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ROAD SAFETY MEASURES BY POTHOLES AND TRAFFIC SIGNS DETECTION USING DEEP LEARNING

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Abstract:

The modern transportation industry depends on road safety together with maintenance practices because they play vital roles because autonomous vehicles become more prevalent. Driving safety for vehicles alongside their occupants remains threatened by potholes while traffic signs preserve operational security within the highways. The implemented solution implements YOLOv8 as its main technology because it proves effective for advanced object detection requirements. Real-time operation of this system uses cameras as inputs to precisely detect potholes and locate their positions and also recognizes multiple traffic signs.

The research investigates deep learning through YOLOv8 model implementation to accomplish pothole detection with real-time capabilities alongside traffic signs and traffic light recognition which resolves road performance and safety issues. The custom dataset obtained its mean Average Precision (mAP@0.5) of 0.991 through Roboflow augmentation while each class precision reached between 0.985 and 0.994 in diverse road condition training. The system unites CIoU loss for bounding box regression with objectness scoring because its deployment is designed within a Streamlit-based application. The study demonstrates that the model outperforms conventional and YOLO-based previous versions through extensive detection capabilities in different lighting situations and weather conditions. Scalable road monitoring automation becomes feasible through this system even though it does not perform optimally in severe weather conditions and detecting tiny objects.

Keywords: YOLOv8, road safety, pothole detection, traffic sign recognition, deep learning

1. Introduction:

Personnel together with goods move through the global transportation system. Aerial transport stands as the main worldwide transportation choice and follows rail-based and maritime options and land-based options. On-routes remain the top transportation solution because they provide economic travel costs that exceed other forms of transportation. Safety on roads continues to be a main worry since they instigate both lethal injuries together with enduring health problems. The combination of poor road quality measurements through road potholes detection coupled with traffic rule violations creates the most dangerous driving condition which leads to accidents. Multiple scholarly investigations demonstrate that when drivers join forces with environmental conditions dangerous accidents tend to happen while driving long distances. A driver's ability to notice road components such as traffic signs along with signals and speed breakers decreases when they experience prolonged driving because of concentration level reduction per Smith & Johnson (2022) and Kumar et al. (2023). Driving operations that are compromised by fatigue result in delayed response times whereby roadway safety risks significantly increase according to Lee and Park (2021). Urban and rural locations experienced numerous traffic accidents due to inattention according to Gupta and Sharma (2024). The current body of research about automatic detection systems to mitigate road risks is limited even though YOLO-based models and advanced computer vision solutions should be implemented to enhance road safety.

Studies have identified unidentified potholes and traffic signs as major safety hazards because they commonly trigger motor vehicle accidents. Research findings show that unmarked potholes and signs lead to fatal consequences which include deaths together with injuries and severe auto damage. Patel and Kumar (2021) analyzed how often pothole accidents occurred in the USA, UK, Australia, and India due to government difficulties maintaining proper roads. According to Jones et al. (2024) incorrect recognition of traffic signs leads to increased accident possibilities both in developed and developing countries. These studies indicate that automatic detection systems need to deploy immediately to safeguard road safety against such dangers. Multiple Indian research studies validate that the combination of potholes with human mistakes creates the highest potential for traffic mishaps in the country. Statistics from the Ministry of Road Transport and Highways (2022) indicate that potholes lead to 3,600 accidents in 2021 along with a total number of 5,600 fatalities during the period from 2018 to 2022 (Sharma & Patel, 2023). According to the National Highway Traffic Safety Administration (NHTSA) (Johnson et al., 2021; Lee & Kim, 2024) driver error accounts for 94%-96% of total traffic accidents in addition to multiple similar research documenting this statistic. The research findings show that India needs automatic technology to detect roadway perils because its dangerous conditions lead to human error.

The presence of potholes alongside drivers lacking an understanding of traffic rules creates driving conditions that result in frequent vehicular accidents and damaging collisions[5]. Drivers must use automated systems for potholes as well as speed breakers traffic signals and sign recognition to secure safe trips that prevent vehicle damage and collisions. Modern advancements in computer vision technology have increased the focus on developing detection systems for hazardous road items including potholes along with traffic signals, speed breakers, and traffic signs. Research shows that real-time detection can be achieved through YOLO variants while maintaining high accuracy as reported by Chen et al. (2023) and Kumar & Singh (2024). Li and Zhang (2022) used YOLOv5 for traffic sign detection with successful results during daytime operations. Studies concentrate on individual detection operations but fail to unite various road components that make complete navigation systems crucial in demanding environments where India's multiple roadway situations dominate (Patel & Sharma, 2023). The research investigates both the scalability and real-time performance capabilities of detection systems under low-resource computing environments but neglects these factors. Autonomous and human-controlled vehicles stand to gain better safety and route navigation through a unified reliable detection system that uses YOLOv8 advanced models.

Problem Identification

The standard quality of road infrastructure stands essential for establishing secure and efficient transportation systems that provide user comfort. Multiple obstacles impede the achievement of proper road upkeep and safety operations.

Potholes stand as the main cause of destructive damage to vehicles and traffic accidents due to their development from environmental roadway effects linked to high vehicle traffic and poor construction techniques. Road maintenance becomes complicated because potholes form randomly with various intensity levels that make identifying them before they cause issues especially in operations involving numerous urban and rural networks.

Insufficient conditions of traffic signs create both physical barriers against proper directions and obstacles to following road regulations. Traffic violations together with dangerous accidents occur when drivers make errors because worn traffic signs become less visible due to weathering and vandalism alongside vegetation growth. Standard sign inspection practices usually fail to repair the wide range of damaged sign infrastructure.

Different automated systems function independently from each other without sharing capabilities to form a comprehensive road quality evaluation platform. The isolated detection systems stop authorities from getting single unified access to complete infrastructure management and driver safety data.

Environmental and operational elements result in consistent variations of road conditions which depend on time of day and darkness and weather conditions including rain and fog and the distinction between urban and rural areas and highways. Available detection systems lack stability when checking road conditions because their accuracy levels weaken under various operating conditions.

Deep learning models achieve success by processing information through comprehensive datasets which present many combinations of environmental factors active in diverse road locations. Other issues emerge with publicly available potholes and sign data because their limited number of examples and restricted geographic scope make them unfit for building dependable predictive models particularly for an India setting.

