

**DAYANANDA SAGAR COLLEGE OF ENGINEERING**

( An Autonomous Institute affiliated to Visvesvaraya Technological University (VTU), Belagavi, Approved by AICTE and UGC, Accredited by NAAC with 'A' grade & ISO 9001-2015 Certified Institution)

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**Department of Artificial Intelligence & Machine Learning**

Project Synopsis



# Multimodal AI Ecosystems: Enabling Secure Autonomous Navigation on Mountain Roads

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# Abstract

Mountainous roads present unique safety risks due to sharp curves, fog, falling obstacles, and weak connectivity, where conventional collision-avoidance systems often underperform. This study proposes an **AI-driven Vehicle-to-Vehicle (V2V) accident-avoidance framework** tailored for such challenging environments. The system integrates a multimodal sensor suite—including LiDAR, radar, GPS, IMU, accelerometer, airbag sensor, and RGB cameras—with secure V2V, Vehicle-to-Cloud (V2C), and

Vehicle-to-Person (V2P) communication to enable real-time hazard detection and cooperative

decision-making. A synthetic dataset generated in the CARLA simulator models critical scenarios such as landslides, falling rocks, and dead-ends. Machine learning algorithms perform sensor fusion and obstacle recognition, while secure communication protocols ensure low-latency, reliable alerts. System performance is evaluated through metrics such as detection accuracy, communication delay, and collision-avoidance success under degraded conditions. Results demonstrate that the proposed framework significantly enhances safety and reliability for intelligent transportation systems in mountainous terrains.

# Introduction / Background

Navigating mountainous terrain presents persistent and complex challenges for road safety. The presence of sharp curves, steep gradients, limited visibility, unpredictable weather, and hazards such as falling rocks or debris contributes to elevated risk levels on these routes. Studies consistently indicate that a significant number of accidents in such environments stem from driver misjudgment, slow reaction times, or insufficient situational awareness. While conventional collision-avoidance systems have demonstrated efficacy in urban contexts, their effectiveness is notably diminished in mountainous areas where both environmental and communication obstacles are pronounced.

Recent advances in Intelligent Transportation Systems (ITS) and Vehicle-to-Vehicle (V2V) communication offer promising avenues to address these challenges. V2V technology enables vehicles to share real-time data about road conditions, traffic flow, and potential hazards, facilitating cooperative and informed decision-making. When combined with AI-driven multimodal perception—which synthesizes information from LiDAR, radar, GPS, inertial sensors, and cameras—vehicles can achieve a nuanced and comprehensive understanding of their immediate surroundings. This integration lays the groundwork for proactive accident-avoidance, even in circumstances where individual sensors or connectivity may be compromised.

Simulation platforms such as CARLA provide a controlled yet realistic environment to model and assess complex mountain driving scenarios. These platforms allow for the creation and evaluation of algorithms under conditions that mirror real-world challenges, including obstructed routes, abrupt dead-ends, and landslides. Furthermore, the development of secure and low-latency communication protocols for V2V, Vehicle-to-Cloud (V2C), and Vehicle-to-Person (V2P) interactions is vital to ensure that information exchange remains reliable and timely.

This paper details the design of a secure, AI-based collision-avoidance framework specifically for navigation in mountainous terrain. The research focuses on three primary areas: (i) the generation of multimodal datasets that reflect the unique risks of mountain environments, (ii) the development of machine learning models for obstacle detection and cooperative navigation, and (iii) the creation of robust communication strategies that sustain performance even under degraded conditions. By addressing these facets, the work aims to demonstrate that integrating advanced collision-avoidance techniques with cooperative V2V systems can substantially enhance road safety in elevated, high-risk regions.

**Limited Adaptation to Mountain-Specific Hazards**: Current collision-avoidance systems are predominantly designed for urban or flat terrains, lacking robust handling of mountain-specific risks like sharp curves, falling rocks, and dead-ends (noted in the V2V review paper's urban focus and the problem statement's terrain challenges).

**Inadequate Multimodal Sensor Integration**: Existing solutions often rely on single sensors or fail to effectively fuse data from LiDAR, radar, GPS, and cameras in degraded conditions (e.g., fog, GPS disruptions), as seen in the collision avoidance paper's limited sensor scope.

**Weak V2V Communication Resilience**: Conventional V2V systems struggle with latency and reliability in low-bandwidth, mountainous regions, with protocols not optimized for signal drops or interruptions (highlighted in the V2V problem statement and Hussein Ali Ameen et al., 2020).

**Lack of Realistic Simulation for Hilly Scenarios**: Many studies use generic simulations that do not replicate the complex dynamics of mountainous environments, limiting the validation of AI models (e.g., Garcia M et al., 2023, which lacks diverse terrain testing).

