# Automated Road Damage Detection Using Drone and Vehicle-Mounted Cameras With Deep learning

Siddharth
*Bachelor of Engineering (CSE),*
Chandigarh University
Mohali, Punjab, India-140413
siddharthnain3@gmail.com

Ankita Sharma
*Bachelor of Engineering (CSE),*
Chandigarh University
Mohali, Punjab, India-140413
ankita.e11389@cumail.in

Diksha
*Bachelor of Engineering (CSE),*
Chandigarh University
Mohali, Punjab, India-140413
diksha22bcs15806@gmail.com

Harsh Kumar
*Bachelor of Engineering (CSE),*
Chandigarh University
Mohali, Punjab, India-140413
hey.harshgopal@gmail.com

Ishu
*Bachelor of Engineering (CSE),*
Chandigarh University
Mohali, Punjab, India-140413
ishuraj154@gmail.com

***Abstract*— The potholes, cracks and surface deformations caused during the road damage are so dangerous to the transportation safety and very expensive in terms of the infrastructure maintenance. This damage should be identified early and in a proper way in effective management of roads. The proposed study is an automated road damage detection system, where in this instance the drone-based and the vehicle-mounted cameras would be used and the real-time image of the road would be made available. Additional deep learning systems, like Convolutional Neural Networks, YOLO and Mask R-CNN, are able to identify and categorize multiple kinds of road damage with high precision. The results of the experiment suggest that it can have high detection accuracy, have high processing speed, and be stable in various road conditions. The given solution reveals the potentiality of integrating autonomous imaging and deep learning of developing scalable and automated tools to conduct proactive maintenance of roads that will ultimately result in enhancing road safety and maintenance time.**

**Keywords— Road Damage Detection, Deep Learning, Drone Imaging, Mask R-CNN, Convolutional Neural Networks, YOLO, Vehicle-Mounted Cameras, Real-Time Detection, Infrastructure Safety, Automated Road Maintenance.**

## I. INTRODUCTION

Modern transportation relies on road infrastructure as one of its foundations, and it has a direct influence on economic development, safety of the population, and its mobility in general. Proper roads minimize wear and tear of vehicles, avoid accidents and facilitated transportation of goods and people.[1] Nevertheless, roads are always stressed concerning the environment, traffic loads, and natural wear resulting in different types of damages including potholes, cracks, rutting, and surface deformations[2]. Early identification of these damages is essential to ensuring the quality of infrastructure and ensuring that the cost of repair is reduced.[3]

The traditional car inspections were on manual surveys which were conducted by field engineers. These inspections are often intensive, labour intensive and susceptible to human error although they would be effective on a small scale.[4] In addition, it is not easy to cover wide road systems and the damage can not be felt in the long run leading to adverse road conditions, high maintenance costs, and safety risks.[5]

The emergence of imaging technology, namely, drones and vehicle-mounted cameras, offer the newly emerged opportunities of efficient road policing.[6] Drones are capable of capturing aerial view of a large area in a limited amount of time compared to a vehicle-mounted camera and therefore provide a detailed ground-level view of the road, hence enabling assessments of the roads to be performed continuously and exhaustively.[7] The resulting combination of these technologies will allow gathering data in multi-perspective and it will ensure an improved detection of road anomalies.[8]

Deep learning has become an effective technique in automated analysis of images. Convolutional Neural Networks (CNNs), YOLO, and Mask R-CNN are a few examples that can be trained to identify and classify the damage with a high accuracy rate in road images in different conditions of lighting and weather.[9] By integrating deep learning with drone and vehicle-mounted imaging, to detect road damages in real-time and on a scale, eliminating the need to rely on manual inspection and enhancing the efficiency of maintenance.[10]

### *A. Problem Statement*

Even with the use of imaging and machine learning technology, a very big gap still needs to be filled in terms of creating an integrated, automated system that can successfully detect and classify the road damage under various conditions of the road in real-time. Current approaches tend to be either not scalable, not robust or not fast, which constrains their practical use in large road networks.

### *B. Research Objectives and Scope*

To develop a robotized system of detection and classification of damages on the roads with drone and vehicle-mounted cameras.

