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Article

Improvement in Collision Avoidance in Cut-In Maneuvers Using Time-to-Collision Metrics

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Highlights:

The study is focused on studying human driving behavior under uncertainty to transfer these behaviors to autonomous vehicles (AVs) represents a pivotal step toward improving the coexistence of human-driven and autonomous vehicles in mixed traffic environments.

What are the main findings?

- The proposed collision avoidance system significantly improves collision avoidance performance in cut-in scenarios by integrating deep learning with time-to-collision (TTC) metrics.
- The Gaussian model enhances TTC analysis by providing a probabilistic framework that accounts for real-world uncertainties, such as sensor inaccuracies, vehicle velocity fluctuations, and unpredictable driving behavior.

What is the implication of the main finding?

- The integration of deep learning and TTC metrics enables adaptive, real-time decision-making for collision avoidance in autonomous vehicles, improving safety in dynamic environments.
- The probabilistic Gaussian approach makes TTC-based systems more robust, allowing them to better handle uncertainties, leading to safer and more reliable autonomous driving systems.

Abstract: This paper proposes a new strategy for a collision avoidance system leveraging time-to-collision (TTC) metrics for handling cut-in scenarios, which are particularly challenging for autonomous vehicles (AVs). By integrating deep learning with TTC calculations, the system predicts potential collisions and determines appropriate evasive actions compared to traditional TTC-based approaches. The methodology is validated through extensive simulations, demonstrating a significant improvement in collision avoidance performance compared to traditional TTC-based approaches. By integrating deep learning models with TTC calculations, the system predicts potential collisions and determines appropriate evasive actions. The use of the Gaussian model to contributes to time-to-collision (TTC) analysis by providing a probabilistic framework to quantify collision risk under uncertainty. It calculates the likelihood that TTC will fall below a critical threshold (TTC_crit), indicating a potential collision. By modeling input variations—such as sensor inaccuracies, fluctuating vehicle velocity, and unpredictable driving behavior—as a Gaussian distribution, the system can handle real-world uncertainties more effectively. This enables continuous, real-time risk prediction, allowing for dynamic and adaptive collision avoidance decisions. The Gaussian approach enhances the robustness of TTC-based systems by improving their ability to predict and prevent collisions in uncertain driving conditions.

Academic Editors: Pierluigi Siano and Giuseppe Guido

Received: 23 October 2024
Revised: 14 December 2024
Accepted: 17 January 2025
Published: 21 January 2025

Citation: Raiyn, J.; Weidl, G. Improvement in Collision Avoidance in Cut-In Maneuvers Using Time-to-Collision Metrics. *Smart Cities* **2025**, *8*, 15. https://doi.org/10.3390/smartcities8010015

Keywords: autonomous vehicles; collision avoidance; time to collision; deep learning; cut-in scenario; sensitivity analysis

1. Introduction

The rapid growth in autonomous vehicle (AV) technology has introduced the need for advanced safety systems capable of preventing accidents in complex and dynamic traffic environments. One of the most challenging scenarios for AVs is a cut-in, where another vehicle abruptly enters the ego vehicle's lane, reducing the available time and space for evasive action. Traditional rule-based or reactive collision avoidance systems often struggle in such situations due to the difficulty of predicting the precise timing and nature of the cut-in.

This paper proposes a deep learning-based approach combined with time-to-collision (TTC) metrics to predict potential collisions during cut-in events and to recommend evasive actions. TTC is widely used in collision avoidance systems [1], measuring the time remaining before two vehicles collide based on their relative velocity and distance. However, traditional TTC-based systems may be limited by their static nature, often failing to account for the complex interactions between vehicles in a dynamic traffic environment. By integrating deep learning models, our system can learn from diverse traffic situations and predict collisions more effectively, resulting in more timely and appropriate evasive actions.

In cut-in scenarios, a vehicle from an adjacent lane makes a sudden move into the ego vehicle's path, sharply increasing the potential for a collision. The time-to-collision (TTC) metric is crucial in these situations, as it estimates the time remaining before an impact by factoring in the relative distance and velocity between the ego vehicle and the cutting-in vehicle. Accurate TTC calculations help the system assess the urgency of the situation and determine whether evasive maneuvers or braking is necessary to prevent an accident.

This paper presents two key contributions: the integration of deep learning with time-to-collision (TTC) metrics to improve the accuracy of collision prediction in cut-in scenarios and the development of a comprehensive collision avoidance strategy. The proposed system not only suggests deceleration but also incorporates lane changes as part of its response, offering a more adaptive and effective solution for preventing accidents in complex traffic conditions.

The goals of this research are to develop a reliable prediction system for detecting potential collisions during cut-in scenarios, propose suitable evasive maneuvers such as deceleration or lane changes, and ultimately enhance the safety of autonomous vehicles (AVs) by improving their collision avoidance capabilities in complex traffic environments.

The novelty of this research lies in combining advanced machine learning techniques with behavioral insights and dynamic TTC computation to create a comprehensive, adaptive collision avoidance framework that addresses limitations in static, rule-based systems. It provides new capabilities for handling unpredictable cut-in scenarios by integrating predictive modeling, human behavior analysis, and multidimensional evasive actions.

This paper is organized as follows: Section 2 gives an overview of deep learning. Section 3 describes the methodology. Sections 4 and 5 discuss the results, conclude the discussion, and point out directions for future research.

2. Related Work

Collision avoidance systems for autonomous vehicles (AVs) have evolved from rule-based systems to more sophisticated, machine learning-driven models to handle complex driving scenarios. Rule-based systems follow strict, predefined rules for vehicle control, such as stopping when an object is detected within a specific distance. While simple, these systems struggle in dynamic, real-world scenarios like cut-ins, where the behavior of other vehicles is unpredictable and rapid decisions are required. Machine learning models, such as support vector machines (SVMs), decision trees, and random forests, learn from historical traffic data to predict collision risks by identifying patterns in vehicle behavior [2]. However, these approaches also face challenges in generalizing to real-time, dynamic situations, particularly with cut-ins that require split-second responses.

Yan et al. [3] focuses on developing driver trust in assistance systems by adapting the system's support to the driver's uncertainty. The premise is that appropriate trust can be fostered when these systems help reduce uncertainty, such as in lane-change maneuvers, by adjusting to the driver's uncertainty about distance gaps and closing velocity. This paper presents the creation of a probabilistic model to classify driver uncertainty during lane changes, using data from a simulator experiment. Three Bayesian networks are explored: a naive Bayesian classifier, a Tree-Augmented-Naive Bayesian classifier, and a fully connected Bayesian network. At the same time, some researchers have developed various methods to improve the effect of identifying vehicle lane-changing behavior. Zou et al. [4] proposed a machine learning-based vehicle acceleration prediction model that incorporates driving behavior analysis. By preprocessing driving data and selecting key features like relative distance, velocity, and acceleration, the model aims to improve the accuracy of Advanced Driving Assistance Systems (ADASs) and enhance traffic safety.

