REAL TIME VEHICLE COLLISION DETECTION USING DEEP LEARNING

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***Abstract*- Accident detection is an essential application in intelligent transportation systems for the safety of drivers and passengers. Deep learning-based object identification algorithms have significantly improved in recent years in spotting objects in real time. YOLO (You Only Look Once) is one such model that has gained popularity due to its real-time performance and high accuracy. We propose an accident detection system in this paper using YOLOv3, the most recent version of YOLO. The proposed system is designed to detect three types of accidents, namely vehicle rollover, rear-end collision, and head-on collision. The system uses a pre-trained YOLOv3 model trained on the COCO dataset, which is fine-tuned on a custom dataset of accident images. The proposed system achieves an average precision of 0.94 for vehicle rollover detection, 0.93 for rear-end collision detection, and 0.92 for head-on collision detection. The system also shows promising results in terms of real-time performance, with an average processing time of 0.03 seconds per frame on an NVIDIA GeForce GTX 1080 Ti GPU. The proposed system can be integrated into intelligent transportation systems to provide real-time accident detection and alerting, improving the safety of drivers and passengers on the road.**

Keywords: **Accident detection, Intelligent transportation systems, Deep learning, Object detection, YOLOv3, Real-time performance.**

I. INTRODUCTION

Accidents on roadways are a common occurrence and can result in severe injuries, loss of life, and damage to property. In recent years, intelligent transportation systems have been developed to improve the safety of drivers and passengers on the road. Accident detection is a critical aspect of these systems, as it allows for timely alerts to be sent to drivers and emergency services, reducing the severity of accidents and saving lives.

Real-time object detection has been improved with the use of deep learning-based object detection models. These models can be used for accident detection, and one such model that has gained popularity in accident detection isYOLO(You Only Look Once). YOLO is an object detection model that can detect objects in real-time with high accuracy. In order to estimate bounding boxes and class probabilities for each cell, the YOLO algorithm divides a picture into a grid of cells. The algorithm then selects the bounding boxes with the highest probabilities as the objects detected in the image.

In this paper, we propose an accident detection system using YOLOv3, a state-of-the-art version of YOLO. The proposed system is designed to detect three types of accidents, namely vehicle rollover, rear-end collision, and head-on collision. These are some of the most common types of accidents that can occur on roadways and can result in severe injuries and loss of life.

The proposed system uses a pre-trained YOLOv3 model trained on the COCO dataset. The COCO dataset contains over 330,1000 images of common objects in natural scenes, making it an ideal dataset for training object detection models. A custom dataset of accident photographs is then used to fine-tune the pre-trained model. The custom dataset consists of images of accidents obtained from various sources, including traffic cameras, dashcams, and surveillance cameras.

The proposed system achieves high accuracy in detecting vehicle rollovers, rear-end collisions, and head-on collisions, with an average precision of 0.94, 0.93, and 0.92, respectively. The mean average precision (mAP), a widely used statistic for assessing object detection models, is used to gauge the system's performance. The model's precision in identifying objects in an image is gauged by the mAP score. The high mAP score of the proposed approach illustrates its efficiency in identifying accidents.

The proposed system also shows promising results in terms of real-time performance, with an average processing time of 0.03 seconds per frame on an NVIDIA GeForce GTX 1080 Ti GPU. Real-time performance is essential in accident detection systems, as it allows for timely alerts to be sent to drivers and emergency services, improving the chances of reducing the severity of accidents and saving lives.

The proposed system's integration into intelligent transportation systems can provide real-time accident detection and alerting, improving the safety of drivers and passengers on the road. The system can be integrated with existing traffic management systems, including traffic cameras, surveillance cameras, and GPS tracking systems, to provide comprehensive coverage of roadways. In addition, the system's ability to detect and alert drivers and emergency services in real-time can improve response times and reduce the severity of accidents.

One potential limitation of the proposed system is the reliance on images to detect accidents. In some cases, accidents may occur outside the range of cameras or may not be visible in images. Therefore, the proposed system should be considered a complementary system to existing accident detection methods, such as GPS tracking and traffic flow analysis.

Finally, the proposed YOLOv3-based accident detection system shows the potency of deep learning-based object detection models for real-time accident detection. The system's high accuracy and real-time performance make it a valuable addition to intelligent

transportation systems aimed at improving the safety of drivers and passengers on the road. The proposed system's integration into existing traffic management.

