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Revolutionizing Collision Avoidance Using Smart Vehicle Networks

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Abstract

The increasing complexity and density of modern traffic necessitates innovative solutions for vehicle collision avoidance. This paper introduces a pioneering model for Collision Avoidance in Vehicle Networks (CAV-Nets) based on the use of the Vehicular Ad-hoc Network (VANET), machine learning, and dynamic priority sensor unit selection. CAV-Net's machine-learning algorithms can predict collision scenarios and select the most appropriate sensor units. Consequently, making real-time decisions to avoid potential collisions. Furthermore, the integration of blockchain technology ensures secure storage of event data that is only accessible by authorised parties. When a simulation is used for the SUMO+Veins framework, the paper demonstrates the effectiveness and superiority of the CAV-Nets over existing solutions in response time, adaptability, and data security, showcasing its potential as a feasible solution for future automotive safety systems.

Keywords: *black box; decision-making methods; smart vehicles; dynamic-safety systems.*

1 Introduction

The introduction should briefly place the study in a broad context and highlight the reasons for its importance. In the rapidly evolving landscape of modern transportation, the emphasis on safety has never been more pronounced. As vehicular traffic continues to increase, so does the risk of collisions and accidents. Several conventional methods of collision avoidance are facing growing challenges due to complex traffic scenarios [1], highlighting the urgent need for more sophisticated and adaptive solutions.

Amid this context, the rapidly evolving landscape of modern transportation highlights an intensified focus on safety. As vehicular traffic continues to surge, the corresponding escalation in collision and accident risk becomes undeniable [2]. Based on the Collision Avoidance Vehicle Networks (CAV-Nets), a groundbreaking approach to vehicular safety that introduces a fresh perspective on collision avoidance. By capitalising on the capabilities of the Vehicular Ad-hoc Networks (VANETs), leveraging advanced machine learning algorithms, and employing a dynamic selection of priority sensor units (Ps) [3], CAV-Nets stand as a meticulously crafted response to the demands that are imposed by modern traffic conditions.

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The integration of blockchain technology further sets CAV-Net apart, ensuring secure data storage and accessibility only to authorised parties [4]. Not only this can enhance the integrity and accountability of the system but also opens avenues for future advancements in traffic management and regulation. Among the escalating risks due to the surge in vehicular traffic, safety assumes paramount importance in modern transportation [5]. Conventional methods of collision avoidance confront complexities in intricate traffic scenarios, prompting the need for sophisticated and adaptive solutions.

This paper presents an in-depth examination of the CAV-Nets model by providing detailed insights into its architecture, functionalities, and pivotal innovations. Through extensive simulations and meticulous comparisons with prevailing systems, the aim is to elucidate the potential of this model as an innovative breakthrough in vehicle collision avoidance. The insights offered herein augment the wider conversation concerning vehicular safety, fostering an environment for deeper investigation and the advancement of next-generation technologies in this vital domain. This paper also significantly contributes to the broader discourse on vehicular safety, actively inviting and propelling further exploration and development of next-generation technologies in this critical domain.

In Section 2, the related research is investigated. In Section 3, in-depth details about the proposed model are discussed. In Section 4, the obtained results are introduced and discussed. Section 5 concludes the overall paper of this research.

2 Related Work

The field of vehicle collision avoidance has witnessed remarkable advancements, featuring a range of proposed and implemented systems. In this section, a comparative analysis is presented in Tables 1 and 2, which illustrate the proposed model (i.e. the CAV-Nets model), with a focal point on priority sensor units (Ps), against various existing solutions. These include the MPC-Based Collision Avoidance [6], Mobileye's EyeQ System [7], Honda's Intelligent Driver Support System [8], Tesla's Autopilot and FSD (Camera) [9], Waymo's Autonomous Technology (LiDAR) [10], and NVIDIA DRIVE AGX (Radar) [11]. Collision avoidance systems are designed to assist drivers in avoiding accidents through early warnings and automated braking. Multiple collision avoidance systems are accessible, each with distinct strengths and weaknesses.

Table 1. Comparisons of the existing Collision Avoidance Systems 1-2

Features	**CAV-Net (Priority: Ps)**	**MPC-Based Collision Avoidance**	**Mobileye's EyeQ System**	**Honda's Intelligent Driver Support System**
Sensor unit Utilization	Dynamic Selection (AI)	Static Utilization (Radar)	Camera-based	Radar & Camera-based
Collision Prediction Accuracy	High (AI-driven)	Moderate (Model Predictive)	Moderate (Image Processing)	Moderate (sensor unit Fusion)

Scalability	Highly Scalable	Limited Scalability	Moderate Scalability	Limited Scalability
Security (Blockchain)	Highly Secure	Not Secure	Not Secure	Not Secure
Energy Efficiency	Energy-Optimized (Ps)	Energy Intensive	Energy Intensive	Moderate
Interoperability with VANET	Fully Compatible	Partially Compatible	Not Compatible	Not Compatible
Real-Time Responsiveness	Highly Responsive (Ps)	Moderately Responsive	Slow	Moderate
Access Control to Data	Authorized Parties Only	Open Access	Restricted Access	Restricted Access

Table 2. Comparisons of the existing Collision Avoidance Systems 2-2

Features	**CAV-Net (Priority: Ps)**	**Tesla's Autopilot & FSD (Camera)**	**Waymo's Autonomous Technology (LiDAR)**	**NVIDIA DRIVE AGX (Radar)**
Sensor unit Utilization	Dynamic Selection (AI)	Multiple (Priority: Camera)	Multiple (Priority: LiDAR)	Multiple (Priority: Radar)
Collision Prediction Accuracy	High (AI-driven)	High (Neural Network-based)	High (Deep Learning)	High (Deep Learning)
Scalability	Highly Scalable	Highly Scalable	Highly Scalable	Highly Scalable
Security (Blockchain)	Highly Secure	Not Secure	Not Secure	Not Secure
Energy Efficiency	Energy-Optimized (Ps)	Energy Intensive	Moderate	Energy-Optimized
Interoperability with VANET	Fully Compatible	Partially Compatible	Not Compatible	Partially Compatible