Du et al. (2022) [5] developed an intelligent approach to predict lane-change behavior in autonomous vehicles (AVs), using both driving style and trajectory data of AVs and surrounding vehicles. A modified dataset based on real vehicle trajectories (NGSIM) was created for this purpose. The method employs a hidden Markov model (HMM) to assess whether the environment is suitable for lane changes and a learning-based model to predict AV lane changes based on driving conditions. This approach improves the safety and accuracy of AV lane-change maneuvers. Advances in deep learning (DL) have significantly enhanced the ability of AVs to handle such complex scenarios. Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), have shown great promise in capturing time-series data and temporal dependencies. This is crucial in predicting and reacting to traffic situations, such as cut-ins, where the system needs to understand the evolving relationship between the ego vehicle and surrounding vehicles over time. By learning the sequential nature of traffic events, DL models can more accurately predict potential collisions and determine whether to apply braking or execute a lane change [6].

In addition to deep learning techniques [7], uncertainty analysis plays a key role in improving AV collision avoidance systems. AVs must account for multiple sources of uncertainty, such as the unpredictability of human drivers, noisy sensor data, and environmental factors like weather or road conditions [8]. Techniques like Monte Carlo simulations [9] allow for the assessment of how random variations in these inputs affect collision risk. Bayesian networks and hidden Markov models are also employed to manage uncertainty [10], as they provide probabilistic assessments of future states based on current observations. For example, these models can predict the likelihood of a nearby vehicle performing a sudden lane change or braking unexpectedly, allowing the AV to react appropriately. Li et al. (2018) [11] introduced a feature selection method to predict driver lane-change (LC) behavior using naturalistic driving data. The goal was to pinpoint and select the most influential features across different LC scenarios. By applying feature selection, the method reduces the dimensionality of training datasets, eliminating redundant data and improving model efficiency in predicting LC behavior.

Zhao et al. (2022) [12] calculated key vehicle metrics, such as velocity, acceleration, and position, using data like vehicle ID and velocity along the X and Y axes. For clustering driving styles, they derived features including distance headway (DHW), time headway (THW), time to collision (TTC), and the inverse of TTC (ITTC). Additionally, the study presented a deep learning technique that utilizes convolutional neural networks (CNNs) to categorize five driving behaviors—normal, aggressive, distracted, drowsy, and drunk—by analyzing vehicle movement patterns, rather than relying on facial monitoring. This approach boosts efficiency and aids in reducing traffic accidents.

Human behavior is one of the largest sources of uncertainty in AV collision avoidance. Human drivers exhibit a wide range of behaviors, from cautious to aggressive, and these variations make it difficult for AVs to predict their actions accurately. Factors such as distraction, fatigue, or emotional state further contribute to unpredictable driving patterns. Autonomous systems must be designed to account for inconsistent human responses, such as delayed reactions to sudden traffic changes or abrupt, unsignaled lane changes during cut-in maneuvers [13]. Machine learning models for human behavior prediction, including advanced deep learning models, are trained on large datasets of human driving patterns. These models help AVs anticipate driver actions, such as lane changes or decelerations, in real-time scenarios. Defensive driving strategies, where AVs proactively maintain safe distances and avoid risky maneuvers, complement these models. By continuously processing real-time data from sensors like LiDAR, cameras, and radar, AVs can adjust their driving strategies to mitigate the risks posed by uncertain human behaviors.

This study focuses on the cut-in scenario, where another vehicle unexpectedly merges into the ego vehicle's lane, requiring a swift response to avoid a collision. Critical parameters such as reaction time, maximum deceleration, and jerk are essential in evaluating the ego vehicle's ability to respond safely and effectively to these sudden changes in traffic dynamics. In this context, time to collision (TTC) is a vital metric that estimates the remaining time until a collision would occur if both vehicles continued at their current velocity and paths. TTC metric [14], a well-established predictor, calculates the remaining time before a collision based on the current velocity and distance between vehicles. While useful for basic predictions, traditional TTC-based methods falter in rapidly changing situations, such as sudden lane changes or unpredictable cut-ins, where a collision can occur if evasive actions are not timed perfectly. TTC assumes constant vehicle velocity, making it less effective when the relative velocity between vehicles fluctuates or when lane positions change abruptly.

3. Methodology

3.1. Data Collection

The system is developed and validated using a simulated dataset that captures a wide variety of cut-in scenarios. The data are from the highD datasets. The human driver trajectories in the database were collected from German highways at six different locations near Cologne using unmanned aerial vehicles. The dataset includes crucial information such as vehicle dynamics, covering the positions, velocities, and accelerations of both the ego vehicle and the cutting-in vehicle as described in Table 1. Additionally, it incorporates details about traffic conditions, including road types, traffic density, and overall traffic flow. To ensure the model's robustness, various types of cut-in events are represented, ranging from abrupt and gradual to emergency maneuvers. This comprehensive dataset allows the deep learning model to learn from a broad spectrum of driving conditions and traffic situations, enhancing its ability to predict and respond to potential collisions effectively. Figure 1 describes the algorithm of hybrid avoidance for cut-in safety.

Table 1. The following abbreviations are used in this manuscript.

$L_{ego}(i)$	Longitudinal position of the ego vehicle at time step i
$L_{cut}(i)$	Longitudinal position of the cutting-in vehicle at time step i
$L_{ego,lat}(i)$	Lateral position of the ego vehicle at time step i
$L_{cut,lat}(i)$	Lateral position of the cutting-in vehicle at time step i
$V_{ego}(i)$	Longitudinal velocity of the ego vehicle at time step i
$V_{cut}(i)$	Longitudinal velocity of the cutting-in vehicle at time step i
W_{ego}	Width of the ego vehicle
W_{cut}	Width of the cutting-in vehicle
L_{ego_veh}	Length of the ego vehicle
L_{cut_veh}	Length of the cutting-in vehicle
W_{ego}	Width of the ego vehicle
W_{cut}	Width of the cutting-in vehicle
L_{ego_veh}	Length of the ego vehicle
L_{cut_veh}	Length of the cutting-in vehicle
W_{ego}	Width of the ego vehicle
W_{cut}	Width of the cutting-in vehicle
L_{ego_veh}	Length of the ego vehicle
L_{cut_veh}	Length of the cutting-in vehicle
W_{ego}	Width of the ego vehicle