**Insufficient Cooperative Decision-Making**: Current frameworks underutilize cooperative navigation and fail to integrate real-time V2V data for proactive safety, especially under SAE Level 2-3 automation (noted in the review paper's safety standards gap).

# Problem Statement

Mountainous roads present severe safety risks due to sharp curves, poor visibility, falling obstacles, and weak connectivity—conditions where conventional collision-avoidance systems often fail. Current solutions rely on single sensors or stable networks, both unreliable in such terrains. While Vehicle-to-Vehicle (V2V) communication improves cooperative safety, it faces challenges with latency, interruptions, and a lack of robust protocols. Similarly, AI-based perception models struggle to adapt to mountain-specific hazards like rockfalls and sudden dead-ends. Hence, there is a need for a **resilient, integrated framework** that fuses multimodal sensing, machine learning, and secure communication to deliver accurate hazard detection and timely alerts in elevated terrains, platforms, and end-users, with the ultimate goal of preventing accidents in these complex environments.

# Objectives of the Project

### Objective 1: Design and simulate multimodal datasets

Create artificial datasets with the CARLA simulator to mimic hazards unique to mountains, like roadblocks, abrupt dead ends, and falling rocks.

Develop realistic multimodal perception inputs for AI model testing and training by combining data from LiDAR, radar, GPS, IMU, and cameras.

### Objective 2: Develop and implement AI-based perception algorithms

Create multimodal sensor fusion machine learning models to precisely identify, categorize, and forecast obstacles in mountainous areas.

Apply cooperative decision-making techniques in practice to empower cars to take preventative collision measures.

### Objective 3: Design and evaluate secure communication protocols

Design communication modules for vehicle-to-person (V2P), vehicle-to-cloud (V2C), and

vehicle-to-vehicle (V2V) that guarantee data integrity, dependability, and low latency in situations with constrained bandwidth.

Assess communication performance to determine how resilient it is to network outages, signal disruptions, and sensor deterioration.

### Objective 4: Analyze and assess overall system performance

Examine the system's performance using metrics like robustness in degraded situations, communication latency, detection accuracy, and avoidance success rate.

Assess the efficacy of combining cooperative V2V communication with AI-based perception to improve road safety in mountainous areas.

# Scope of the Project

### What the project will cover:

To model mountain-specific hazards, such as sharp curves, poor visibility, unpredictable weather, inadequate communication infrastructure, obstacles (boulders, falling trees, or accidents), dead ends, GPS signal disruptions, lighting conditions, and communication difficulties, synthetic multimodal datasets were developed using the CARLA simulator.

Design and execution of AI/ML models for obstacle detection, risk prediction, multimodal sensor fusion (combining information from LiDAR, radar, GPS, IMU, and RGB cameras), and collaborative

decision-making in simulated environments, with an emphasis on proactive accident prevention.

For V2V, V2C, and V2P interactions, secure, low-latency communication protocols are developed and tested with a focus on data integrity, authentication, and resilience in low-bandwidth or degraded network conditions that are common in mountainous regions.

Metrics like obstacle detection accuracy, communication latency, collision avoidance rate, system resilience to sensor degradation, and overall safety improvements are used to evaluate performance in simulated

real-world mountain environments (aligned with SAE Level 2-3 automation for partial/conditional autonomy).

Exploring IoT concepts for real-time data exchange and machine learning algorithms to manage hazards unique to hills, such as sharp turns and steep gradients.

### What the project will not cover:

Deployment of real hardware, testing of actual vehicles, or integration with real sensors and vehicles (for example, no field trials or Raspberry Pi prototypes; all work is done in simulation to ensure safety and viability).

Unforeseen hazards (such as general traffic congestion or pedestrian-heavy environments) or non-mountainous terrains (such as urban, flat, or highway scenarios).

Advanced subjects that go beyond the main goals, like complete vehicle-to-infrastructure (V2I) integration, cybersecurity that is resistant to quantum errors, or human factors like long-term behavioral studies and driver psychology.

Live cloud service integrations (e.g., no real-time AWS or external servers; simulated V2C only). SAE Level 4-5 full automation (e.g., no driverless operations in all conditions).

### Possible application domains:

Intelligent Transportation Systems (ITS) with an emphasis on tourism, logistics, and emergency services for tough terrains like the Western Ghats, the Himalayas, or other highland areas of India.

Reduction of accidents and emissions in remote areas contributes to UN Sustainable Development Goals (SDGs) like SDG 9 (Industry, Innovation, and Infrastructure), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action) through extension to disaster management (e.g., landslide or debris alerts via V2P) and sustainable transport initiatives.

