Journal of Multi Disciplinary Engineering Technologies
ISSN(P) 0974-1771 ISSN(O) 2581-9372
Volume 19, Issue 02 DOI: https://doi.org/10.64992/jmdet.vol.19.issue.2.8

State of the Art and Future Directions of Deep Learning Driven Collision Avoidance Mechanisms in Vehicular Ad Hoc Networks

Jolly Parikh[1], Kirti Sharma[1*], Parikshat Singh[1]

[1]Department of Computer Science and Engineering, Bharati Vidyapeeth's College of Engineering, New Delhi, 110063, India.

*Corresponding author(s). E-mail(s): kirti.sharma@bharatividyapeeth.edu ;
Contributing authors: jolly.parikh@bharatividyapeeth.edu;
parikshatsingh18@gmail.com;

Abstract

Evolution of Intelligent Transportation Systems (ITS) has led to the transformation of modern vehicular safety strategies, particularly due to incorporation of Artificial Intelligence (AI) in collision avoidance technologies. These AI-enabled systems are designed in order to minimize the risk of accidents. To achieve this, real-time data is exchanged through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication frameworks. This study explores the Technological Components of Autonomous Vehicular Systems. Core components of Intelligent Transportation Systems (ITS), Methodology to be adopted in AI-based collision avoidance Systems and Use case of AI-based collision avoidance System thereby emphasizing the role of connected vehicle communication in enhancing awareness and minimizing response delays. It also discusses the contribution of various AI methodologies, as in predictive modeling and reinforcement learning, which help systems learn from previous events and dynamically adjust to new traffic conditions. Few challenges identified are sensor inaccuracies, latency in data transmission, cybersecurity risks, and privacy concerns which must be addressed for ITS systems to achieve broader adoption. The future scope proposed in this area is incorporating emerging technologies such as 5G connectivity, for enabling ultra-fast communication speeds; edge computing, which facilitates for local and immediate data processing; and federated learning, which enables AI model training across distributed devices without the need for centralized data storage.

Keywords: Artificial Intelligence (AI), Autonomous Vehicles, Reinforcement Learning, Edge Computing

Received 19 May 2026; Revised 26 May 2026; Accepted 13 July 2026; Available online 20 July 2026

1 Introduction

In the modern era, road safety has become a paramount concern, especially with the increasing number of vehicles on the road. Traditional vehicle safety features, such as airbags, seat belts, and anti-lock braking systems, have improved vehicle safety, yet they only function once an incident has occurred. As traffic environments become more complex, these traditional systems are not sufficient to ensure safety under all scenarios. New approaches are therefore necessary that address these limitations, that can identify and predict a collision before it actually happens. This is where the AI-based collision avoidance systems in the context of connected vehicular networks come into the picture. An AI-driven collision avoidance system uses complex algorithms to combine local sensors with information from a decentralized vehicle-to-infrastructure network [1], thereby getting a better understanding of the entire environment in which the vehicle is located and then proactively predict the conflicts to take appropriate action without human interaction. Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) is the integral part in developing the AI-based collision avoidance system. V2V allows the vehicles to share their respective real time parameters such as position, velocity, trajectory, road conditions with other neighboring vehicles thus being able to share alerts for the hazards and congestion. The Vehicle to Infrastructure system connects each and every vehicle with roadside infrastructure elements such as traffic lights, traffic signals, and sensors; the bidirectional communication between infrastructure and vehicles allows the vehicles not only to get the immediate danger but also future risk assessment by taking into account dynamic parameters such as the traffic conditions, signals, environment etc. AI-based collision avoidance systems rely on machine learning (ML). In vehicular safety applications, machine learning algorithms are trained using historical traffic data and real-time sensor information. They identify patterns, predict potential hazards, and make autonomous decisions. For example, if the car in front suddenly brakes, the system analyzes the data from the car's sensors to assess the chance of a crash. It then responds by adjusting the vehicle's speed or activating emergency brakes to prevent an accident. The more driving situations these systems encounter, the more precise they become over time. They learn to handle a variety of traffic patterns and road conditions. Deep learning systems, especially convolutional neural networks (CNNs), offer essential perceptual skills for avoiding collisions. These models process different types of sensor inputs—cameras, radar, LiDAR—to detect and categorize objects, even in poor conditions like fog, rain, or darkness. Connecting with vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication enhances local perception [2]. It also improves situational awareness. This allows the system to anticipate hazards beyond the sensor range and refine predictions about collision risks through continuous environmental modeling. The main advantage of an AI-powered collision avoidance system is its near-instant reaction time. It operates on a millisecond scale, which human cognitive processing cannot match. While a human driver needs critical split seconds to see a hazard and hit the brake, an autonomous system has already processed information from multiple sources and executed a defensive maneuver. This delay can be the difference between a near-miss and a fatal crash in high-speed or emergency situations. Besides speed, these systems overcome human sensory limits by tracking surrounding vehicles and predicting overall traffic patterns at the same time. This ability depends on a multi-layered setup of local sensors, edge computing units, and communication modules. Onboard tools, including LiDAR, radar, and computer vision cameras, continuously map the vehicle's surroundings to monitor pedestrians, road shapes, and obstacles. Deep learning algorithms then process this real-time data to control autonomous braking, steering adjustments, or speed changes. However, widespread use depends on solving key engineering challenges. Issues like sensor performance in bad weather, data transmission delays, cybersecurity risks, and data privacy concerns must be addressed before these systems can be fully trusted on public roads. AI-based collision avoidance systems face critical deployment barriers. Sensor reliability suffers under adverse weather—rain, fog, and snow degrade radar and LiDAR accuracy. V2V/V2I communication introduces additional risk through network latency and data loss, potentially delaying critical warnings. Integration challenges add to these technical issues. The existing vehicles are mostly not equipped with sensors and V2X hardware for cooperative systems, and the road infrastructure is not uniformly equipped for V2I communication. This technological gap between legacy and modern systems constrains large-scale effectiveness until improved uptake and investment in infrastructure take place. Despite these challenges, AI-based collision avoidance systems are a promising way to improve road safety. As these systems develop, with advances in AI, sensor technology and communication networks, their capabilities will only continue to improve, leading to safer and more efficient transportation systems. In this paper, we discuss the role of AI in collision avoidance and describe the technological breakthroughs, communication architectures, real world applications and future prospects of connected vehicle networks. The core novelty of this work lies in highlighting the architectural synergy of Edge Computing, Vehicle-to-Everything (V2X) communication, and Federated Deep Reinforcement Learning (FDRL) to form a highly scalable, real-time collision avoidance framework. Unlike traditional centralized systems that suffer from prohibitive latency and data privacy constraints, this work shows importance of decentralizing the computational load by deploying optimized AI algorithms directly to the network edge. It shows how by leveraging cooperative Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication streams, the system can expand the vehicle's situational awareness far beyond localized sensor horizons. It emphasizes on the integration of an FDRL paradigm which allows multiple edge nodes to collaboratively train and refine the decision-making policy without sharing raw, sensitive vehicular data. This unique combination ensures deterministic, millisecond-level execution while fundamentally improving model generalization and communication efficiency in dynamic, real-world traffic environments. The rest of the paper has been divided into sections where section 2 discusses the technological components of autonomous vehicular systems, section 3 discusses the core components of an ITS system. The Methodology to be adopted in AI-based collision avoidance Systems is discussed in section 4. The use case of AI-based collision avoidance System has been discussed in section 5,6,7. The section 8 concludes the study.