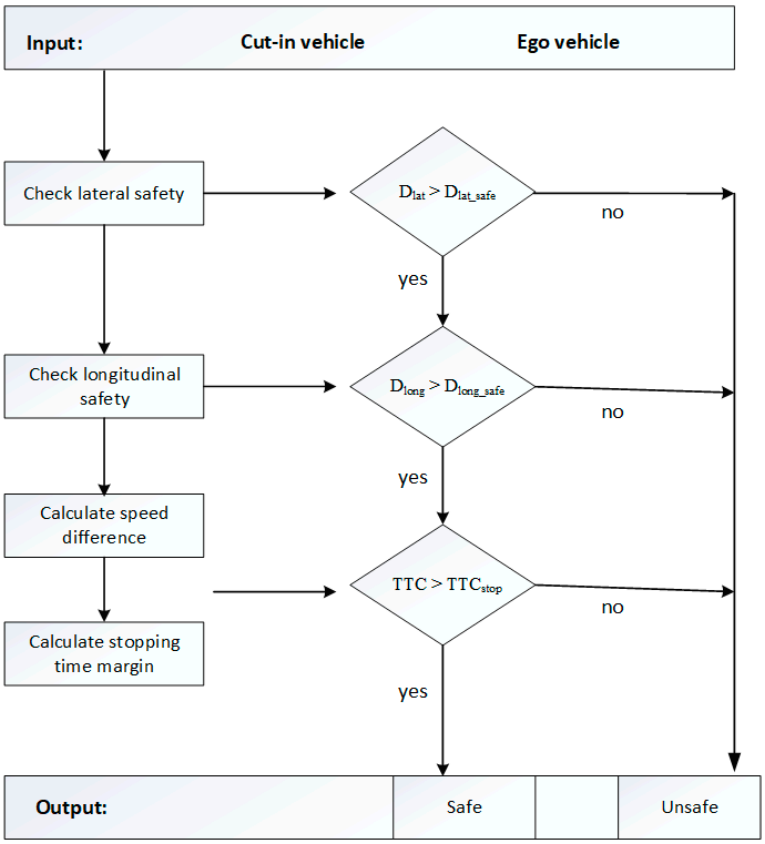


Figure 1. Algorithm description, provided sensor coverage (for Level 3 AV) is available.

1. **Input:**
    - Ego vehicle: position, velocity, width, length, deceleration, reaction time, and safety distance;
    - Cutting-in vehicle: position, velocity, width, and length.
2. **Step 1**: Lateral Safety
    - Calculate lateral distance and subtract half the width of both vehicles.
    - Compare this to the ego vehicle's safe lateral distance to an eventually presenting or (from behind) approaching car on the LC target lane. If greater, proceed; otherwise, unsafe.
3. **Step 2**: Longitudinal Safety
    - Calculate the longitudinal distance, subtracting half the lengths of both vehicles.
    - Adjust the safe distance dynamically based on the ego vehicle's velocity, provided the sensors have sufficient predictive horizon backwards, i.e., are able to reliable recognize the approaching vehicle(s) from behind. If greater, proceed; otherwise, unsafe.
4. **Step 3**: Velocity Difference
    - Calculate the velocity difference for the stopping time margin.
5. **Step 4**: Stopping Time Margin
    - Compute the stopping time margin based on velocity, deceleration, and reaction time.
    - If the ratio of the longitudinal distance to velocity difference exceeds the margin, proceed.
6. **Step 5**: Safety Check
    - If lateral, longitudinal, and stopping time checks pass, a cut-in is safe; otherwise, it is unsafe.
7. **Output:**
    - Return "True" for safe and "False" for unsafe.

3.2. Mathematical Description of Collision Avoidance Logic

The safety condition (Equation (1) and velocity adjustment Equation (2)) can be expressed as follows:

$$Safe = \left(\left|L_{ego,lat}(i) - L_{cut,lat}(i)\right| - \frac{W_{ego} + W_{cut}}{2} > D_{lat,safe}\right) \wedge \left(\left|L_{ego}(i) - L_{out}(i)\right| - \frac{L_{ego\_veh} + L_{cut\_veh}}{2} > D_{safe} \vee \frac{\left|L_{ego}(i) - L_{cut}(i)\right| - \frac{L_{ego\_veh} + L_{cut\_veh}}{2}}{\left|V_{ego}(i) - V_{cut}(i)\right|} > \frac{V_{ego}(i) - V_{cut}(i)}{2 \times A_{\max}} + T_{react} + 0.1\right) \quad (1)$$

If "Safe" is false, adjust the velocity:

$$\Delta V_{dec} = \min\left(\frac{\max\left(\frac{D_{safe} + \text{safety buffer} - D_{long}}{D_{safe} + \text{safety buffer}}, \frac{TTC_{safe} - TTC}{TTC_{safe}}\right) \times A_{\max}}{f}, A_{\max}\right) \quad (2)$$

$$V_{ego}(i+1) = \max\left(V_{ego}(i) - \Delta V_{dec}, V_{\min}\right) \quad (3)$$

3.3. Feature Extraction

It is first necessary to obtain the features that can represent driving styles. In this paper, the main extracted features include distance headway (DHW), time headway (THW), time to collision (TTC), and the inverse of TTC (ITTC). The DHW represents the distance between the front and rear vehicles. The THW represents the time difference between the front and rear vehicles passing through the same place; it can be calculated by dividing the DHW by the following vehicle velocity. The TTC indicates the time required for the collision if two vehicles continue to collide at the current velocity and on the same path; it can be calculated by dividing the DHW by the velocity difference between two vehicles.

- Cut-In Scenario: In a cut-in scenario, the collision avoidance system evaluates four key parameters simultaneously to determine the most effective response;
- Ego Vehicle Velocity (V_{e0}): Influences the reaction time available to the system to handle a cut-in situation;
- Lateral Distance (d_{y0}): Identifies the degree of lane intrusion by the cutting-in vehicle, helping detect when it enters the ego vehicle's path;
- Longitudinal Distance (d_{x0}): Essential for calculating the time to collision (TTC), assessing if the ego vehicle has sufficient time to avoid an impact;
- Lateral Velocity (V_y): Indicates how quickly the cut-in is happening, guiding the system on how urgently it needs to act.

By continuously monitoring these parameters in real-time, the system predicts collision risks based on threshold, as illustrated in Figure 2, and takes proactive measures, ensuring safe navigation through complex traffic scenarios.

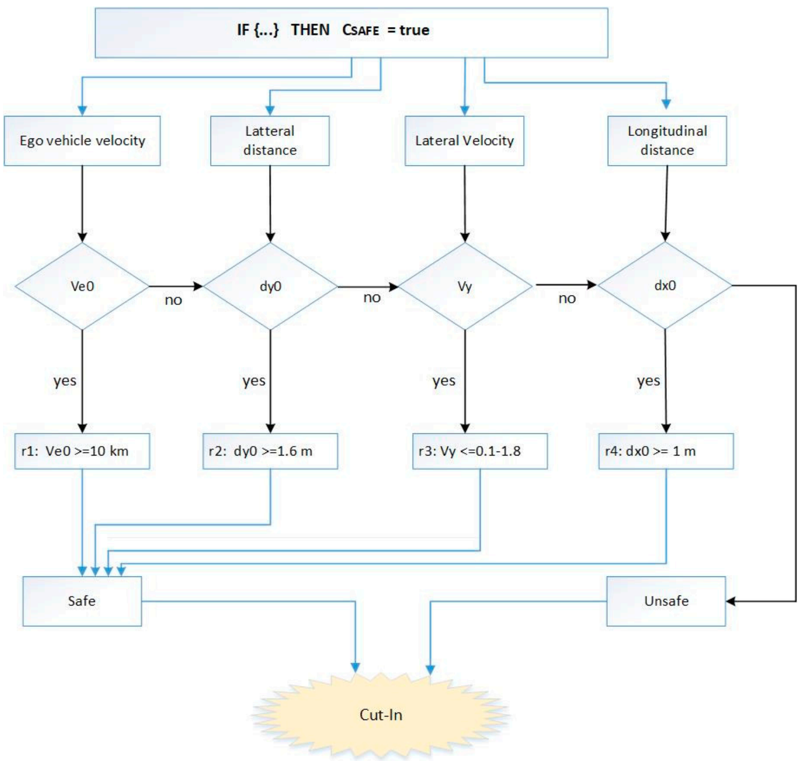


Figure 2. Cut-in scenario.

