

IMPROVING SAFETY AT SHARP CURVES: A DYNAMIC STRATEGY FOR MIXED TRAFFIC CONDITIONS

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Abstract

Sharp curves pose significant hazards due to narrow, poorly maintained roads and limited visibility. In heterogeneous traffic conditions, risky driver behaviours such as overtaking and speeding further exacerbate these dangers. Traditional collision prevention methods, including convex mirrors, sensor-based systems, and headlights, have limited effectiveness in addressing these risks. A user perception survey revealed strong acceptance of a proposed driving assistance system: 79.22% of participants found flashing LED signals effective in alerting drivers, 80.26% noted reduced overtaking, and 88.31% expressed overall support for the system. The YOLOv5 machine learning algorithm was utilised to analyse video data, successfully detecting vehicles and distinguishing them from the background. The proposed curve collision warning system combines cameras and signal boards to monitor vehicles approaching curves at excessive speeds. It issues real-time visual warnings to prompt corrective actions, achieving accuracy and precision above acceptable thresholds. Performance evaluations demonstrated the system's potential to significantly reduce curve-related accidents and improve driver response times. These findings highlight the transformative capability of the system in enhancing road safety through real-time collision avoidance, offering a measurable reduction in risks associated with sharp curves.

Keywords: Collision Avoidance; Dynamic Warning Systems; Road Safety; Sharp Curves; Vehicle Detection; YOLOv5 Algorithm

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Introduction

Background

Despite significant commitments and efforts, road accidents remain one of the leading causes of death, disability, and hospitalisation in the country. Road features such as straight roads, curved roads, sharp turns, and potholes are prone to accidents, as exceptional care, skill, and attention are required to navigate these challenges.

Indian roadways exhibit highly mixed traffic conditions with wide variances in the static and dynamic properties of vehicles. These vehicles occupy any available lateral space on the road and often do not maintain proper lane discipline. One of the most difficult and critical manoeuvres on undivided roads is overtaking slower-moving vehicles using the opposing lane, even when oncoming traffic is approaching. This cannot be avoided, especially in mixed traffic situations where there is a constant speed differential between fast and slow-moving vehicles.

According to the road accident report by the Ministry of Road Transport and Highways (MORTH, 2022), the highest percentage of accidents occurred on straight roads, followed by curved roads. In hilly terrains, the situation is even more dangerous due to the lack of visibility for vehicles navigating hairpin curves. Horizontal curves have been identified as a major contributing factor to lane departure crashes. These curves are a crucial part of highways, enabling smooth directional changes Li *et al.* (2012). However, they may pose safety concerns due to the absence of curve warning signs and challenges in vehicle handling Li *et al.* (2015).

According to the Federal Highway Administration (FHWA), approximately 25% of fatal collisions involve horizontal curves, particularly on two-lane rural roads. Common crash scenarios on horizontal curves include running off the road or crossing into the opposite lane Persaud *et al.* (2000). For example, if a vehicle approaches a right-turn horizontal curve at a speed exceeding the design speed, it may not have sufficient centripetal force to remain in its lane. Consequently, the vehicle could drift to the left, potentially leading to a head-on collision with oncoming traffic.

Overtaking involves lane changing, adjusting speed, and accurately estimating the relative speeds of the overtaking and overtaken vehicles, as well as the speed and distance of oncoming traffic Mocsari, (2009). Human error remains the leading cause of curve-related crashes.

Numerous technologies have been developed to assist drivers in navigating curves and performing

safe overtaking manoeuvres. However, limited research has been conducted on the effectiveness of these methods in mixed traffic conditions, particularly in India. This study addresses this gap by examining the dynamics of curve-related crashes and evaluating advanced driver assistance strategies tailored for mixed traffic conditions.

In-vehicle Technology

The development of existing curve speed warning systems involves issuing a single speed warning or employing traffic control devices to alert approaching drivers. The advanced driving assistance system (ADAS) was developed to assist car drivers by enhancing vehicle and road safety through a secure human-machine interface. ADAS uses automated technologies, including sensors and cameras, to identify surrounding obstacles or driving errors and take appropriate action. Sensors are crucial in vehicles for detecting traffic, assisting with parking, monitoring CO₂ levels, and providing driver warnings, among other functions Guerrero *et al.* (2018).

Depending on the components installed in the vehicle, ADAS can enable varying degrees of autonomous driving. Examples include lane departure warning systems (LDW), over-speed warnings, and blind spot warnings Gouribhatla and Pulugurtha, (2022).