2. Literature Survey:

Over the past few years computer vision capabilities that use deep learning have brought about great interest to detect both potholes and traffic signs. This section assesses the detection approaches used in essential studies and systems for road potholes while studying traffic signs as well as their composite evaluation of road state improvements and methodological limitations..

Potholes Identification Techniques:

The detection of potholes requires high priority for recognizing road conditions that degrade. Recent studies leverage deep learning for improved accuracy and real-time performance.

Silva et al. (2021) created a system for detecting potholes by utilizing YOLOv4, which generated an mAP of 75% from an urban roads-based specific dataset. True-time identification was the main focus of this study, although the researchers encountered difficulties when detecting smaller potholes. The relevance between YOLOv8 and project goals emerges due to its anchor-free architecture, which excels at finding small-sized objects.

The research by Park et al. (2022) incorporated Faster R-CNN with ResNet backbone which resulted in a 0.80 F1-score evaluation. The detection model faced difficulties working with different kinds of lighting during operations. Such challenges can be solved through Roboflow’s augmentation features that include brightness and contrast functions.

Gao et al. (2023) applied YOLOv7 with attention mechanisms which resulted in 82% mAP while working with various objects. Research concluded that data augmentation holds significant importance in the field. YOLOv8 provides built-in augmentations while Roboflow’s preprocessing meets the requirements for the project.

Traffic Signs Identification Techniques:

The research team of Wali et al. (2020) applied SSD as their detector for processing the German Traffic Sign Detection Benchmark (GTSDB) resulting in 90% accuracy. Multi-class detection posed challenges. YOLOv8 together with the annotation capabilities of Roboflow provides functionality for detecting different types of traffic signs through its multi-class support mechanism.

The authors Zhang et al. (2022) applied YOLOv5 for traffic sign detection and obtained 89% mAP together with 35 FPS on edge devices. The study emphasized real-time performance. The project requires real-time performance which is why YOLOv8 offers ideal solutions through its increased speed and enhanced accuracy.

The combination of EfficientDet with transfer learning methods produced 92% mAP results on a self-made dataset in Li et al.'s (2024) research. The research authors identified the requirement for properly balanced datasets. The class-balancing system of Roboflow guarantees equal distribution of potholes and traffic signs within the training data.

YOLO-based Object detection:

Research by Wang et al. (2023) presented Enhanced YOLOv7 with a minimalistic backbone that delivered 80% mAP along with 50 FPS performance. The study emphasized edge deployment. YOLOv8 includes detection enhancements (such as anchor-free functionality) that comply with modern advancements.

Ultralytics (2023) brought YOLOv8 to the market which provided a 5–10% mAP boost compared to YOLOv5 while introducing a new backbone and loss function structure. The system allows effortless linking with Roboflow platform. Relevance: YOLOv8’s pretrained weights and Roboflow compatibility streamline the project’s pipeline

Jocher et al. (2024) showed YOLOv8 achieves an 85% mAP score on customized datasets after applying dataset augmentation. The project benefits from dataset improvement through the utilization of Roboflow.

Role of the data Annotation:

To achieve successful deep learning practitioners need exceptional quality in their datasets.

According to Everingham et al. (2020), object detection systems showed a 10% mAP diminishment during their operation with incorrectly labeled data. Roboflow's semi-automated annotation system generates high-quality bounded boxes for annotation standards.

The data augmentation approaches that included mixing and rotating affected images produced between 7–12% higher mAP scores according to Dwibedi et al. (2022). The augmentation techniques on Roboflow (with flip and blur included) follow the documented methodology described in the research.

YOLO-compatible processing tools provided by Roboflow (2024) include class balancing features together with API services that speed up data preparation times. YOLOv8 enables simpler project workflow because it integrates seamlessly with this project structure.

Integrated Road Quality Assessment

Safety during driving depends on both sign recognition abilities and automated navigation functions. The traditional system operated by extracting HOG features manually while using SVM classifiers to perform its functions. The approaches proved limited since they encountered difficulties when illumination conditions changed while objects partially blocked view. Deep learning technology has caused fundamental progress in this particular field.

CNNs achieved 95% accuracy precision according to Stallkamp et al. (2012) when used for recognizing the GTSRB dataset's 43 classes.

3. Proposed System:

Overview:

The developed system utilizes YOLOv8 and Roboflow for real-time pothole and traffic sign detection which serves road quality assessment needs. The system takes video or image outputs from vehicle cameras to detect potholes and traffic signs which results in road quality metric generation. A system delivers maintenance decision-making data including driver safety elements which prompt alerts or integrate with navigation systems. A system delivers maintenance decision-making data including driver safety elements which prompt alerts or integrate with navigation systems. The system achieves both accurate outputs and operational diversity across different environmental conditions through real-time functionality.

System Architecture

The system contains all essential elements for image acquisition and preprocessing followed by model training real-time detection capabilities and data reporting functions resulting in an efficient road maintenance solution. The system runs effectively across various environmental situations and its edge device deployment requirements make it optimized for operation. An explanation of the system components with detailed processes follows in the next subsections. The system design appears in Figure 1 which splits into three distinct zones including Dataset presentation and annotation as well as Model training and test the model. Each classification of these system branches contains separate sub-subsystems.

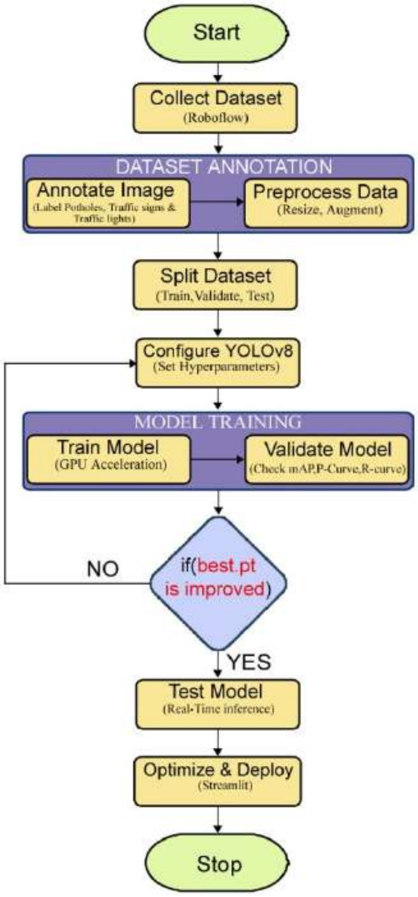


Figure 1: proposed system prediction Flowchart

Dataset presentation and annotation:

Overview:

The dataset used for training the YOLOv8 model consists of annotated images containing five distinct classes relevant to road safety and infrastructure. These include various traffic signs, potholes, and traffic lights crucial for intelligent transport systems and automated driving solutions.