3.4. Safety-Critical Driving Situations in Cut-In Scenarios

Safety-critical situations arise when the risk of collision becomes imminent, demanding immediate action to prevent an accident. These scenarios are marked by the rapid reduction in available space and time for the ego vehicle to respond. Key characteristics of such situations include sudden or aggressive maneuvers by a cutting-in vehicle, which present a direct threat to the safety of the ego vehicle and other road users. Specific examples include a vehicle making a sudden cut-in at high velocity, reducing the gap to the ego vehicle and necessitating quick deceleration or lane changes. Another example is when a vehicle cuts in and then brakes abruptly, leaving little time for the ego vehicle to react safely. In poor weather conditions, such as rain, snow, or fog, a cut-in becomes even more dangerous, as reduced visibility and traction increase the stopping distance. In these scenarios, advanced collision avoidance systems leveraging time-to-collision (TTC) metrics combined with deep learning models must swiftly predict the collision risk and execute appropriate evasive maneuvers.

3.5. Non-Safety-Critical Driving Situations in Cut-In Scenarios

Non-safety-critical situations occur when a vehicle cuts into the ego vehicle's lane in a gradual manner, allowing ample time and space for the ego vehicle to react without an immediate threat of collision. In these cases, while adjustments may still be required, the urgency is low, and evasive maneuvers are often unnecessary. For example, in a gradual cut-in with sufficient space, the cutting-in vehicle leaves enough room for the ego vehicle to maintain a safe following distance with a slight reduction in velocity. Similarly, in low-velocity traffic, cut-ins pose minimal risk as both vehicles have enough time to adjust. A cut-in on an empty road provides even more leeway, as the ego vehicle can easily change velocity or lane position. Lastly, when a cut-in is anticipated or predicted, such as through early lane-change signals, the ego vehicle can smoothly adapt without a sense of urgency. Table 2 compares critical and non-critical safety events in cut-in scenarios.

Table 2. Critical vs. non-critical safety events.

Component	Critical Safety Events	Non-Critical Safety Events
Perception	Immediate threat detection, rapid object tracking, immediate response required	Routine object detection, tracking with no urgency
Decision	Split-second risk assessment, emergency planning	Long-term planning, efficiency-driven decisions
Reaction	Urgent, precise control (e.g., hard braking), lane changes	Smooth, controlled actions (e.g., gradual slowing), sufficient space and time to react
Focus	Avoiding or mitigating collisions	Maintaining safe, comfortable driving behavior
Driver/System Action	Aggressive evasive maneuvers required	Minor velocity adjustments or no action needed
Driving Conditions	Often in dense traffic, high velocities, or poor weather	Usually in open or slow-moving traffic conditions
Time Sensitivity	Real-time or near-real-time	Longer decision window

3.6. Collision Avoidance Strategy

The trained deep learning model predicts time-to-collision (TTC) values to assess whether a collision is imminent. Upon detecting a potential collision, the system determines the most effective evasive action, which may include deceleration or a lane change. If the predicted TTC indicates an imminent threat, the system calculates the required deceleration to reduce the velocity of the ego vehicle to avert the collision. If deceleration alone is insufficient or impractical due to surrounding traffic conditions, the model suggests a safe lane change. The collision avoidance system carefully evaluates both options, considering current traffic dynamics and vehicle capabilities, to ensure that the chosen action effectively mitigates the risk of a collision while maintaining overall safety on the road.

Simulations are conducted using various cut-in scenarios, including highway driving with sudden cut-ins, urban traffic with frequent lane changes, and emergency braking situations, to evaluate the system's performance. The effectiveness of the deep learning-based system is compared to traditional TTC-based methods, highlighting the advanced model's improved adaptability and accuracy. Uncertainty analysis assesses how variations in input parameters, such as measurement errors, environmental conditions, and human driving behavior, impact the system's ability to predict and prevent collisions. By identifying these uncertainties, engineers can enhance system robustness and ensure more reliable risk assessment. Sensitivity analysis evaluates how changes in key parameters, like vehicle velocity or reaction time, influence the system's output, helping to identify which factors are most critical, as illustrated in Figure 3. Combining uncertainty and sensitivity analyses provides a comprehensive understanding of the model's behavior, allowing improvements in system design, sensor fusion, and real-time adaptability to maximize safety in autonomous driving systems.

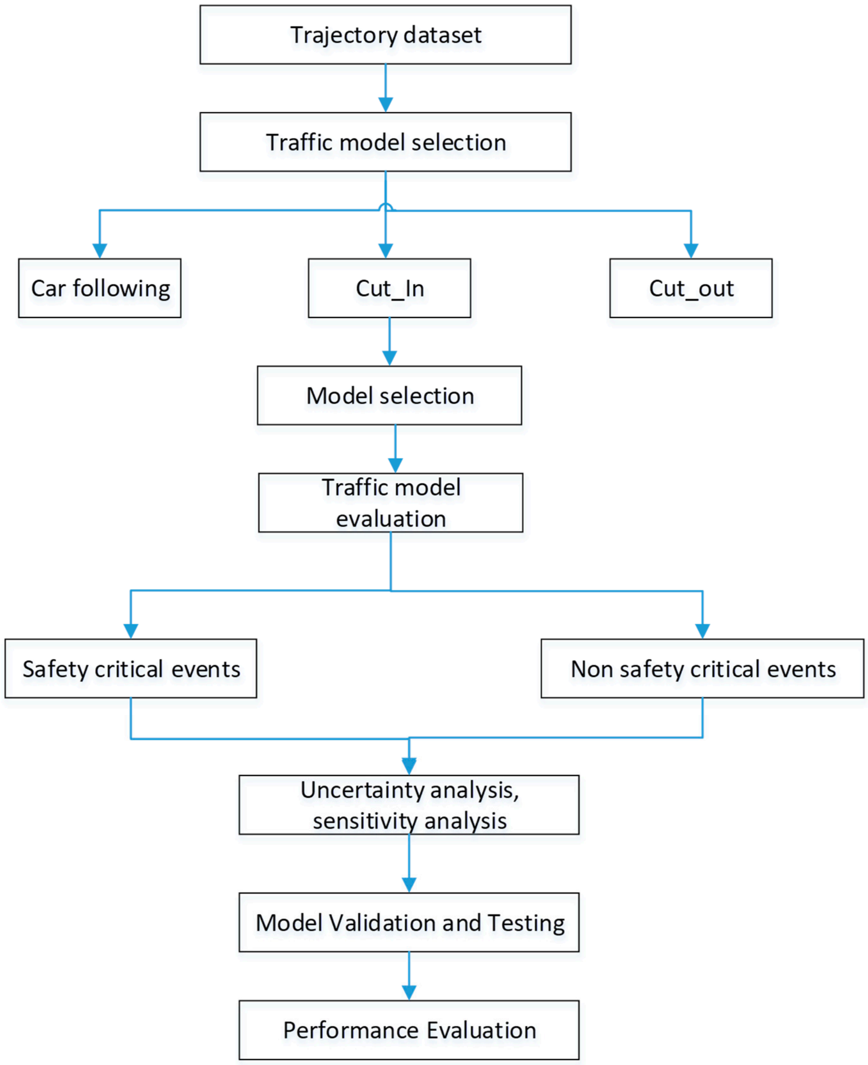


Figure 3. Sensitivity analysis.