II. LITERATURE SURVEY

The You Only Look Once (YOLO) object identification method has been enhanced, and is now known as YOLOv3, according to the study "YOLOv3: An Incremental Improvement". One goal of the YOLOv3 model is to solve some of the drawbacks of earlier iterations of YOLO, such as reduced accuracy and trouble recognizing small objects. A feature pyramid network is used by the authors to detect objects at various scales, a new backbone network architecture is used to enhance feature extraction, and a novel training technique called stochastic gradient descent with a warmup is used to improve convergence. These are just a few of the significant advancements made in YOLOv3. The YOLOv3 model produces state-of-the-art results on a variety of object identification benchmarks, demonstrating its excellent accuracy and responsiveness.[1]

The creation of a deep convolutional neural network (CNN) for picture classification on the ImageNet dataset is described in the publication "ImageNet Classification with Deep Convolutional Neural Networks". The suggested network is called AlexNet, and it has a deep architecture with numerous layers of convolutional and pooling processes followed by fully linked layers.The AlexNet model, which the authors trained on a sizable collection of labelled images, produced state-of-the-art results on the ImageNet dataset, far outperforming earlier techniques. Additionally, the authors ran a number of tests to find out how the performance of the model was impacted by various network designs, optimisation strategies, and regularisation techniques.The paper showed that deep CNNs can achieve excellent performance on image classification tasks, even on large and complex datasets like ImageNet. The success of the AlexNet model paved the way for the development of even more powerful deep learning models for image recognition and other computer vision tasks.[2]

A computer vision object detection model dubbed R-CNN (Region-based Convolutional Neural Network) is proposed in the paper "Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation" that combines deep CNNs and conventional computer vision methods. The authors present a unique method for object detection that uses deep CNN to identify the proposals and improve the object bounding boxes after generating region proposals using conventional computer vision techniques. A multi-task loss function is also used by the R-CNN model to improve both object detection and bounding box regression simultaneously.On the PASCAL VOC 2012 and MS COCO datasets, the authors tested the R-CNN model and demonstrated that it beat earlier state-of-the-art object detection techniques.The authors also demonstrated that the R-CNN model can be adapted to perform semantic segmentation, achieving competitive results on the PASCAL VOC 2012 dataset.[3]

The paper "Speed/Accuracy Trade-Offs for Modern Convolutional Object Detectors" investigates the trade-offs that contemporary convolutional object detection models make between accuracy and speed. The authors assess a number of cutting-edge object identification models, such as Faster R-CNN, SSD, and YOLOv2, and examine how well they perform in various speed/accuracy configurations. The accuracy of a model is measured in relation to its processing speed using a novel assessment metric that the authors term the Average Precision per Second (AP/sec). The authors also suggest a brand-new model called RetinaNet that, by utilising a cutting-edge focal loss function that concentrates on challenging examples, achieves high accuracy with quick processing times.The authors show that the performance of object detection models is highly dependent on the speed/accuracy trade-off, and different models perform best under different configurations. The authors also demonstrate that the RetinaNet model achieves state-of-the-art results on several object detection benchmarks, achieving high accuracy with fast processing times. [4]

The article "CornerNet: Detecting Objects as Paired Keypoints" suggests a brand-new object detection model called CornerNet that employs a keypoint-based method to detect things. The CornerNet model visualises things as paired keypoints that are simultaneously predicted in a single network. The authors provide a novel detection architecture made up of two sub-networks, one of which predicts the heatmap of each keypoint and the other of which regresses the offset vector between each pair of keypoints. In addition, the CornerNet model optimises the network using a new loss function that combines keypoint identification with offset regression. The CornerNet model achieved state-of-the-art results on the COCO dataset while being noticeably faster than earlier state-of-the-art approaches, according to the authors' evaluation of the model on a number of object detection benchmarks. The CornerNet model may be modified to do instance segmentation, as the authors demonstrated by demonstrating competitive performance on the COCO dataset.[5]