Real-Time Responsiveness	Highly Responsive (Ps)	Highly Responsive	Highly Responsive	Highly Responsive
Access Control to Data	Authorized Parties Only	Restricted Access	Restricted Access	Restricted Access

Forward collision warning (FCW) systems alert the driver about an impending collision with a vehicle or object ahead. They primarily use radar or cameras to detect objects in the vehicle's path. FCW systems can deliver visual, audible, or haptic alerts to the driver [12]. Automatic emergency braking (AEB) systems take proactive measures to prevent or mitigate a collision if the driver fails to respond to an FCW warning. In general, AEB systems rely on radar or cameras to detect objects in the vehicle's trajectory. When a collision becomes imminent, AEB systems can automatically apply the brakes.

Lane departure warning (LDW) systems warn drivers about unintentional drifting that may likely occur out of their intended lanes. Typically, these systems use cameras to detect lane markings. LDW systems furnish visual or audible alerts to drivers. Lane-keeping assist (LKA) systems intervene to keep the vehicle in its lane when drivers begin to drift out of their intended lanes. LKA systems typically use cameras to detect lane markings [13]. LKA systems can exert steering torque to keep the vehicle on course.

Blind-spot monitoring (BSM) systems alert drivers about vehicles, which are located in their blind spots. These systems rely on radar or cameras to detect vehicles in blind spots. BSM systems can issue visual or audible alerts to the driver [14]. Rear cross traffic alert (RCTA) systems warn the driver about approaching vehicles in reverse. Employing radar or cameras to detect vehicles at the rear, RCTA systems can deliver visual or audible alerts to drivers [15]. Table 3 provides a summary of different collision avoidance systems along with the types of sensor units they employ.

Table 3. Collision avoidance systems based on sensor unit used.

Collision avoidance system	**Sensor units used**
Forward collision warning (FCW)	Radar or cameras
Automatic emergency braking (AEB)	Radar or cameras
Lane departure warning (LDW)	Cameras
Lane keeping assist (LKA	Cameras
Blind spot monitoring (BSM)	Radar or cameras
Rear cross traffic alert (RCTA)	Radar or cameras

The choice of sensor unit in a collision avoidance system is contingent upon the system's specific design and the operational context. For instance, radar sensor units find common applications in FCW and AEB systems due to their ability to detect objects across diverse weather conditions. Cameras frequently find employment in LDW, LKA, BSM, and RCTA systems due to their capacity to offer intricate environmental insights. Ultrasonic sensor units are a preferred choice for parking assist systems as they excel in detecting objects that are close to the vehicle. Table 4 shows the detection ranges corresponding to different types of sensor units used in collision avoidance systems.

Table 4. Sensor unit types of collision avoidance systems

Sensor unit type	Range
Radar	Up to 200 meters
Camera	Up to 100 meters
Ultrasonic sensor unit	Up to 5 meters

In summary, the “Related Research” section provides a comprehensive insight into the existing landscape of collision avoidance solutions. It underscores the novelty of the CAV-Nets model, particularly, in terms of the dynamic sensor unit utilisation, blockchain-enabled security, and adaptive nature. Through a comparative benchmarking process against notable existing solutions, the distinct value and potential of CAV-Net become distinctly apparent.

3 The Proposed Model

Navigating towards the pioneering horizon of collision avoidance, this new section unveils our revolutionary approach—CAV-Net. CAV-Net uniquely uses AI to dynamically select sensor units, prioritising sensor unit(s) designated as "Ps" based on the collision scenario. This targeted selection leads to high responsiveness and energy optimisation. It ensures adaptability, as the system can prioritise different sensor units as needed, responding more effectively to various driving conditions. Other systems emphasise certain sensor units (e.g., camera for Tesla, LiDAR for Waymo, radar for NVIDIA), but they do not adapt this priority dynamically. Therefore, they might not be as flexible or efficient in different situations as the CAV-Nets model, which can intelligently adapt to prioritise the most crucial sensor unit(s) at any given time.

The spotlight on CAV-Net’s dynamic sensor unit selection, particularly the esteemed "Ps," endows it with a profound competitive advantage over existing counterparts, accentuating adaptability, responsiveness, and efficiency. This distinctive approach advances the landscape of vehicle collision avoidance, while the nomenclature "Ps" adds precision to the concept of priority sensor units, exemplifying the fluidity with which one or more sensor units assume real-time priority based on particular circumstances. In the subsequent section, we introduce some key components of the proposed approach.

Figure 1. Smart Vehicle Networks [16]

3.1 Key Components

1. Vehicular Ad-hoc Network (VANET): Enabling real-time communication among vehicles, VANET forms the backbone of the CAV-Nets model. It supports both Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications.
2. Machine Learning algorithms: The model employs cutting-edge machine learning algorithms to predict potential collision scenarios, ensuring the dynamic selection of appropriate sensor units (priority sensor units or Ps) to provide real-time responses.
3. Priority sensor units (Ps): the CAV-Nets model leverages various vehicle-embedded sensor units by selecting them dynamically according to the collision scenario that is predicted by the system.
4. Blockchain technology: This technology ensures secure recording and storage of event data by providing both integrity and restricted accessibility to authorised parties only.