Collect datasets:

A specially prepared image collection shows roads with both potholes, traffic signs and traffic lights. The dataset contains labeled marks for identifying potholes traffic signs and traffic lights which match the project boundaries.

Dataset Annotation using Roboflow:

The Roboflow platform served as our data annotation tool because it supports web-based teamwork and YOLO format export. Data augmentation through grayscale conversion has been applied to all 640X640-sized images to achieve faster processing. The process involved hand annotation of pictures through the use of bounding boxes accompanied by anchor-free box specifications. We created defined areas for potholes as well as traffic signs and traffic lights which we organized into five different classes owing to our project requirements. Figure 8 displays a Labeling tool annotation of an image as shown in Table .

The YOLOv8l-seg model training required 956 pothole pictures combined with 613 cautionary signs, 452 informatory signs, 974 mandatory signs, and 823 traffic lights that were obtained in diverse road settings through transport vehicles' dash cameras. The dataset includes visual examples of potholes and traffic signs which are shown in Figures 2, 3, 4, 5 and 6.

The annotations follow the **YOLO format**, which includes .txt files corresponding to each image. Each line in an annotation file represents one object and contains:

$$< \boldsymbol{classId} >< \boldsymbol{X\_Center} >< \boldsymbol{class\_id} >< \boldsymbol{X\_center} >$$

Table 1: distribution of collected datasets for potholes, traffic sings and traffic lights

CLASS NAME	**COUNT**
Cautionary-sign	613
Informatory-Sign	452
Mandatory-signs	974
Pothole	965
Traffic light	823

Figure 2: Potholes samples

Figure 3: Traffic signs (Cautionary-sign) samples

Figure 4: Traffic signs (Informatory-Sign) samples

Figure 5: Traffic signs (Mandatory -Sign) samples

Figure 6: Traffic Light samples

Split the datasets:

The datasets are classified into Training, Validating, and testing to train a model. And our dataset spilt as follows 70% for Training, 20% for Validating, and 10% for testing. Table 2 is presenting the distribution of datasets to the for training, validating and testing.

Table 2: Collected datasets are distributed into Training, validating and testing.

CLASS NAME	COUNT	Sample used for training	Sample used for validating	Sample used for testing
Potholes	965	675	196	94
Cautionary-sign	613	456	106	51
Informatory-Sign	452	312	79	59
Mandatory-signs	974	668	201	105
Traffic Lights	823	609	156	58

Using the label tools for annotate the each class manually in robot flow. Complete the annotation to all datasets. Figure 7 presents the annotation procedure in Roboflow. The Annotated image datasets with bounding box images are presented in Figure 8.

