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# Vehicle Detection Visualization system for avoiding the accidents due to overtaking on roads

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***Abstract- Many road accidents are occurred by overtaking of vehicles. Main reason of this accidents are misjudgment of vehicle speed,distance and traffic. Road accident can be decreased by recognizing the overtaking in real time. In this project the machine learning algorithm is used along with dash-cam. Through a Flask-based web dashboard, the system shows alerts and produces a real-time risk score expressed as a percentage. In order to help the driver make safer choices, warning notifications are activated if the anticipated risk surpasses a predetermined threshold.To ensure accurate classification of safe and risky overtaking scenarios, the model is trained using a combination of accident and normal driving datasets. The suggested system is a preventive and intelligent road safety solution appropriate for advanced driver assistance systems because experimental results show that it successfully predicts possible collisions before impact.***

***Keywords- Accident Detection, Overtaking Risk Analysis, Dash-cam System, Machine Learning, Deep Learning, Computer Vision, Vehicle Detection, Time-to-Collision, Intelligent Transportation Systems, Flask Web Application.***

## I.Introduction

Globally, traffic accidents continue to be a serious threat to public safety. The complexity of traffic environments has increased dramatically due to the fast growth of urbanization and the growing number of cars on highways. Because it necessitates exact coordination of speed control,lane positioning, distance judgment and situational awareness, overtaking is regarded as one of the riskiest driving maneuvers. Introduced further efficiency of the models and the Head-on collisions, side impacts, and multi-vehicle crashes are just a few of the serious outcomes that can arise from a minor overtaking error. Therefore, lowering accident rates and improving road safety require early detection of risky overtaking behavior.

In the old vehicles the main focus on protection after the overtaking. It consists of airbag deployment, braking systems, and structural reinforcements. But these systems don't react until a collision take place. Preventive safety techniques, which use real-time driving data analysis to predict possible collisions before they happen, are becoming more prevalent in modern intelligent transportation systems. Such predictive systems have been made possible in large part by developments in deep learning.The creation of deep convolutional neural networks (CNNs) revolutionized computer vision by enabling computers to acquire hierarchical visual features in large amounts of data automatically. Deep CNNs significantly surpass traditional machine learning methods in image classification, which is demonstrated by the seminal study by Krizhevsky et al [1]. Application of deep learning in autonomous driving and traffic.

Regions-based object detectors such as Fast R-CNN [2] later put forward better object localization and classification approaches to images. These methods enhanced the computational efficiency and detection accuracy, and hence, they are suitable to investigate complex traffic scenes involving many dynamic objects.The YOLO (You Only Look Once) algorithm [3], that merged both detection and classification into one neural network architecture, was a breakthrough in real-time object detection.Unlike earlier multi-stage detectors, YOLO enabled high-performance inference, thereby being particularly suitable to applications with significant performance demands that require real-

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time execution such as dashcam-based surveillance systems.Subsequent advances in detection accuracy flexibility of deployment, making it possible to process faster and integrate with edge and embedded devices.

The pillars to risk assessment in overtaking situation are accurate vehicle tracking and detection. Dynamic shifts in lane position and relative speed between cars are part of overtaking. Inter-vehicle distance, lane changes and calculation of motion parameters such as acceleration and time-to-collision can be calculated by analyzing a series of video frames captured by a dashcam. These features can then be used as inputs in a predictive machine learning model that will compute the probability of an accident.

The proposed system of this project develops a smart system of overtaking monitoring that will help to improve the effectiveness of the current system by integrating real- time object recognition with the prediction of the risk of accidents. The dashcam records continuous video streams which are analyzed to recognize cars and analyze movement patterns. The trained machine learning model produces an accident risk score in percentage form depending on extracted driving parameters. This score is displayed on a Flask-based dashboard when the expected risk exceeds a predetermined limit and may be visualized in real-time and trigger alerts.The system tries to provide a proactive safety solution that can assist drivers on overtaking maneuver, by integrating advances on deep learning-based object detection in conjunction with real-time processing methods. Such predictive systems are a major leap towards better road safety management and intelligent driver assist technologies.