- To deploy and optimize deep learning designs to detect road damages in real-time and with high accuracy.
- To record the performance of the system in a way that it determines the detection accuracy, processing speed, and robustness of the system in different types of roads and environmental conditions.
- To offer a scalable model which can help municipal officials and transportation authorities in taking into

account the proactive planning of road maintenance, in terms of improving the overall road safety and the sustainability of the infrastructure.

## II. Related work

### A. Traditional Methods

Traditionally, the method of road condition estimation has been dependent on the manual checks made by field engineers. These checks include visual inspection and in some cases basic measurements to calculate irregularities of surfaces.[11] Although manual techniques are good in small-scale observations, it is labor-intensive and time-consuming and is susceptible to human error. Moreover, they offer minimal coverage and frequently fail to cover damages on the first stages that may intensify with the passing of time. Road images that are captured by cameras have also been processed using image processing methods e.g. edge detection and thresholding. [12]These techniques are however sensitive to the parameters used and cannot work in different lighting, weather or road surface conditions thus restricting their usability in practice.[13]

### B. Current Automated Methodologies.

In order to defeat the shortcomings of manual inspection, scientists have investigated the idea of automated road monitoring by placing cameras and vehicle-mounted cameras on cars. [14]Such systems are capable of recording real-time information when vehicles pass roads and this provides better and extensive coverage. It has also been seen that the drones such as Unmanned Aerial Vehicles (UAVs) are also deployed to monitor the road conditions and provide high-resolution aerial imagery, as well as allow the fast inspection of large areas. Together with GPS and mapping technology, these automated solutions provide the possibility of detecting and reporting damages in locations. Most of these techniques, however, are handcrafted feature extraction, and hence not very good at generalizing across roads and contexts.[15]

### C. Deep Learning in Road Damage Detection.

The past few years have experienced a drastic change towards deep learning methods in road damage detection. Convolutional Neural Networks[16] have been extensively utilized to determine the image of a damaged and undamaged road surface and have shown high accuracy rate over the conventional image processing algorithms.[17] This is done by object detection models, which are YOLO (You Only Look Once) and SSD (Single Shot Detector), which can detect multiple instances of damage in a single image in real-time. Segmentation based models such as the Mask R-CNN and U-Net also enable localization of road damage at the pixel level thus enabling accurate detection of cracks, potholes, and other abnormalities.[18]

### D. Limitations of Prior Work

Although these were made, there are a number of limitations evident in literature. Other studies are limited by small and non-diverse datasets, which constrain the generalizability of the models to other road categories, light, and weather conditions.[19] Live processing is also a problem particularly with high-resolution drone images or multi-camera vehicle data. Also, the majority of systems prioritize the drone or vehicle-mounted imagery but can rarely combine both to increase the detection coverage and accuracy.[20]

### E. Research Gaps

The review identifies some of the critical gaps that the present research intends to overcome. A single system that would integrate both drone and vehicle-mounted cameras to keep full control over the roads is required. It needs strong deep learning models that can be used to detect objects in various conditions in real time. In addition, there are no scalable solutions that can be used to minimize the reliance on manual checks and ensure high accuracy and efficiency.

## III. Methodology

### A. Data Collection

The quality and the diversity of the dataset used is very crucial in identifying the nature of the road damage. This study is based on a combination of publicly available information and the pictures taken by the researcher. Public datasets include RDD2020 ( Road Damage Dataset 2020 ), GPRD ( German Pavement Road Dataset ) that include thousands of labeled photos of the different categories of road damage including potholes, cracks and rutting that were taken under different weather and lighting conditions. These datasets, and also supplemented, are collected using custom data through the use of drones and vehicle-mounted cameras. The general road infrastructure and the larger patterns of damage can be proposed by the use of aerial imagery which can be acquired using a camera mounted on drone-like vehicles, and a close-up perspective of the localized damage can be obtained by using a camera mounted on the vehicle. In order to enhance the model strength, the high-resolution images are captured under the various types of roads which include urban, rural, highways, and various conditions that are dependent on the environment. With a collected mixed dataset it is possible to have good generalization of the system to real world applications.