Research and academic resources for modeling V2V ecosystems, which could help develop safer road regulations in developing nations.

# Proposed Methodology / Approach

**Simulation and Data Generation**: With sensors like LiDAR (point clouds), radar (range data), GPS/IMU (position/heading), and RGB cameras (images), we can use the CARLA simulator to generate synthetic multimodal datasets for mountain scenarios (such as obstacles like boulders/trees, falling debris, dead ends, GPS disruptions, and low visibility). According to the V2V problem statement, scenarios will incorporate

environmental elements such as abrupt turns, weather fluctuations, complicated terrain, obstacles or incidents, lighting, and communication difficulties.

**Sensor Fusion and Perception**: Using deep learning models (e.g., Convolutional Neural Networks (CNNs) for object detection from images or Multi-Layer Perceptrons for risk classification) and multimodal sensor fusion techniques (e.g., Kalman filters for integrating GPS/IMU data with LiDAR/radar) to process and fuse data, motivated by the machine learning algorithms section of the collision avoidance paper for hilly risk prediction.

**AI-Based Prediction and Decision-Making**: For collision prediction and emergency scenario detection, use supervised machine learning algorithms (e.g., Random Forest or Neural Networks) that have been trained on simulated data to manage hazards like abrupt turns, steep gradients, or driver fatigue. Using the AI-based perception system in the problem statement and the automation levels in the review paper, cooperative decision-making will mimic SAE Level 2-3 automation (partial control with warnings, such as LED alerts in sim).

**Secure Communication Protocols**: Using Python-based simulation (e.g., socket programming with AES encryption for integrity and authentication), create unique low-latency protocols for V2V (vehicle-to-vehicle data sharing, e.g., broadcasting obstacle alerts), V2C (cloud-based warnings), and V2P (person/passenger notifications). These protocols should be robust to low-bandwidth or degraded network conditions typical of mountainous terrains, with a focus on DSRC/WAVE-like standards.

**Evaluation**: Assess performance using metrics such as communication latency (less than 100 ms), collision avoidance rate, detection accuracy (e.g., >90% as targeted in the collision paper), and resilience (e.g., under simulated sensor/network degradation or GPS disruptions). Utilize visualization graphs, akin to the accuracy/loss plots in the collision paper.

## Potential Extensions/Experiments (ML-Heavy and Communication-Centric Upgrades):

If the baseline pipeline performs effectively, the project can be extended in two directions. On the **perception side**, advanced deep learning methods such as transformer-based multimodal fusion, real-time object detection (e.g., YOLO), and clustering techniques can be explored to improve obstacle recognition and identify accident-prone regions under varying weather and terrain conditions. On the **communication side**, more resilient protocols can be modeled, including secure offline V2V schemes, C-V2X with 5G for low-latency communication, and enhanced cryptographic or trust-based mechanisms to ensure data integrity

in limited-bandwidth mountain regions. Together, these extensions provide opportunities to test the adaptability, robustness, and scalability of the framework in more realistic and challenging scenarios.

### Tools, frameworks, and technologies:

**Simulation**: CARLA (open-source autonomous driving simulator) for generating datasets and testing scenarios, with potential integration of digital twin concepts for multi-vehicle interactions.

**Programming**: Python 3.x for scripting, data processing, and simulation integration.

**Machine Learning**: TensorFlow or PyTorch for building and training fusion/prediction models; libraries like OpenCV for image processing, NumPy/SciPy for data handling, scikit-learn for basic ML algorithms, and NetworkX/Torch for graph-based cooperative modeling if extended.

**Visualization/Evaluation**: Matplotlib/Seaborn for graphs (e.g., accuracy/loss, latency plots), Jupyter Notebooks for prototyping and experimentation. No additional installs needed beyond standard libs (assuming college lab access to VTU Consortium resources).