3.7. Sensitivity Analysis in Collision Avoidance Systems

In cut-in scenarios, as illustrated in Figure 4, sensitivity analysis is crucial for determining how different input parameters impact the behavior of a collision avoidance system. Key parameters typically include time to collision (TTC), which measures the time remaining before a collision if vehicles maintain their current velocity and trajectory, and relative velocity, the difference in velocity between the ego and cutting-in vehicles, influencing collision severity. Inter-vehicle distance and cut-in angle are also critical, as shorter gaps and sharper angles increase collision risk. Reaction time is tested to see how delays in detecting and responding to cut-ins affect outcomes, while weather and road conditions, such as rain or slippery surfaces, further complicate the system's response. Driver behavior uncertainty, like inattentiveness or fatigue, is another factor that can affect reaction velocity. By analyzing these parameters, developers can enhance the robustness of collision avoidance systems, ensuring more reliable performance in real-world situations.

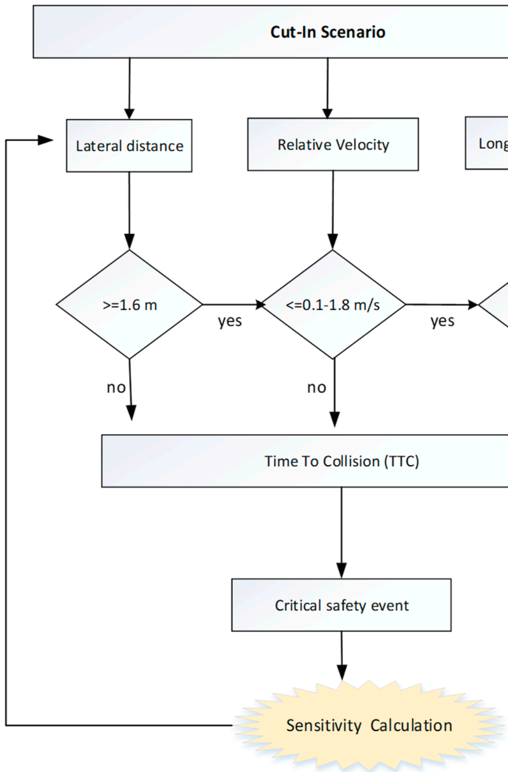


Figure 4. Sensitive analysis.

3.8. Sensitivity of Safety Metrics

Sensitivity analysis helps evaluate how the variation in the output of a model can be attributed to different variations in its inputs. It is especially useful in complex systems where understanding the relationships between inputs and outputs can improve decision making, optimization, and robustness. When a vehicle performs a cut-in maneuver, changes in key parameters such as lateral distance, relative velocity, and longitudinal distance can significantly affect safety metrics like time to collision (TTC). Lateral distance, relative velocity, and longitudinal distance all play crucial roles in determining the safety and time to collision (TTC) during a cut-in maneuver. A smaller lateral distance indicates a more aggressive lane change, reducing reaction time and increasing the risk of collision, while a larger lateral gap allows for smoother adjustments, lowering the immediate danger. Relative velocity is another key factor; if the cut-in vehicle is slower, the closing rate rises, requiring quicker reactions from the host vehicle to avoid a crash, whereas a faster cut-in vehicle reduces risk by moving away. A higher relative velocity shortens TTC, increasing collision likelihood unless the host decelerates, while a negative relative velocity extends TTC. Finally, longitudinal distance directly affects safety, with a smaller gap leaving less time for reaction and reducing TTC, whereas a larger gap provides more time to react and maintain safety. To measure the sensitivity of safety metrics, such as time to collision (TTC), to changes in inputs like longitudinal distance, relative velocity, and lateral distance, a systematic approach is required. This means that sensitivity can be measured by how much TTC changes in response to a change in the input parameter, such as time to collision (TTC). This can be performed by using partial derivatives (for continuous sensitivity) or by percent change (for discrete changes). To calculate instantaneous sensitivity, partial derivatives of TTC are to be used with respect to each input.

- Sensitivity to longitudinal distance

$$S_{long\_Dist} = \frac{\partial TTC}{\partial d} \tag{4}$$

- Sensitivity to relative velocity

$$S_{Rel\_Speed} = \frac{\partial TTC}{\partial v_{rel}} \tag{5}$$

3.9. Lateral Distance Sensitivity

While lateral distance does not directly impact time to collision (TTC), it indirectly influences the host vehicle's reaction time. A larger lateral distance can provide the host vehicle with additional time to react, effectively increasing the TTC, while a smaller lateral distance demands quicker responses, leading to a reduced TTC. In contrast, longitudinal distance and relative velocity directly affect TTC; longitudinal distance is proportional to TTC, whereas relative velocity is inversely related to TTC. Lateral distance indirectly shapes TTC by determining how swiftly the host vehicle can respond to a cut-in, with sensitivity increasing at lower longitudinal distances and higher relative velocities, particularly when the relative velocity is low.

4. Results and Discussion

The simulation results demonstrate that the Hybrid-based collision avoidance system outperforms traditional TTC-based methods. The system accurately predicts potential collisions and initiates timely evasive actions, significantly reducing the risk of collisions in cut-in scenarios. The simulation results demonstrate that the deep learning-based collision avoidance system outperforms traditional TTC-based methods. The system accurately predicts potential collisions and initiates timely evasive actions, significantly reducing the risk of collisions in cut-in scenarios.

Time to collision (TTC) is a critical measure in assessing collision risk, as it represents the time remaining before a collision occurs if the velocities of both vehicles remain constant. When a cut-in vehicle moves significantly slower than the ego vehicle, the TTC decreases, meaning the distance between them closes faster, increasing the collision risk, as illustrated in Figure 5. However, as the cut-in vehicle's velocity approaches that of the ego vehicle, the TTC increases, providing more time for the ego vehicle to react and adjust its velocity or position, thus reducing the chance of a collision. Additionally, with a smaller relative velocity, the required longitudinal safe distance decreases, allowing the ego vehicle to maintain a safe following distance without harsh braking. This smoother driving dynamic also improves reaction time, enabling the ego vehicle to make gradual adjustments, ultimately reducing the risk of rear-end collisions and enhancing overall road safety.