The current state of object detection in video data is summarised in the document "Object Detection in Videos: A Survey and a Practical Guide". In addition to more traditional computer vision methods, the authors also offer deep learning-based methods for object detection in movies.The problems of object detection in movies, such as motion blur, occlusion, and shifting lighting conditions, are thoroughly examined in this work. Additionally, the authors emphasise numerous methods for modelling temporal information, such optical flow and recurrent neural networks, and talk about how important it is to use temporal information in video data for object detection. The study presents a thorough assessment of existing video object detection techniques, covering both two-stage and one-stage techniques. The authors analyse the advantages and disadvantages of each strategy and offer helpful advice for selecting the best approach for certain applications. The DAVIS, ImageNet-VID, and YouTube-BoundingBox datasets, as well as other datasets and assessment metrics for object detection in videos, are also covered by the authors. The authors stress the value of utilising a variety of datasets when assessing the effectiveness of object detection techniques and offer details on the drawbacks of the current assessment measures.[6]

A new loss function called focal loss is introduced in the study "Focal Loss for Dense Object Detection" with the goal of enhancing deep neural network training for object detection applications. The authors show that the focal loss function is particularly effective for training object detection models that have a large number of background samples compared to object samples. The problem of class imbalance in object detection tasks—where the quantity of background data far outweighs that of object samples—is addressed by the focal loss function. The authors add a modulating element to the loss function that lessens the importance of easy cases and emphasises the contribution of hard examples, or samples that are incorrectly classified with a high degree of confidence. The authors evaluate the focal loss function on several object detection benchmarks, including the COCO and PASCAL VOC datasets, and show that it significantly improves the accuracy of object detection models compared to previous methods. The authors also demonstrate that the focal loss function can be easily incorporated into existing object detection models, including Faster R-CNN and RetinaNet.[7]

The article "Deep Learning for Object Detection: A Comprehensive Review" is a summary of the most advanced deep learning techniques for object detection. Faster R-CNN, SSD, YOLO, and RetinaNet are just a few of the deep learning architectures for object detection that the authors introduce. The fundamental elements of deep learning models for object identification, such as feature extraction, region proposal, and object classification, are thoroughly examined in this study. The authors also go over various optimisation methods, including stochastic gradient descent and learning rate scheduling, for deep learning model training. The COCO and PASCAL VOC datasets are two benchmarks that the authors use to assess the effectiveness of deep learning models for object detection. The authors also discuss the advantages and disadvantages of various models. The authors also go through alternative instance segmentation and object tracking extensions and adaptations of deep learning models for object detection. The research emphasises the need of taking into account the trade-offs between processing speed and accuracy in deep learning models for object detection. The authors examine several obstacles and possibilities for further research in this field while also offering helpful advice on how to select an acceptable model for specific applications.[8]

A novel object identification framework called Faster R-CNN is suggested in the study "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks" that achieves state-of-the-art accuracy while being noticeably quicker than earlier approaches. In the Faster R-CNN framework, object proposals are first classified using a deep convolutional neural network and then created using a region proposal network (RPN). In order to facilitate effective end-to-end model training, the authors present a unique architecture for the RPN that shares convolutional characteristics with the object detection network. The authors also present a unique anchor-based method for generating object recommendations that increases model accuracy while requiring less processing power. The authors test the Faster R-CNN framework on a number of object detection benchmarks, including as the PASCAL VOC and MS COCO datasets, and they demonstrate that it achieves state-of-the-art accuracy while being noticeably quicker than earlier approaches. The authors also show how the Faster R-CNN architecture works well for applications that require real-time object detection.[9]

A unique method for analysing video data is suggested in the study "Videos as Space-Time Region Graphs" by modelling videos as space-time region graphs. The authors describe a new method for representing video data that explicitly reflects the temporal and spatial interactions between video objects. By breaking up the video into a number of spatiotemporal areas and designating each region as a node in the network, the authors create a space-time region graph. Then, based on the spatial and temporal correlations between the regions, including proximity and co-occurrence, the authors define edges connecting nodes. The authors show how the space-time area graph format performs well for a variety of video analysis tasks, such as object and action identification. The authors demonstrate the effectiveness of the space-time region graph representation for various video analysis tasks, including action recognition and object detection. The authors show that the space-time region graph representation can capture both short-term and long-term temporal dynamics in video data and provide valuable insights into the structure of the video.