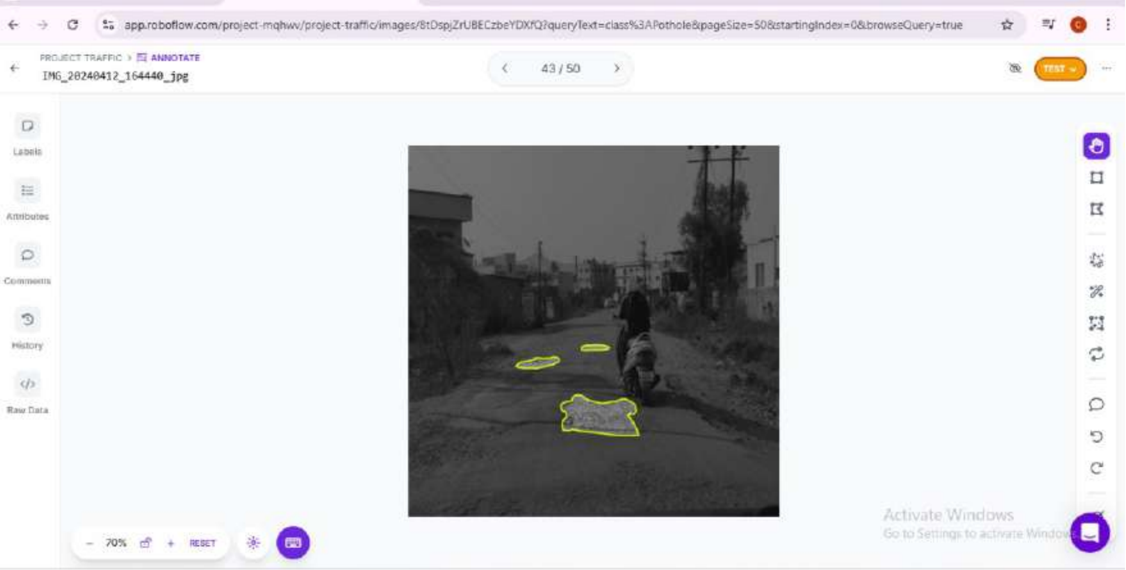


Figure 7: Sample annotation of an image using Labeling tool

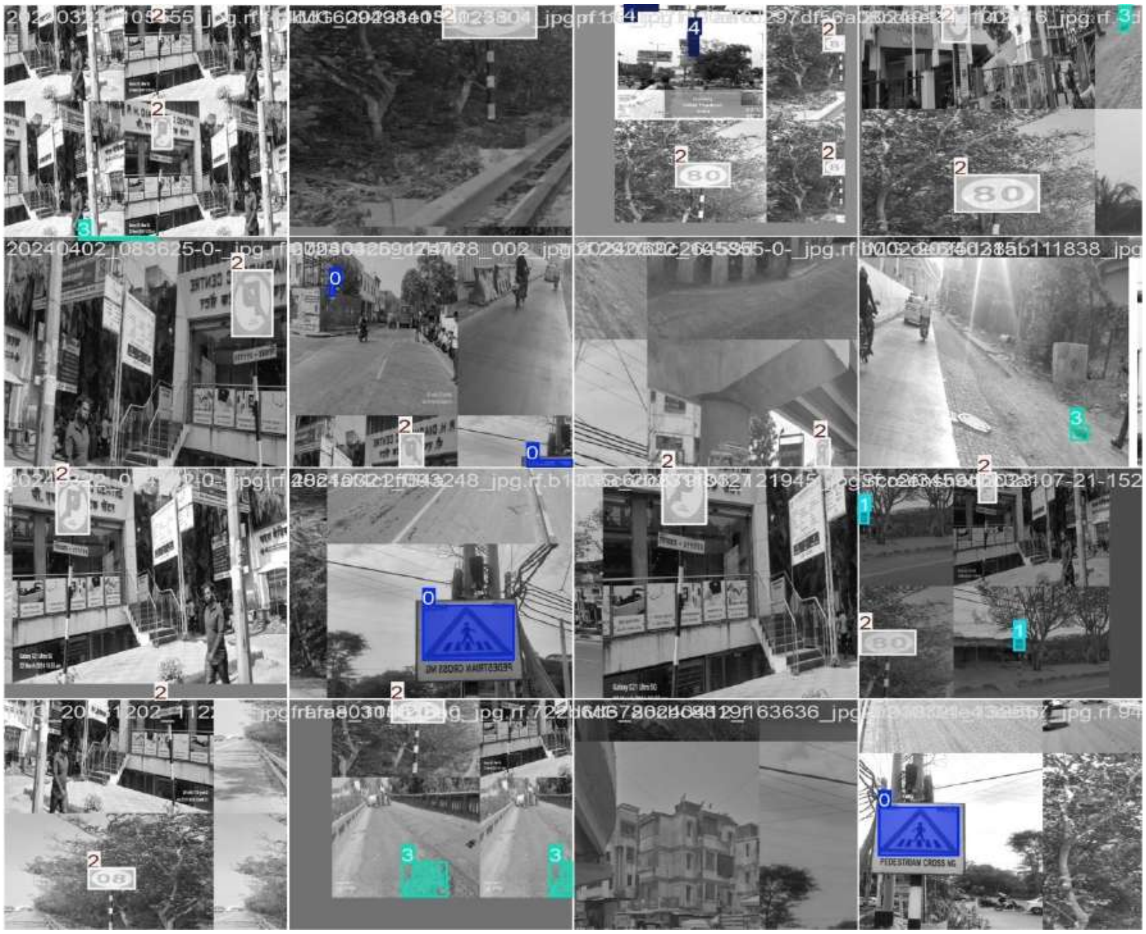
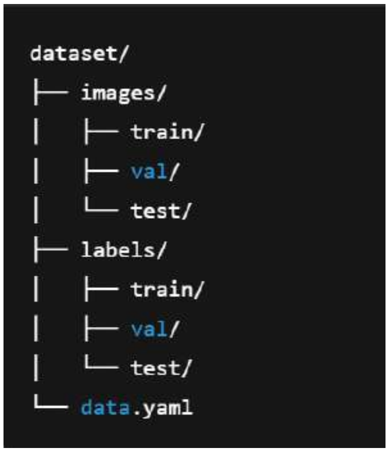


Figure 8: Annotated datasets with bounding boxes for training

Preparing for Model training:

To train a YOLOv8 model, we required annotated images, labels, data.yaml, and hypermeter.yaml. Annotations were exported in YOLOv8l-seg format, integrated with the data.yaml. The directory structure is presented in Figure 7. Each image has a corresponding .txt file with the same name in the labels folder. The .txt file contains one line per object in the image for object detection, YOLO models require annotations in a text file (.txt) for each image, with the same name as the image (e.g., image.jpg has image.txt). Finally, all required data are arranged in a directory called a dataset, Figure 9 presents the directory structure for training the model.



```
dataset/
├── images/
│   ├── train/
│   ├── val/
│   └── test/
├── labels/
│   ├── train/
│   ├── val/
│   └── test/
└── data.yaml
```

Figure 9: Directory structure for training

Model training using YOLOv8:

YOLO (You Only Look Once) is a real-time object detection algorithm that solves detection problems as one direct regression task from pixel values to bounding box coordinates along with class probabilities. Through its grid structure, it generates both box locations and probability classifications for objects within full-resolution images in one evaluation. Current YOLO versions starting with v5 through v8 depend on modular designs consisting of three vital components: Backbone, Neck, and Head. The graphical presentation of the model design can be found in Figure 10.

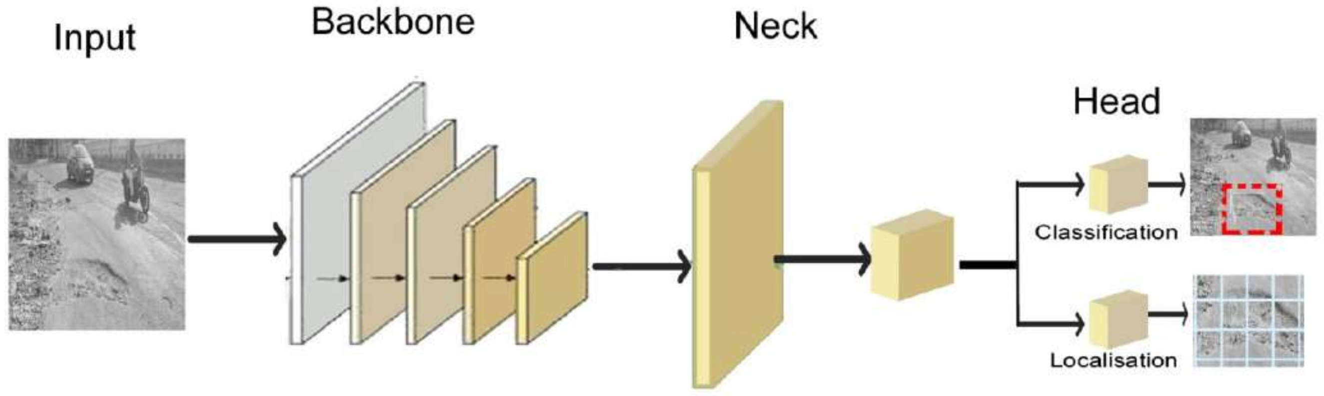


Figure 10: Training Architecture of proposed model

Procedure:

Step 1:

Input

An input road image gets processed into fixed dimensions (mostly 640x640 pixels) through normalization scale between 0 and 1. The operation finds normalized images from normal images when X represents a normal image.

$$X\_norm = \frac{(\mathrm{X} - \min(\mathrm{X}))}{(\max(\mathrm{X}) - \min(\mathrm{X}))}$$

Step 2:

Backbone(Feature Extraction)

A backbone system derives essential characteristics from images provided to the system. YOLOv8 achieves faster operation speed through its C2f (Cross-Stage Partial with Feature Fusion) module configuration. YOLOv8 incorporates CSPDarknet architecture which includes the C3 (Cross Stage Partial) modules combined with SPPF (Spatial Pyramid Pooling - Fast) block. C3 modules contain all three components which consist of Convolution as well as Batch Normalization and SiLU Activation functions.