Hazoor *et al.* (2022) compared the available sight distance (ASD) and stopping sight distance (SSD) and developed an intelligent speed adaptation (ISA) system to assist drivers in choosing an appropriate speed on road sections with restricted visibility. The system operates in two ways: by alerting the driver with a visual warning and an audio warning.

Bassani *et al.* (2019) compared ASD and SSD to analyse actual visibility conditions. The study showed that most drivers employed strategies that resulted in stopping distances shorter than the available sight distance, thereby maintaining safe driving conditions. Some drivers slowed down, others increased their lateral distance from sight obstructions along the roadside, some did both, and some did neither. According to preliminary research, the safety benefits of a vehicle speed reduction strategy far outweigh those of a lateral lane shift.

In-road Technologies

These types of technologies are used outside the vehicle and are accessible to all road users.

Compared to in-vehicle technology, they are more economical.

Suthan *et al.* (2022) utilised cameras and sensors on the roadside to detect vehicles. The proposed method assists vehicles approaching from the opposite direction by detecting vehicles on one side of the curve. Its objective is to categorise various vehicles travelling in one direction on the curved road and to alert vehicles travelling in the opposite direction via a display board. The information on this display board includes the type of vehicle, the time required to pass a vehicle at the curve, and the number of vehicles on the curve.

Asaithambi and Shravani (2017) used the moving car method to collect overtaking data and the registration plate method to analyse traffic flow, composition, and overtaking. Song *et al.* (2019) employed vehicle detection algorithms for vehicle classification.

Existing Methodologies Adopted in Curves

To avoid head-on collisions on curves, several methodologies have been adopted. The existing methods used on curves to prevent collisions include sensors, reflecting mirrors, headlights, and horns.

Anand *et al.* (2019) mentioned the use of ultrasonic sensors for vehicle detection. This method involves placing two ultrasonic sensors at the curve and calculating speed by measuring the distance between the sensors and the time required for a vehicle to cross these points.

On roadways, driveways, and alleyways where there are blind spots or restricted visibility, convex mirrors are also used to enhance driver safety. These mirrors have a bulged reflecting surface that reflects light at different angles, providing a wider field of view. This method is mainly used in hilly areas, as it shows the view of oncoming vehicles approaching the curve. However, a significant drawback of this system is that the mirror's surface fades over time, and it is ineffective at night, in foggy conditions, and during rainy seasons.

When navigating hairpin corners, both headlights and horns are commonly used. Headlights are typically used at night by flashing high beams but are less effective during the day. Horns can also be unreliable due to varying volume levels and environmental noise interference.

Driver negligence is the primary cause of traffic accidents. Hairpin turns are particularly accident-prone due to limited communication and visibility. Therefore, drivers should exercise extreme caution when navigating sharp curves.

Another major drawback of driving on curved roads is traffic congestion, primarily due to unorganised vehicle movement. To reduce collisions caused by overtaking manoeuvres on

curves, it is essential to study the vehicles passing through these areas. Proper analysis can inform the development of a suitable curve warning system to discourage unsafe overtaking.

This study aims to detect and classify vehicles on curved roads using image processing techniques and to reduce traffic accidents during overtaking manoeuvres by implementing an appropriate curve warning system. The study also investigates public perception of this new curve warning assistance through a user perception survey.

Methodology

Study Area

The Selected study location is a segment of Ponkunnam Road, part of NH 183 in the Kottayam district. This location was chosen due to its sharp curve, limited sight distance, and high accident rate, making it representative of challenging driving conditions commonly found on similar roads in the region. Approximately 25% to 30% of fatal accidents occur on curved sections, with accident severity being higher compared to straight sections (Yuan-yuan *et al.*, 2011). As shown in Figure 1, the study stretch is a two-lane undivided carriageway that experiences mixed traffic, including vehicles of varying speeds and dimensions. These characteristics provide a suitable context for analysing curve-related crashes and driver behaviour under constrained conditions. Figure 2 provides a photograph of the curved road section, highlighting its geometric features and potential safety concerns.



Figure 1. Shows Location Selected for the Study (Source: Google Earth Pro)



Figure 2. Shows Snapshot of Study Area

Data Collection

Data collection was conducted in two phases. The first phase involved capturing traffic videography at the selected hairpin curve, while the second phase gathered user feedback through a perception questionnaire survey. For the survey, questions were posed to users at the study location, and a Google form was distributed to a broader audience. The questionnaire was designed to be simple and easy to understand for anyone familiar with navigating the hairpin curve.