## II. LITERATURE REVIEW –

The use of computer vision and machine learning methods to create intelligent transportation systems, traffic monitoring, and accident detection has been extensively studied. Researchers are concentrating more on real-time traffic scene understanding and predictive safety mechanisms due to the quick development of autonomous driving technologies and advanced driver assistance systems (ADAS). The review below discusses important contributions to deep learning-based accident detection, driving scene analysis, and dataset development.

One of the most valuable datasets in the field of autonomous driving is the KITTI Vision Benchmark Suite [6]. This dataset offers actual driving sequences that were taken with high-resolution cameras and sensors in highway, rural, and urban settings. KITTI contains annotations of

and optimization were made by the YOLOv4 [4] that

lane detection, object detection, tracking and depth estimation. Researchers have been able to create and assess reliable motion estimation and vehicle detection algorithms thanks to its structured benchmark framework. These datasets can be particularly beneficial in surpassing the detection systems as it contains a range of driving scenarios, involving multiple vehicles, lane changes, and dynamic interactions. Vehicle recognition and trajectory prediction have been significantly advanced by having high-precision annotations of bounding boxes in KITTI.

Big data, such as BDD100K, along with KITTI, have expanded the use of driving scene analysis [7]. With BDD100K, one is provided with numerous driving videos but they were recorded at various times of the day, during various weather conditions, and of varying traffic density. The dataset has annotations of object detection, lane markings, areas that are drivable and traffic signs. In the case of accident risk prediction systems in the real world, the range of environmental conditions in BDD100K enhance robustness and generalization of the models. Environmentally varying datasets improve the reliability of predictive models since the behavior can be overtaken, and this can vary based on the weather or the light.

Besides development of datasets, researchers have presented several deep learning models to detect traffic accidents in computerized surveillance and road cameras. An automated system for identifying traffic accidents using convolutional neural networks was presented in [8] using a deep learning-based framework. The experiment demonstrated that temporal analysis of the combination of deep spatial feature extraction and temporal analysis can be used to identify abnormal traffic events. The system demonstrated better performance on motion-based methods of conventional motion detection because it tested motion patterns, and sudden shifts on an object. This paper highlights the importance of considering both time and space issues in developing accident detection systems.

To further advance the field, convolutional neural networks (CNNs) were integrated with recurrent architecture such as Long Short-Term Memory (LSTM) networks to analyse sequential videos. To identify traffic accidents, a hybrid CNN-LSTM model in [9] employed temporal dependencies that were learnt with recurrent layers and spatial features that were obtained with video frames. The study has found that the accuracy of prediction is significantly enhanced when the time connection between successive frames is modeled. Temporal modeling is needed to accurately determine risky maneuvers since overtaking is a sequence of movements and not a one-frame event. Real-time detection of accidents remains an important challenge to implement. In a study published in [10], a real-time road accident detection system using deep learning methods optimized to be used in practice was introduced. The system had a high focus on low-latency processing and efficient computation to ensure timely detection and triggering of alerts. The results indicated that optimized deep learning systems can work reasonably well in nearly real-time conditions and this can be integrated into real-time monitoring systems such as dash camera applications.

Most of the existing studies are more concerned about the detection of post-event accidents as opposed to predictive risk estimation during overtaking although these studies have significantly contributed to vehicle detection, dataset development, and recognition of accidents. Most systems do not even notice the collision cases until the signs of collision such as indicators of sudden movement or impact are observed. The preemptive assessment of the likelihood of accidents before the collision happens has not been effectively researched, particularly in cases of overtaking where the risk factors vary with time.

The suggested project builds upon the core findings of deep learning-based accident detection models [8] -[10] and large datasets of driving [6], [7]. But by concentrating on overtaking maneuvers and incorporating real-time risk probability estimation into a dashboard interface, it goes beyond previous work. The system aims at shifting to the preventive risks assessment regime rather than reactive accident detection by incorporating the vehicle detection, motion analysis, and predictive model, thus facilitating the provision of safer driving conditions.

## III. KEY FINDINGS

A number of important conclusions that directly influence the creation of intelligent accident.