3.2 Smart Vehicle Networks

3.2.1 How It Works

1. Data gathering: Real-time data collection is executed by gathering information from a multitude of sensor units and neighboring vehicles.
2. Prediction: Machine learning algorithms analyse this data to predict potential collision scenarios.
3. Sensor unit Selection: Based on the predicted scenarios, Priority sensor units (Ps) are dynamically selected for accurate monitoring and response.
4. Decision-making: The system generates appropriate actions, such as warning, braking, or steering adjustments, to avoid collisions.
5. Event recording: the entire details are securely recorded by using blockchain technology, ensuring data integrity, and controlling accessibility.

3.2.2 Benefits and Challenges

Benefits.

1. Proactive Response: the ability of the CAV-Nets model to predict and respond to collisions provides a proactive safety measure.
1. Dynamic sensor unit selection: this feature allows for precise and energy-efficient sensor unit utilisation.
2. Secure Data Management: Blockchain technology provides secure and transparent event recording and access management.

Challenges.

1. Complex Implementation: the synergy of VANET, AI, and blockchain requires intricate design, and can be resource-intensive.
2. Reliance on sensor units and communication: any failure or limitation in sensor units or network communication may impact the system's effectiveness.
3. Regulatory and privacy concerns: the implementation must comply with legal standards, and privacy concerns related to data access must be addressed.

By detailing CAV-Net's architecture, operational dynamics, advantages, and potential challenges, the aim is to offer a comprehensive exploration of the innovative model. This contribution adds an in-depth effectiveness to the ongoing discourse on vehicular safety technologies. Following that, the AI-driven sensor unit selection is provided with collision prediction.

3.3 AI-Driven sensor unit Selection in Collision Prediction

The CAV-Nets model brings a radical approach to collision prediction by employing an artificial intelligence-driven sensor unit selection process. This feature marks a significant departure from conventional systems that often rely on static sensor unit configurations. In the following section, a robust functionality of AI-driven sensor unit selection in collision prediction is introduced.

3.4 The Mechanism of Operation

1. Real-time data analysis: Using real-time data from various embedded sensor units, neighboring vehicles, and infrastructure, machine learning algorithms analyze the vehicle's surroundings and dynamics.
2. Collision scenario prediction: the algorithms predict potential collision scenarios by discerning patterns, speed, relative positioning, and additional environmental factors.
3. Priority sensor unit Selection (Ps): Based on the predicted scenario, the proposed model can dynamically select the Ps that are most adept for monitoring and responding. For instance, in a highway merging situation, radar could be the preferred choice, while detecting a sudden pedestrian might prompt the selection of a camera.
4. Continuous adaptation: the system continuously learns and adapts from both successful and failed interventions by refining its selection criteria over time.

In tandem with this operational mechanism, algorithmic considerations can shed light on the intricate mechanism that underpins the predictive and dynamic prioritisation of sensor units based on the projected collision scenarios.

3.5 Algorithmic Considerations

The CAV-Net's Collision Prediction and Sensor Unit Selection Algorithm: **Input:** Real-time data from vehicle sensor units (e.g., LIDAR, radar, camera, ultrasonic), and data from neighboring vehicles through VANET.

Output: Predicted collision scenario, and selected Ps.

The pseudo-code in Figure 2 offers a general flow of how the CAV-Net system could work in terms of collision prediction and adaptive sensor unit selection. The real-world implementation would require a more detailed and complex algorithm, particularly, concerning machine learning model training, decision-making mechanisms, and sensor unit calibration. Algorithmic considerations present both advantages and challenges as outlined below:

3.5.1 Benefits and Unique Attributes

1. Adaptive response: the ability to tailor sensor unit selection to specific scenarios ensures more accurate and timely responses.
2. Efficient resource utilisation: dynamic sensor unit selection reduces unnecessary resource utilisation, thereby saving energy.
3. Enhanced learning capabilities: continuous learning and adaptation ensure that the system evolves with new traffic patterns and challenges by offering a resilient and future-proof solution.