2 Technological Components of Autonomous Vehicular Systems

Technological components contributing to the success of autonomous vehicular systems can be enumerated as, Algorithms, edge computing framework, Federated Deep Reinforcement Learning.

2.1 Autonomous Vehicles' Collision Avoidance Algorithms

The authors of article [3] present techniques used in autonomous vehicles to prevent collisions. The collision avoidance algorithms, as shown in figure 1, used in ITS fall into three

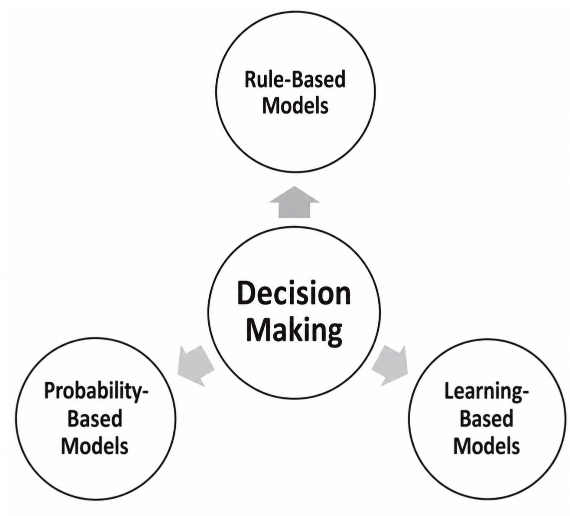

Fig. 1: Decision-making algorithms

main categories: reactive, predictive, and hybrid approaches. Reactive algorithms, such as rule-based logic and potential field methods, give fast response but are less efficient in complex situations. Predictive algorithms, which utilize path planning and motion prediction (e.g., using Kalman filters or RNNs), demonstrate higher accuracy but are computationally expensive. Hybrid approaches combine both to balance real-time responsiveness and environmental awareness. Figure 2 depicts the framework of collision avoidance algorithm. Amalgmation of AI with sensor networks lead to improvement in environmental perception and decision-making under uncertainty [4].