Survey respondents were carefully selected to ensure reliable and diverse data collection. Participants included regular users of the study road segment, such as drivers of two-wheelers, cars, buses, and heavy vehicles, who provided first-hand insights into the challenges of navigating the curve. Selection criteria also considered driving experience (at least two years), familiarity with the study location, and representation across different vehicle types and age groups. This approach ensured a comprehensive understanding of the factors contributing to accidents and the effectiveness of potential safety interventions.

Traffic Video Collection

Traffic videos were recorded using two cameras positioned at strategic locations on either side of the curve to capture oncoming vehicles. The cameras were placed parallel to the traffic flow at elevated positions. The placement of the cameras was crucial for accurate vehicle detection, as minimizing vehicle overlap reduces the risk of smaller vehicles being obscured by larger ones. Positioning the cameras at a high elevation helped decrease the chances of overlapping compared to ground-level placement. Once the cameras were fixed, they remained in the same position throughout the data collection process to ensure consistency.

A total of seven hours of traffic footage was collected during peak and off-peak periods: from 8:00 am to 10:30 am, 12:00 pm to 2:00 pm, and 4:00 pm to 6:30 pm. Two hand-held cameras and two tripods were used for recording. The weather conditions were sunny and warm, providing stable lighting for clear video footage. However, challenges such as glare during midday and shadow variations in the morning and evening could potentially impact vehicle detection accuracy. Vibrations caused by wind or other environmental factors were monitored and minimized to maintain steady footage throughout the survey.

User Perception Survey

In this study, a user perception survey was conducted using a four-section questionnaire. The

primary objective of the user perception study was to analyse users' views on the questions posed to them Pattnaik and Ramesh (1996). Face-to-face interviews provided several advantages, including the opportunity to explore complex topics through detailed explanations and to encourage respondents to give accurate answers Schroder, (2016).

The first section included basic questions about gender, age, driving experience, occupation, purpose of the trip, and frequency of travel through hairpin roads. The second section focused on their comfort level while navigating existing hairpin road sections. The third section inquired about their experiences with conventional assistance systems (e.g., convex mirrors), while the fourth section asked about the proposed new advanced assistance system. Questions about the new system were presented by showing a CAD drawing of its proposed operation.

The survey sample size comprised 384 participants, representing a broad cross-section of road users who frequently travel on hairpin curves. The sample included drivers of various vehicle types (e.g., two-wheelers, cars, buses, and heavy vehicles) and diverse demographic characteristics, such as age, gender, and driving experience. Stratified sampling was used to ensure proportional representation of these groups, reflecting the broader population of road users in the study area. This representative approach ensures that the survey findings are generalizable and provide meaningful insights into user perceptions.

Data Analysis

The collected video graphic data was used to detect vehicles using YOLOv5. Vehicle detection is crucial for autonomous driving, driver assistance, and traffic monitoring Dong *et al.* (2022). The increasing number of vehicles and related accidents necessitates effective safety measures Chen *et al.* (2013). Accurate vehicle localization is fundamental to intelligent systems, including autonomous driving, surveillance, and object tracking Mahmood *et al.* (2019).

The first step involved using OpenCV to convert the traffic video into frames. Thirty frames were obtained per second, meaning the camera recorded 30 distinct images per second (30 fps). The next step was to annotate each image. In image processing, annotation involves adding labels, text, or other graphical elements to images. This was done using LabelImg, a widely used open-source tool for creating bounding boxes and assigning class labels. Annotation was the most time-consuming process in the workflow because it was performed manually.

Labelling in annotation involves categorizing objects, features, or aspects of an image or video. This includes identifying the object and assigning a specific class or title, such as car, person, or tree. By labelling images with categories, the algorithm learns to recognize and classify similar objects in new images. The quality of labelling is crucial to the machine learning model's performance, as poor labelling could reduce accuracy and effectiveness. Overall, labelling is essential to annotation because it provides machine learning models with the necessary context to learn about and accurately classify images.

Despite the advantages of the YOLOv5 model and image augmentation techniques, certain limitations exist. The model struggles with occlusions, where a vehicle is partially obscured by another object, leading to missed detections or misclassifications. Additionally, YOLOv5 can produce false positives, particularly in cluttered or complex backgrounds where non-vehicle objects might be incorrectly identified as vehicles. Variations in lighting, such as poor visibility at night or glare from headlights, can also affect detection accuracy.