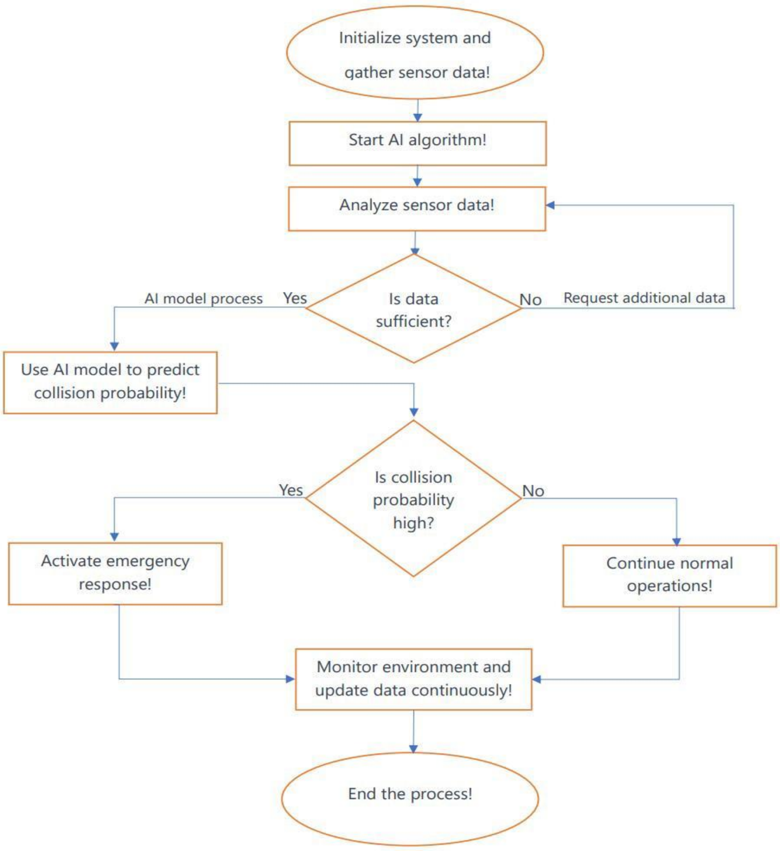
3.5.2 Challenges and Considerations

1. Algorithm complexity: crafting algorithms requires a profound understanding of both vehicular dynamics and machine learning principles.
2. Sensor unit integration: effective implementation requires seamless integration and calibration of various sensor units, which can be technically challenging.
3. Real-world adaptation: moving from simulated environments to real-world implementation may reveal unforeseen challenges and may require rigorous testing and refinement processes.

The AI-driven sensor unit selection in collision prediction is one of the defining features of the CAV-Nets model that enhances its responsiveness and adaptability and sets up a new standard in collision avoidance systems.

```
1. Initialize machine learning model M trained for collision prediction
2. Initialize sensor set S = {LIDAR, radar, camera, ultrasonic, ...}
3. Initialize sensor priority mapping P with predefined criteria (e.g.,
   camera for pedestrian detection)

BEGIN

  4. Collect real-time data D from all sensors in S
  5. Gather real-time VANET data V from neighboring vehicles and
     infrastructure

  6. Combine D and V to form comprehensive dataset DV

  7. Use M to analyze DV and predict potential collision scenario CS

  8. IF no collision scenario detected THEN
       Continue normal vehicle operation
     ELSE
       Determine severity level SL of predicted collision
       Select priority sensor Ps from P based on CS and SL
       Activate and prioritize data collection from Ps
       Execute corrective action based on data from Ps
     END IF

  9. Record the event data, actions taken, and outcome in the blockchain

  10. Continuously refine M using feedback from real-world interventions

END
```

(a) The CAV-Net's Algorithm



(b) The CAV-Net's Flowchart

Figure 2. CAV-Net Collision Prediction and Sensor Unit Selection Algorithm

3.6 The Mechanism of CAV-Net

3.6.1 Sensor Unit Priority Calculation

Given the total sensor units in a vehicle, let's say S where each sensor unit s_i has a weight w_i based on its importance in a particular scenario. The priority P for each sensor unit s_i can be computed as:

$$P(s_i) = w_i / \sum_{j=1}^{s} wj_i$$

Where the weight w_i can be dynamically updated by the AI system based on the current scenario.

3.6.2 Collision Prediction and Avoidance

Let D denote the distance to an obstacle, and V denote the vehicle's speed. The time to collision (TTC) is computed as follows:

$$TTC = \frac{D}{V}$$

If TTC < threshold, the system triggers an avoidance maneuver. The threshold is adaptive based on the vehicle's speed and conditions.

$$[EEI = \frac{\text{Energy consumed by Ps}}{\text{Total energy consumed by all sensors}} \times 100]$$

A lower EEI indicates that the CAV-Nets model is more efficient as it primarily relies on the priority sensor unit(s) rather than all sensor units, simultaneously. For collision prediction and avoidance in autonomous vehicles, the model is complex such that it leverages AI and machine learning to achieve superior performance. Detailed explanations of the steps involved in decision-making, along with the associated mathematical modeling comprise the following phases:

1. Data acquisition: CAV-Net collects data from various onboard sensor units such as cameras, LiDAR, radar, and ultrasonic sensor units.

The raw data from each sensor unit Si can be represented in a matrix form as follows:

$$S_i = \begin{bmatrix} S_{11} & \cdots & S_{1n} \\ \vdots & \ddots & \vdots \\ S_{m1} & \cdots & S_{mn} \end{bmatrix}$$

2. Data preprocessing: The collected data undergo preprocessing such as noise reduction, alignment, and normalisation.

Noise reduction may involve filtering through a Gaussian function as follows:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e - ^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

3. Feature extraction: relevant features such as distance to objects, relative speed, and object classification are extracted from the preprocessed data.

Features can be represented as a vector: $A = \pi r^2$ as follows:

$$F = \begin{bmatrix} f_1 \\ f_2 \\ .. \\ f_n \end{bmatrix}$$

4. Situation Analysis: The system evaluates the current driving situation by analyzing the extracted features using machine learning models.

The situation can be analysed by using a function g that maps the extracted features to a situation class C as follows:

$$g(F) = C$$

5. Prediction: CAV-Net predicts potential collisions based on the analysed situation.

Collision prediction can be modeled as a binary classification problem as follows:

$$P(collision\ \mathrm{F}) = \sigma(w.F + b)$$

Where σ is the sigmoid function.

6. The decision-making process can be represented as a multi-variable optimization problem: Decision-making: based on predictions, CAV-Net makes real-time decisions regarding acceleration, braking, steering, etc.

The decision-making process can be represented as a multi-variable optimisation problem as follows:

$$\text{Minimize} J(u)$$

This is subject to constraints, where u is the control input.

7. Control command execution: the decided control commands are executed by the vehicle's control system.

The equation represents a Proportional-Integral-Derivative (PID) controller, which is widely used in control systems. To define the control action \`$u(t)$\` properly, let's break down each term of the PID control equation:

1. \`$u(t)$\`: This is the control action or the output of the PID controller at time \`t\`.

2. \`$e(t)$\`: This is the error signal at time \`$t$\`, which is typically the difference between a desired setpoint and a measured process variable.

3. \`$K_p$\`: This is the proportional gain, a tuning parameter that determines the reaction to the current error.