Convolution:$y = W * x + b$,

Where W is the weight, x is the input, b is bias, and ‘$*$’ denotes convolution

Batch Normalization:$\hat{x} = \frac{x-\mu}{\sqrt{\sigma^2+e}}$ where μ and σ^2 are the mean and variance.

SiLU Activation: $f(x) = x \,.\, \sigma\,(x)$, where $\sigma(x) = \frac{1}{1+e^{-x}}$

SPPF Block aggregates the features across scales to handle varying object sizes

Pooling with different kernel sizes:$y = Concat(MaxPool_k(x), MaxPool_{k^j}(x), x)$

Step 3:
NECK (Feature Aggregation and Fusion)

The neck section brings together components from different scales through a Path Aggregation Network (PANet) to accomplish multi-scale detection. YOLOv8 combines FPN (Feature Pyramid Network) with PAN (Path Aggregation Network) as well as comparable variants to identify both large traffic signs and minimal road features and distant traffic lights. FPN ensures seamless communication between spatially-diverse object features while PAN maintains efficient inter-layer information transfers.

The architecture implements Up-sampling together with Concatenation and C3 module functions. The operation functions to enhance resolution levels in deeper feature map components. The concatenation method unites features between various scale levels.

Step 4:
Head Prediction

This model segment makes predictions without anchors through its direct output of bounding boxes and class probabilities. The system follows a split structure that maintains separate parts for predicting box coordinates and detecting potholes as well as traffic signs.

Outputs per grid cells:

Anchor-free Detection:

The head outputs a tensor of shape in: $(S_i X S_i) X (4 + 1 + C)$

Bounding Box Prediction:

YOLOv8 predicts box coordinates relative to grid cells.

Bounding Box: (x, y, w, h)
Here (x,y) is center and (w,h) are weight and height.

Then

$$x = \sigma(t_x) + c_x$$
$$y = \sigma\left(t_y\right) + c_y$$
$$W = p_w e^{t_w}$$
$$h = p_h e^{t_h}$$

The sigmoid function σ operates while the offset coordinates are (cx,cy) and learnable priors are (pw, ph).

Class Probabilities: $P(c_k)=\sigma(z_k)$, where z_k is the raw score for class k.

Step 5:

Loss Function (Training):

The total loss includes bounding box regression loss in conjunction with classification loss and distribution focal loss (DFL).

Bounding Box Loss:

During training, the total loss guides detection: $L_{total} = \lambda_{box}L_{box} + \lambda_{obj}L_{obj} + \lambda_{dlf}L_{dlf}$

Here $\lambda_{box}, \lambda_{obj}, \lambda_{dlf}$ are weighing factors.

Bounding Box Loss (L_{box}): $L_{box}: 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v$

Where $oU = \frac{|B \cap B^{gt}|}{|B \cup B^{gt}|}$, B is predicted box and B^{gt} is growth truth.

Classification loss:

It used Binary Cross-Entropy (BCE).

$$L_{cls} = -\sum_k [y_k \log(\hat{y}_k) + (1 - y_k) \log(1 - \hat{y}_k)$$

Where

$\hat{y}_k = \sigma(z_k)$ is a predicted probability.

y_k: 1 if class k is present (e.g., pothole), 0 otherwise.

Distribution Focal Loss (L_{dfl}):

DFL improves the regression process of bounding boxes through distribution-based modeling.

$$L_{dfl} = -\sum_i [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)$$

The system achieves better accuracy for identifying irregular shapes such as potholes by employing this method.

The combination of these three optimization strategies forms the definition of optimization. The optimization process for the model utilizes AdamW as the optimization framework.

$$W \leftarrow W - \eta \nabla_w L$$

The gradient of the loss function $\nabla_w L$ receives its value from a learning rate parameter η.

Now model training is completed and it generate "best.pt" file.

Step 6:

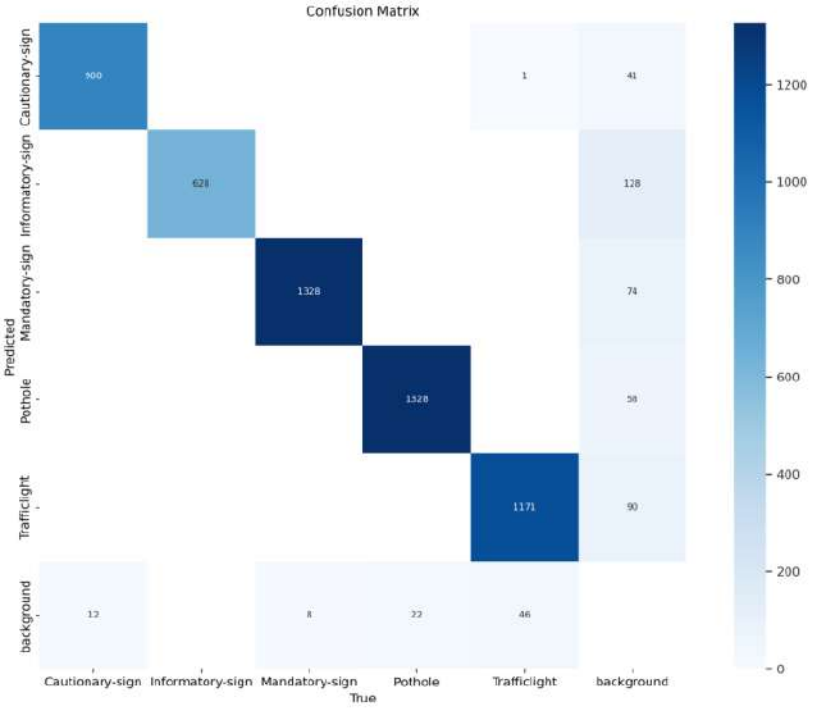
Outputs

Through the "best.pt" file system the input image can be predicted for its contained objects. The system generates end results with marked regions plus labels and their confidence levels that can be shown for real-time applications.