2.2 Edge-Assisted ML-Aided Uncertainty-Aware Vehicle Collision Avoidance at Urban Intersections

The work of [5, 6], proposes an edge-computing-enabled framework for collision avoidance, specifically designed for urban intersections, where traffic complexity is high. Figure 3 presents the scenario in urban areas. By combining real-time sensor data and V2I communication with AI that actually accounts for unexpected variables, the model can accurately spot crashes before they happen. Even better, it cuts down on lag by crunching all that data right at the edge—meaning on the vehicle itself—instead of waiting for a slow reply from a distant cloud server. Figure 4 presents the delay components involved in collision avoidance system. These architectures can estimate the riskiness of potential vehicle trajectories more precisely by determining how confident they are in their predictions. This decentralized system can predict hazards and react more quickly and accurately than centralized architectures, and consequently achieve more robust collision avoidance in dense and dynamic environments.

2.3 Vehicles Control: Collision Avoidance Using Federated Deep Reinforcement Learning

The authors of article [7, 8] proposed a Federated Deep Reinforcement Learning (FDRL) approach to control multiple vehicles collaboratively while preserving data privacy. Unlike conventional centralized models that require uploading raw driving data to a central server,

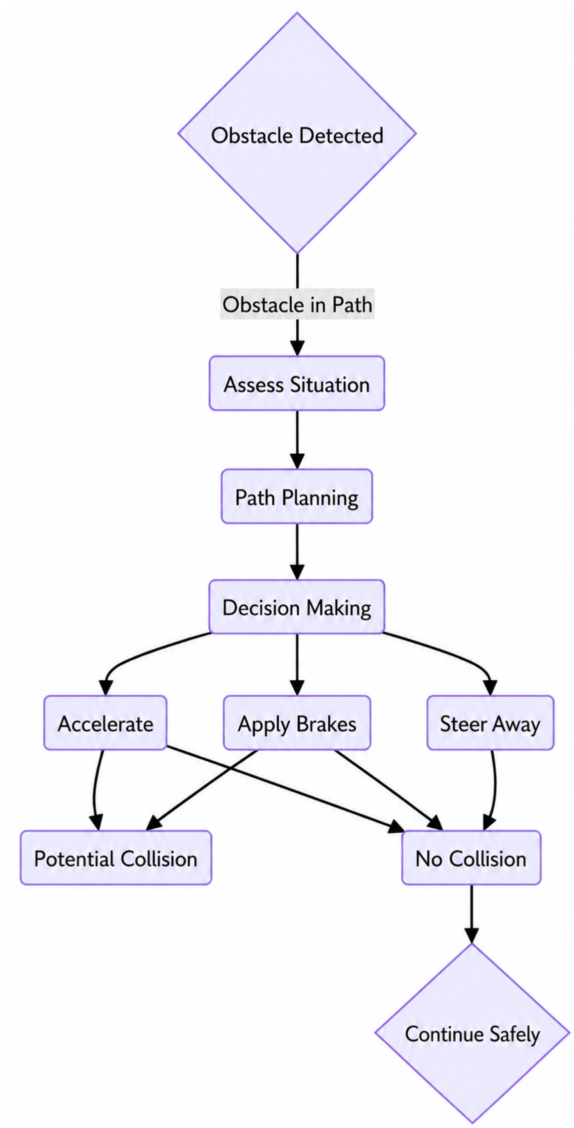

Fig. 2: Framework of collision avoidance algorithm

FDRL trains local models on each vehicle and shares only the learning parameters. This ensures that sensitive vehicle data remain local and at the same time also take advantage from shared learning across fleets. The reinforcement learning agent is trained to make decisions of accelerating or braking which would avoid potential collisions, even in high-speed and multi-agent scenarios [9]. The federated learning setup not only enhances privacy but also facilitates faster convergence and more reliable decision-making. Figure 5 presents the FDRL approach to control multiple vehicles.

2.4 V-CAS: A Real-Time Vehicle Anti-Collision System Using Vision Transformer on Multi-Camera Streams

The V-CAS framework as shown in figure 6, utilizes Vision Transformer (ViT)-based models for real-time anti-collision systems, combining data from multiple cameras for enhanced

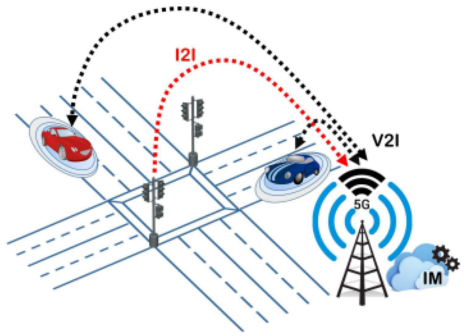

Fig. 3: An edge computing-based scenario, including an IM collecting data generated by the vehicles and the road infrastructure and transmitting alarms in case of imminent collisions