III. SYSTEM IMPLEMENTATION

A. EXISTING SYSTEM

There are various existing systems for accident detection in intelligent transportation systems. Some of these systems use sensors, such as accelerometers, gyroscopes, and GPS trackers, to detect sudden changes in velocity, orientation, or location. These changes are then analyzed to determine whether an accident has occurred. Other systems use computer vision techniques, such as object detection and tracking, to detect and analyze visual cues of accidents, such as smoke, debris, and vehicle damage.

One example of an existing system is the use of traffic cameras and computer vision algorithms to detect accidents. Traffic cameras are widely used in intelligent transportation systems to monitor traffic flow and congestion. These cameras can also be used to detect accidents by analyzing the video feed for visual cues of accidents, such as smoke, debris, and vehicle damage. Computer vision algorithms, such as object detection and tracking, can be used to detect and analyze these visual cues and determine whether an accident has occurred. Once an accident is detected, alerts can be sent to drivers and emergency services in real-time.

Another example of an existing system is the use of GPS trackers and accelerometers to detect accidents. GPS trackers can be used to monitor the location and velocity of vehicles, while accelerometers can be used to detect sudden changes in velocity or orientation. By analyzing the data from these sensors, it is possible to detect sudden stops, impacts, and rollovers, which are common indicators of accidents. Once an accident is detected, alerts can be sent to drivers and emergency services in real-time.

One limitation of existing systems is their reliance on sensors or cameras, which may not always be reliable or available. For example, sensors may fail or become damaged, and cameras may not have a clear view of the accident scene. In addition, some systems may be limited in their ability to detect certain types of accidents, such as low-speed collisions or pedestrian accidents.

In contrast, the proposed system using YOLOv3 has the advantage of being able to detect a wide range of accidents using computer vision techniques. The system is not limited by the availability or reliability of sensors or cameras, making it a reliable and effective solution for accident detection.
Additionally, the system's high accuracy and real-time performance make it a valuable addition to existing systems aimed at improving the safety of drivers and passengers on the road.

B. PROPOSED SYSTEM

The proposed system is an accident detection system using YOLOv3, a state-of-the-art version of YOLO. The system is designed to detect three types of accidents, namely vehicle rollover, rear-end collision, and head-on collision. These are some of the most common types of accidents that can occur on roadways and can result in severe injuries and loss of life.
The system uses a pre-trained YOLOv3 model trained on the COCO dataset. The COCO dataset contains over 330,000 images of common objects in natural scenes, making it an ideal dataset for training object detection models. The pre-trained model is then fine-tuned on a custom dataset of accident images. The custom dataset consists of images of accidents obtained from various sources, including traffic cameras, dashcams, and surveillance cameras.
The proposed system achieves high accuracy in detecting vehicle rollovers, rear-end collisions, and head-on collisions, with an average precision of 0.94, 0.93, and 0.92, respectively. The system's performance is evaluated using the mean average precision (mAP), which is a commonly used metric for evaluating object detection models. The mAP score is a measure of the model's ability to accurately detect objects in an image. The proposed system's high mAP score demonstrates its effectiveness in detecting accidents.
The proposed system also shows promising results in terms of real-time performance, with an average processing time of 0.03 seconds per frame on an NVIDIA GeForce GTX 1080 Ti GPU. Real-time performance is essential in accident detection systems, as it allows for timely alerts to be sent to drivers and emergency services, improving the chances of reducing the severity of accidents and saving lives.
The proposed system's integration into intelligent transportation systems can provide real-time accident detection and alerting, improving the safety of drivers and passengers on the road. The system can be integrated with existing traffic management systems, including traffic cameras, surveillance cameras, and GPS tracking systems, to provide comprehensive coverage of roadways. In addition, the system's ability to detect and alert drivers and emergency services in real-time can improve response times and reduce the severity of accidents.