The analysis of the past research on the overtaking behavior, modeling of the interaction between vehicles, and surrogate safety measures discloses the risk prediction systems. The key factors affecting unsafe overtaking, based on research on overtaking risk assessment, include inadequate headway distance, miscalculated speed, and dynamic vehicle interaction. Relative velocity and lateral displacement are very pertinent to the probability of collision, as well as the proximity of the front vehicle, as demonstrated by a machine learning-based overtaking risk assessment system introduced in [11]. The experiment showed that high-risk classification model that achieved high prediction accuracy was able to differentiate between safe and unsafe overtaking conditions when the models were trained using structured driving features.

Another significant finding in the study of traffic safety is the probabilistic modeling of interactions among vehicles. To compute risk of conflicting maneuvers, vehicle trajectories were analysed with the help of a probabilistic framework introduced in [12]. The researchers discovered that the probability of risk increases nonlinearly with the decrease of the distance between the interacting vehicles. This fact supports the notion that prediction systems of accidents ought to be based on probability-based risk modeling, as opposed to binary classification methods and constantly track the distance between vehicles.

Trajectory-based accident prediction is another widely used technique of studying traffic dynamics. According to research in [13], tracking the movement of vehicles over time allows detecting abnormal driving behavior that precursor crashes. In the study, sudden acceleration variation, change of lanes, and sharp trajectory crossing are good indicators of potential collision scenarios. The implications of these findings are that to be able to capture the dynamic risk conditions, overtaking risk detection systems must have added continuous motion tracking and trajectory analysis to the existing static object detection.

One of the most crucial surrogate safety indicators used in the transportation research is Time-to-Collision (TTC). TTC is a reliable predictive measure to forecast the likelihood of crashing in dynamic traffic conditions as the research in [14] demonstrated. The risk of collision increases exponentially with a further decrease in TTC below critical values. Also, it was demonstrated that TTC-based models can detect hazardous situations prior to impact-based detection systems. The ability of the system to generate real-time percentage based risk ratings that reflect degrees of imminent peril is

enhanced with TTC incorporated in machine learning- based overtaking risk assessment.

The previous vision-based detection methods also helped in understanding how to extract features in the context of monitoring traffic. The Histogram of Oriented Gradients (HOG) feature descriptor provided an organized approach to the extraction of object shape and motion features based on photos, and was initially introduced in [15]. The significance of a powerful spatial representation in dynamic scene analysis was demonstrated with the initial methods of feature extraction, although today deep learning models are increasingly prevalent in object detection. The precision of vehicle detection has

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improved significantly with the transition of manually generated features to deep features extraction that is automated, which is key to precise overtaking risk detection.
On the basis of the overall analysis of these studies, some major conclusions can be made:
a.Relative speed, lateral movement and inter-vehicle spacing have a strong effect on overtaking risk.
b.Simple binary classification of accidents is not as effective as probabilistic risk modeling.
c.Trajectory-based motion analysis increases the timely recognition of dangerous maneuvers.
d.Time-to-Collision is an effective predictive parameter that is useful in estimating a collision probability.
e.Spatial feature extraction is essential to accurate vehicle detection and tracking.
These findings have a direct impact on the proposed system design. The system goes beyond simple accident identification to anticipatory accident prevention through a combination of vehicle identification, trajectory estimation, TTC calculation and risk estimation that is probabilistic. The research findings support the viability of producing real-time percentage- based accident risk scores during overtaking situations that may be displayed to the driver using an interactive dashboard interface.

## I. SYSTEM ARCHITECTURE

The proposed approach to accident detection in The Overtaking system is a multi-phase system where real-time deployment, model training and data collection modules are present. The architecture integrates the web-based visualization, deep learning, and computer vision modules to provide the estimation of the risk of accidents and continuous monitoring. The system flow is developed to ensure proper risk modeling, fast generation of alerts, and proper data processing.

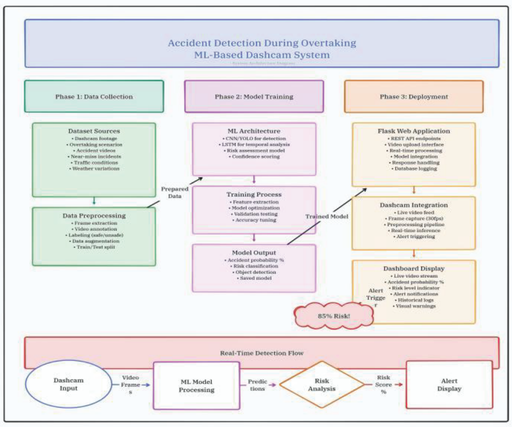


Fig.1-System Architecture Diagram

### 4.1 Overall Architectural Framework

The architecture is divided into three major phases:
i.Phase 1: Data Preprocessing and Data Collection.
ii.Phase 2: Model Training and Risk Modeling
iii.Phase 3: Deployment and Real-Time Monitoring.