Proposed Architecture/Workflow Diagrams

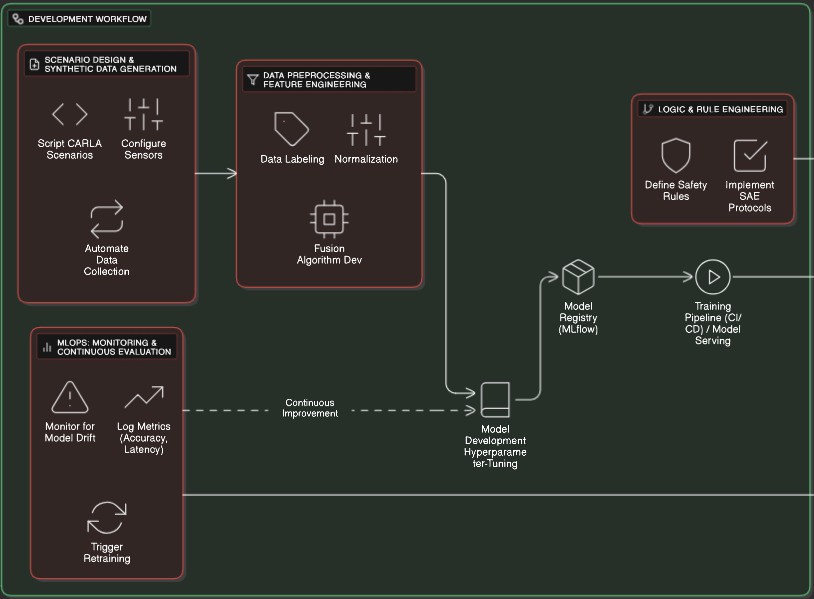


Fig 1 - Development Workflow

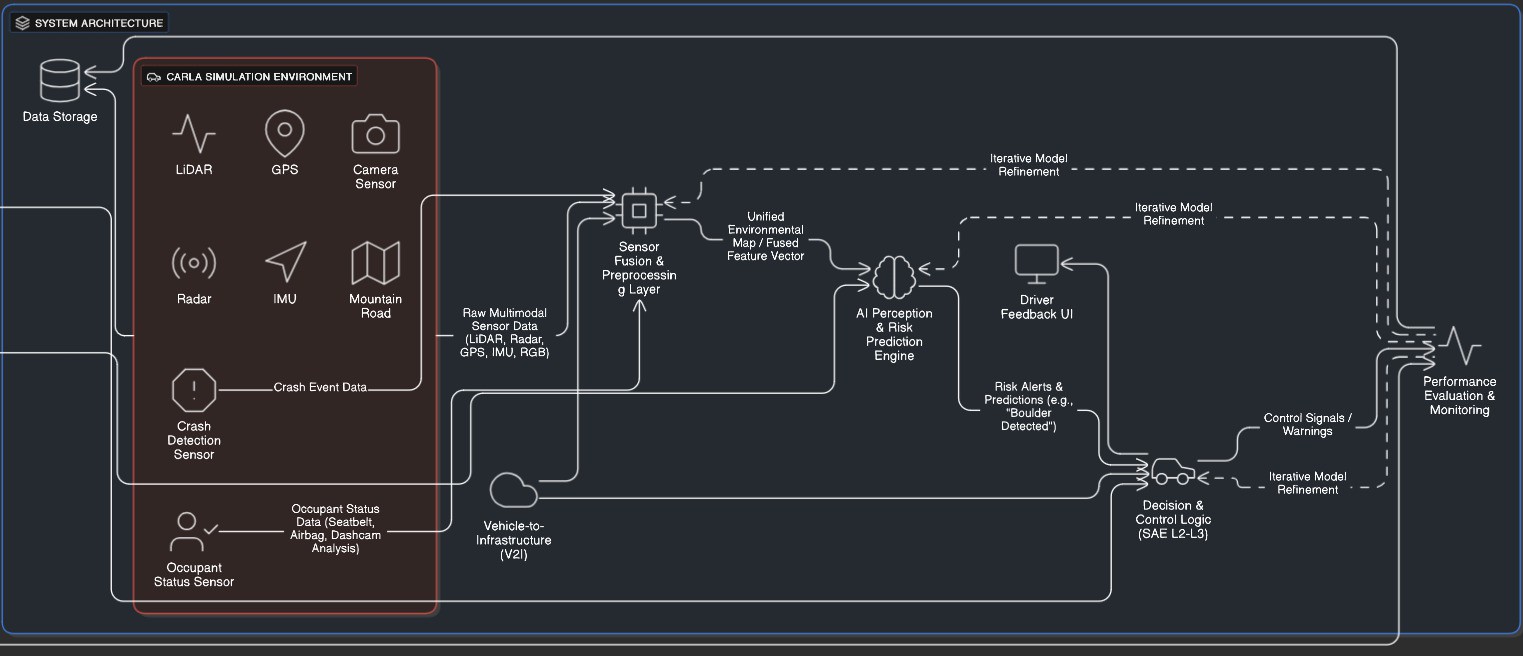


Fig 2 - System Architecture

# Expected Outcomes / Deliverables

### Functional Prototype / Software / Hardware system:

Using the CARLA simulator, a working simulation-based prototype showcasing a mountainous collision avoidance system was created. The prototype will consist of:

A synthetic multimodal dataset that replicates situations such as boulders, falling obstacles, dead ends, sharp curves, and GPS disruptions (e.g., LiDAR point clouds, radar ranges, GPS coordinates, IMU data, and RGB camera images).