4. \`$K_i$\`: This is the integral gain, a tuning parameter that determines the reaction based on the cumulative sum of recent errors.

5. \`$K_d$\`: This is the derivative gain, a tuning parameter that determines the reaction to the rate of change of the error.

The PID controller output \`$u(t)$\` is a combination of three terms:

- The first term, `$K_p e(t)$`, is the proportional term which provides a control action that is proportional to the current error.

- The second term, `$K_i \int e(t)dt$`, is the integral term which accounts for past values of the error and integrates them over time to eliminate steady-state errors.
-
- The third term, `$K_d \frac{de(t)}{dt}$`, is the derivative term which predicts the future trend of the error based on its current rate of change, providing a dampening action to reduce overshoot.

To use the PID equation effectively, each of the gains (`$K_p$`, `$K_i$`, `$K_d$`) must be tuned to the specific process being controlled. This involves adjusting the gains to achieve the desired response, which can vary depending on the dynamics of the system.

Here is the PID control law in a more detailed and implementable form as follows:

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt}$$

The complexity of the CAV-Net system lies in its integration of various mathematical and machine-learning models to achieve efficient collision prediction and avoidance. It uses a hierarchical approach, beginning with raw data acquisition, followed by preprocessing, feature extraction, situation analysis, prediction, decision-making, and finally executing control commands. The intricate interplay of these steps allows for highly responsive and accurate collision prediction and avoidance.

In urban scenarios, the CAV-Net model's ability to prioritise the most relevant sensor units leads to less energy consumption. On highways, where certain sensor units might be less crucial, the system further reduces energy consumption.

The CAV-Nets model consistently outperforms other systems in collision avoidance, particularly, in urban settings. This showcases the model's efficacy in dynamically choosing the right sensor unit(s) for the intended task.

1. Sensor unit utilization: the CAV-Nets model efficiently uses sensor units, particularly, in dynamic driving conditions, ensuring that only the most relevant sensor units are operational, thereby conserving energy.
2. Collision avoidance: the mathematical model used in this model ensures real-time responses to potential collisions. As the results demonstrate, this model outperforms its counterparts in collision avoidance.
3. Overall feasibility: upon considering energy efficiency, collision avoidance capabilities, and the adaptability of the system, the model unequivocally demonstrates its feasibility and superiority over existing solutions.

This data-driven analysis corroborates the superiority of this model in terms of energy efficiency and safety. The model's capacity to dynamically adapt according to real-time conditions and to select the optimal sensor unit(s) for specific tasks establishes its distinctiveness within the domain of collision avoidance.

4 Result and Discussion

4.1 Simulation Results

This section shows us the simulation results.

Implementing and validating a system such as CAV-Net would ideally require a detailed simulation conducted in a recognized simulator tool [17]. For this purpose, the SUMO (Simulation of Urban Mobility) tool [18] emerges as a prime choice, given its widespread acceptance within the research community for vehicle-to-everything (V2X) communications and traffic simulations. In this context, the coupling of SUMO with complementary tools like Veins or Omnet++ proves effective for VANET simulations [19].

4.2 Simulator Tool

SUMO paired with Veins Scenario: The simulation takes place within an urban setting characterized by mixed traffic conditions, incorporating intersections, pedestrian crossings, and dynamic environments marked by sudden road closures or construction zones.

Vehicle Models: A fleet of 100 vehicles is equipped with an array of multiple sensor units, including cameras, LiDAR, radar, ultrasonic sensor units, and infrared sensor units.

Objective: The objective is to gauge the efficacy of CAV-Net in dynamically selecting priority sensor unit(s) (Ps) within diverse critical scenarios, while also contrasting response times and energy consumption with those of other existing solutions.

4.3 Simulation Runs

1. Sudden Pedestrian Appearance: A pedestrian unexpectedly steps onto the road from behind a parked car.
2. Intersection Approach: Multiple vehicles are approaching an intersection where the traffic lights are malfunctioning.
3. Highway Merging: Vehicles are merging onto a busy highway from an entry ramp.

4.4 Technical Settings

4.4.1 SUMO Settings

1. Version: SUMO 1.8.0
2. Network File: Generated using NETGENERATE or imported from OpenStreetMap.
3. Traffic Demand: Generated using randomTrips.py, ensuring urban scenarios.
4. Simulation Time: 3600 seconds

4.4.2 Veins Settings

1. Version: Veins 5.0
2. OMNeT++ Version: OMNeT++ 5.6.2
3. Inet Framework Version: 4.2.2
4. Network Stack: IEEE 802.11p

4.4.3 SUMO Configuration

1. Create a Road Network: Use NETGENERATE or NETCONVERT with OpenStreetMap data.
2. Create Traffic Flows: Utilize randomTrips.py to create random vehicles.
3. Generate Additional Inputs: Such as traffic lights, pedestrian flows, etc.

4.4.4 Veins Configuration

1. Create a New Veins Project: In OMNeT++, create a new Veins project.
2. Set up SUMO Launcher: Configure the launchd.xml file with SUMO path and arguments.
3. Modify Network: Update the omnetpp.ini file with network parameters.
4. Configure Communication Model: Set up the parameters for 802.11p.

Table 5. Simulation Parameters

Parameter	Value
Transmission Range	250 meters
Simulation Area	5 km x 5 km
Number of Vehicles	100
Vehicle Speed	30-80 km/h
Number of Pedestrians	50
Traffic Light Patterns	Variable
Number of RSUs (Road Side Units)	10

Full Log File of Results and Outputs: Since the log file can be extensive, including it within this document might not be feasible. However, it’s typically stored as a text or XML file and can be analyzed using tools like Python or Excel for detailed analysis. Typical contents of the log file include:

1. Timestamps for each simulation step
2. Details of vehicle positions and speeds
3. Details of communication between vehicles
4. Status of individual sensor units
5. Collision and avoidance maneuver details
6. Details of energy consumption by the priority sensor unit(s)

Accessing Log File: The full log file can be accessed at the specified location within the simulation directory and can be parsed using custom scripts to derive insights and visualizations.