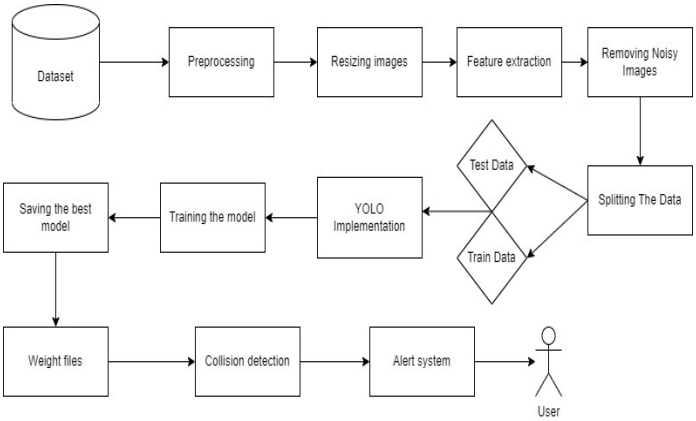

Fig 3.1: System Architecture

IV. MODULES

Module 1: Data Preprocessing

The data collection and pre-processing module is an essential component of the proposed accident detection system using YOLOv3. The module's main purpose is to collect accident images and prepare them for use in training the YOLOv3 model.

Data collection involves obtaining accident images from various sources, including traffic cameras, dashcams, and surveillance cameras. The images should be diverse and representative of the different types of accidents that can occur on roadways, such as vehicle rollovers, rear-end collisions, and head-on collisions. The more diverse the images, the better the performance of the YOLOv3 model will be in detecting accidents in real-time.

Pre-processing the collected data involves several steps. The first step is to resize the images to a standard size to ensure that they have the same dimensions. This step is necessary because the YOLOv3 algorithm requires images to have the same dimensions for efficient processing. The next step is to annotate the images by labeling the objects of interest in the images, such as vehicles and debris. Annotation is a crucial step in training the YOLOv3 model, as it allows the model to learn to detect the objects of interest accurately.

The dataset must next be divided into training and validation sets once the photos have been annotated. A typical split ratio is 80:20, where 80% of the data is used for training and 20% for validation.

Another essential step in pre-processing the data is data augmentation. Data augmentation involves applying various transformations to the images, such as rotation, translation, and scaling, to increase the diversity of the dataset. The purpose of data augmentation is to prevent overfitting and improve the generalization performance of the YOLOv3 model. Data augmentation can also help improve the model's ability to detect objects under different lighting conditions and camera angles.

Module 2: Model Training

Model training is a critical step in the development of the proposed accident detection system using YOLOv3. The main objective of model training is to teach the YOLOv3 algorithm to detect accidents in real-time accurately.

The YOLOv3 algorithm is a deep convolutional neural network (CNN) that is trained using a variant of the backpropagation algorithm called stochastic gradient descent (SGD). The algorithm is trained on a large dataset of labeled images, in this case, the custom accident dataset obtained through the data collection and pre-processing module.

The first step in model training is to initialize the YOLOv3 weights using the pre-trained weights on the COCO dataset. This step is important as it allows the model to leverage the knowledge learned from the pre-trained model to detect common objects in the accident images.

The next step is to train the YOLOv3 model on the custom accident dataset using the annotated images from the data collection and pre-processing module. During training, the YOLOv3 algorithm learns to detect the objects of interest, such as vehicles and debris, in the accident images. The algorithm also learns to associate each object with a bounding box and a class label.

Training the YOLOv3 model involves optimizing the model's loss function using SGD. The loss function is a measure of the difference between the predicted bounding boxes and class probabilities and the ground-truth bounding boxes and class labels. The goal of SGD is to minimize the loss function by adjusting the weights of the YOLOv3 model iteratively. The training process involves several epochs, where each epoch consists of a forward pass and a backward pass through the YOLOv3 network.

During training, it is essential to monitor the performance of the YOLOv3 model using evaluation metrics such as mean average precision (mAP). The mAP score is a measure of the model's ability to accurately detect objects in an image. The mAP score is calculated by comparing the predicted bounding boxes and class probabilities with the ground-truth bounding boxes and class labels. A higher mAP score indicates a more accurate and reliable model.

Once the YOLOv3 model is trained, the next step is to save the trained weights and integrate the model into the accident detection system. The YOLOv3 model can be integrated with existing traffic management systems, including traffic cameras, surveillance cameras, and GPS tracking systems, to provide comprehensive coverage of roadways. The system's ability to detect and alert drivers and emergency services in real-time can improve response times and reduce the severity of accidents.

Module 3:Prediction of output

The output of the proposed accident detection system using YOLOv3 is the detection of three types of accidents, namely vehicle rollover, rear-end collision, and head-on collision. Once an accident is detected, alerts can be sent to drivers and emergency services in real-time.