For obstacle detection and collision prediction, an AI-driven perception module that combines sensor fusion (e.g., Kalman filters with CNNs) and machine learning models (e.g., Random Forest or Neural Networks) to generate risk alerts.

A decision-making module that mimics automation at SAE Levels 2-3 (e.g., slowdown actions in the CARLA environment or virtual warnings).

A software package that contains Python scripts that encapsulate the pipeline (for example, using TensorFlow, OpenCV, and socket libraries) and is documented for use in academic settings and future research.

### Performance metrics (e.g., accuracy, efficiency, cost-effectiveness):

**Detection Accuracy**: Using the ML evaluation metrics from the collision avoidance paper as a benchmark, reach >90% accuracy in obstacle detection and collision prediction.

**Latency**: In accordance with the low-latency objectives of the V2V problem statement, make sure that

real-time processing for risk detection and decision-making within the simulation has an average latency of less than 100 ms.

**Collision Avoidance Rate**: Collision Avoidance Rate: Aim for a >85% success rate in avoiding simulated collisions in all test scenarios, as confirmed by CARLA iterative testing.

**Resilience**: As motivated by the problem statement's resilience focus, exhibit resilience with <10% performance degradation under imitated sensor degradation (such as noisy LiDAR) or environmental challenges (such as fog, poor lighting).

**Cost-Effectiveness**: It is feasible for academic projects with no hardware expenses due to its minimal resource usage (e.g., open-source tools like CARLA and Python libraries).

### Usability / societal benefit:

**Usability**: The prototype will be easy to use, allowing researchers and students to train models, change scenarios, and view results (such as accuracy graphs using Matplotlib) through a Jupyter Notebook interface. Tutorials for replication at Dayananda Sagar College or other VTU institutions will be included in the documentation.

**Societal Benefit**: Reduce accidents brought on by sudden obstacles or poor visibility by offering a scalable framework for testing autonomous vehicle technologies, which will improve road safety in mountainous areas (such as the Western Ghats and the Himalayas). encourages safer, more environmentally friendly modes of transportation in order to support UN SDGs such as SDG 9 (Industry, Innovation, and Infrastructure) and SDG 11 (Sustainable Cities and Communities). Potential use in emergency services and tourism logistics, which could lower mortality rates (the review paper estimates that 40,000 people die in Europe each year).

# Significance / Applications

### Academic contribution:

The project advances research in Intelligent Transportation Systems (ITS) by developing a simulation-based framework tailored for mountainous terrain, addressing a gap in current literature where most V2V and collision avoidance studies focus on urban or flat environments (as noted in the V2V review paper).

Introduces a novel application of multimodal sensor fusion (LiDAR, radar, GPS, IMU, cameras) and machine learning (e.g., CNNs, Random Forest) for predicting hilly-specific risks like sharp curves, falling obstacles, and dead-ends, building on the collision avoidance paper's ML focus.

Provides a reusable CARLA-based dataset and codebase for academic institutions like Dayananda Sagar College, enabling further exploration of autonomous vehicle safety in challenging terrains, potentially contributing to VTU's research ecosystem.

Offers a benchmark for evaluating SAE Level 2-3 automation in simulated environments, aligning with the review paper's automation levels and supporting future studies on higher autonomy levels.

### Industrial/commercial relevance:

Offers a scalable prototype for automotive companies (e.g., Tata Motors, Mahindra) to test collision avoidance algorithms in mountainous regions like the Himalayas or Western Ghats, where traditional systems falter due to poor visibility and communication (as per the V2V problem statement).

Provides a cost-effective pre-deployment tool for validating AI perception systems, reducing the need for expensive real-world trials, which could appeal to startups or R&D divisions in India's growing autonomous vehicle sector.

Supports logistics and tourism industries by enhancing safety for vehicles navigating elevated terrains, potentially integrating with fleet management systems for real-time risk assessment (future extension with communication).

Aligns with global trends in smart transportation, offering a foundation for collaboration with international firms testing V2V technologies, as highlighted in the review paper's discussion of connected vehicle advancements.

### Societal/environmental benefits (can link to SDGs if relevant):

Improves road safety in remote mountainous areas by reducing accidents caused by sudden obstacles or poor conditions (e.g., the review paper cites 40,000 annual deaths in Europe, a trend applicable to India’s hilly regions), directly supporting SDG 3 (Good Health and Well-being).

Promotes sustainable transport solutions by enabling efficient navigation and accident prevention, contributing to SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action) through lower emissions from reduced collisions.

