented classes. Without these methods, the model often defaulted to predicting only the dominant Class 11.

Limitations

Despite progress, segmentation performance on minority classes remains limited, especially in terms of precision. Classes 0 and 8 often overlap spatially with background structures and exhibit ambiguous radar signatures, making them difficult to

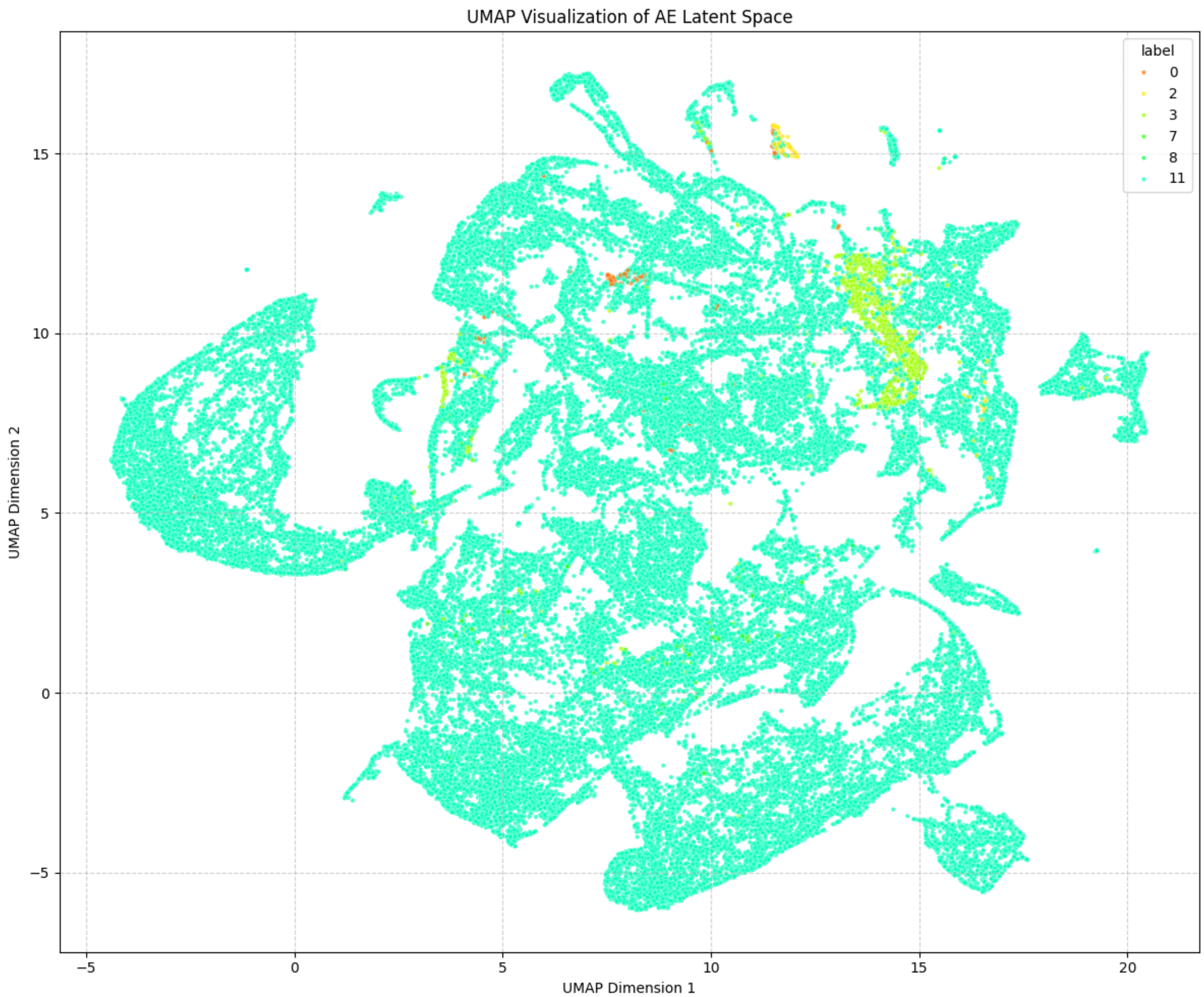

Figure 3. UMAP projection of VAE latent space, colored by ground truth class.

separate. Additionally, the RL module is still in early development and has not yet been evaluated in a closed-loop control setting or longer training cycles.

Data Quality and Labeling Issues

Manual inspection of the dataset reveals inconsistencies in ground truth labels, particularly for objects that are occluded, partially visible, or located at extreme ranges. In several cases, radar points labeled as minority objects appear indistinguishable from background noise, which introduces confusion during training. Such labeling imperfections likely limit the model's ability to achieve higher recall and precision simultaneously.