### B. Data Annotation

The deep learning models are being subdued with the necessity of aptly tagged datasets. The labels on all the images of the collected and public data are manually added with the assistance of labeling tools (LabelImg is utilized to locate objects and LabelMe is utilized to handle segmentation purposes). Bounding boxes and masks of areas of damage are respectively over damage in object detection models (e.g., YOLO), and segmentation models (e.g., Mask R-CNN, U-Net) respectively. All the annotated examples are sorted out, depending on their type, i.e. pothole, crack, rutting, or undamaged surface. What matters is the quality of annotations and their consistency, inconsistent labeling can lead to low model performance. Further, the sample of the data is also cross-validated with a number of annotators in order to establish high labelling accuracy.

### C. Model Training

The information is separated into training, validation and testing samples, in the 70:15:15 ratio, and all the sets of samples are expected to represent all the types of damages. Transfer learning is applied to utilize the earlier trained models such as the YOLOv8 or the Mask R-CNN that save training time and converge more frequently, as well as where the dataset is smaller. The hyperparameters, including the learning rate, the batch size, and the number of epochs and the type of the optimizer, are optimally and systematically tuned by using the validation set to reach the optimal performance related to detection. The data augmentation methods employed are rotation, horizontal / vertical flipping, manipulations of brightness, scaling, and random cropping to enhance the training data and go further in generalizing the models. The process of training takes the form of an iterative update through backpropagation and gradient descent to minimize a loss function that is considered appropriate to the model being trained (e.g. cross-entropy loss in classification and classification and localization loss in object detection).

### D. Evaluation Metrics

The suggested models are evaluated using the assistance of a number of performance indicators:

Accuracy: This is the percentage of the correct number of instances classified by all the classes.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \ldots(i)$$

Precision: The word precision is used to describe the percentage of the number of instances of damage identified that are correctly predicted out of all the positives that are predicted.

$$Precision = \frac{TP}{TP + FP} \quad \ldots(ii)$$

Recall (Sensitivity): It is the ability of the model to detect all the actual cases of damage and minimizing the defections.

$$Recall = \frac{TP}{TP + FN} \quad \ldots(iii)$$

F1-score: The harmonic mean unites precision and recall as a measure of performance of the model that is balanced.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad \ldots(iv)$$

Intersection over Union: IoU is applied especially in object detection and segmentation, and describes the overlap between the predicted region that a prediction algorithm had predicted is damaged and the ground truth, which is a fine-grained measure of localization performance.
A combination of this set of measures provides an impression of classification and quality of localization.

### E. Software and Tools

The entire implementation method is in Python using a deep learning platform of either TensorFlow or PyTorch. OpenCV is used to perform image pre-processing, image resizing, image normalization and image augmentation and visualization of model prediction is done using OpenCV as well. CUDA-enabled GPU device training speeds up the training process, and enables training of high-resolution images of both drones and vehicle-mounted cameras to be trained effectively. The version of software, random seeds, and training settings are documented with a lot of care, which ensures that the methodology can be applied and tested on other road datasets, or applied during real-time operations.

## IV. Proposed System

### A. Novelty

The proposed system presents some of the main innovations that can be distinguished in terms of the approaches to road damage detection that are currently used. First, it combines drone and vehicle-mounted cameras ensuring the aerial view and the ground-level view, which guarantees complete coverage of the road surfaces and minimizes the blind sight that is observed when a single source of imaging is used. Second, the system is based on the recent deep learning models such as YOLOv8, Mask R-CNN, and EfficientDet that apply to the real-time object recognition and pixels segmentation to identify different types of damages, such as potholes, cracks, and rutting.
In addition, the system is used to implement a severity evaluation mechanism and, therefore, prioritize the maintenance activity based on the size, the depth, and the nature of damage. It is not just a detection but an actionable intelligence to the infrastructure management. The synchronization of the multi-source information of the vehicles and drones is another novelty, which improves solidity in various environments, illumination, and the nature of roads.
Finally, the system is devoted to the real-time processing and the scalable deployment, that is why it may be applied to large-scale road networks. Unlike most of the existing methods that are either offline or single source, with regards to analysis or visualization, this approach of methodology will allow real time monitoring and automatic reporting in addition to geo-tagged visualization which will in turn enhance the effectiveness and efficiency of road maintenance programs. In general, the system offers an end-to-end, practical solution to proactive and automated management of road infrastructure to fill the gaps of the previous research in terms of coverage, accuracy, and real-time applicability.