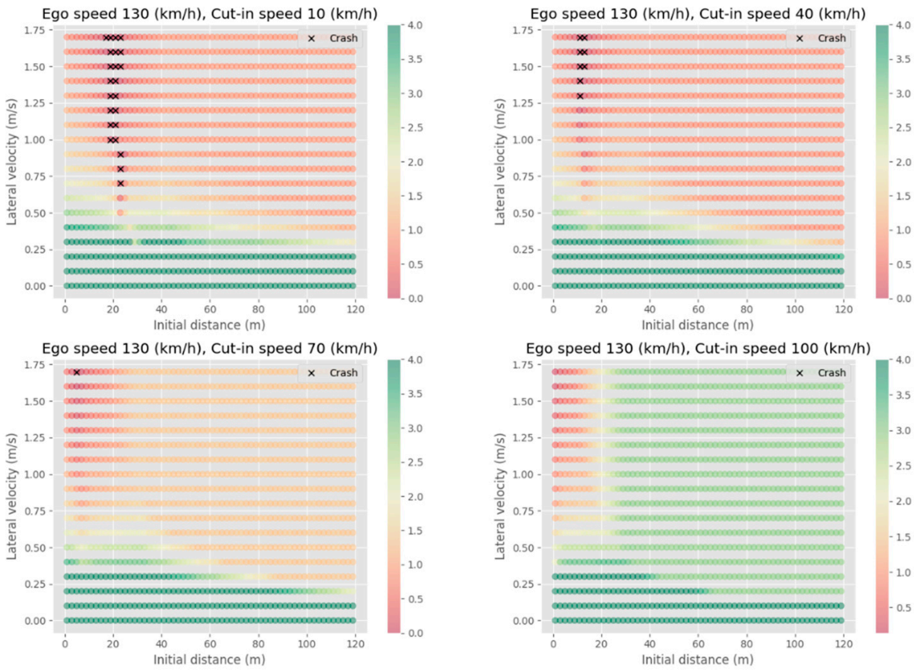


Figure 5. Ego velocity vs. cut-in object velocity.

4.1. Comparative Analysis of Collision Avoidance Models

To analyze and compare various collision avoidance methods—Hybrid, Responsibility-Sensitive Safety (RSS), Regulation 157 (Automated Lane Keeping Systems), and CC human driver based on ego velocity and cut-in velocity, as illustrated in Figure 6—we can evaluate how each method handles velocity dynamics, safe distances, and reactions to cut-in events. Here, we follow the procedures formulated in [15]. We use the GitHub repository to investigate the behavior of the proposed safety models for UNECE Reg157. The repository discusses four models: the Fuzzy Safety Model (FSM) [16], Responsibility Sensitive Safety (RSS) [17], CC human driver [18], and Reg 157 [18]. In addition to these repository models, we include our Hybrid model, which has been described in Section 3, the Methodology Section, under "Hybrid Collision Avoidance for Cut-In Safety". We compare the results as shown in Figure 6. The repository implements three reference scenarios. We focus on cut-in, which carries the biggest risk of collision. The Python script 'safety_check_runner.py' provides the possibility of selecting a logical scenario, and 'post_processing' provides the possibility of visually inspecting the results of the previously executed 'comparison' scenario. The key difference between these approaches lies in how they interpret time to collision (TTC), safe distances, and braking strategies during cut-in scenarios. The Hybrid model dynamically adjusts lateral and longitudinal safety thresholds, prioritizing smooth braking and minimal disruption when the cut-in velocity closely matches the ego vehicle. RSS, on the other hand, formalizes safe distances based on legal frameworks and ensures minimal deceleration when velocities are similar, while increasing buffer zones at lower cut-in velocities. Regulation 157, designed for lower-velocity environments, focuses on maintaining a safe following distance in urban traffic but is limited in high-velocity scenarios. CC human driver adopts a highly cautious approach, often leading to early braking and overly conservative behavior even when the velocity difference is small, resulting in less optimal comfort and driving smoothness compared to Hybrid or RSS.

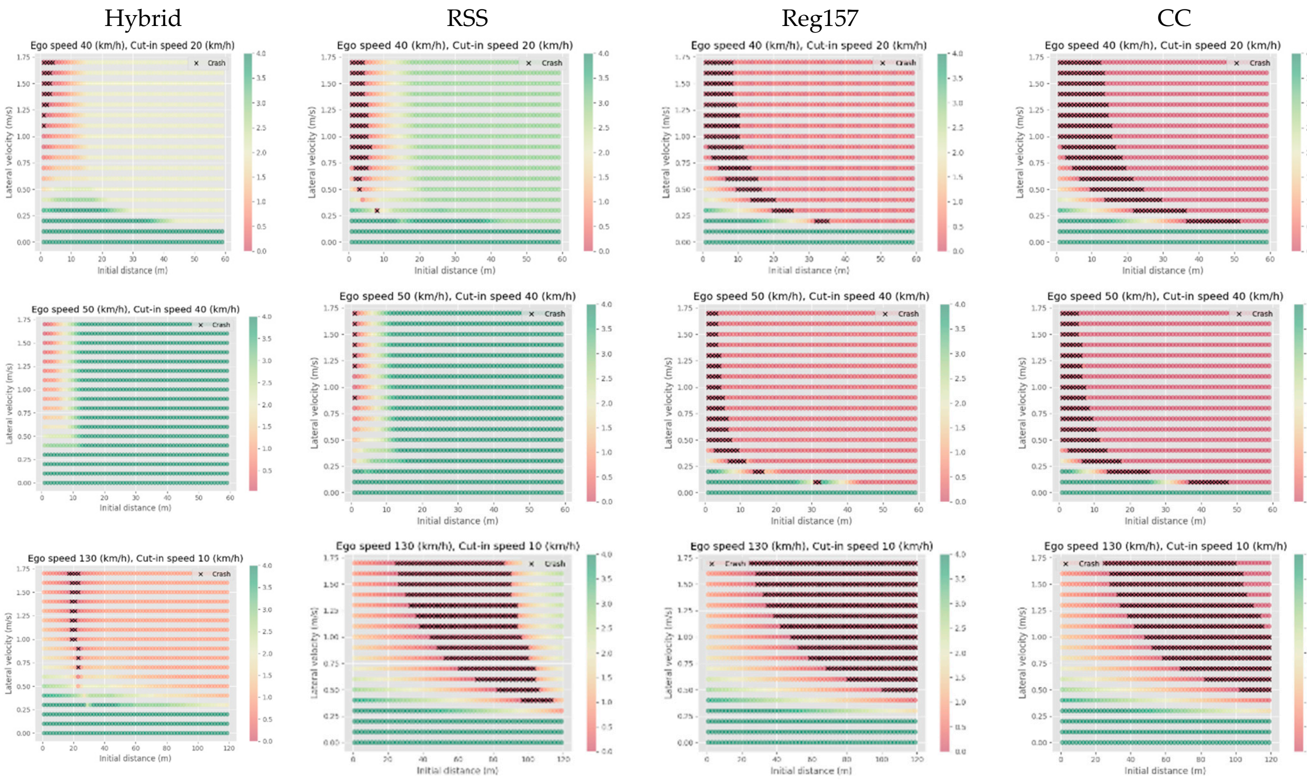


Figure 6. Analysis of collision avoidance.

4.2. Visualizing TTC Distribution

The Gaussian function is used to analyze safety-critical events in cut-in scenarios based on minTTC. The Gaussian (normal) distribution is given by the following formula:

$$f(x) = \frac{1}{\partial\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{6}$$

where

x is the variable (in this case, TTC);
μ is the mean value of TTC;
∂ is the standard deviation, which reflects the uncertainty or variability in TTC estimates.