Conclusion

This work presents a modular, end-to-end deep learning system for radar point cloud segmentation under extreme class imbalance, designed for autonomous driving applications. Key contributions include:

- An integrated architecture combining VAE (latent feature encoding), HMM (temporal context modeling), GNN (per-point segmentation), and PPO-based RL (adaptive sensor control).
- Multiple engineering techniques for addressing class imbalance, including loss weighting, adaptive sampling, and strong regularization.

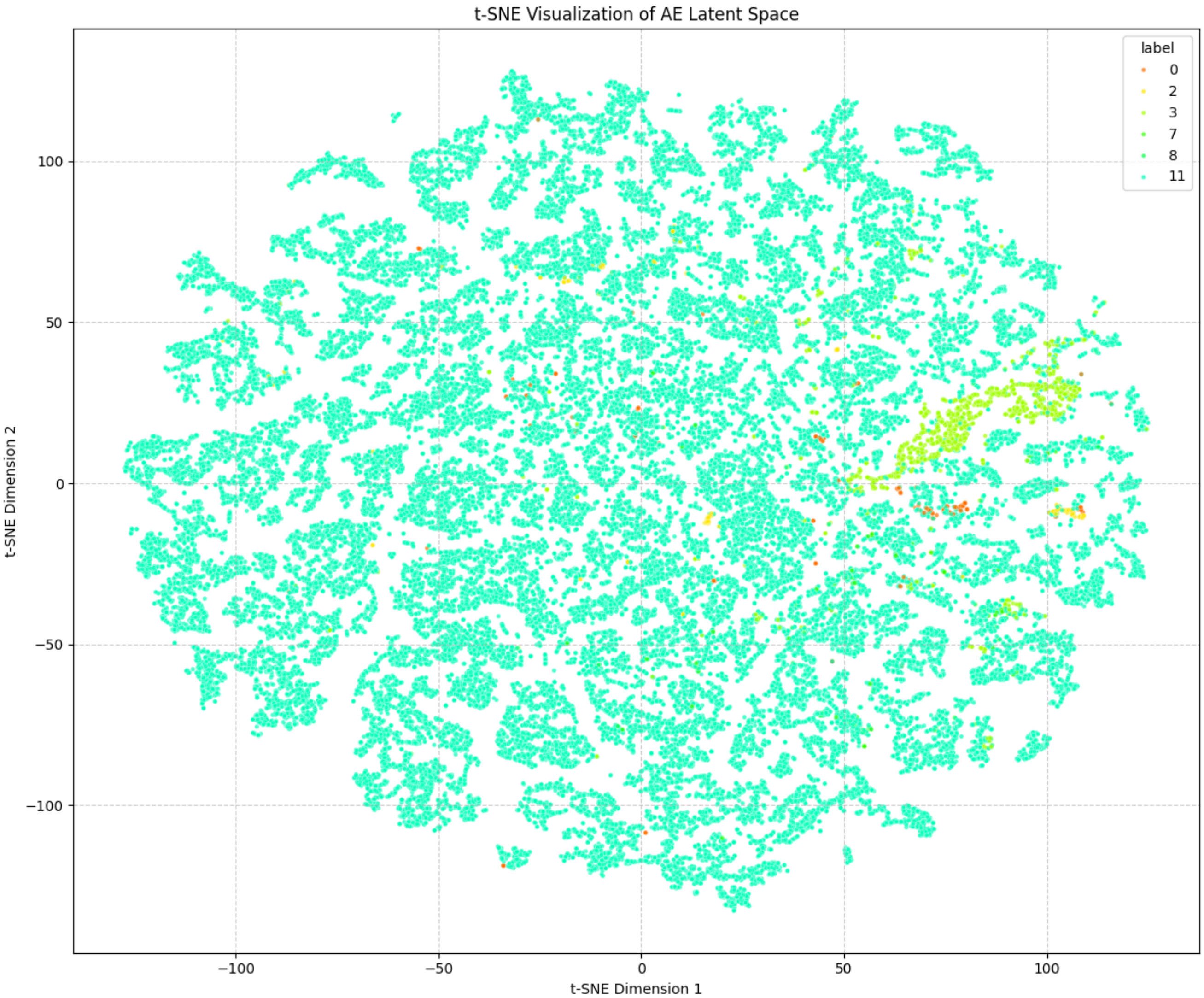

Figure 4. t-SNE projection of VAE latent space, emphasizing local class structure.