In this study, target vehicles were classified into 14 categories: car front, car back, truck front, truck back, motorcycle front, motorcycle back, cycle front, cycle back, auto front, auto back, LCV front, LCV back, bus front, and bus back. The details of the annotated vehicle categories in YOLO are shown in Table 1.

Table 1. Annotation Categories Details used in YOLO

Annotation Categories Used in YOLO			
Car Front	0	Cycle Back	7
Car Back	1	Auto Front	8
Truck Front	2	Auto Back	9
Truck Back	3	LCV Front	10
Motorcycle Front	4	LCV Back	11
Motorcycle Back	5	Bus Front	12
Cycle Front	6	Bus Back	13

The annotation of a vehicle is completed after drawing a bounding box around each vehicle and selecting the annotation category of that vehicle. For example, in Figure 3 bounding box is drawn to all the vehicles which can be seen by a green rectangular box around each vehicle, and selecting the annotation category (i.e., for auto) is also seen in that figure.

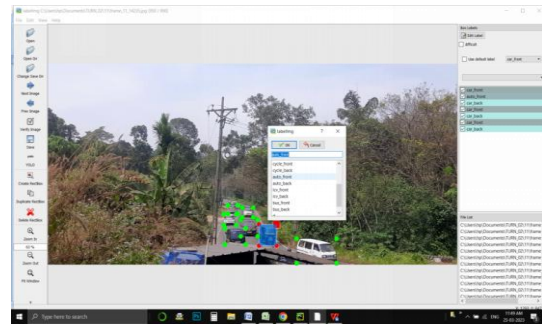


Figure 3. Shows Annotation of vehicles in labelling

Dataset Size prepared for training

Data size is very important for training purposes. The accuracy and performance of image processing can be significantly impacted by the amount of the dataset employed. The dataset size was carefully chosen to balance computational efficiency and model performance, avoiding over fitting from a small dataset and excessive training time from a very large one. A diverse set of images, capturing variations in lighting, weather, vehicle orientations, and traffic densities, ensured robust feature learning and effective generalization to real-world scenarios. Figure 4 shows the size of vehicles annotated using the labelling tool before augmentation.

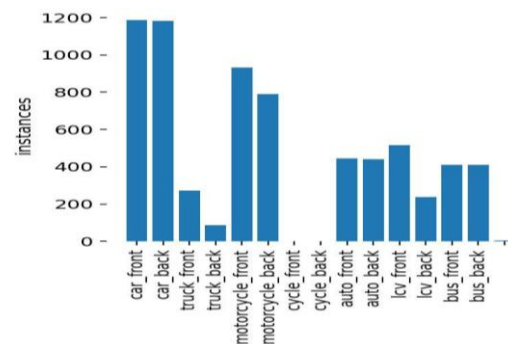


Figure 4. Annotated Size of Vehicles before Augmentation

Augmentation is another useful technique, in image processing, the approach of augmentation involves generating new copies of pre-existing images to increase the size of a dataset. To produce fresh images that are close to the original ones but not the same, this technique involves making numerous transformations to the original images, such as rotating, scaling, cropping, flipping, or adding noise. In machine learning applications like image classification, object recognition, and segmentation, augmentation is frequently used to enhance the performance and generalization of the

models Zhang *et al.* (2022). Figure 5 shows the result obtained after augmentation, here the size of the dataset prepared in the previous stage is increased.

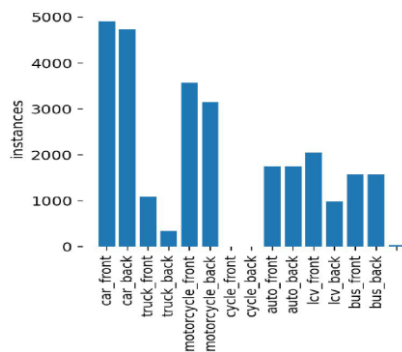


Figure 5. Shows Data Size After Augmentation for Training

After augmentation the dataset is ready for the training process. The next step is to divide the dataset into training and testing datasets. The dataset before augmentation contains a total of 6,860 images and the dataset after augmentation contains a total of 27,150 images. The training and testing set are divided into a 70:30 ratio. That means 19,005 images were used for the training dataset and 8145 images were used for testing purposes and evaluated by algorithms.

Training process

Training begins by splitting the dataset into training and testing sets. YOLOv5l, obtained from GitHub, was used to train the model according to the requirements of this study. The training process was carried out using Google Colab. Before starting the training, it was necessary to specify training parameters such as batch size, image size, and the number of epochs, as these are crucial for the model's training process.