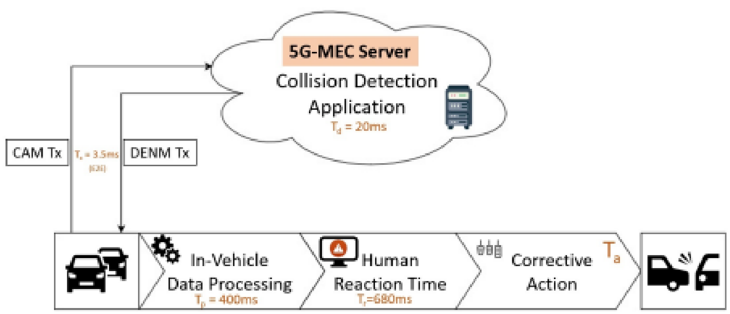

Fig. 4: The latency components in collision avoidance

environmental perception [10]. Unlike traditional convolutional models, Vision Transformers enable better spatial understanding of the environment, especially in scenarios involving multiple dynamic agents. A novel architecture was proposed that fuses data from front, rear, and side cameras and feeds it into a transformer-based neural network that predicts collision risks. The real-time performance is made possible through hardware-optimized implementations and a multi-threaded image pipeline. When evaluated on urban datasets, V-CAS achieved a higher precision-recall balance compared to state-of-the-art CNN-based systems. Advanced deep learning architectures, when paired with multi-sensor inputs, can significantly improve collision risk detection in complex scenarios as shown in figures 7 and 8.

3 Core components of Intelligent Transportation Systems (ITS)

3.1 Vehicle-to-Vehicle (V2V)

Vehicle-to-vehicle communication technology - commonly described as V2V - is a smart technology that enables vehicle data to exchange from one vehicle to another. Communication for V2V technology is based on dedicated short-range communications (DSRC). This isn't exactly new technology, it's been around for decades, but V2V systems will have the

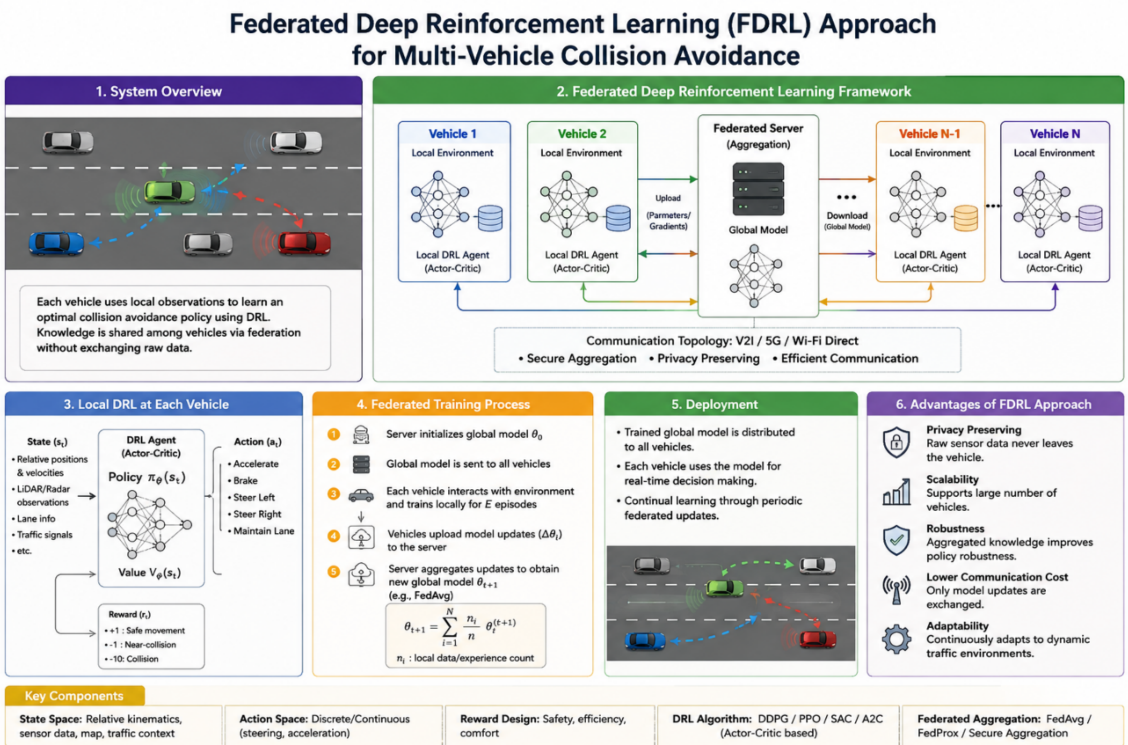

Fig. 5: Federated Deep Reinforcement Learning (FDRL) approach to control multiple vehicles

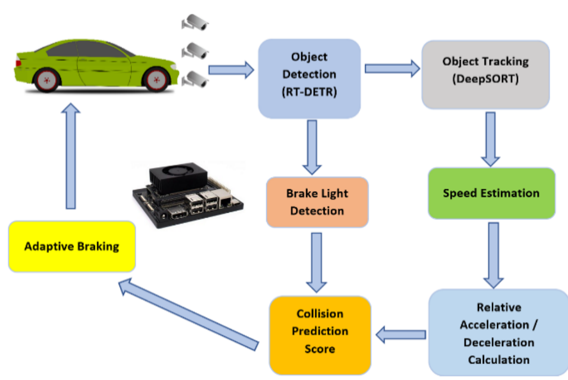

Fig. 6: Basic Architecture of VCAS

greatest impact on vehicle safety applications once it is widely available, such as advancing crash avoidance. V2V communication allows vehicles to gather information about the speed and location of nearby V2V-enabled cars using a wireless communication protocol similar to Wi-Fi. This information helps alert drivers to possible dangers, which can lead to fewer accidents and less traffic congestion. V2V can detect risky traffic and road conditions, terrain problems, and weather threats from up to 300 meters away. V2V can make driving a safer and more predictable experience for everyone on the road. In 2015, the University of Michigan launched M-City, the first controlled environment for testing connected