### B. System Overview

The suggested system comprises drone and vehicle-mounted cameras to create a unified method of detecting the damage on the road. Using both air and ground level images, the system records road anomalies at various scales enhancing both coverage and accuracy of detention. Deep learning models are used to identify, categorize and determine the extent of various damages on the roads like potholes, cracks, and rutting. The findings are displayed in the form of web or mobile dashboards where geo-tagged damage maps are used to enable municipal authorities and maintenance departments to focus on repairing the roads, thereby making the system conducive when it comes to real-time, scalable monitoring of roads.

### C. Data Acquisition

#### 1) Drone Imagery

The high resolution aerial images of road networks are collected by drones. The pictures are taken at heights of 20 to 50 meters, a compromise between details and coverage. State-of-the-art cameras ([?]12 MP) guarantee that a tiny crack is observed. Flight paths are also predetermined in over-lapping grid patterns to ensure full coverage of roads and reduce blind spots to allow proper detection of large areas.

*2) Vehicle-Mounted Cameras*

The drone images are supplemented by vehicle-mounted cameras that capture the close-up shots of the roads. Cameras are positioned at places of strategic value i.e. in the front bumper, sides and the back of the vehicle to ensure that they record multi-angle shots. The system captures the images at 15-30 FPS in order to ensure continuous coverage as the vehicle progresses along with different speed, including images that might not be captured by the drones.

*3) Preprocessing*

Images obtained are fed through a number of preprocessing processes that improve the performance of the models. Normalization normalizes the pixel intensity values, whereas data augmentation, which can be rotation, flipping, scaling, and brightness changes, enhances diversity of the datasets and boosts generalization. Noise is used to eliminate influences of shadows, motion blur, or environmental artifacts so that the deep learning models can get a high-quality input to be detected well.

## D. Detection & Classification

*1) Deep Learning Models*

It makes use of modern deep learning architectures like YOLOv8, which is an object detector that operates in real-time, and Mask R-CNN, an object detector that leaves pixel-level segmentation, and EfficientDet, an object detector that can operate with a small deployment size. These models enable the system to identify and organize road damages effectively in varying magnitudes and situations.

*2) Multi-Class Detection*

The detected damages fall into various classes, such as potholes, cracks longitudinal, transverse, or alligator, and rutting or surface deformations. Multi-class classification guarantees that the maintenance teams get the comprehensive data about the nature of the damage, which is critical in classifying repair measures.

*3) Post-Processing*

After detected, bounding boxes or segmentation masks are created to demonstrate regions of damage. It is evaluated by the extent or intensity of damage and duplicate identifications that occur due to a coincidence of a drone and vehicle image are removed to eliminate any errors.

## E. Visualization & Reporting

The final product is an interactive form of dashboards, and with their assistance, it is possible to follow the state of affairs on the roads in real-time. The geo-tagged maps will show the precise location of the damages relative to the statistical descriptions that will reveal the amount of damages, the nature as well as the scale of damages in the road networks. This simplifies the process of making definite maintenance plans and allows making decisions regarding infrastructure basing on the data.

## F. System Architecture

The system also includes architecture that is anchored on five system layers. The Data Acquisition Layer obtains the images of the vehicle cameras and the drones. Preprocessing Layer enhances the photos by cleansing and standardization and performs augmentation and noise reduction. Detection Layer is a method that uses deep learning models to detect and classify damages. Post-Processing Layer reduces detections, assesses severity and removes duplicates. Finally, the Visualization and Reporting Layer provides reports using dashboards and geo-maps so as to act.