Batch size refers to the number of samples processed at once during the training process. During each batch, the model updates its weights based on gradients computed on that batch of data. In this study, a batch size of 64 was selected. Image size represents the input image dimensions that the model uses for training, and it significantly impacts model performance. Here, an image size of 640 was applied. An epoch is the number of times the entire dataset is passed through the model during training. Increasing the number of epochs can enhance model performance. For this study, eight epochs were used, meaning the entire dataset was passed through the YOLO architecture eight times. Training was conducted in two ways: using the dataset before augmentation and after augmentation.

After the training process, results were obtained in the form of a confusion matrix and model weights. The weights obtained after training represent the learned parameters of the model, which are used to make predictions on new, unseen data. Once training was complete, the model was used for inference, where new input data was fed into the model, and the learned weights were used to make predictions. The quality of these predictions depended on the accuracy of the learned weights and the quality of the input data. The finally obtained model weight is used for the development of the curve collision warning process.

Curve collision warning process

According to the National Highway Traffic Safety Administration (NHTSA), the most significant human factors contributing to roadside accidents include driver distraction, fatigue, familiarity with the roadway, blood alcohol content, age, and gender Stephan and Newstead (2014), with driver inattention accounting for 30% of these accidents Roque *et al.* (2015). In this study, a warning system using red flashing lights was implemented to alert drivers entering curves. These lights were found to be more noticeable than conventional convex mirrors. By alerting drivers to the presence of vehicles on the curve, the warning system effectively reduced the tendency to overtake, promoting safer driving behaviour.

Decision sight distance

Decision Sight Distance (DSD) is the distance at which motorists can identify a hazard or signal in a road environment, select an appropriate speed and path, and safely execute the necessary actions Alexander and Lunenfeld, (1975). In this study, DSD was used to determine the optimal location for placing warning signals. Figure 6 illustrates the placement of cameras and signals on the road, with signals positioned at the DSD from the road's transition point towards the straight section.

Concept behind curve collision warning

The curve collision warning system used two cameras and two flashing red LED signals. The cameras were installed at both ends of the curve, facing the approaching straight legs, while the signals were placed at the DSD from the curve's transition point. This setup enabled drivers entering the curve to be aware of the presence of vehicles on the curve, helping them avoid overtaking slower-moving vehicles and encouraging them to reduce speed before entering the curve.

A CAD drawing in Figure 6 provides a clear pictorial representation of the curve collision warning system. The diagram shows two

approaching roads—Approaching Road 1 and Approaching Road 2—converging at a curve. The road is divided into two regions: a green region and a red region, illustrating the warning zones designed to enhance driver safety and reduce collision risks.

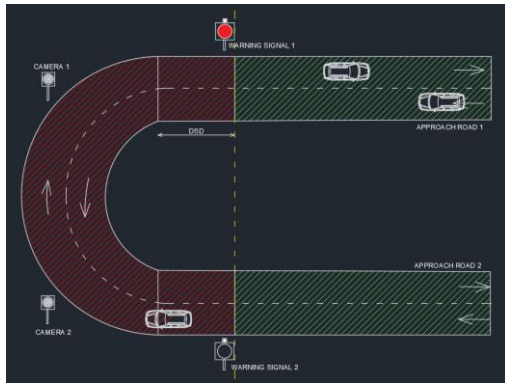


Figure 6. Pictorial Representation of Placing Signal and Camera on Road

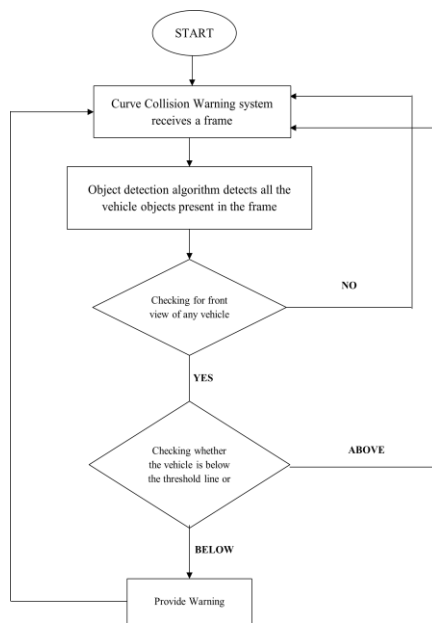


Figure 7. Shows Flow Chart of Warning Process

Figure 7 shows the flowchart for providing a warning. First, a curve collision warning system was developed in Python, and then a video was input into the system. The system receives each frame, considering only the front view of vehicles. The object detection algorithm checks whether the front view of a vehicle is present in the frame. If no front view is detected, the frame is skipped, and the next frame is analysed. If a front view is detected, the system proceeds to the next step.

