CAPSTONE PROJECT

SIMULATION-BASED EVALUATION OF AUTONOMOUS VEHICLE'S RELIABILITY AND PERFORMANCE IN ADVERSE WEATHER CONDITIONS

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Project Group Number: CSERGC0018 | Course Code: CSE439
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Introduction to Autonomous Vehicles

Transformative Technology

- Safer transportation by minimizing human error, a leading cause of road accidents
- More efficient mobility with optimized routes and traffic management
- Environmentally sustainable with reduced fuel consumption and emissions
- Enhanced accessibility for elderly and disabled individuals

The Weather Challenge

Weather-related accidents account for a significant portion of road incidents:

⚠ Reduced visibility in fog, rain, and night conditions

⚠ Sensor degradation leading to misinterpretation of surroundings

⚠ Increased risk of navigation failures and collisions

Critical Sensor Suite

Cameras

Provide visual perception for object recognition and lane detection

Affected by: Rain (blurred lenses), fog (reduced contrast), night (low visibility)

LiDAR (Light Detection and Ranging)

Creates detailed 3D point clouds of the environment

❄ Affected by: Precipitation (scattered beams), fog (attenuated signals), snow (sensor accumulation)

Radar

Detects moving objects and measures their velocity

⚡ Affected by: Heavy rain (noise), storms (false positives/missed detections)

Problem Statement and Objectives

Problem Statement

Autonomous vehicles face significant challenges in adverse weather conditions:

- ⚠ Heavy rain, fog, storms, and low-light scenarios impair critical sensors (cameras, LiDAR, and radar)
- ⚠ Compromised perception, navigation, and decision-making capabilities
- ⚠ Increased risk of misinterpretations, potentially causing collisions or navigation failures
- ⚠ Weather-related accidents account for a significant portion of road incidents

Scope of the Study

- Sensor Analysis: Camera and LiDAR degradation in adverse weather
- Simulation: CARLA to model realistic weather effects
- Data Preprocessing: Noise filtering and augmentation
- Model Evaluation: Comparing five models for best performance

Project Objectives

Real-time Data Collection
Train suitable machine learning models using simulators

Review Existing Technologies
Evaluate simulation platforms and data preprocessing techniques for mitigating adverse weather effects

ML/DL Analysis
Analyze the role of ML and DL in enhancing sensor performance during challenging weather conditions

Weather Impact Evaluation
Evaluate the impact of different weather conditions on the performance of various sensors used in AVs

Future Research Areas
Identify technological gaps and suggest potential avenues for future research to improve AV system robustness

Research Alignment

This project builds upon our Springer to be published paper: "The Influence of Adverse Weather on the Reliability and Performance of Autonomous Vehicles"

Methodology: Simulation & Dataset

Simulation Platform: CARLA 0.9.13

CARLA (Car Learning to Act) is an open-source simulator for autonomous driving research, providing:

Key Strengths

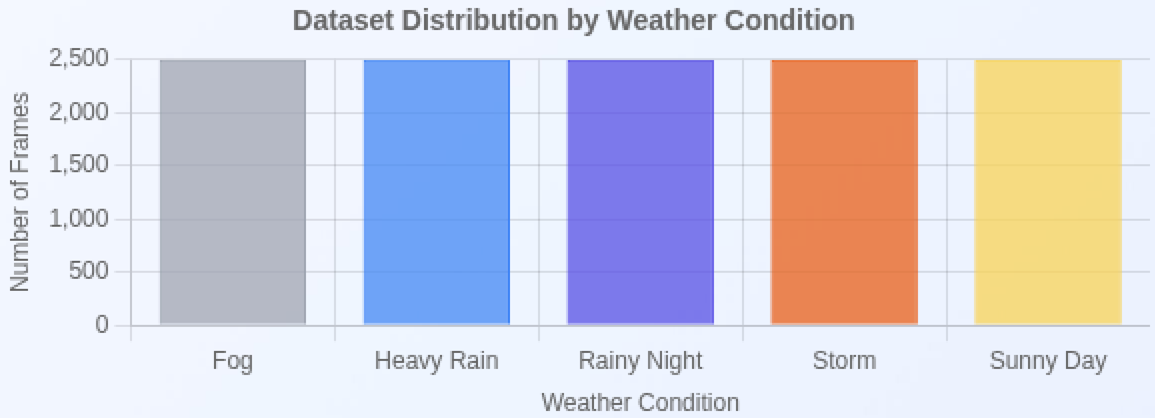
- Realistic 3D urban environments with dynamic traffic
- Comprehensive sensor suite emulation (cameras, LiDAR, radar, GPS)
- Customizable weather parameters (precipitation, fog density, sun altitude)
- Python API for ML framework integration (PyTorch)