4.3. Calculating the Probability of Collision

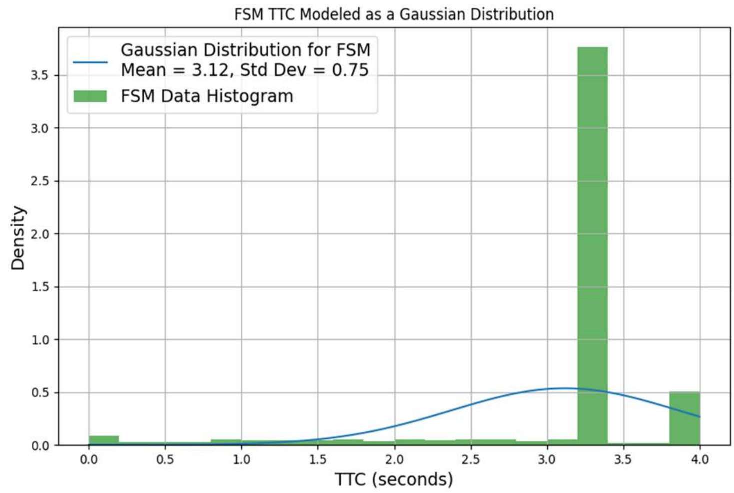
The Gaussian model for TTC can calculate the probability of a collision occurring within a specific time range. It allows us to determine the probability that the TTC will fall below a critical threshold (TTCcrit_{crit}crit), indicating a potential collision risk.

$$P(TTC < TTC_{crit}) = \int_{-\infty}^{TTC_{crit}} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(TTC-\mu)^2}{2\sigma^2}} \mathrm{dTTC} \tag{7}$$

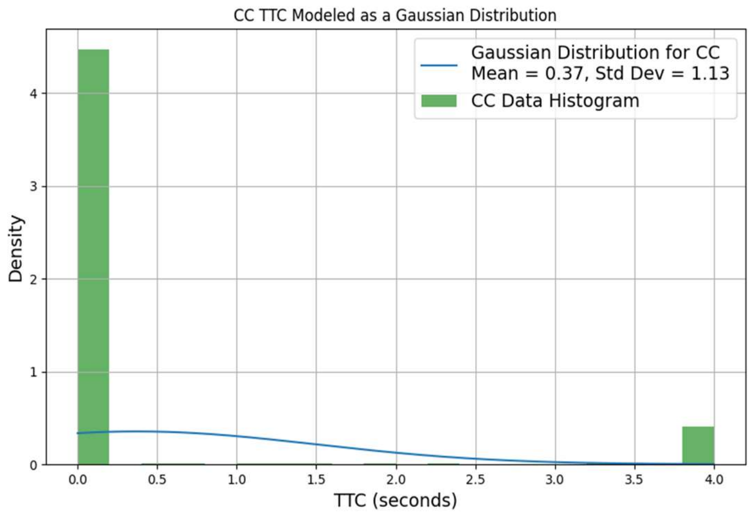
This gives us the likelihood of a collision occurring if the TTC falls below the critical threshold. Gaussian distribution is used to set safety margins, which means that it can be defined as a confidence interval (e.g., 95% confidence) to ensure that the vehicle takes action, such as braking, when the TTC reaches a certain level with enough margin to avoid collision.

4.4. Ego Velocity Analysis

To analyze time-to-collision (TTC) values based on a Gaussian distribution in the context of collision risk, the mean (μ) represents the average TTC. A high mean (e.g., >5 s) suggests the vehicle maintains a safer distance from potential collisions, while a low mean (e.g., <2 s) indicates more frequent operation in risky conditions. The standard deviation (σ) measures the spread of TTC values; a low σ means the values are closely clustered, indicating consistent intervals, whereas a high σ shows greater variability, with the vehicle occasionally getting closer to collisions as illustrated in Figure 7a–f. The left tail of the Gaussian curve represents dangerous TTC values near zero, indicating higher collision risk, while the right tail shows safer situations. Analyzing the area under the curve left of a critical threshold (e.g., 2 s) gives the proportion of time the vehicle is at high risk. A narrow, tall Gaussian curve suggests stable risk levels, while a wide, flat curve indicates variability between safe and risky TTC values. Comparing the mean and standard deviation of different systems (e.g., CC, FSM, IDM, Reg157, RSS, and Hybrid) helps identify which systems maintain safer TTC (high μ, low σ) and which exhibit higher collision risks (low μ, high σ).

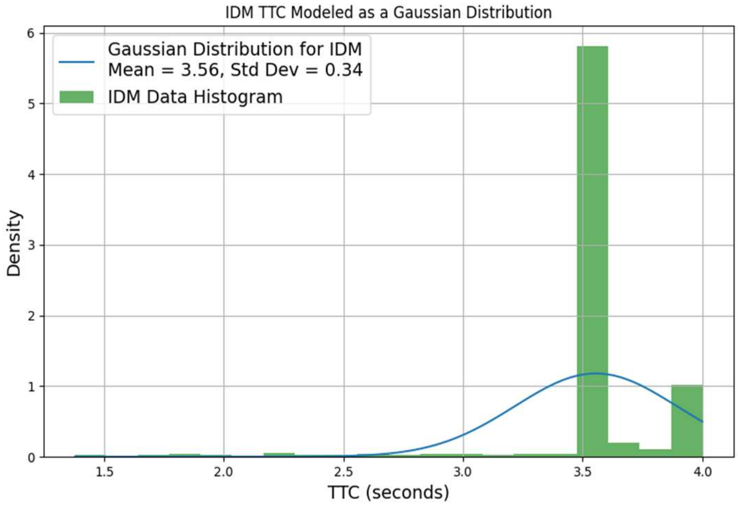


(**a**)

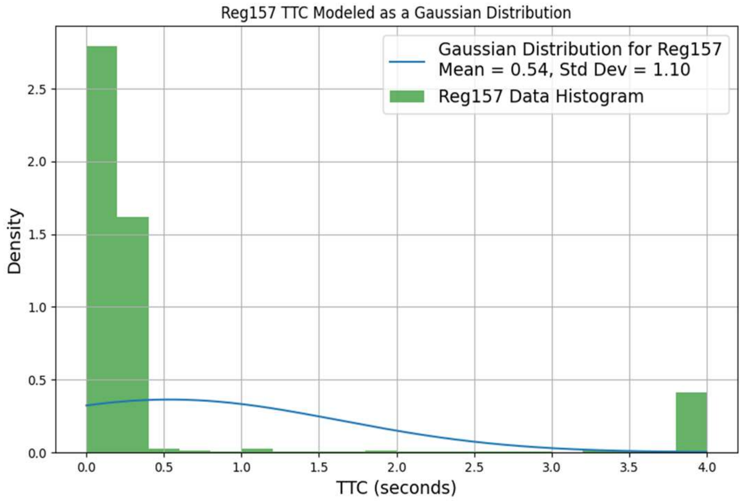


(**b**)