Fig. 7: Day and Night Collision Prediction using VCAS on Car Crash Dataset

Fig. 8: Multi-Camera Object Detection using V-CAS OD Model in Day and Night

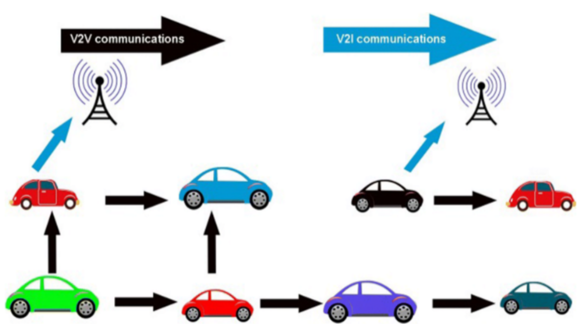

Fig. 9: Vehicle-to-Vehicle (V2V)

and automated driving technologies. M-City provides a chance for car manufacturers and tech companies to explore connected car technology, including V2V and self-driving features. Verizon invested in M-City as part of a group of 15 leadership companies focused on promoting innovation in the automotive sector. In 2016, the U.S. DOT released a Notice of Proposed Rulemaking (NPRM) to require V2V systems in all new cars. The National Highway Traffic Safety Administration (NHTSA) also aims to support the life-saving potential of V2V communication. V2V network is shown in figure 9.

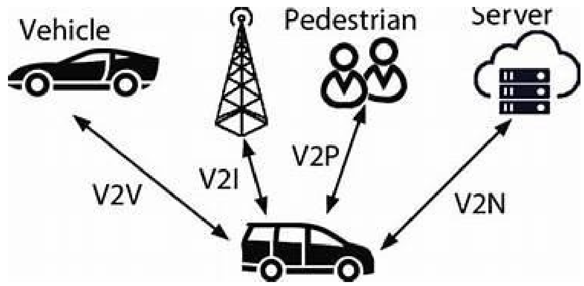

Fig. 10: Vehicle-to-Infrastructure (V2I)

3.2 Vehicle-to-Infrastructure (V2I)

V2I stands for vehicle to infrastructure. Figure 10 shows the layout of V2I network. This network uses the environment and information related to the surrounding road to gather information about conditions such as the volume of traffic, weather alerts, bridge clearance level, traffic light signals. This information is wirelessly broadcasted to the driver so that the driver is notified of the conditions which require their attention which will contribute towards improving the drivers safety. Smart traffic lights enabled with V2I technology will allow drivers to view and understand the conditions on the road, so that arrival time estimates are reliable, thereby improving driver and customer communication. The V2I is a key component of the Intelligent Transport Systems (ITS) initiative in the US, which provides the support framework and framework for adoption of technologies in the US Department of Transportation (DOT). V2I technology has a great potential in future for better driver- assistance features such as smart parking, autonomous vehicles, and in better city planning for city lanes and parking spaces.

4 Methodology to be adopted in AI-based collision avoidance Systems

4.1 Overview of the Approach

An AI-based collision avoidance methodology synthesizes real-time data processing, vehicle-to-everything (V2X) communications—specifically vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I)—and AI-driven decision-making to mitigate collision risks within connected vehicular networks. The underlying model would presume a network of intelligent vehicles equipped with a heterogeneous sensor suite (including LiDAR, radar, GPS, and cameras) interconnected to enable cooperative data and insight sharing.

4.2 System Architecture

The architecture comprises of four major layers: (a) Perception Layer which captures real-time data from various onboard sensors (LiDAR, radar, cameras) as well as external sources through V2V and V2I communication. The data includes vehicle speed, position, lane information, surrounding objects, weather conditions, and road curvature. (b) Communication Layer which utilizes Dedicated Short-Range Communication (DSRC) and 5G-enabled Cellular-V2X (C-V2X) to transmit and receive data between vehicles (V2V) and roadside infrastructure (V2I). This enables the system to ensure low latency (¡50 ms) to support real-time decision-making. (c) Processing Layer which processes incoming data streams using edge computing nodes deployed either in vehicles or nearby infrastructure. This layer reduces the latency by not relying on distant cloud servers, (d) Decision-Making Layer where, AI algorithms analyze the data from the sensors and the communication network to predict the probability of a collision and generate control signals for braking, lane change and acceleration.