Limitations

- Limited dynamic weather transitions
- High computational demand for realistic rendering
- Weather effects may not fully replicate extreme conditions

Dataset Details

26GB | **12,500 frames** | **5 weather presets**



Data per Weather Preset (2,500 frames each):

- RGB images (front, left, right, back)
- LiDAR point clouds (.npy)
- JSON metadata
- Sensor fusion annotations

Metadata Example (Simplified):

```
{
  "steering": 0.031,
  "throttle": 0.0,
  "brake": 0.699,
  "speed": 8.097,
```

Model Architectures Comparison

Advanced CNN ⋆

- ResNet backbone, fusion
- Parameters: ~25M
- 12,500 frames
- GAN restoration
- VRAM: ~5GB

CNN

- ResNet-18, regression
- Parameters: ~10M
- 10,000 frames
- CLAHE, normalization
- VRAM: ~4GB

TransFuser++

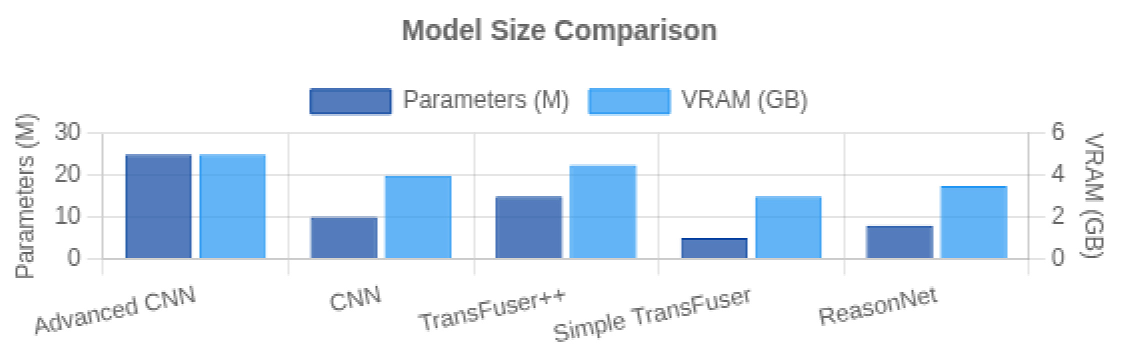
- Enhanced transformer
- Parameters: ~15M
- 12,500 frames balanced
- Advanced techniques
- VRAM: ~4.5GB

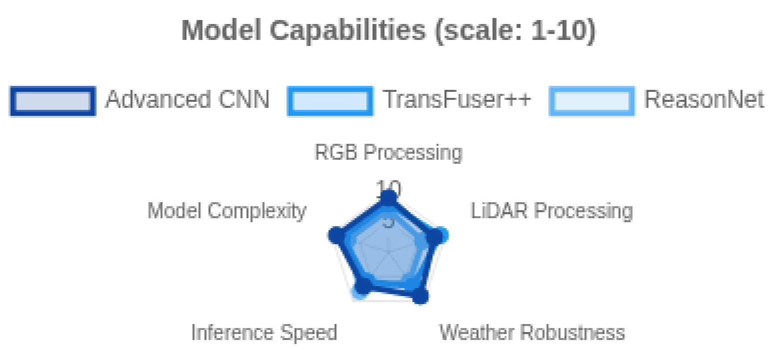
Simple TransFuser

- Layers transformer
- Parameters: ~5M
- 12,500 frames
- Advanced techniques
- VRAM: ~3GB

ReasonNet

- LSTM-based, temporal
- Parameters: ~8M
- 12,500 frames, temporal
- Time-series smoothing
- VRAM: ~3.5GB