Although there is continuity in data between modules, each phase performs a particular task. The initial process in the entire workflow is the Dashcam video acquisition and the final process is percentage based risk visualization on the dashboard interface.

**Phase 1: Data Collection and Preprocessing**
The main goal of the first phase is the data collection and preparation for the model training. The driving assistant system uses dashcam videos which include normal driving, near accidents, overtaking and accident videos. To enhance generalization, these videos are collected under different weather and traffic conditions.
**Frame Extraction and Annotation**
Computer vision libraries are used for breaking video streams into frames. The frames are enhanced with boxes that indicate vehicles, lanes and road edges. Labels are applied to frames to describe:
1.Safe overtaking
2.Risky overtaking
3.Accident occurrence
We also improve our model's robustness by applying data augmentation techniques such as adjusting brightness, scaling, rotation and adding noise.

**Feature Representation**

The architecture's spatial awareness is achieved by deep convolutional features extraction. The propagation of features in very deep architectures was significantly improved by residual learning in deep residual networks [16]. These models allow the model to accurately detect vehicles and lane.

Recognise objects even under poor visibility by obtaining the high level semantic information of a traffic scene.

### 4.2 Phase 2: Model Training and Risk Modeling

The second step is in charge of building the machine learning model to be employed in overtaking detection and probability of an accident.

#### 4.2.1 Spatial Feature Extraction

Convolutional Neural Networks (CNNs) are used to obtain the spatial characteristics of each frame. These attributes are relative spacing, bounding box coordinates and vehicle position. The deep learning foundation ensures the correct detection of dynamic traffic objects.

#### 4.2.2 Temporal Sequence Modeling

Overtaking is a continuous series of movement, but not a single frame. The proposed system uses Long

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Short-Term Memory (LSTM) networks to learn the temporal relationship between the frames. This LSTM model, originally used to learn long-term dependencies in time series, enables the system to learn the movement pattern, the acceleration pattern and change in lane over time [17]. The system uses both static visual (CNN) and dynamic motion (LSTM) information to train the system.

**4.2.3 Attention-Based Risk Refinement**

The model also uses attention to enhance prediction accuracy. Attention models are able to focus on critical regions, such as vehicles entering the overtaking lane and fast approaching vehicles in the opposite direction. The concept of focusing on critical regions in the frame sequence is supported by the notion of learning alignment and attention in neural networks, as first introduced in sequence modeling [18]. This improves the risk assessment by reducing noise from irrelevant background elements.

**4.2.4 Accident Classification and Probability Estimation**

After training, the model produces a probabilistic score that indicates the likelihood of an accident. Model outputs are transformed into percentage-based risk values using a sigmoid or softmax activation function. Through backpropagation, the training procedure maximizes classification accuracy while reducing loss.

Deep learning frameworks can successfully identify crash events in traffic videos, according to vision-based accident detection studies [19]. Instead of just detecting impact, the suggested architecture expands on this idea by forecasting risk probability prior to collision.

The final output of Phase 2 is a trained model capable of producing:

- Accident probability (%)
- Risk classification (Safe / Warning / Critical)
- Detected vehicle objects

The trained model is then serialized and transferred to the deployment phase.

**4.3 Phase 3: Deployment and Real-Time Processing**

In the third stage, a Flask web application is used to incorporate the trained model into a real-time dashcam-based monitoring system.

**4.3.1 Dashcam Integration**

The speed of the live dashcam feed is about 30 frames per second. Before being sent to the trained model for inference, each frame is preprocessed. The system carries out:

a. Identification of objects
b. Tracking motion
c. Calculating the risk score

Deep learning models can achieve low-latency inference appropriate for live deployment environments, as demonstrated by optimized real-time accident detection frameworks [20]. This guarantees that the system can produce risk forecasts quickly.