In the following step, the program determines whether the vehicle crosses the threshold line. If the vehicle is above the threshold line, it means the

vehicle will not cross it, and no danger warning is displayed. However, if the vehicle crosses the threshold line (i.e., is below the threshold line), the system detects the presence of a vehicle entering the curve and activates a danger warning for drivers using red LED signals. The threshold line is positioned at the Decision Sight Distance (DSD) from the transition line and is indicated by a yellow line.

Results and Discussion

This section presents the results obtained from the user perception study, vehicle detection process, and curve collision warning process. For the user perception study, the findings are discussed in four sections. The results of the vehicle detection process are presented using a confusion matrix. In the curve collision warning process, the outcomes from speed calculations, determination of decision sight distance, and the confusion matrix are included.

User perception study

Out of the total 385 responses collected from the study area, 53.2% were male and 46.8% were female. In the survey, age was classified into three categories. Most participants were in the age group of 18-30 years (37.6%), followed by 31-45 years (35%), and 27.4% were over 45 years. The majority of the data were collected from people with more than 15 years of driving experience (32.5%), indicating well-experienced drivers. The least response was from the zero years category (5.2%), representing people who travel as passengers and participated based on their travel experience. Most travellers (42.3%) commuted for work purposes, followed by shopping (20.8%), education (20.0%), other purposes (9.1%), and recreation (7.8%). In terms of travel frequency through the curves, 29.4% were daily travellers, followed by monthly (27.3%), weekend (24.9%), and infrequent travellers (18.4%).

In the next section of the survey, users responded to questions based on their experiences while travelling through the curves. A total of 63.6% of participants felt unsafe while navigating the curves. Regarding the effectiveness of current driving assistance technologies, 58.2% indicated that these systems were less effective in enhancing road safety on curved roads. Additionally, 75.3% reported not experiencing smooth travel while negotiating the curves. In terms of overall satisfaction when navigating a hairpin curve compared to a regular road, 39.7% were highly dissatisfied, and 36.4% were dissatisfied.

Table 2. Relative Important Index (RII)

Factors Considered	Strongly Agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly Disagree (1)	RII	Rank
Road Surface Quality	105	150	49	32	49	0.72	4
Pavement Markings	111	177	48	19	30	0.77	3
Sign Boards	154	145	47	12	27	0.80	2
Landscaping and advertisement boards	103	136	67	31	48	0.71	5
Presence of Heavy Vehicles	193	116	33	11	32	0.82	1

In rating scale surveys, the Relative Importance Index (RII) is a statistical tool used to determine the relative significance of the factors considered for the study Ko *et al.* (2009). Pecheux *et al.* (2004) examined the influence of signals and the presence of heavy vehicles in their research. In this study, five factors were evaluated: road surface quality, pavement markings, presence of signboards, landscaping and advertisement boards, and the presence of heavy vehicles. Responses were collected on a 1 to 5 rating scale, with users rating these factors based on their experiences while travelling through the curves. The RII was calculated to identify the most influential factor among the five. Table 2 shows the calculation of the Relative Importance Index (RII), revealing that the presence of heavy vehicles was the most influential factor for drivers, with an RII of 0.82.

$$RII = \frac{5n_5 + 4n_4 + 3n_3 + 2n_2 + 1n_1}{A * N} \quad (1)$$

Where,

- n_5 = no. of respondents for strongly agree
- n_4 = no. of respondents for agree
- n_3 = no. of respondents for neither agree nor disagree
- n_2 = no. of respondents for disagree
- n_1 = no. of respondents for strongly disagree
- A = Highest weight (here $A = 5$)
- N = Total number of responses

Currently, convex mirrors and curve warning signboards are the primary methods used to warn drivers about upcoming curves. Of the respondents, 93.5% were familiar with these systems, while 4.9% did not pay any attention to them. About 49.4% of users only notice these mirrors when they are very close to them, and 16.1% reported difficulty in using them, with most of these being females and younger drivers.

Three statement-based questions were posed to the users. The first statement was, “The convex mirror gives a distorted size and shape to the vehicle coming towards us.” In response, 45.71% agreed,

and 19.22% strongly agreed. This is because convex mirrors distort the shape and size of reflected images due to the way light rays are reflected. The image appears smaller and is compressed or “squished” towards the edges. This distortion occurs because the light rays reflect at varying angles, leading to a compressed and distorted view.