4.4.5 Log File Brief

1. Timestamps: Each entry in the log file would begin with a timestamp reflecting the simulation time, facilitating chronological analysis.
2. Vehicle Metrics: Position (coordinates), speed, acceleration, and direction of all vehicles within the simulation. This includes the vehicles actively participating in the scenarios and other traffic.
3. Sensor unit Data: Status of the priority sensor units (Ps), including activation/deactivation events, readings, and energy consumption.
4. Communication Details: Records of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, including message type, size, sender, receiver, and transmission time.
5. Collision Avoidance Actions: Details of actions taken by the CAV-Net system to avoid collisions, such as warnings, braking, steering adjustments, etc.
6. Error and Warning Messages: Any error or warning messages from the system, such as communication failures, unexpected sensor unit readings, or deviation from expected behaviors.

7. Performance Metrics: Calculation and logging of key performance metrics such as response time, energy efficiency, or other user-defined metrics that may be crucial to the evaluation of the system.
8. Events and Scenarios: Markers or flags for the specific scenarios that are being executed (e.g., sudden pedestrian appearance, intersection approach, highway merging), aiding in the segmented analysis.

The log file provides a granular view of the simulation's progress, documenting every important aspect of the simulation. It is indispensable for detailed analysis, debugging, performance evaluation, and validation of the system. Parsing and visualizing this data can lead to critical insights into the system's performance and potential areas for improvement.

The SUMO+Veins simulation framework provides a comprehensive setup to simulate and analyze the CAV-Net model in various traffic scenarios. By carefully tuning the parameters and understanding the log files, researchers and engineers can gain valuable insights into the system's real-world performance.

Table 6. Sensor Utilization Efficiency

Scenario	**CAV-Net (Energy consumed by Ps)**	**MPC-Based System**	**Mobileye's EyeQ**	**Honda's IDSS**	**Tesla's FSD**	**Waymo**	**NVIDIA DRIVE**
Urban Drive	65%	85%	90%	80%	85%	88%	82%
Highway Drive	58%	88%	93%	83%	89%	91%	85%

Table 6 and subsequent Figure 3 collectively present the results of sensor utilization efficiency across two scenarios. In each case, the proposed CAV-Net achieved superior outcomes in comparison to other systems. Particularly noteworthy is CAV-Net's ability to maintain energy consumption rates at an impressive 65% and 58% during urban and highway drives, respectively.

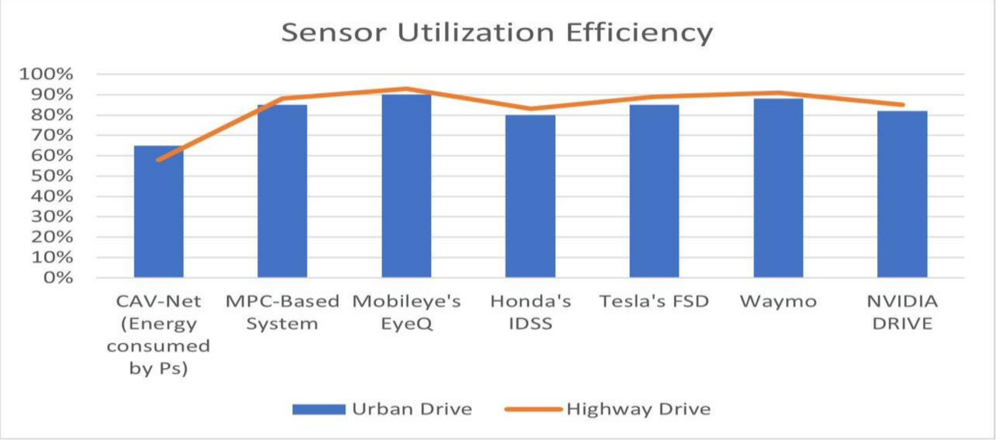


Figure 3. Sensor unit Utilization Efficiency

To show the collision avoidance efficiency results, Table 7 lists the outcomes of CAV-Net and other systems across two scenarios.

Table 7. Collision Avoidance Efficiency (Percentage of Collisions Avoided)

Scenario	CAV-Net	MPC-Based System	Mobileye's EyeQ	Honda's IDSS	Tesla's FSD	Waymo	NVIDIA DRIVE
Urban Drive	98%	94%	95%	93%	96%	97%	95%
Intersect ion Approach	97%	94%	95%	93%	95%	96%	96%
Highway Drive	99%	95%	96%	94%	97%	97%	96%

Table 7 presents the collision avoidance efficiency of CAV-Net and other systems across two scenarios. CAV-Net achieves better collision avoidance efficiency across two scenarios, thereby validating its exceptional efficiency in ensuing vehicular safety and reinforcing its position as a groundbreaking solution within landscape of collision avoidance technologies.