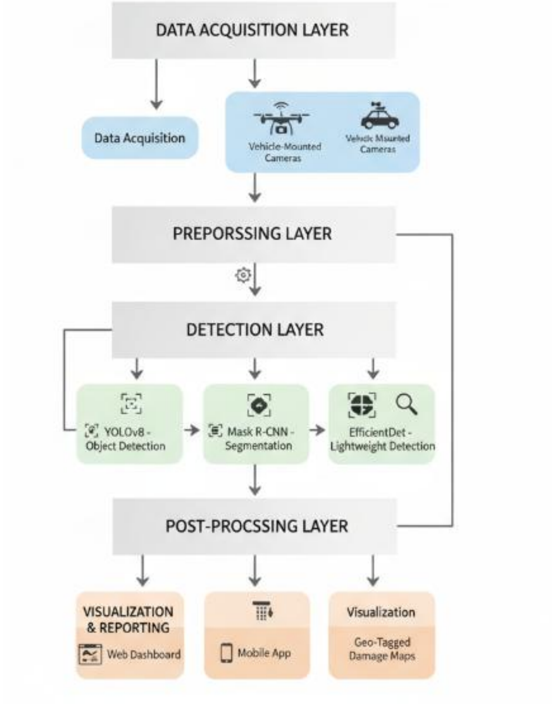


Fig 1: System Architecture

## G. Workflow

This begins by the collocated drones and vehicles gathering images concurrently. The photos are processed and fed to deep learning models to come up with inferences. Detected damages are optimized in the post-processing process and combined in order to reduce redundancy. Finally, the results are described in geo-tagged maps which are interactive dashboards to provide actionable information to the maintenance personnel to facilitate them correct the roads on time.

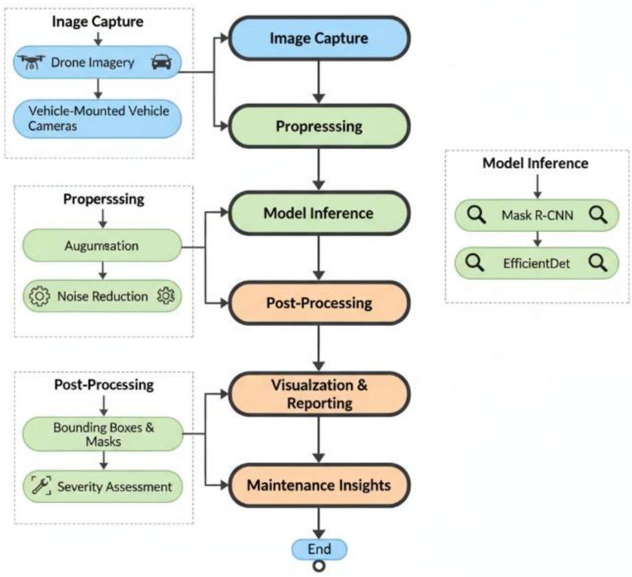


Fig 2: Workflow

### H. Experimental Setup

#### 1) Hardware Specifications

The system is trained and preprocessed using NVIDIA RTX 3080/3090 GPUs and inferred using Intel i9 or Xeon CPUs. Its RAM is at least 32 GB in order to accommodate high resolution pictures. The drones used are DJI Phantom 4 pro and Mavic 3 that have a flight altitude of 20-50 m and vehicle mounted cameras with a 1080p-4K video in different angles.

#### 2) Software Environment

It is coded on Python, with deep-learning implementation and support (TensorFlow or PyTorch), image preprocessing (OpenCV) and a GPU (CUDA/cuDNN) acceleration. All the software version and all the training set are documented to be copied.

#### 3) Implementation Details

The data is broken down into training set, validation set and test set in a ratio of 70: 15: 15. The models are learnt over a period of 50-100 epochs with 8-16 batch sizes depending on the memory of GPUs. It employs a learning rate of 0.001 that is decreasing and transfer learning to increase convergence.

#### 4) Test Scenarios

The tests of the system occur in the roads of different kinds: urban roads and heavy traffic, mixed surface, rural roads with uneven and narrow structure, highways with long distance and intensive traffic. The tests are done under varying light and weather conditions so as to determine stability and feasibility of application in the real world.

## V. Result and Discussion

### A. Performance Evaluation

Several deep learning models such as YOLOv8, Mask R-CNN, and EfficientDet were tested on the proposed system and different datasets and real-life situations. To evaluate each model, performance metrics were accuracy, F1-score, Intersection over Union (IoU) and detection speed (FPS). Table 1 summarizes the results and indicates that YOLOv8 was the fastest in terms of detection and reasonable accuracy and that the best localization accuracy was found in the case of pixel-level segmentation by using the Mask R-CNN. EfficientDet was a lightweight alternative with even-performance that was appropriate to deploy to edges.

### B. Comparative Analysis

Comparison of the models shows trade off on speed and accuracy. YOLOv8 is the most suitable to use in real-time detection because it supports high FPS, and hence can be used in live monitoring of moving vehicles or a drone. However, mask R-CNN is slower but has better localization and segmentation of cracks and minor potholes, which is essential in determining the severity. EfficientDet is a low-weight implementation that can be deployed to low-power edge hardware without losing much accuracy. Such comparisons aid in choosing the best applicable model based on deployment demands be it in real time speed or high resolution accuracy.