The second statement was, “Using a convex mirror on a curve makes it difficult to judge the distance of an oncoming vehicle.” In this case, 39.74% agreed, and 28.31% strongly agreed. This is because objects reflected in a convex mirror appear smaller than they are, and the farther they are, the smaller they seem. Consequently, accurately estimating the distance of an oncoming vehicle becomes challenging, especially if it is far away.

The third statement addressed visibility during adverse weather conditions: “During the rainy season, it is difficult to judge the distance of oncoming vehicles using a convex mirror, which causes stress and reduces safety.” Here, 39.74% agreed, and 29.87% strongly agreed.

From the analysis of these three statements, it is evident that the current driving assistance system, which relies on convex mirrors and warning signboards, is less effective in providing safe guidance for drivers.

A new advanced driving assistance system has been developed to overcome the drawbacks of conventional systems, such as convex mirrors. This system enables users to detect the presence of vehicles on curves from a greater distance, allowing them to reduce speed before entering the curve. Additionally, it provides warnings at night, whereas mirrors are ineffective during night-time and rainy conditions.

User feedback indicates that the LED warning system outperforms traditional systems like mirrors and signboards by addressing issues such as distorted images, difficulties in judging distances, and poor performance in low-visibility conditions. While 58.2% found conventional systems ineffective, the LED system delivers clear, real-time warnings, enhancing driver confidence and reducing

stress. It offers reliable performance in adverse weather and night-time, providing a smoother and safer driving experience compared to traditional methods.

Analysis of Risk Factors

According to the analysis, 35.6% of respondents identified the presence of heavy vehicles travelling in the opposite direction as the primary cause of accidents. This is because heavy vehicles, such as buses and trucks, require more space while negotiating curves and often encroach on the lane of oncoming vehicles. Meanwhile, 37.4% attributed accidents to a combination of factors, including following vehicles too closely, slow reaction times, abrupt lane changes, and limited visibility of oncoming vehicles.

Four statement-based questions were analysed in this section, revealing positive user responses. The first question asked whether the presence of flashing LED signals increases drivers' alertness when navigating curves. In response, 47.2% agreed, and 31.95% strongly agreed. Compared to convex mirrors, LED signals are more noticeable due to the blinking red lights, which are visible from a greater distance.



Figure 8. Shows Detection of Vehicles Using Vehicle Orientation Dataset

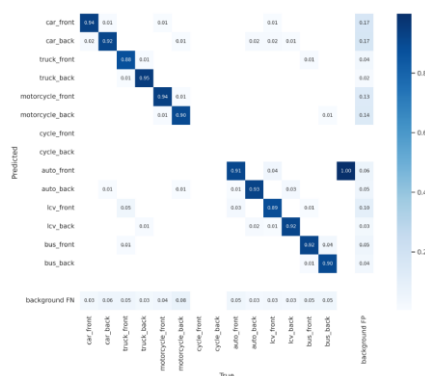


Figure 9. Shows Confusion Matrix from Second Model Training

For the second statement, 47.53% agreed and 32.73% strongly agreed that the LED warning signals reduce risky overtaking behaviour. Additionally, 41.04% agreed and 43.12% strongly agreed that the system improves overall safety by providing effective guidance. Over half of the respondents supported the idea that the system reduces the tendency to overtake, enhances safety, and alerts drivers to the presence of oncoming vehicles before entering curves.

The analysis clearly shows that the current driving assistance systems have significant limitations, leading to user discomfort. Consequently, users acknowledged that the new driving assistance system has a positive impact.

Vehicle detection process

Before training the model, the vehicle detection algorithm was tested using the vehicle orientation dataset obtained from GitHub. Figure 8 shows the results of vehicle detection using this dataset. The results indicate that certain vehicle categories, such as auto-rickshaws and light commercial vehicles (LCVs), were not correctly detected and were misclassified as other vehicle categories. For example, the rear view of an auto-rickshaw was misclassified as the front of a car. The figure also shows the detection accuracy, which was lower for all categories except cars.

The accuracy of detecting vehicles is improved after the first training process. Vehicle categories like the truck front, truck back, LCV front, and LCV back show an accuracy of less than 0.9 except all show better accuracy of prediction. So, to improve the accuracy of the prediction augmentation process is done with the prepared dataset and created a new dataset after augmentation. Then again, the model is trained using the dataset obtained from the augmentation process (second training process). Figure 9 is the confusion matrix obtained after the augmentation process. The second confusion matrix obtained shows a well-improved result from the first confusion matrix. So, the weight file from the second training process is used for the curve collision warning process.