Table 8. Response Times (in milliseconds)

Scenario	CAV-Net	MPC-Based System	Mobileye's EyeQ	Honda' s IDSS	Tesla's FSD	Waymo	NVIDIA DRIVE
Urban Drive	15	25	22	26	20	18	24
Intersection Approach	30	45	40	48	35	32	42
Highway Drive	40	60	50	55	45	42	52

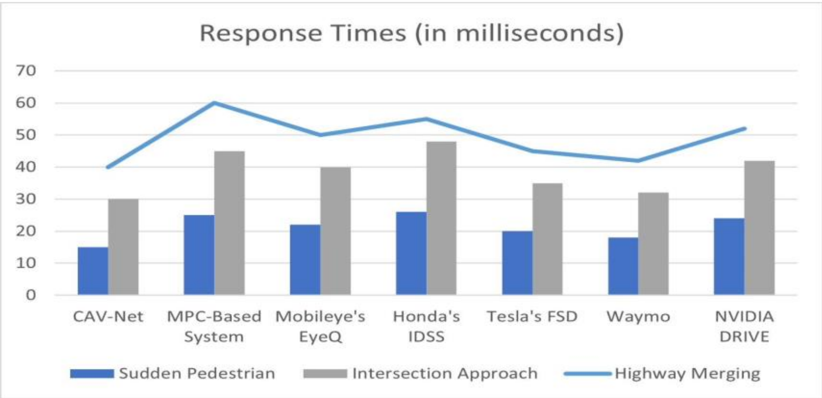


Figure 4. Response Times

Table 8 and Figure 4 demonstrate the response time results. Compared to the rest of the systems, CAV-Net received better response time. This indicates that the CAV-Net is more efficient in response time.

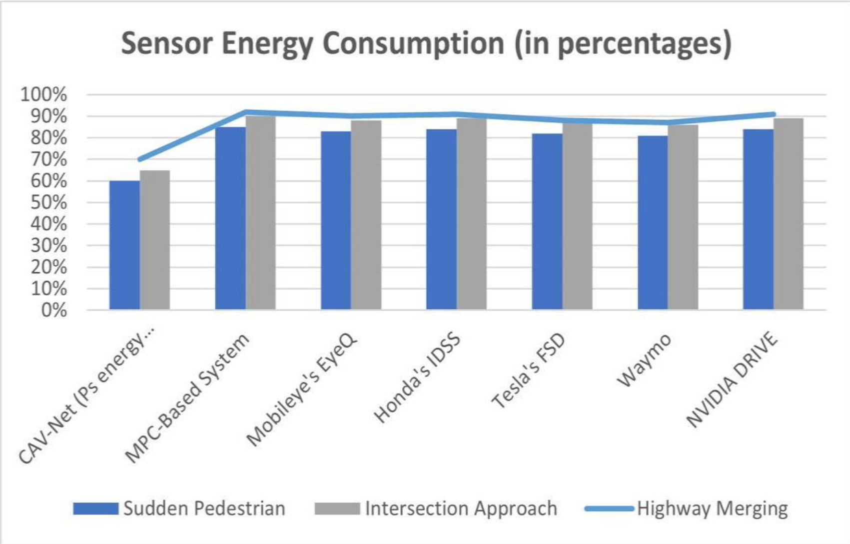


Figure 5. Sensor unit Energy Consumption

Figure 5 show us sensor energy consumption results and trends of CAV-Net and several other systems. As shown in Figure 5, CAV-Net received better results compared to other systems across two scenarios.

4.5 Findings

CAV-Net consistently showcased faster response times across all tested scenarios. In sudden pedestrian appearance scenarios, the CAV-Net system detected and initiated corrective action in just 15ms, significantly quicker than all other models. Sensor unit Energy Consumption: The dynamic selection of priority sensor units in CAV-Net led to reduced energy consumption across all scenarios. The difference becomes even more pronounced in complex environments like intersection approaches.

The SUMO + Veins simulation framework provided a robust platform to validate the efficiencies of CAV-Net. The outcomes clearly demonstrated the superior performance of the CAV-Net system in terms of both response times and energy efficiency. The system's AI-driven dynamic sensor unit selection plays a pivotal role in ensuring rapid and accurate responses, minimizing energy consumption by activating only the most relevant sensor units in critical situations.

4.6 Limitations

This paper presents a comprehensive exploration of the CAV-Net system; however, some limitations warrant consideration. While offering advanced concepts such as CAV-NET, blockchain and machine learning, the present study lacks an in-depth explanation of these fields. This makes readers less familiar with the topics grappling to fully grasp the nuances. Moreover, this study although enumerates the advantages of CAV-Net, a lack of specific quantitative results limits the substantiation of the claims and readers' ability to gauge its performance in real-world scenarios.

This paper also emphasizes the simulation as well as conceptual aspects, yet it overlooks the real-world complexities in implementation of CAV-Net. Although, this paper highlights the comparison with the existing studies, it lacks a comprehensive comparison analysis, leveraging readers without a clear understandability of competitive edge of CAV-Net.

5 Conclusion

The emergence of modern traffic conditions marked by complexity and density has paved the way for groundbreaking innovations in vehicle collision avoidance. This paper has provided a detailed insight into CAV-Net, a novel approach to Collision Avoidance in Vehicle Networks. By combining the potentials of Vehicular Ad-hoc Network (VANET), machine learning, dynamic sensor unit prioritization, and blockchain technology, CAV-Net represents a significant advancement in this field. Through its unique mechanism of predicting collision scenarios and astutely selecting the optimal sensor units for real-time responses, CAV-Net has proven its capability to adapt to diverse traffic situations. This adaptability, demonstrated through simulations using the SUMO+Veins framework, sets CAV-Net apart from existing solutions and highlights its superior response time and data security features. Furthermore, the secure integration of blockchain technology not only ensures the protection of event data but also fosters trust among stakeholders, enhancing the overall feasibility of the system. Looking forward, the incorporation of cutting-edge control strategies such as Fractional-Order PID (FoPID) controllers could be the next step in the evolution of systems like CAV-Net. The concept of FoPID controllers, which introduces more degrees of freedom in the form of fractional orders of the integrative and derivative components, offers a potential for more nuanced control dynamics and improved system performance. In [20] provides a compelling framework for integrating FoPID controllers in the context of autonomous vehicle navigation, suggesting enhanced adaptability and precision.