### C. Case Studies

On-site testing was performed on urban, rural, highway roads, and on drone-mounted and vehicle-mounted cameras. Drones had great coverage and were especially useful in identifying large potholes and rutting statuses whereas vehicle-mounted cameras were able to identify small cracks and textures on the surface. The system was able to measure road damages in urban conditions that included occlusions such as parked vehicles and shadows. On the one side, the rural roads with surface variations revealed the power of data augmentation and deep learning models, and on the other side, there were highways that showed that the system can obtain high speed data.

### D. Key Observations

There were a number of trends and observations in the experiments. YOLOv8 demonstrated stability in different lighting conditions and sometimes missed small cracks when there was poor lighting as compared to the case with the Mask R-CNN. False positives or false negatives were sometimes caused by the environmental conditions like wet roads, heavy shadows and motion blur. The integration of drone and vehicle data allowed reducing the number of such errors, which validated the usefulness of multi-perspective imaging. The severity assessment module could categorize the damages as minor, moderate and severe that provided an actionable information in the maintenance planning.

### E. Visualization of the Road Damage Detection.

The damages identified are reflected in maps as annotated and geo-tagged. Segmentation masks and bounding boxes easily Visualize what areas are damaged and a severity score is given with each case. Figures 1 and 2 show aerial and ground shots as a sample detection by drone and vehicle-mounted cameras and suggests the complementary natures of the views. The visualized tools enable the rapid interpretation of the teams in the maintenance department that supports the intentional corrections and efficient resources distribution.

TABLE I: Model Performance

| Model | Accuracy(%) | F1-score(%) | IoU (%) | FPS |
|---|---|---|---|---|
| YOLOv8 | 92.5 | 0.91 | 88.2 | 45 |
| Mask R-CNN | 94.1 | 0.93 | 91.5 | 12 |
| EfficientDet | 90.8 | 0.89 | 86.0 | 30 |

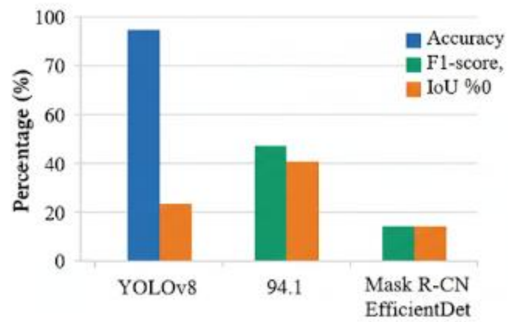


Fig 5: Model Performance Comparison

## VI. Future scope

The proposed road damage detection system provides solid grounds to the further enhancement and actual applications. One of them is multi-sensor fusion, because LiDAR and thermal cameras can be combined with RGB cameras to ensure more detailed information about roads, track the state of subsurface damages, and become more precise under poor lighting (low light or wet roads). The attachment to the city traffic and infrastructures management systems can aid in prioritizing the repair job automatically and streamlining the traffic flow in the process of the maintenance.

Real time alert system can also be used to improve maintenance crews to take action in case of a critical damage before it is too late. The drones or car-mounted computers may have edge computing installed to compute in situ and reduce latency as well as dependence on cloud-computing. Finally, the AI-based analytics, as the result of the collected data will allow predictive maintenance of the road infrastructure according to the trends of the degradation process and streamline the process of its repair to minimise costs and turn the existing reactive way of road infrastructure work into the proactive one.

## VII. Conclusion

This paper discloses an automated road damage detection system, which works using drone cameras and vehicle mounted cameras on the concept of deep learning. It is highly precise, rapid and resolved and can monitor the different types of roads in the various environmental conditions in real time. The approach provides information of the maintenance planning by the object detection, segmentation and severity analysis enabling the operation of the practical maintenance plans.

The proposed remedy will be able to drastically improve road safety and efficiency in terms of maintaining infrastructure since it will result in reduced use of manual inspection and the possibility of making decisions based on the data. Massive implementation of the system can be done with further enhancements such as multi-sensor, edge computing, and predictive analytics, which can bring a great advantage to the society, i.e., safer roads, reduced maintenance costs, and enhanced mobility in cities.

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