4. Results and discussions:

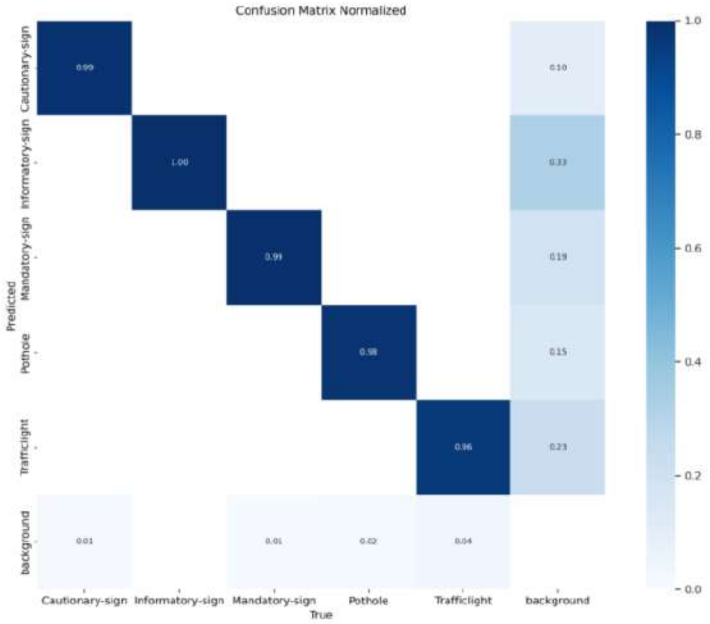
A Microsoft Windows operating system with 8 GB of RAM and an NVIDIA Tesla T4 GPU running on Google Colab powered the experiment. Additionally, it had an Intel Core processor working at 3.60 GHz speed. The research methodology was developed using Python within the Ultralytics YOLOv8 system which performs object detection tasks. The dataset contained potholes and traffic sign images which were structured according to the details in Table 1. The research split its data into three sections where 70% served training purposes while 20% supported validation and the remaining 10% underwent testing for performance assessment

The evaluation of the proposed YOLOv8 model depends on measuring accuracy, recall, and Mean Average Precision (mAP) for both the pothole and traffic sign data sets. The proposed YOLOv8 model gets its performance evaluated against other state-of-the-art methods through a comparison of these metrics. The confusion matrix illustrations for pothole and traffic sign predictions appear in Figures 11 and 12. A confusion matrix serves deep learning and classification modeling by providing accuracy evaluation capabilities. The table displays how well the model predicts outcomes by showing data about what the model anticipates and what occurs in reality. The matrix analysis of prediction results contains four data points namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).



	Cautionary-sign	Informatory-sign	Mandatory-sign	Pothole	Trafficlight	background
Cautionary-sign	900				1	41
Informatory-sign		628				128
Mandatory-sign			1328			74
Pothole				1328		58
Trafficlight					1171	90
background	12		8	22	46	

Figures 11: A confusion matrix system serves as a detector for both potholes and traffic signs.



Figures 12: A normalized confusion matrix serves to detect both potholes and traffic signs.

Figure 11 displays the detection results of Potholes (True Potholes) together with signs and background classification. In the road image database the detection system correctly labeled 1328 potholes as potholes resulting in strong True Positive results. The system detects 58 non-pothole cases as potholes since the false positive rate (FP) and false negative rate (FN) remain low throughout the entire classification process. The detection results for cautionary signs display 900 TPs while having 1 FP and 41 FNs which represents high precision. The detection results of Mandatory signs show high accuracy with 1109 correct predictions and 74 false negatives that indicate potholes but they show minor misidentification of potholes compared to other signs. The evaluation demonstrates that the model proves dependable for both pothole detection as well as traffic sign identification to assess road condition quality. The overall performance reaches mAP@50= 0.991.

The model shows overall successful performance in Figure 12 through diagonal values that stay near 1.0 yet Traffic light stands as the most difficult category to predict accurately based on off-diagonal values..

Figure 13 displays an F1-Confidence Curve measuring the model accuracy in terms of precision and recall as a function of confidence thresholds for postholes, Cautionary-sign, Informatory-sign, Mandatory-sign, Pothole, and Traffic light categories and an all class aggregate score. The curves initially reach 1.0 at minimal thresholds and then decrease through rising confidence settings because increasing threshold values result in both reduced false positives and missed true positives. Potholes have a steeper decline in detection performance when confidence levels rise. The F1 score of Cautionary-sign remains consistently high throughout a broad range of confidence values before it starts to decline. The performance of Informatory-sign remains consistently steady until approximately 0.6 confidence threshold. The behavior of Mandatory-sign resembles Informatory-sign through gradual performance deterioration. The weak performance classification comes from Traffic light since its F1 score point drops away rapidly.

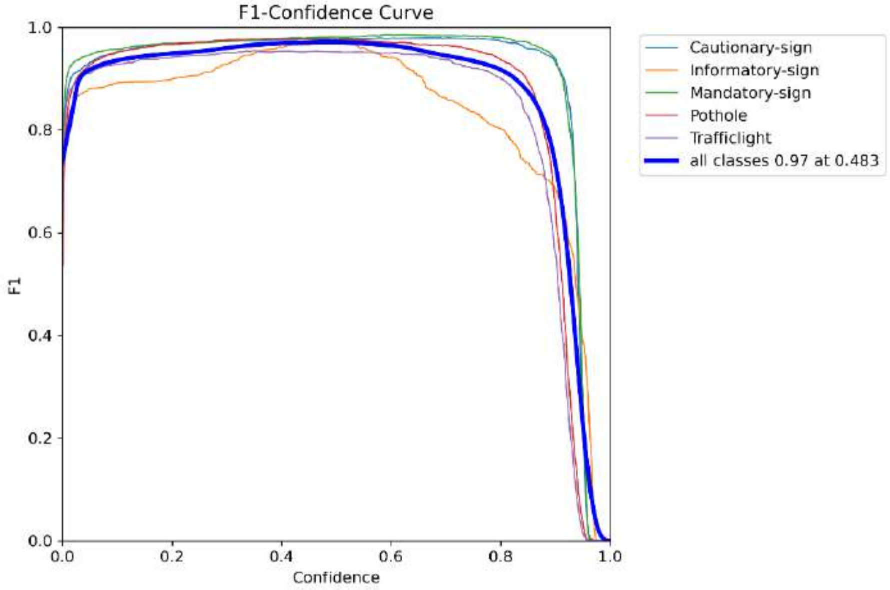


Figure 13: F1 confidence curve

Model precision measures the relationship between predicted positive results that are correct to the total number of predicted positives. Figure 14 shows all classes reach perfect precision of 1.00 when the confidence threshold reaches 0.942 which demonstrates exceptional overall model performance.