Enhances emergency response capabilities (e.g., landslide alerts via future V2P extensions) in disaster-prone areas, aiding rural communities and aligning with SDG 9 (Industry, Innovation, and Infrastructure).

Encourages eco-friendly tourism and logistics in elevated regions by minimizing environmental damage from accidents, fostering sustainable development in ecologically sensitive zones.

# Literature Survey (Brief)

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| --- | --- | --- | --- | --- | --- |
| **Sl#** | **Paper Title** | **Author Details** | **Year** | **Methodology** | **Limitations**  **Mentioned** |
| [1] | Cooperative Merging via Online Speed Replanning: A  Model-Free Approach With V2V Communication Packet Drop Compensation | Zejiang Wang, Anye Zhou, Adrian Cook, et al. | 2025 | Model-Free ULMPC for speed planning, V2V packet drop compensation,  Real-time  co-simulation (SUMO + high-fidelity dynamics  + real V2V logs) | Assumes synchronized V2V communication. Real-world validation focused on merging, not general mountainous navigation. |

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| [2] | A Real-Time  Terrain-Adaptive Local Trajectory Planner for High-Speed Autonomous Off-Road Navigation on Deformable Terrains | Siyuan Yu,  Congkai Shen, James Dallas, et al. | 2025 | Nonlinear MPC with  combined hard/soft constraints, UKF for terrain parameter estimation, Neural Network terramechanics model, Experimental validation | Formulation and  testing are for off-road deformable terrain; direct application to mountainous paved roads may need adjustment. |
| [3] | Terrain adaptive trajectory planning and tracking on deformable terrains | J. Dallas, M. P. Cole, P. Jayakumar, T. Ersal | 2021 | MPC with LGR collocation, Neural Network terramechanics model, UKF for terrain estimation | Low update rate (2 Hz). Poor scalability in cluttered environments. Limited to simulation validation. |
| [4] | Combined speed and steering control in high-speed autonomous ground vehicles for obstacle avoidance using model predictive control | J. Liu, P.  Jayakumar, J. L. Stein, T. Ersal | 2017 | Nonlinear MPC for simultaneous obstacle avoidance and path tracking in unstructured environments | Does not account for terrain deformability. Focused on rigid terrain models. |
| [5] | Integrated vehicle-following control for  four-wheel-independe nt-drive electric vehicles against  non-ideal V2X communication | J. Liu, Z. Wang,  L. Zhang | 2022 | Integrated control design compensating for V2X communication issues like packet drops and delays | Focus is on vehicle-following  platoons on flat roads, not on cooperative obstacle avoidance in complex terrain. |
| [6] | A study on model fidelity for model predictive  control-based obstacle avoidance in  high-speed | J. Liu, P.  Jayakumar, J. L. Stein, T. Ersal | 2016 | Compares vehicle models (3DoF, 10DoF) for use in MPC for obstacle avoidance, evaluating the  trade-off between | The study is performed in a simulation. Does not incorporate communication or cooperative elements. |

autonomous ground vehicles

fidelity and computational load

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| [7] | Online terrain  estimation for autonomous vehicles on deformable terrains | J. Dallas et al. | 2020 | Unscented Kalman  Filter (UKF) for  real-time estimation of key terrain parameters (e.g., sinkage exponent) | The estimation  framework is presented and validated in simulation; real-world experimental validation is not provided. |
| [8] | Autonomous Driving Merging Method Based on Deep Reinforcement Learning | H. Wang et al. | 2023 | Deep Reinforcement Learning (DRL) for autonomous merging decisions and control | High computational cost; requires extensive training data. Performance in real-time mountainous terrains has not been validated. |
| [9] | Strategies for Coordinated Merging of Vehicles at Ramps in New Hybrid Traffic Environments | Multiple authors from Changsha University of Science & Technology | 2025 | Classified cooperative merging strategy for mixed CAV/HDV traffic, SUMO-based simulation | Focused on highway ramps, not specifically on mountainous terrain. Limited  real-world validation. |
| [10] | Cybersecurity Risks Assessment of Coordinated Ramp Merging in Mixed Traffic Environments | X. Zhao et al. | 2024 | Assessment framework for cybersecurity vulnerabilities in  V2V-based coordinated  merging systems | Focused on security risks, not on core navigation or terrain adaptation algorithms. |

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| --- | --- | --- | --- | --- | --- |
| Sl# | Paper Title | Author Details | Year | Methodology | Limitations  Mentioned |