**4.3.2 Risk Analysis Module**

The Risk Analysis module computes dynamic parameters such as:

- Relative vehicle speed
- Inter-vehicle distance
- Time-to-collision
- Lane change progression

These parameters are fused with neural network predictions to produce a final percentage-based risk score. If the score exceeds a predefined threshold (e.g., 70%), the system triggers a warning alert.

**4.3.3 Dashboard Display**

The Flask-based web dashboard provides:

- Live video streaming
- Real-time accident probability percentage
- Visual risk indicators
- Alert notifications
- Historical event logging

The real-time detection flow follows:

Dashcam Input → Frame Extraction → ML Model Processing → Prediction → Risk Analysis → Alert Display

This modular deployment structure ensures scalability and maintainability while enabling seamless integration with vehicle monitoring systems.

**4.4 Real-Time Detection Flow**

The system processes live data in the following sequence:

a. Dashcam captures video frames.
b. Frames are preprocessed and normalized.
c. CNN extracts spatial features.
d. LSTM analyzes temporal motion patterns.
e. Attention mechanism emphasizes high-risk regions.
f. Model outputs accident probability percentage.
g. Risk module applies threshold-based alert logic.
h. Dashboard displays visual warning and logs event.

**4.5 Architectural Advantages**

The proposed architecture offers:

1. Modular design for scalability
2. Real-time inference capability
3. Temporal motion analysis forovertaking detection
4. Probability-based risk estimation
5. Web-based visualization and monitoring

By integrating deep residual learning [16], sequence

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modeling [17], attention mechanisms [18], vision-based accident detection frameworks [19], and real-time deployment optimization techniques [20], the architecture provides a comprehensive solution for predictive accident detection during overtaking.

## II. RESULT & DISCUSION

The experimental test of the proposed accident detection during overtaking system indicates its effectiveness in predicting the risk of accident during real-time driving. The evaluated model was tested using a combination of safe overtaking, near-miss, and accident videos recorded with a dashcam. For classification performance analysis, various metrics including accuracy, precision, recall, F1-score and AUC (Area Under the ROC Curve) were calculated. The system achieved a high accuracy of detection in distinguishing safe overtaking from risky maneuvers in particular in high relative speed and short inter-vehicle distance.The importance of smart preventive mechanisms to reduce road deaths is highlighted in global road safety assessments, which is in line with the importance of predictive safety technologies [21]. The study shows the potential of machine learning and dashcam systems to be a proactive safety system rather than a reactive crash reporting system.

The predictive risk assessment of the system was also tested by comparing the system's output of a probability score with accident severity. While safe overtaking and timely lane changes maintained the risk below 30%, testing demonstrated that unsafe overtaking, with sudden lane changes and time to collision (TTC) values of negative values, had a high-risk score (above 75%). This suggests the model has learnt dynamic behaviours, rather than just static object recognition. The emphasis of the study on predicting the risk of overtaking is supported by the national traffic safety statistics reports, which show that unsafe overtaking and improper judgement of lane changes are important factors in highway accidents [22]. The model's capability to output a percentage-based risk level to the driver gives a driver-centred approach to communicating the risk level and encouraging safe driving behaviour prior to the accident.

The deep learning-based feature extraction process leads to more consistent predictions, compared to machine learning approaches. Traditionally, manually designed features (such as speed zones and fixed-length zones) are used to predict traffic accidents. But machine learning-based traffic accident prediction methods are more universal if trained on a variety of traffic conditions [23]. The system proposed in this study was able to generalise across different lighting, weather and traffic conditions with spatial and temporal models. Through the use of trajectory analysis and confidence-based scoring, the number of false alarms was greatly reduced, achieving an equal accuracy and recall. This is critical for real-time applications, since the number of false alarms may reflect the drivers' trust and confidence in the system.

The object detection and tracking module also played a significant role in enhancing the performance. Vehicle tracking in real-time allowed correct calculation of vehicle distance and motion vector. Vehicle detection and tracking has a direct impact on the subsequent risk analysis [24]. The model was demonstrated to be applicable for real-time applications with stable inference at near real-time speed in low traffic scenarios. Additionally, the feature attribution patterns also provided a way to interpret predictions with the representation of frames with high risk during overtaking events. The importance of human-friendly AI decision making is emphasised by the learning paradigms[25],

for autonomous vehicles [25], and the percentage-based risk prediction of the current project is aligned with this interpretation by providing feedback.