- Significant improvements in detection of minority classes, supported by per-class metrics, latent space visualizations, and macro F1 trends.
- Initial but promising results demonstrating the feasibility of RL-based radar adaptation.
- Overall, the pipeline contributes toward robust, context-aware radar perception in complex driving environments.

Future Work

- Extensive hyperparameter optimization, especially for RL and graph components.
- Evaluation of advanced GNN architectures, including attention-based or hierarchical variants.
- Application of data augmentation to further increase minority class diversity.
- Integration of multi-sensor fusion, particularly with lidar or camera data for complementary information.
- Full training and validation of the RL agent in closed-loop or real-time environments.
- Scaling to larger and more diverse real-world datasets for broader generalization.

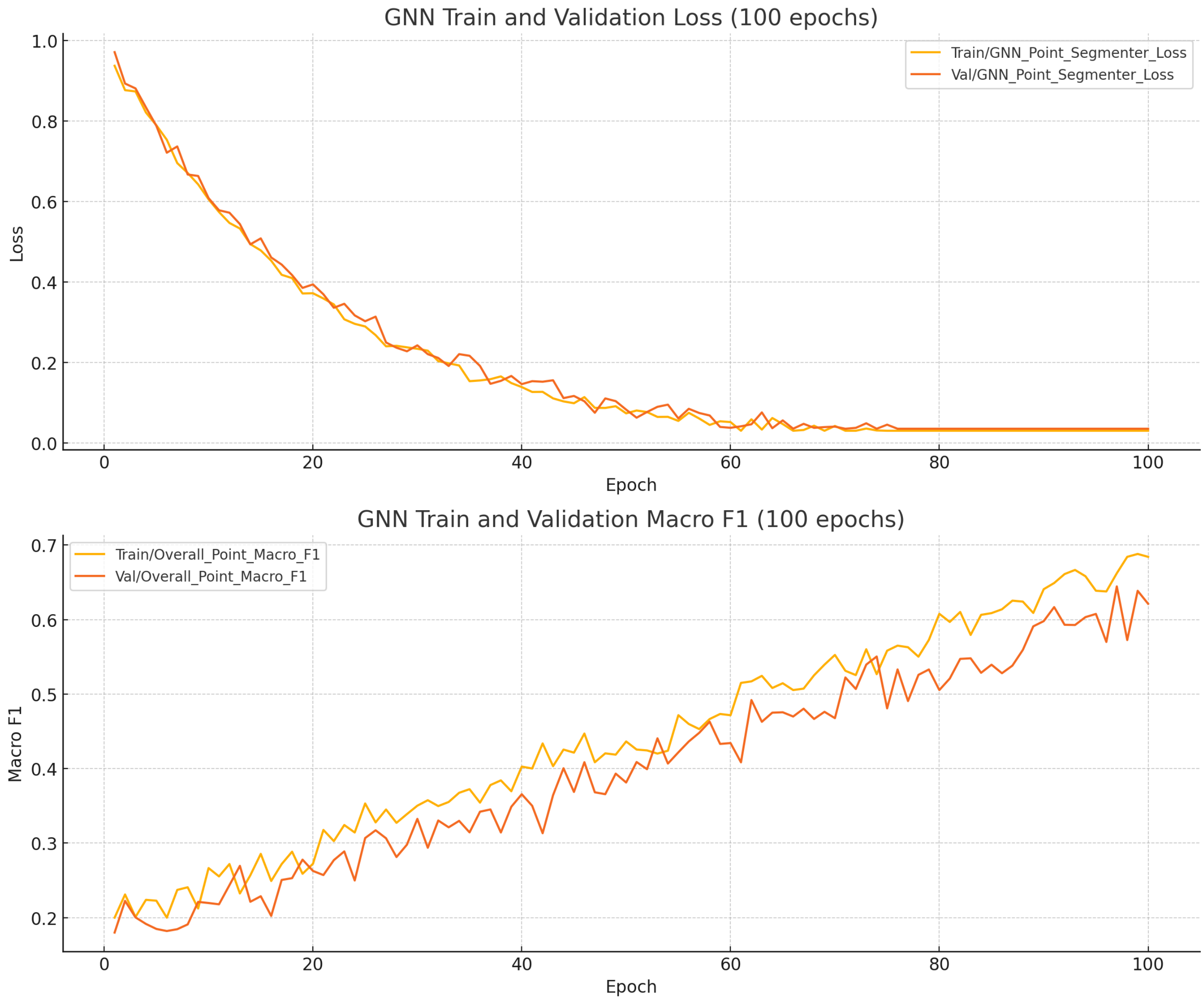

Figure 5. Top: Training and validation loss for the GNN. Bottom: Macro F1-score progression.