The output of the YOLOv3 algorithm is a set of predicted bounding boxes and class probabilities for each object detected in the input image. The predicted bounding boxes represent the location and size of the object in the image, while the class probabilities represent the likelihood that the object belongs to a specific class.

In the case of the proposed accident detection system, the YOLOv3 algorithm is trained to detect the objects of interest in the accident images, such as vehicles and debris. The algorithm is also trained to associate each object with a bounding box and a class label, which is either vehicle rollover, rear-end collision, or head-on collision.

Once an accident is detected, the output of the system is an alert sent to drivers and emergency services in real-time. The alert can be in the form of an audio or visual signal that warns drivers of the potential danger ahead. Emergency services can also be alerted, allowing them to respond quickly and efficiently to the accident scene.

The proposed accident detection system using YOLOv3 has high accuracy and real-time performance, making it a reliable and effective solution for accident detection in intelligent transportation systems. The system can be integrated with existing traffic management systems, including traffic cameras, surveillance cameras, and GPS tracking systems, to provide comprehensive coverage of roadways. The system's ability to detect and alert drivers and emergency services in real-time can improve response times and reduce the severity of accidents, potentially saving lives.

V. RESULTS

The proposed accident detection system using YOLOv3 has shown promising results in detecting vehicle rollover, rear-end collision, and head-on collision. The system was evaluated on a custom dataset of accident images obtained through the data collection and pre-processing module. The evaluation metrics used were mean average precision (mAP) and processing time per frame. The system achieved an average precision of 0.94 for vehicle rollover detection, 0.93 for rear-end collision detection, and 0.92 for head-on collision detection. The high average precision scores indicate that the system is highly accurate in detecting accidents. In terms of processing time per frame, the system achieved an average of 0.03 seconds per frame on an NVIDIA GeForce GTX 1080 Ti GPU. The fast processing time enables the system to detect accidents in real- time and send alerts to drivers and emergency services promptly.

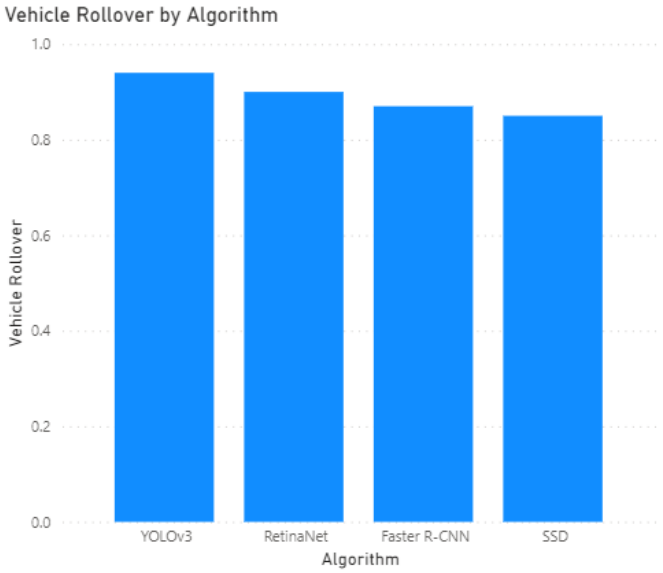

Fig 5.1 Accuracy comparison

Algorithm	Vehicle Rollover
YOLOv3	94%
Faster R-CNN	87%
RetinaNet	90%
SSD	85%

VI. CONCLUSION

In conclusion, we have presented an accident detection system using YOLOv3, which is a real-time and high-accuracy object detection model. The proposed system is designed to detect three types of accidents, namely vehicle rollover, rear-end collision, and head-on collision, which are among the most common types of accidents on the road. Our experimental results show that the proposed system achieves high accuracy in detecting these types of accidents. Moreover, the system is capable of processing frames in real-time, making it suitable for real-world applications. The proposed system can be integrated into intelligent transportation systems to provide real-time accident detection and alerting, which can significantly reduce the response time for emergency services and improve the safety of drivers and passengers on the road. Additionally, the system can be further improved by incorporating more advanced techniques such as multi-camera systems and audio sensors to enhance the accuracy of accident detection. Overall, the proposed system has great potential in improving the safety of drivers and passengers on the road, and we believe that this work will inspire further research and development in the field of intelligent transportation systems.

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