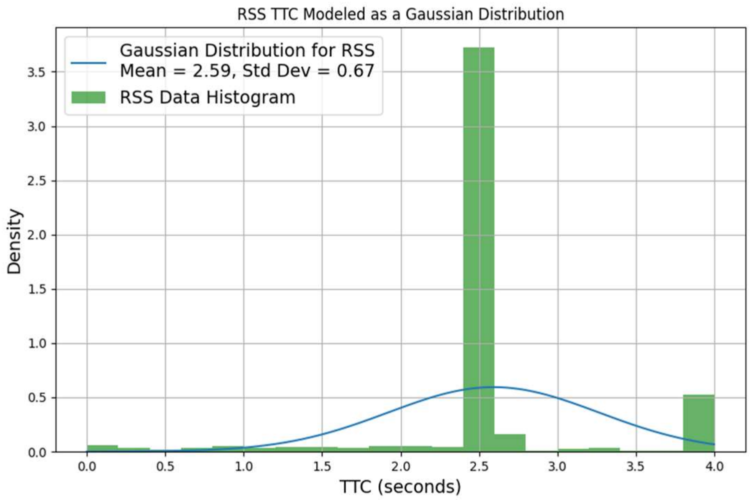
Figure 7. *Cont.*



(**c**)

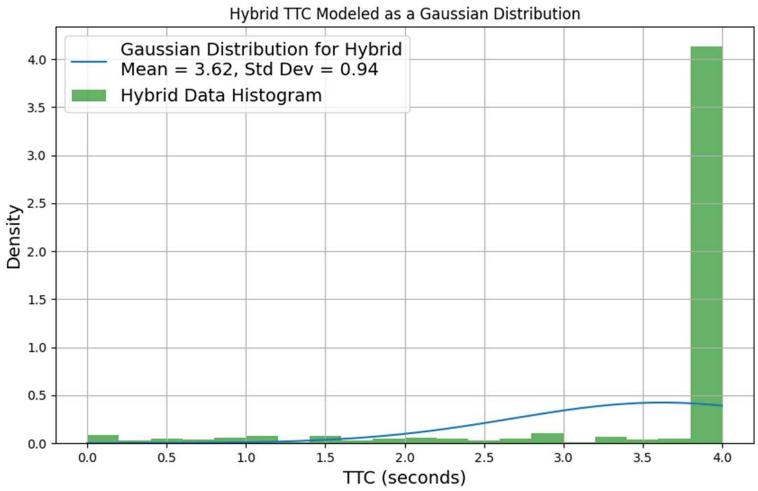


(**d**)



(**e**)

Figure 7. *Cont*.



(**f**)

Figure 7. (**a**) TTC modeled distribution in low velocity for FSM. (**b**) TTC modeled distribution in low velocity for CC. (**c**) TTC modeled distribution in low velocity for IDM. (**d**) TTC modeled distribution in low velocity for Reg157. (**e**) TTC modeled distribution in low velocity for RSS. (**f**) TTC modeled distribution in low velocity for Hybrid.

Figure 8 illustrates a comparison of collision avoidance models based on time to collision (TTC), and Gaussian Width of Curves highlight key performance differences. The Hybrid and IDM models emerge as the most effective, offering smooth adjustments across wide and narrow curves and maintaining optimal TTC without harsh braking. RSS ensures safety but overcompensates on narrower curves, impacting velocity efficiency, while FSM handles wide curves well but slows excessively as curves tighten. Both CC and Regulation 157 struggle at high velocities, with overreactions leading to inefficient TTC management, particularly in curve narrowing.

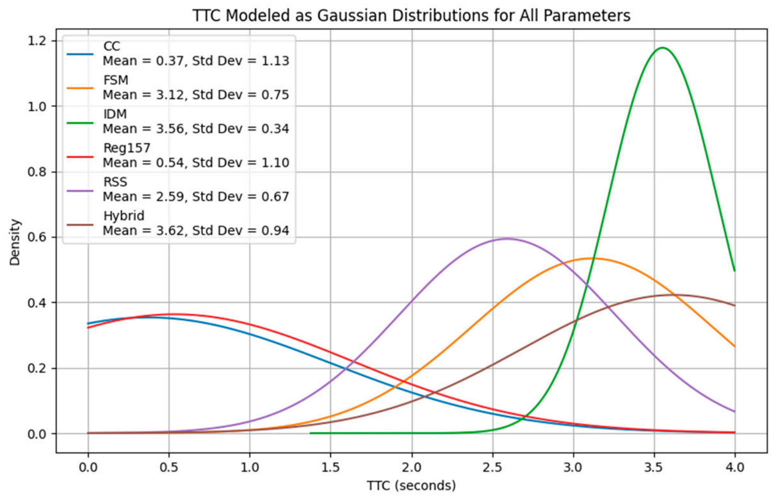


Figure 8. TTC modeled as Gaussian distribution for high velocity.

The TTC analysis confirms Hybrid and IDM as the top performers, with high mean TTC values (3.62 and 3.56, respectively), reflecting their ability to predict safe distances in cut-in scenarios. In contrast, CC and Reg157 exhibit significantly lower mean TTC values (0.37 and 0.54), indicating poorer risk assessment and inconsistent behavior, while FSM and RSS show moderate performance. Overall, Hybrid and IDM are the most reliable for collision prediction, whereas CC and Reg157 may need further refinement for high-velocity scenarios.

5. Conclusions

This paper presents a deep learning-based collision avoidance system for autonomous vehicles, specifically targeting cut-in scenarios. By leveraging TTC and advanced predictive models, the proposed system significantly improves road safety. The methodology and simulation results demonstrate the potential of deep learning in enhancing collision avoidance strategies for autonomous driving.

The sensitivity analysis reveals that when relative velocity is low, small changes in velocity have a significant impact on time to collision (TTC) because even slight increases in velocity drastically reduce the time to potential impact. Conversely, at higher relative velocities, changes in velocity have a smaller effect on TTC since the sensitivity decreases as the square of relative velocity grows. This insight is crucial for designing driver assistance systems and collision avoidance algorithms, where understanding how TTC responds to velocity variations is essential for enhancing vehicle safety and preventing collisions. Future work will focus on validating the proposed system in real-world scenarios, integrating additional sensor data to improve prediction accuracy, and exploring advanced multi-agent strategies to address the complexities of dynamic traffic environments, further advancing the safety and adaptability of autonomous driving technologies.

Author Contributions: Conceptualization, J.R. and G.W.; methodology, J.R.; software, J.R.; validation, J.R.; formal analysis, J.R.; investigation, J.R.; resources, J.R.; data curation, J.R.; writing—original draft preparation, J.R.; writing—review and editing, J.R.; visualization, J.R.; supervision, J.R.; project administration, G.W.; funding acquisition, G.W. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by Project 101076165—i4Driving within Horizon Europe under the call HORIZON-CL5-2022-D6-18 01-03, which is programmed by the European Partnership on 'Connected, Cooperative and Automated Mobility' (CCAM).

Data Availability Statement: Data will be made available on request.

Acknowledgments: We are grateful to the Smart Mobility Project of the European Commission Joint Research Center and in particular to Konstantino Mattas and Biagio Ciuffo for introducing us to the regulations and to the open research questions and for sharing with us the repository of the code, which we used to integrate our model for comparison.

Conflicts of Interest: The authors declare no conflicts of interest.

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