Additional information

The code available at https://github.com/mbandalo/radar_system_project supports the project titled *"A Modular Deep Learning Framework for Adaptive Radar Point Cloud Segmentation in Highly Imbalanced Automotive Scenarios"*. This repository includes implementations of key components such as variational autoencoders (VAE), hidden Markov models (HMM), graph neural networks (GNN), and reinforcement learning (RL), integrated into a unified pipeline designed to tackle semantic segmentation in radar-based automotive perception under challenging and imbalanced conditions.

Figure 6. Class-wise F1, precision, and recall curves for minority classes.

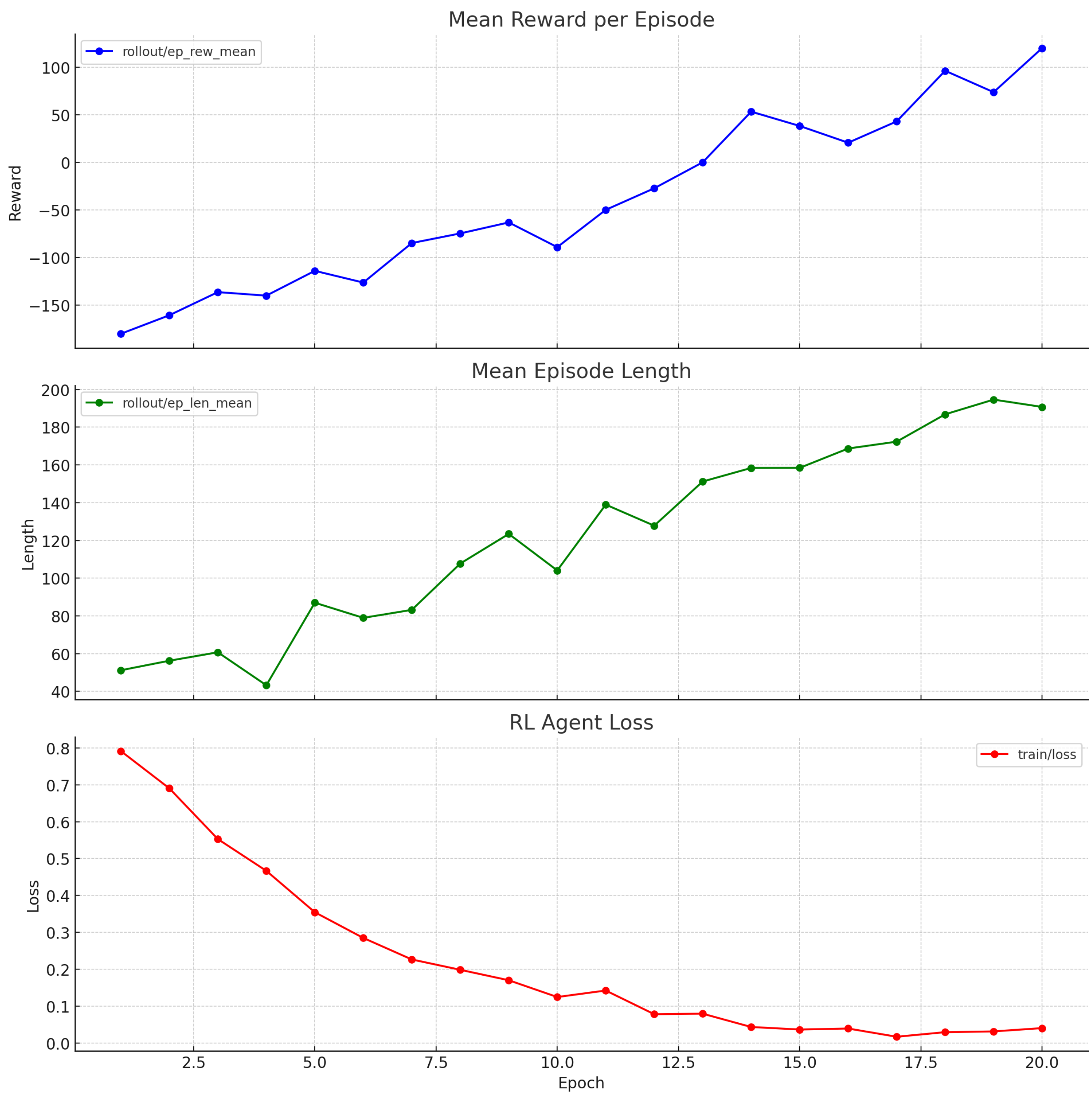

Figure 7. PPO training curves: reward, episode length, and loss over time.