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| [1] | {CARLA}: {An}  Open Urban Driving Simulator | Alexey Dosovitskiy, German Ros, Felipe Codevilla, et al. | 2017 | Open-source simulator for autonomous driving research, supports flexible sensor suites, environmental conditions, traffic scenarios, and ROS integration | Primarily focused on urban environments; limited native support for extreme mountainous terrain or deformable soils. |
| [2] | Optimal control-based eco-ramp merging system for connected and automated vehicles | Z. Zhao, G. Wu, Z. Wang,  M. J. Barth | 2020 | Optimal control framework for  eco-friendly cooperative merging of CAVs | Does not address packet drops in V2V communication or challenging terrain conditions. |
| [3] | A tutorial survey on vehicle-to-vehicle communications | S. Zeadally, J. Guerrero, J. Contreras | 2020 | Comprehensive review of V2V communication technologies, protocols, applications, and challenges | Survey paper; does not propose new algorithms or validation methods. |
| [4] | Robust H∞ path following control for autonomous ground vehicles with delay and data dropout | R. Wang, H.  Jing, C. Hu, F. Yan, N. Chen | 2016 | Robust control strategy for path tracking that accounts for communication delays and data dropout | Focused on path tracking, not specifically on cooperative merging or complex terrain navigation. |
| [5] | A novel decision-making  strategy for CAV merging at highway on-ramps | Kherroubi et al. | 2023 | Decision-making strategy for CAV merging that considers vehicle interactions and traffic flow states | Evaluated in simulation; limited consideration of communication uncertainties or off-road terrain. |
| [6] | A cooperative control strategy for merging connected vehicles | L. Xu et al. | 2022 | Cooperative strategy optimizing relative positions and speeds between vehicles for improved merging efficiency | Assumes ideal communication and does not address challenging terrain or packet loss. |

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| [7] | A platoon-based cooperative optimal control method for CAV merging under heavy traffic conditions | Y. Xue et al. | 2023 | Optimal control for CAV platoon merging in heavy traffic, improving efficiency and safety | Focused on highway on-ramps with heavy traffic, not specifically on mountainous or deformable terrain. |
| [8] | An adaptive, personalized speed guidance system for merging at highway service area on-ramps | H. Li et al. | 2022 | Personalized speed guidance system for merging, incorporating safety assessments | Focused on service area ramps; limited applicability to general mountainous terrain navigation. |
| [9] | Impact of speed trajectory optimization on energy consumption during highway merging processes | L. Yang et al. | 2023 | Analysis of how speed trajectory optimization affects energy consumption during merging | Focused on energy consumption, not on overall safety or communication reliability in challenging terrains. |
| [10] | Social interactions of merging behaviors in congested traffic at highway on-ramps | H. Wang et al. | 2023 | Study of social interaction behaviors during merging in congested traffic | Focused on human driver behavior, not solely on CAVs or autonomous systems. |
| [11] | A cooperative merging strategy based on an optimal final state phase diagram for mixed traffic environments | J. Shi et al. | 2024 | Cooperative merging strategy using optimal final state phase diagrams for mixed traffic | It may not fully address the complexities of unstructured mountainous environments or severe communication dropouts. |
| [12] | A cooperative control strategy based on an improved variable time headway for merging of CAV platoons | M. Pang et al. | 2023 | Improved variable time headway strategy for cooperative merging of CAV platoons | Primarily designed for highway platoons, performance in mountainous terrain with obstacles has not been validated. |

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| [13] | A hierarchical model optimization control method for vehicle merging | N. Chen et al. | 2023 | Hierarchical model optimization control for improving traffic efficiency during merging | Complexity may hinder real-time implementation in resource-constrained edge devices. |
| [14] | An optimal maneuver planning and trajectory control method for vehicle merging | N. Chen et al. | 2022 | Optimal maneuver planning and trajectory control for vehicle merging | Requires significant computational resources; may not be suitable for real-time applications in dynamic environments. |
| [15] | An adaptive coordinated variable speed limit strategy based on deep reinforcement learning | Cheng et al. | 2023 | DRL-based adaptive variable speed limit strategy for coordinating speeds between highway mainlines and on-ramps | Focused on speed coordination, not on full trajectory planning or obstacle avoidance in mountainous areas. |