4.3 AI Models and Techniques Used in AI-based collision avoidance Systems

The AI-based collision avoidance system comprises of a combination of: (a) Convolutional Neural Networks (CNNs) for image processing from camera feeds (to detect nearby vehicles and lane boundaries), (b) Recurrent Neural Networks (RNNs) with LSTM cells for sequence prediction (to model the trajectories of surrounding vehicles), (c) Reinforcement Learning (RL) agents which are trained to perform optimal maneuvers in different traffic scenarios, such as emergency braking, obstacle avoidance, and safe overtaking, (d) Sensor Fusion Algorithms as in Kalman Filter, Bayesian Fusion etc. which combine data from radar, LiDAR, and GPS to enable precise object localization.

4.4 Simulation Environment to be used in AI-based collision avoidance Systems

To validate the conceptual model, simulations can be carried out using the following platforms: (a) CARLA Simulator: An open-source simulator for autonomous driving research. It allows modeling urban environments, dynamic traffic, and pedestrian movement, (b) SUMO (Simulation of Urban Mobility): This is used to model the traffic flow and generate synthetic V2V/V2I communication data, (c) TensorFlow and PyTorch: These can be used for training and evaluating deep learning models, (d) Edge simulation tools (such as AWS Greengrass or custom virtual machines) These can mimic edge computing setups.

4.5 Evaluation Metrics

The performance of the ITS can be evaluated based on few key metrics: (a) Collision Prediction Accuracy, which gives percentage of true positive predictions (i.e., correctly predicted collisions), (b) False Positive Rate (FPR) which signifies the instances where the system falsely predicted a collision, (c) Latency determining the time delay between threat detection and control signal execution, (d) Intervention Success Rate that informs about how often the system successfully prevents a potential collision, (e) Communication Overhead which informs about the usage of bandwidth during the communication and the delay experience during exchange of messages in the V2V/V2I networks.

5 Use case of AI-based collision avoidance System

5.1 System Overview

The system improves vehicle safety by combining real-time sensor data with information shared between vehicles (V2V) and road infrastructure (V2I). Using AI-driven prediction models, it identifies potential collisions and responds appropriately—alerting the driver in semi-autonomous vehicles or taking direct action like emergency braking or steering correction in fully autonomous ones. The architecture consists of integrated modules that

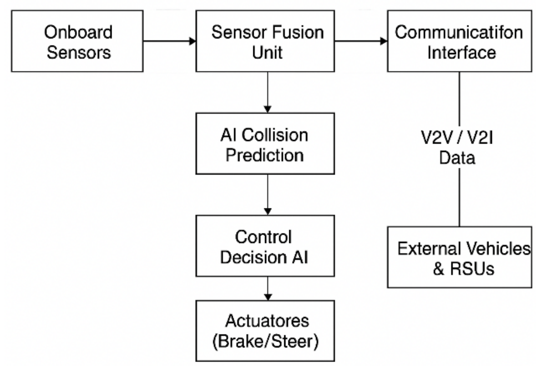

Fig. 11: System Flow Diagram

work together to detect hazards and prevent accidents. Figure 11 gives the system flow diagram.

5.1.1 Data Collection Module

This module takes the data from various sensors and communication channels within the vehicular environment at real time. Visual data from cameras can be used for lane detection, object classification, radar and lidar sensors provide data related to distance, velocity and contour of an object. Location and motion of the vehicle are provided by GPS and IMU sensors. V2V communication data packet carrying information about nearest vehicle such as speed, braking action and direction and V2I communication data packet which consist information about traffic light, warnings to pedestrians and environmental information is also processed. The raw data collected are stored at one point and it will be transferred to the preprocessing stage for more processing.

5.1.2 Sensor Fusion and Preprocessing Unit

Collecting data from all sensors is important for creating a coherent, accurate model of the vehicle's surroundings. The proposed system uses a Bayesian Sensor Fusion model that recieves data from LiDAR, radar, and GPS to eliminate inconsistencies caused by sensor noise or environmental effects. Visual data from cameras is pre-processed using CNN-based filters for extracting the features and detecting the objects. Outputs from this unit include Lane positioning, Distance and speed of surrounding vehicles, Pedestrian presence, Traffic signal status, Drivable space mapping.

5.1.3 AI-Powered Collision Prediction Engine

The collision prediction engine is a key component of the system and consists of (a) Recurrent Neural Networks (RNNs) with LSTM for trajectory prediction of close moving objects, (b) Graph Neural Networks (GNNs) to model the relations between multiple traffic participants [11], (c) Risk Evaluation Module that assigns collision likelihood scores based on the predicted trajectories and proximity .

5.1.4 Decision-Making and Control Module

Activating immediately after the AI engine, this module translates raw predictive metrics into decisive vehicular maneuvers. At its core is a Rule-Based Reinforcement Learning

(RRL) agent, trained in high-fidelity simulated environments to evaluate and navigate distinct risk profiles. Depending on the critical nature of the threat, the agent selects from a deterministic matrix of actions: immediate braking, micro-steering corrections, autonomous lane changes, or immediate driver alerts. To maintain real-time operational safety, the entire pipeline—from threat prediction to physical execution—concludes within a strict 100 ms window.