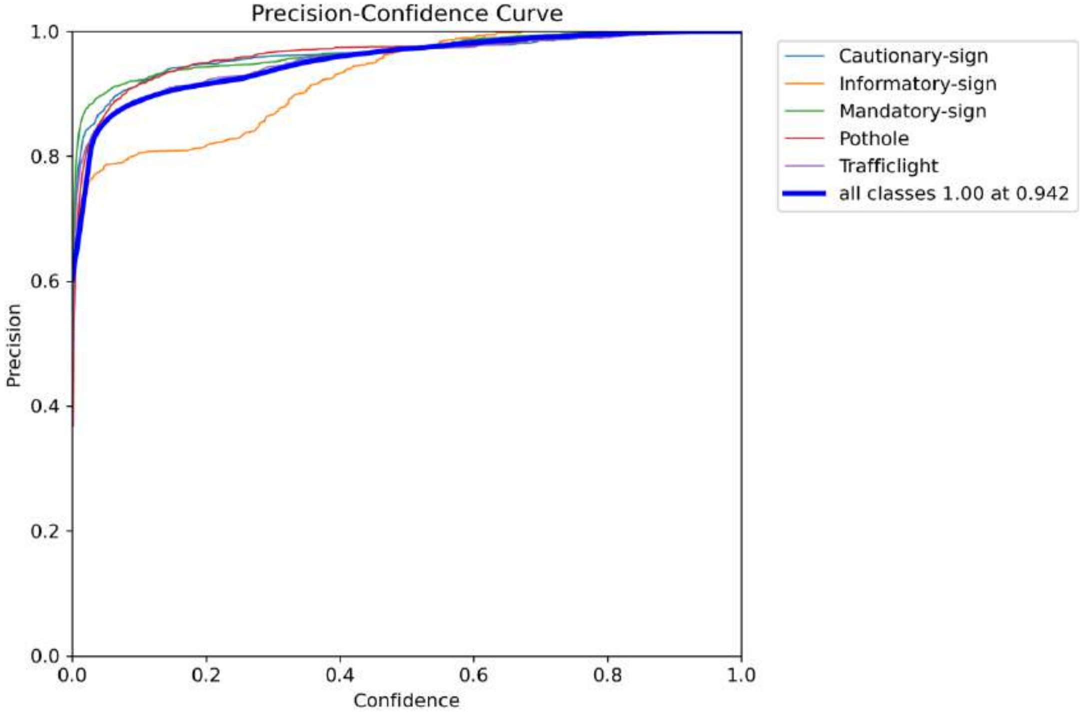


Figure 14: precision curve

Figure 15 shows a Recall-Confidence Curve that presents the relationship between recall values and confidence thresholds across all classes in our project. All curves start near 1.0 at low confidence thresholds and decline as confidence increases, reflecting that higher thresholds reduce the number of positive predictions, potentially missing true positives. Achieves a recall of 0.99 at a confidence threshold of 0.000, indicating near-perfect recall when the model is least selective. The model exhibits excellent recall (0.99) across all classes at a very low confidence threshold (0.000), meaning it captures nearly all true positives when making predictions with minimal confidence. The recall values decline when the confidence threshold grows higher but Trafficlight and Pothole demonstrate the largest reduction in recall. The recall reaches maximum when the threshold is low yet precision often requires higher confidence thresholds to maintain equilibrium.