Common Components Across Models

All models utilize preprocessing techniques specific to their architecture, implement sensor fusion at different stages, and output control signals through an MLP or policy-based layer

Implementation Details

Data Collection

1. **Dataset Size:** 26GB with 12,500 frames across five weather presets
2. **Sensor Setup:** RGB cameras (800x600) from four angles (front, left, right, back) and LiDAR (100,000 points)
3. **Execution:** Python scripts via CARLA's PythonAPI with automated collection across weather conditions

CARLA 0.9.13 | RGB (800x600) | LiDAR | 5 Weather Presets

Training & Validation

Training Configuration:

- Model-specific batch sizes (2-4) and epochs (20-50)
- FP16 precision to optimize VRAM usage
- AdamW optimizer with learning rates 1e-4 to 1e-5
- Loss functions: MSE for regression, BCE for classification tasks

Validation Steps:

- Data integrity checks (missing frames, corrupted files)
- Visualization of preprocessed sensor data
- Loss curve monitoring for overfitting detection
- Comparison with CARLA leaderboard benchmarks

PyTorch | CUDA | FP16 | TensorBoard

Collection → Preprocessing → Training → Validation →

Testing Scenarios and Evaluation Metrics

Fog Scenario

Navigation in Town05 with fog_density=80

- Camera: Low contrast, blurred features
- LiDAR: Attenuated signal, limited range
- Test: Lane keeping, obstacle detection

Heavy Rain Scenario

Lane maintenance with precipitation=90

- Camera: Droplets on lens, distortion
- LiDAR: Scattered beams, false readings
- Test: Path following, collision avoidance

Rainy Night Scenario

Obstacle avoidance in low light conditions

- Camera: Minimal visibility, reflections
- LiDAR: Limited by rain and darkness
- Test: Object recognition, navigation

Storm Scenario

Handling dynamic weather changes

- Camera: Rapid lighting changes, rain
- LiDAR: Inconsistent readings, noise
- Test: Stability in changing conditions

Sunny Day Scenario

Baseline performance evaluation

- Camera: Optimal visibility, some glare
- LiDAR: Clear point clouds, full range
- Test: Benchmark for comparison

Testing Levels

Unit Testing

Testing preprocessing, fusion, model components

Integration Testing

Verifying sensor-to-control pipeline

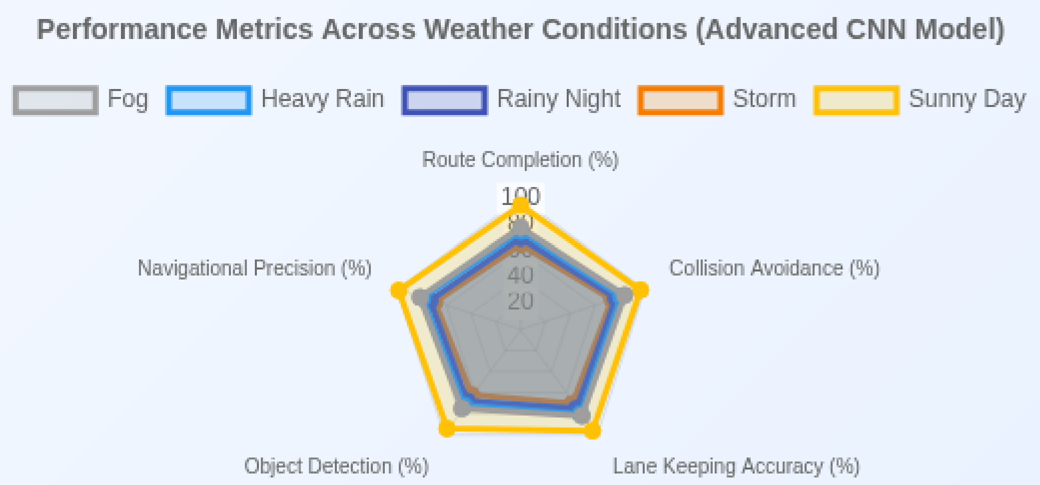
System Testing

End-to-end driving in CARLA

Acceptance Testing

Comparing model performances against metrics

Evaluation Metrics



Results and Key Findings

Model Performance Ranking

1 **Advanced CNN**
Highest route completion, lowest collision rate
Robust across all presets