Curve collision warning process

Speed was manually calculated by measuring a known distance and the time taken to cross it. The analysis aimed to determine the speed characteristics of vehicles passing through the study stretch. The free-flow speed of vehicles over one hour was considered to analyse the design speed. Spot speed data, which refers to the measurement of individual vehicle speeds, was utilised.

Figure 10 shows the cumulative frequency versus speed graph, from which a design speed of 43 km/hr (98th percentile speed) was obtained. This speed was then used to calculate the Decision Sight Distance (DSD) for determining the offset from the transition region of the road. The DSD was calculated using the 98th percentile speed from the graph, assuming a driver reaction time of 2.5 seconds.

$$DSD = 0.278 \times V \times T$$

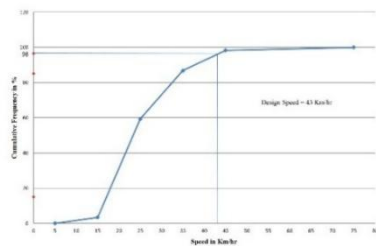


Figure 10. Shows Cumulative Frequency vs Speed

The DSD value obtained was used as the threshold distance from the transition point of the road. The weight files from the training process were used as input for the curve collision warning process. Only vehicles crossing the threshold line were considered, and a danger warning was issued accordingly.

Figure 11 shows the detection of hazardous vehicles on both sides of the road when they cross the threshold line specified for this study. A danger warning is given to vehicles entering the curve by crossing the threshold line. If a vehicle enters the left leg of the curve, the curve collision warning system detects its presence within the curve and provides a red indication on the right side of the curve.



Figure 11. Shows Detecting the Dangerous Vehicle Coming into The Curve

Confusion Matrix of Curve Collision Warning Process

A confusion matrix for the curve collision warning system was developed using one hour of

data. Table 3 shows the confusion matrix results for this system. The accuracy achieved was 0.945, and the precision was 0.98.

Table 3. Confusion Matrix for Curve Collision Warning Process

PREDICTED VALUE	ACTUAL VALUE			
	Total 384	Positive Danger	Negative Danger	
	Positive Danger	200 (True Positive)	4 (False Positive)	
	Negative Danger	17 (False Negative)	163 (True Negative)	
		217	167	384

Conclusion

Ensuring safety at hairpin turns remains a critical challenge in road transport. A substantial 63.6% of travellers feel unsafe navigating these curves, primarily due to a lack of awareness of heavy vehicles on the opposite side. The current convex mirror system is considered ineffective by 58.2% of respondents, with 34.5% particularly females and younger drivers avoiding its use due to issues such as distorted vehicle images, difficulty in assessing speed and distance, and poor visibility during rain.

In contrast, 79.22% of participants found flashing LED signals effective in alerting drivers, and 80.26% noted a reduction in overtaking behaviour due to these signals. Furthermore, 88.31% of respondents supported the new driving assistance system, reflecting strong approval for its implementation.

The YOLO algorithm has proven to be a faster and more accurate vehicle detection tool compared to other programs, with YOLOv5l delivering reliable results when compared to manual counts. However, additional training is required to accurately detect various vehicle types, such as auto-rickshaws and commercial trucks, in Indian traffic conditions. Improved annotation and augmentation processes are essential for enhancing detection accuracy.

The proposed curve collision warning system effectively detects vehicles approaching curves and provides a Decision Support Distance (DSD), enabling drivers to make informed decisions and adjust their speed accordingly. This system is pivotal in mitigating the risks of accidents, including rollovers and head-on collisions, by promoting safer navigation through sharp curves.

The study highlights the effectiveness of innovative systems like flashing LED signals and YOLO-based vehicle detection in enhancing safety

at hairpin turns, while emphasising the need for further research. Future enhancements could include AI-driven adaptive features to adjust signals based on real-time conditions, improved training of detection algorithms for diverse traffic scenarios, and integration with V2X communication for seamless vehicle-system interaction.

Implementation challenges, such as infrastructure limitations, weather resistance, driver awareness, and system maintenance, can be addressed through solutions like solar-powered systems, weather-proof hardware, awareness campaigns, and predictive maintenance tools. By overcoming these challenges and leveraging advanced technologies, the proposed curve collision warning system has the potential to significantly reduce accidents and improve road safety.

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