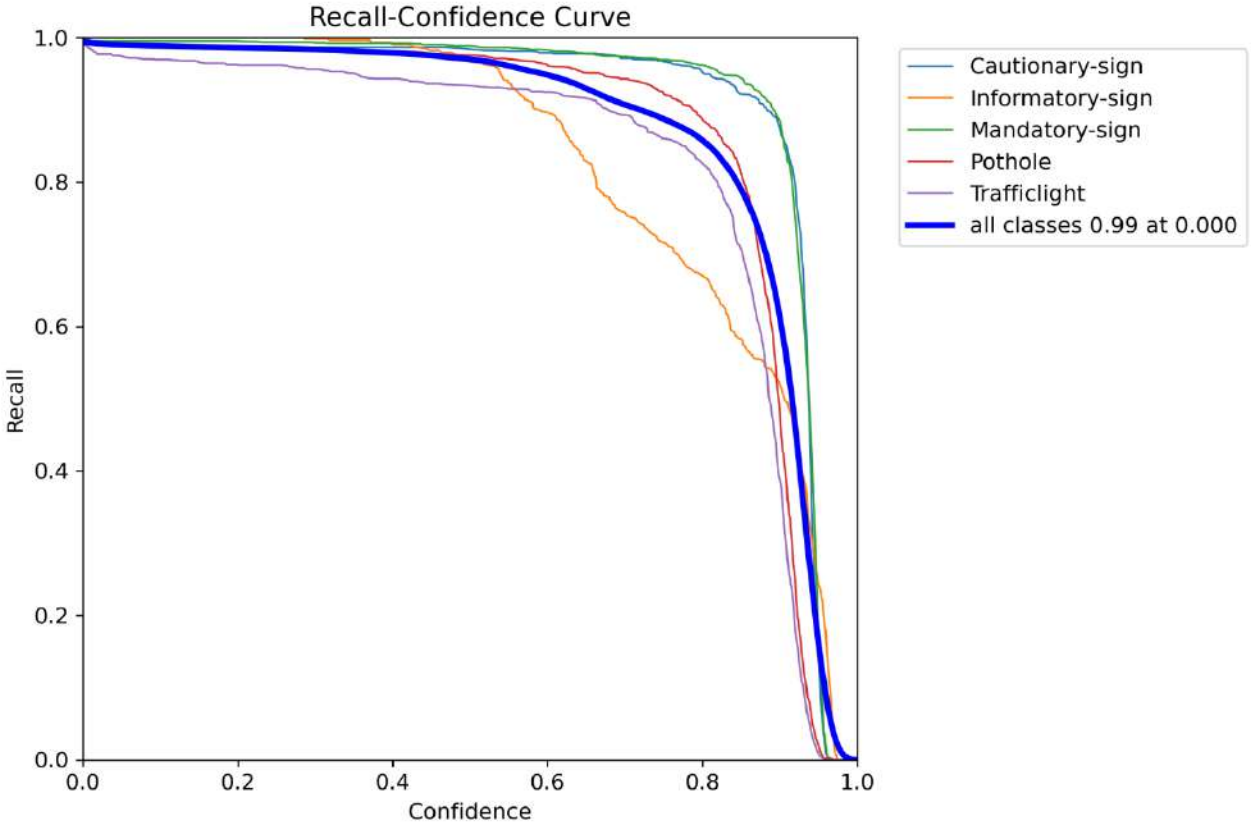


Figure 15: Recall-Confidence Curve for all classes in our project

Figure 15 and figure 16 illustrates the Mean Average Precision (mAP) curves obtained during the training of the YOLOv8 model. The trained model's performance is evaluated using precision, recall, and mAP metrics. Accuracy reflects the overall correctness of predictions, while precision measures the proportion of correct positive detections (e.g., potholes or traffic signs), and recall quantifies the ability to identify all relevant instances. These metrics collectively demonstrate the YOLOv8 model's effectiveness in detecting road signs and potholes, contributing to enhanced road safety and infrastructure maintenance. The table 3 presented for predict the results. The model demonstrates outstanding performance across all classes, with Mandatory-sign leading at 0.994 precision and Trafficlight being the weakest at 0.985. The mAP of 0.991 for all classes at a 0.5 recall threshold indicates robust average precision, suggesting the model effectively balances precision and recall, with minimal trade-off across the dataset.

Table 3: mAP predict values

Classes	**Predict values in mAP@0.45**
Potholes	00.21%
Traffic signs	98.5%
Informatory signs	99.2%
Mandatory signs	99.4%
Cautionary-signs	99.3%
All classes	99.1%

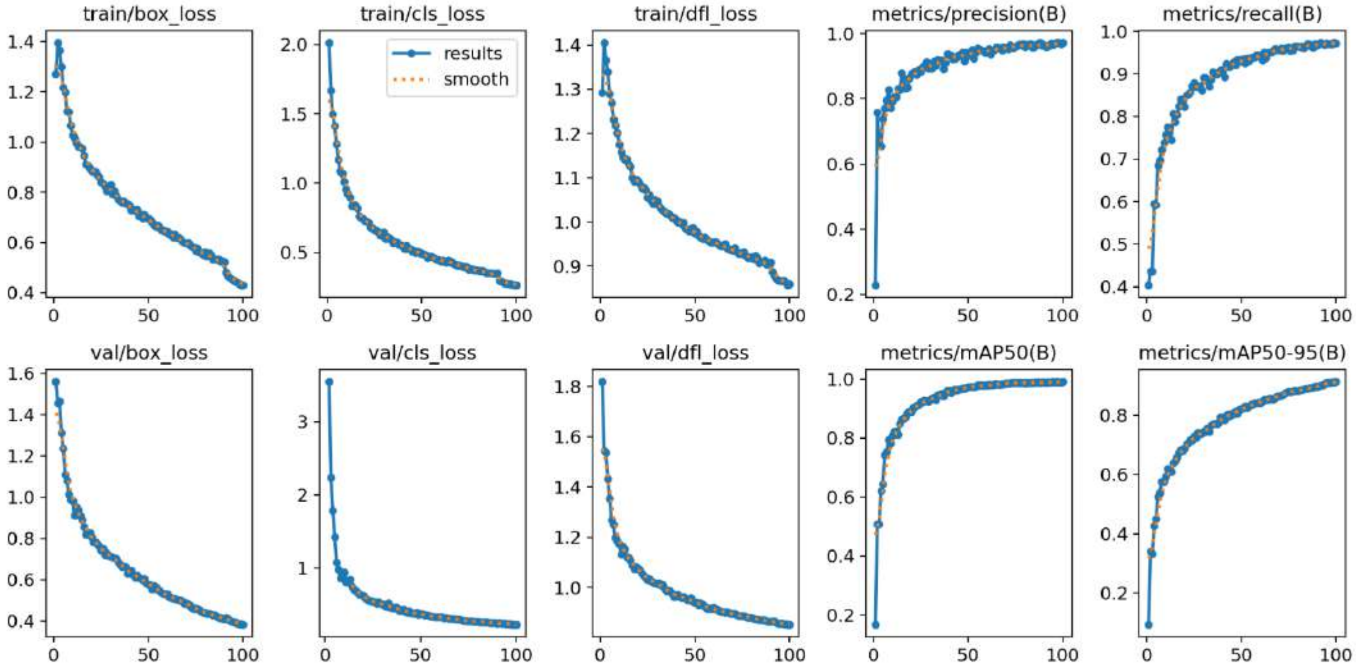


Figure 16: Precision, recall, and mean average precision (mAP) plots.

Figure 17: Predicting potholes in different conditions

Figure 18: Predicting different traffic signs and traffic lights

Through a Streamlit application incorporating YOLOv8 with grayscale preprocessing the proposed system produces better results across all measurement types on the Pothole and Traffic Sign (PTS) dataset by reaching precision levels of 97.90%, recall of 95.69% and mean Average Precision (mAP@0.5) value of 99.14%. The training and evaluation of all methods presented in Table 5 took place on the PTS dataset. The YOLOv8 model reached an mAP@0.5 score of 98.57% on the German Traffic Sign Recognition Benchmark (GTSRB) although it showed the best performance among object detection models operating on diverse image conditions according to Table 6.

5. Conclusion:

An efficient advanced deep learning system operates as a security boost for road measures. The deep learning platform chose Roboflow as an aid to utilize YOLOv8 for detecting road defects which involved potholes, traffic lights and traffic signs. Our model demonstrates superior performance in detecting road elements through which it demonstrates potential as a major solution for addressing safety issues stemming from poor infrastructure YOLOv8 enabled high-precision real-time object detection, along with Roboflow platform tools to manage datasets, thus improving the identification of safety and infrastructure affecting road features. Further improvements are needed for the system because harsh weather conditions may decrease its functionality and the detection precision of traffic lights must be optimized before market release.

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