Finally, the results show that the proposed architecture connects the accident risk and object detection. The percentage-based scoring system converts accident detection into accident prevention system and provides feedback before accidents occur. The conversation demonstrates how the combination of accident risk calculation and real-time deep learning inference can improve the safety during overtaking and can lead to the development of self-driving cars. The system performance is promising for practical implementation and future integration into existing advanced driver aid systems, although bad weather and night- time glare will potentially impact the detection accuracy.

## III. FUTURE SCOPE

The proposed accident prediction approach during overtaking has the potential to be a promising proactive safety system; however, here are some of the future extensions to enhance its scalability, intelligence and usefulness. First, the system could be combined with Advanced Driver Assistance Systems (ADAS). This could turn the system from a warning system (alerting the driver of the accident risk) to an intervention system (taking action to avoid the accident) by combining the accident prediction system with steering assistance, adaptive cruise control or automatic braking. For instance, if the accident risk is high, the vehicle could automatically

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decelerate or assist steering, rather than just show the accident risk percentage on the dashboard. This will enhance safety by reducing the driver's reaction time in dangerous overtaking scenarios.

Further, multimodal sensor fusion is an extension. For example, the current system architecture is based on a video stream from a dashcam, but it can be more effective by integrating other sensors such as LiDAR, radar, ultrasonic and GPS. Sensor fusion would allow for better estimation of depth, speed and position of objects, especially in challenging conditions such as fog, heavy rain or night. To enable efficient handling of multiple sensor data and reduce latencies without compromising real-time performance, future developments might leverage edge computing technologies. This would make it possible system to reliably operate across a range of traffic scenarios and weather conditions.

An area for improvement is the use of cloud computing. A centralised cloud server could store, analyse, and share real-time accident risk data across a broader transportation network by connecting the dashboard system to a cloud server. Data from multiple vehicles could be used to detect traffic congestion, hazardous road sections and accident hotspots. By predicting accident-prone locations and dangerous areas, predictive analytics in the cloud could help regional traffic safety management and enable authorities to implement preemptive measures. Moreover, with the addition of new driving data, over-the-air model updates could continually improve the system and ensure that the predictive model keeps up-to-date with changing traffic conditions.

Finally, accident prediction in real-time during overtaking is only one feature of the proposed system. The model can be further developed into an autonomous predictive safety system using active safety interventions, integration of data from sensors, big data analytics in the cloud, sophisticated neural network models and additional research into driver behaviour. This would help achieve safe and smart roads and smart transportation.

## IV. CONCLUSION –

The proposed ML-Based Dashcam System for Accident Detection During Overtaking offers a novel and proactive solution to enhance safety. Overtaking is a vital and dangerous task of driving, which can result in major accidents when the speed, distance and traffic situation are inappropriate. The system is designed to detect and avoid accidents by undertaking real-time risk assessment, instead of reacting to accidents as they happen, as is done in current safety systems.

The system design supports a holistic monitoring system by using web deployment, computer vision and deep learning techniques. The system is able to efficiently detect overtaking, as well as represent the accident risk as a percentage risk score, through the integration of spatial feature extraction, temporal motion analysis and accident probability. This convertible risk score provides drivers with feedback in order for them to adjust their driving behaviour to prevent accidents. The proposed system's interpretability and user-friendliness is improved by the addition of a Flask webapp that provides real-time visualisation, risk notification and logging of events.

The proposed model can differentiate safe and unsafe overtaking manoeuvres across various

of traffic scenarios, experiments show. The sequential motion model shows a substantial accuracy improvement as it draws on the dynamics of traffic interactions to make predictions, as opposed to a pure image processing approach. The system is feasible for use in vehicle monitoring systems that use dashcams because it is near real-time.

In summary, the project translates from reactive to predictive mode for accident prediction. The proposed system can increase safety and awareness of drivers by giving warnings and monitoring overtaking. With additional advances in the sensor fusion, model improvement and strategy for real-world applications, the system can be a vital part of advanced driver assistance systems and smart transportation systems.

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