5.1.5 V2V/V2I Communication Interface

The communication interface is capable of transmitting the status and intentions of the vehicle to nearby vehicles (V2V), collecting information from roadside units (RSUs), traffic signals and cloud servers (V2I), and providing secure and low latency communication using 5G NR-V2X and DSRC protocols. This component allows vehicles to share their current state and predicted maneuvers, which enables collaborative collision avoidance and improves coordination in complex traffic situations.

5.2 Key Innovations and Advantages

The proposed framework advances vehicular safety through four key innovations. First, real-time edge computation processes sensor data locally on the vehicle, eliminating cloud dependency and achieving the ultra-low latency critical for time-sensitive collision avoidance. Second, trajectory-based AI prediction shifts the paradigm from reactive to proactive safety, enabling the system to anticipate and mitigate hazards before they materialize. Third, V2V communication enables collaborative risk assessment across the traffic network, leveraging collective intelligence to enhance situational awareness in complex scenarios. Finally, the architecture incorporates privacy-preserving federated learning, allowing fleet-wide model improvement through collaborative training without transmitting sensitive raw data, ensuring both performance enhancement and user privacy protection.

6 Mathematical approach

6.1 Time to Collision (TTC)

The collision risk can be predicted using the *Time-to-Collision (TTC)* parameter, which is expressed as

$$\mathrm{TTC} = \frac{d}{|v_r|} \tag{1}$$

where:

- d is the distance between the vehicle and the obstacle,
- v_r is the relative velocity, defined as the difference between the vehicle's speed and the obstacle's speed.

If the computed TTC is less than a predefined threshold (e.g., 2 s), the system generates a collision warning or automatically initiates braking to prevent a potential collision.

6.2 Safe Distance Formula (Minimum Following Distance)

The minimum safe distance between two vehicles can be estimated using the following equation:

$$d_{\text{safe}} = vt_r + \frac{v^2}{2a} \tag{2}$$

where:

- d_{safe} is the minimum safe distance between two vehicles,
- v is the vehicle speed,
- t_r is the reaction time (typically 1.5 s for AI-based systems),
- a is the deceleration rate (e.g., 9.8 m/s^2 for emergency braking).

The calculated safe distance is used to determine whether the current distance to the vehicle ahead is sufficient to avoid a collision. If the actual distance is less than d_{safe}, the collision avoidance system initiates an appropriate response, such as issuing a warning or applying the brakes automatically.

6.3 Collision Probability Estimation

The probability of collision can be estimated using the following equation:

$$P_{\text{collision}} = 1 - e^{-\lambda \cdot \text{TTC}} \tag{3}$$

where:

- $P_{\text{collision}}$ is the probability of collision,
- λ is the risk coefficient, which is learned through AI training or determined based on traffic density,
- TTC is the Time-to-Collision, as defined in Equation 1.

This equation transforms the Time-to-Collision (TTC) value into a collision probability that enables the AI-based collision avoidance system to make informed decisions, such as issuing warnings or initiating automatic braking.

6.4 Fused Object Position (Kalman Filter for Sensor Fusion)

$$\hat{x}_k = \hat{x}_{k-1} + K_k \left(z_k - H\hat{x}_{k-1} \right) \tag{4}$$

Where:

- $\hat{x}_k$ = Estimated position at time k,
- z_k = Measurement (e.g., from LiDAR),
- H = Observation model,
- K_k = Kalman gain.

This is used in sensor fusion, where GPS, radar, and camera data are combined to get accurate positions of nearby objects.

6.5 Neural Network Activation (AI Model's Output Layer)

$$y = \sigma(Wx + b) \tag{5}$$

where:

- x = Input vector (sensor data, trajectory info),
- W = Weights,
- b = Bias,
- σ = Activation function (like sigmoid),
- y = Output (collision risk score, recommended action)

7 Simulation and Results

7.1 Simulation Setup

A simulation framework built upon CARLA and SUMO under a deep learning environment was implemented and utilized to assess the AI collision avoidance mechanism [12]. CARLA was utilized to generate realistic urban scenarios with several autonomous vehicles interacting within heavy traffic at different weather and light settings. Machine virtual instances were emulating the edge computing to allow the simulation of the decision making time delay. Every single model was deployed on the machine virtual instances with input consisting of live streams from the simulated cars sensors, whereas they were trained and evaluated by PyTorch and TensorFlow (CNN, RNN-LSTM, RL agents).

7.2 Experimental Scenarios

The scenarios designed to test system robustness and response can be enlisted as, (a) Scenario 1: Sudden vehicle braking ahead in urban traffic, (b) Scenario 2: Obstacle detection in low-visibility weather (fog and rain), (c) Scenario 3: Intersection with cross-traffic and V2I signal delay, (d) Scenario 4: Highway lane merging with collaborative V2V prediction. Each scenario tested key system features: prediction accuracy, communication latency, and autonomous response effectiveness. Table 3 depicts the results obtained in each scenarios.