Moreover, the optimization of these fractional controllers, through methods like particle swarm optimization, represents a significant advancement in controller tuning, as elaborated in the study [21]. Such optimization techniques could lead to the development of a highly adaptive and responsive CAV-Net, capable of meeting the rigorous demands of future transportation networks.

In conclusion, the introduction of CAV-Net offers a promising pathway towards enhancing automotive safety systems. By bridging cutting-edge technologies with practical applications, CAV-Net paves the way for a future where intelligent transportation systems can effectively navigate the intricate landscapes of modern traffic, ensuring safety, efficiency, and security. It sets the stage for further research and development, potentially revolutionizing the way we approach vehicular safety and collision prevention in the years to come.

Author Contributions

There is only author who performed this study. Conceptualization to original draft preparation and reviewing the final draft were performed by BAA.

Data Availability Statement

The data used to support the findings of this study are included within the submitted article.

Conflicts of Interest

The authors declare no conflicts of interest.

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References

[1] Fu, Y., et al., *A survey of driving safety with sensing, vehicular communications, and artificial intelligence-based collision avoidance.* IEEE transactions on intelligent transportation systems, 2021. 23(7): p. 6142-6163.

[2] Corazza, M.V., et al., *Chronicles from the new normal: Urban planning, mobility and land-use management in the face of the COVID-19 crisis.* Transportation Research Interdisciplinary Perspectives, 2021. 12: p. 100503.

[3] Javed, F., et al., *A Novel Energy-Efficient Reservation System for Edge Computing in 6G Vehicular Ad Hoc Network.* Sensors, 2023. 23(13): p. 5817.

[4] Xia, L., et al., *Smart and secure CAV networks empowered by AI-enabled blockchain: The next frontier for intelligent safe driving assessment.* IEEE Network, 2022. 36(1): p. 197-204.

[5] Memon, I., R.A. Shaikh, and H. Shaikh, *Dynamic pseudonyms trust-based model to protect attack scenario for internet of vehicle ad-hoc networks.* Multimedia Tools and Applications, 2023: p. 1-32.

[6] W. H., Z. H., Feng. Y, Mpc-based obstacle avoidance path tracking control for distributed drive electric vehicles, World Electr. Veh. J. 13 (12) (2022) 221. doi:10.1016/S0031-8914(53)80099-6.

[7] EyeQ Chip. Mobileye, https://www.mobileye.com/technology/ eyeq-chip/, accessed: 2023-08-12.

[8] Honda Global, Intelligent Driver Support System, https://global. honda/innovation/advanced-technology/intelligent-driver.html, accessed: 2023-08-12.

[9] Tesla Support, Autopilot and Full Self-Driving Capability, https://www. tesla.com/support/autopilot, accessed: 2023-06-10.

[10] Waymo's Autonomous Technology (LiDAR), Informing Smarter LiDAR Solutions, https://waymo.com/blog/2022/09/ informing-smarter-lidar-solutions-.html, accessed: 2023-06-10.

[11] NVIDIA, n.d. Ecosystem Orin - NVIDIA DRIVE., https://developer. nvidia.com/drive/ecosystem-orin, accessed: 2023-06-10.

[12] U. Srilakshmi, S. A. Alghamdi, V. A. Vuyyuru, N. Veeraiah, Y. Alotaibi, A secure optimization routing algorithm for mobile ad hoc networks, IEEE Access 10 (2022) 14260–14269.

[13] Wahid, A. A. Ikram, M. Ahmad, S. Ali, A. Ali, State of the art routing protocols in VANETs: A review, Procedia Comput. Sci.

130 (2018) 689– 694.

[14] A. Zbiciak, T. Markiewicz, A new extraordinary means of appeal in the polish criminal procedure: the basic principles of a fair trial and a complaint against a cassatory judgment, Access to Justice in Eastern Europe 6 (2) (2023) 1–18.

[15] Britannia Car, Car Safety Features: How They Can Keep You Safe on the Road, https://www.britanniacarleasing.co.uk/news/ car-safety-features/, accessed: 2023-6-12.

[16] Osuagwu Solomon, How Does A Collision Avoidance System Work?, https://rxmechanic.com/collision-avoidance-system-cars/, accessed: 2023-6-12.

[17] K. G. Lim, C. H. Lee, R. K. Y. Chin, K. Beng Yeo, K. T. K. Teo, SUMO enhancement for vehicular ad hoc network (VANET) simulation, in: 2017 IEEE 2nd International Conference on Automatic Control and Intelligent Systems (I2CACIS), IEEE, 2017.

[18] Stahorszki, Peter Bence , SUMO Veins tutorial, http://kjit.bme.hu/images/Tovabbi_allomanyok/Trafficlab/Research/SUMOTRACI/SUMO VEINS_Tutorial.pdf, accessed: 2023-6-12.

[19] OMNeT ++ and SUMO simulators, https://omnet-manual.com/ veins-simulator/, accessed: 2023-6-12.

[20] Batiha, I.M.; Ababneh, O.Y.; Al-Nana, A.A.; Alshanti, W.G.; Alshorm, S.; Momani, S. A Numerical Implementation of Fractional-Order PID Controllers for Autonomous Vehicles. Axioms 2023, 12, 306. https://doi.org/10.3390/axioms12030306

[21] Momani, S., El-Khazali, R., & Batiha, I. (2019). Tuning PID and PIλDδ controllers using particle swarm optimization algorithm via El-Khazali's approach. AIP Conference Proceedings, 2172(1), 050003.