2 **CNN**
Strong overall performance
Slightly higher collisions

3 **TransFuser++**
Good sensor fusion capabilities
Struggles in stormy conditions

4 **Simple TransFuser**
Moderate performance
⚠ Limited by simpler architecture

5 **ReasonNet**
Lowest overall performance
Sensitive to temporal noise

Advanced CNN Superiority

- Robust feature extraction with ResNet backbone
- GAN-based preprocessing enhances quality
- Multi-modal fusion leverages all sensor data

Weather Impact Analysis

Fog | Heavy Rain | Rainy Night | Storm | Sunny Day

Advanced CNN maintained >75% route completion even in the harshest conditions (storms), while others dropped to 40-60%

Hardware Findings

DGX A100 accelerated training by 60%, while consumer-grade RTX 3060 supported inference with <100ms latency using FP16 precision

Dataset Impact

The 26GB dataset with balanced weather coverage ensured comprehensive training, though edge cases like blizzards were missing

Preprocessing Value

Model-specific techniques significantly enhanced data quality, with GANs showing the most improvement for RGB in adverse conditions

Challenges and Limitations

High Priority

Model Exploration

Testing reinforcement learning or graph neural networks could improve adaptability in dynamic weather

Requires high resources | Challenges for consumer hardware

Proposed Solution: Hybrid approach combining RL and lightweight CNN for scalable deployment

Timeline: Future research direction requiring additional computational resources

Medium Priority

Edge Cases

The dataset lacks rare scenarios like blizzards or sudden fog, critical for real-world robustness

Dataset expansion needed | Rare weather conditions

Proposed Solution: Expanding dataset with 1,000 additional frames covering rare scenarios

Timeline: Near-term implementation requiring additional data collection

High Priority

Real-World Validation

Transitioning to real sensors (e.g., Velodyne LiDAR) faces simulation-reality gaps

Sim-to-real transfer | Test track validation

Proposed Solution: Hybrid testing with artificial weather and domain adaptation techniques

Timeline: Long-term implementation requiring physical test environment

Low Priority

Optimization

Reducing latency for real-time inference on consumer-grade hardware

Hardware constraints | Real-time performance

Proposed Solution: Model quantization and pruning to reduce computational demands

Timeline: Ongoing process with current 100ms latency sufficient for most applications

Research Impact

Despite these challenges, our findings align with recent publications and contribute valuable insights to the field. The identified limitations represent opportunities for future research rather than insurmountable barriers to implementation.

Conclusions and Future Work

Key Conclusions

- **Simulation Effectiveness**
  CARLA 0.9.13 enables controlled, scalable evaluation of AVs in various challenging weather conditions using both consumer and high-performance hardware
- **Model Architecture Findings**
  Advanced CNN significantly outperforms other architectures in adverse weather, with highest route completion rates and lowest collision rates
- **Preprocessing Impact**
  Model-specific preprocessing techniques (e.g., GAN-based restoration, SOR filtering) substantially improve sensor data quality and model performance
- **Hardware Scalability**
  System operates effectively on consumer hardware (RTX 3060) with optimizations, while scaling seamlessly to high-performance systems (DGX A100)

Future Research Directions

- **Dataset Expansion**
  Include rare edge cases like blizzards, sudden fog transitions, and extreme low-light conditions to enhance model robustness
- **Advanced Model Architectures**
  Explore reinforcement learning and graph neural networks for improved adaptability in dynamic weather conditions
- **Real-World Validation**
  Transition from simulation to test tracks with real sensors and artificially created adverse weather conditions
- **Model Optimization**
  Apply quantization and pruning techniques to further reduce inference latency for real-time applications

> *Our findings demonstrate that multi-modal fusion and advanced preprocessing are critical for weather resilience in autonomous vehicles. This project establishes a foundation for safer and more reliable transportation solutions in challenging environments.*
>
> **– Project Team CSERGC0018**

Thank You!

We appreciate your attention to our capstone project. We welcome any questions or feedback on our simulation-based approach to enhancing autonomous vehicle reliability in adverse weather conditions.

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