# Work Plan / Timeline & Finances

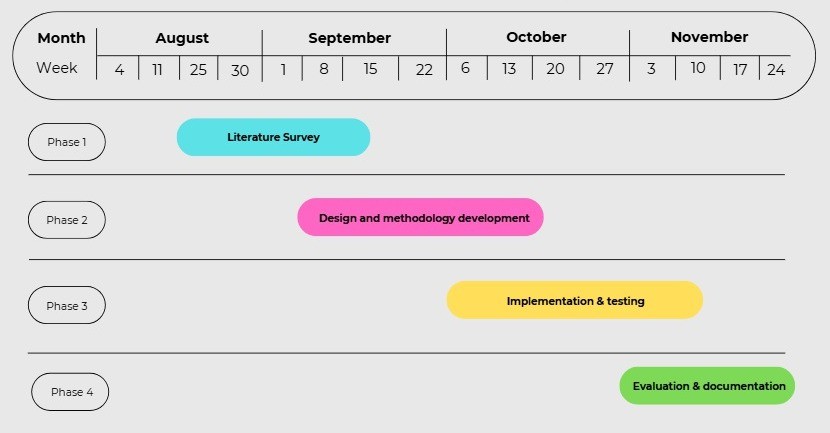
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Fig 3 - Phases Timeline

## Phases Timeline (2025)

Phase 1 → Aug 25 – Sept 7

Phase 2 → Sept 8 – Sept 28

Phase 3 → Sept 29 – Nov 9

Phase 4 → Nov 10 – Nov 30

**Estimated Expenditure – Include Project expenditures like H/w, S/w, cloud expenditures, Printing/stationary expenditures & Miscellaneous**

|  |  |  |
| --- | --- | --- |
| **SL.**  **No** | **Description** | **Amount** |
| **1** | **Printing/stationery** | **RS.3000/~** |
| **2** | **Miscellaneous** | **RS.1000/~** |
| **Total** | | **RS.4000/~** |

# Resources Required

### Hardware:

High-performance computing system with GPU support (e.g., NVIDIA CUDA-enabled GPU) for training and testing AI models.

Simulation workstation capable of running CARLA with real-time rendering.

Standard sensors (for experimental setup, if extended): LiDAR, radar, GPS module, IMU, and RGB cameras.

Networking equipment (Wi-Fi modules, router, or DSRC-enabled devices for communication protocol testing).

### Software:

CARLA Simulator (v0.9.16 or above) for dataset generation and scenario simulation.

Python libraries: TensorFlow/PyTorch for AI model development, OpenCV for image processing, Scikit-learn for analytics.

ROS (Robot Operating System) is or socket-based messaging framework for communication protocol design.

MATLAB/Simulink for control algorithm prototyping (optional).

Network simulation tools (e.g., NS-3 or OMNeT++) for evaluating V2V communication performance.

### Dataset:

**Synthetic dataset** generated via CARLA simulator (mountain terrain scenarios such as boulder falls, landslides, and roadblocks).

Integration of **open-source multimodal datasets** like nuScenes and DeepSense-V2V for benchmarking and comparison.

Custom labeled data for obstacle detection and hazard classification.

1. **References (mention in IEEE format all the papers referred to in the literature survey section tables)**

|  |  |  |
| --- | --- | --- |
| **Sl.**  **No.** | **Title** | **DOI** |
| [1] | A Real-Time Terrain-Adaptive Local Trajectory Planner for High-Speed Autonomous Off-Road Navigation on Deformable Terrains | [10.1109/TITS.2024.3520520](https://doi.org/10.1109/TITS.2024.3520520) |
| [2] | Terrain adaptive trajectory planning and tracking on deformable terrains | [10.1177/09544070251320679](https://doi.org/10.1177/09544070251320679) |
| [3] | Combined speed and steering control in high-speed autonomous ground vehicles for obstacle avoidance using model predictive control | [10.1109/TVT.2017.2707076](https://doi.org/10.1109/TVT.2017.2707076) |

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| --- | --- | --- |
| [4] | Integrated vehicle-following control for  four-wheel-independent-drive electric vehicles against non-ideal V2X communication | [10.1109/tvt.2022.3141732](https://doi.org/10.1109/tvt.2022.3141732) |
| [5] | A study on model fidelity for model predictive control-based obstacle avoidance in high-speed autonomous ground vehicles | [10.1080/00423114.2016.1223863](https://doi.org/10.1080/00423114.2016.1223863) |
| [6] | Online terrain estimation for autonomous vehicles on deformable terrains | [10.1016/j.jterra.2020.03.001](https://doi.org/10.1016/j.jterra.2020.03.001) |
| [7] | CARLA: An Open Urban Driving Simulator | [10.48550/arXiv.1711.03938](https://doi.org/10.48550/arXiv.1711.03938) |
| [8] | Optimal control-based eco-ramp merging system for connected and automated vehicles | [10.1109/IV47402.2020.9304709](https://doi.org/10.1109/IV47402.2020.9304709) |
| [9] | Temperature Fluctuations of Different Vertical Scales in Raw and Processed U.S. High Vertical-Resolution Radiosonde Data | [10.1175/JTECH-D-24-0012.1](https://doi.org/10.1175/JTECH-D-24-0012.1) |