7.3 Analysis of Results

The edge-based architecture demonstrated strong real-time performance, yielding a high prediction accuracy and maintaining latency below the 50 ms constraint. The model used uncertainty-aware AI to process real-time sensor data and V2I communications, enabling highly accurate collision prediction. This resilience was heavily supported by V2X-enabled connectivity, which supplied early warnings that significantly enhanced vehicular maneuver timing. Bandwidth usage across the V2V and V2I channels remained well within established limits, proving that the underlying communication network can scale effectively in practical, real-world environments.

8 Conclusion

The rapid development of connected and autonomous vehicle technologies has ushered in a new era of road safety, with Artificial Intelligence (AI) playing a central role in mitigating collision risks. This research presented a comprehensive survey discussing how advanced AI algorithms, robust sensor fusion techniques, and low-latency communication protocols enable real-time hazard detection and proactive vehicle control. It explains a modular approach, consisting of data collection from onboard and external sources, intelligent processing through edge computing, and decision-making powered by machine learning models such as RNNs and reinforcement learning agents. Furthermore, it shows how the integration of V2V and V2I data significantly enhances the system's awareness of the broader traffic environment, making the solution scalable and applicable to dense urban traffic as well as highway scenarios. In conclusion, AI-powered collision avoidance systems would offer a transformative solution to improving road safety in connected vehicular networks. As technology continues to advance, future work will focus on real-world deployment, federated learning for cross-vehicle model updates, and further reduction in latency to enhance the reliability and robustness of such systems.

Declarations

- The authors received no specific funding for this study.
- The authors declare that they have no conflicts of interest to report regarding the present study.
- No Human subject or animals are involved in the research.
- All authors have mutually consented to participate.
- All the authors have consented the Journal to publish this paper.
- Authors declare that all the data being used in the design and production cum layout of the manuscript is declared in the manuscript.

References

[1] Zhang, Y., Lin, Y., Wu, D.: Ai-driven collision prediction in connected vehicle environments using deep learning. IEEE Transactions on Intelligent Transportation Systems **24**(1), 89–100 (2023) https://doi.org/10.1109/TITS.2023.3240123

[2] Ahmed, M., Kumar, S., Bhattacharya, P.: A review of v2v and v2i communication systems for intelligent transportation networks. Journal of Transportation Technologies **14**(2), 125–137 (2024) https://doi.org/10.4236/jtts.2024.142008

[3] Liu, S., Cong, S., Yang, L.: Survey of research on autonomous driving testing with large models. Communications in Transportation Research **5**, 100179 (2025) https://doi.org/10.1016/j.commtr.2025.100179

[4] Li, F., Zhao, W.: Real-time sensor fusion for autonomous vehicle navigation: A bayesian framework. Sensors **23**(4), 1122 (2023) https://doi.org/10.3390/s23041122

[5] Selvaraj, D.C., Vitale, C., Panayiotou, T., Kolios, P., Chiasserini, C.F., Ellinas, G.: Edge-assisted ml-aided uncertainty-aware vehicle collision avoidance at urban intersections. IEEE Transactions on Intelligent Vehicles **11**(5), 573–589 (2026) https://doi.org/10.1109/TIV.2023.3296190

[6] Chen, L., Han, Q.: Edge intelligence for real-time collision avoidance in autonomous driving. Future Internet **17**(1), 1–18 (2025) https://doi.org/10.3390/fi17010002

[7] Elallid, B., Abouaomar, A., Benamar, N., Kobbane, A.: Vehicles control: Collision avoidance using federated deep reinforcement learning. In: 2023 IEEE Global Communications Conference (GLOBECOM), pp. 4369–4374 (2023). Corpus ID: 260681158

[8] Wang, X., Liu, T.: Deep reinforcement learning for collision-free path planning in urban scenarios. Neural Computing and Applications **35**, 4567–4580 (2023) https://doi.org/10.1007/s00521-022-07536-2

[9] Singh, A., Chopra, N.: Vehicle safety and ai: An analysis of decision-making algorithms in high-speed scenarios. Autonomous Systems Journal **8**(2), 74–85 (2024) https://doi.org/10.1016/asj.2024.05.004

[10] El-Sayed, H., Rana, M.: Design and implementation of v2x-enabled autonomous driving frameworks. IEEE Access **11**, 104332–104345 (2023) https://doi.org/10.1109/ACCESS.2023.3287845

[11] Mahajan, K., Srivastava, R.: Ai-based cooperative driving systems using graph neural networks. International Journal of Vehicular Technology **2024**, 1–11 (2024) https://doi.org/10.1155/2024/5378943

[12] Azfar, T., Huang, K., Tracy, A., Misiewicz, S., Liu, C., Ke, R.: Traffic co-simulation framework empowered by infrastructure camera sensing and reinforcement learning. Journal of Intelligent Transportation Systems, 1–19 (2025) https://doi.org/10.1080/15472450.2025.2559410