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# Smart road maintenance: real-time surface damage detection and mapping with YOLOv8

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**ABSTRACT**

The degradation of road surfaces presents considerable obstacles for the management of urban infrastructure. This study presents a deep learning model based on YOLOv8 that can find many types of road faults, like potholes, longitudinal cracks, transverse cracks, and alligator cracks, using pictures, video streams, and live webcam feeds. The suggested system can find things with an accuracy of 91.2%, and the confidence levels range from 60% to 95%. Streamlit has been utilized to develop a web interface that makes it easier to use in real life. It makes it easy for users to choose inputs and provides outputs with notes and boundary boxes. GPS makes it possible to find problems with great accuracy, and a graphical dashboard presents damage categories and confidence levels in real time. Road maintenance is considerably more efficient with automated detection, location mapping, and easy-to-understand visualization. It is also easier to keep a check on smart municipal infrastructure. The results demonstrate that using computer vision and geospatial analytics together could make it easier to automatically check road conditions and make better decisions about how to run a city.



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## 1. INTRODUCTION

Road infrastructure represents a vital concern for the Indian economy and transportation sector. India possesses a road network spanning five million kilometers, making it one of the largest in the world. Rapid urbanization and increasing vehicle density have placed significant strain on infrastructure, particularly in rapidly expanding cities. Adverse road conditions contribute to traffic congestion, increased vehicle operating expenses, safety hazards, and economic detriments, necessitating the implementation of efficient and scalable road repair methodologies. Manual surveys take a lot of time and effort, and they sometimes show bias and inconsistency when checking Indian roads. Because the road network is so big, it is not practicable to check it by hand all the time. In recent times, there have been notable enhancements in automated road damage detection using deep learning techniques. The use of smartphones to detect potholes and road surface conditions has shown promising outcomes, offering an effective means of conducting low-cost infrastructure inspections [1], [2]. Geolocation has also helped accurately locate the road defects that were detected for proper maintenance plans [3]. The advanced techniques in YOLO, YOLOv5, along with its lightweight counterparts, have increased detection accuracy while decreasing computational cost [4]–[7].

Benchmarking databases like RDD2022 have contributed to developing robust road damage detection techniques under various environmental conditions [8]. CNN-based techniques have also been used successfully for pothole detection [9], [10]. Recently, several research works have proposed advanced frameworks for object detection, using lightweight architectures, feature pyramid networks, attention, and advanced methods for feature fusion in order to improve pavement damage detection [11]–[16]. Deep neural networks, advanced versions of YOLO algorithm, and hybrid computer vision approaches have shown superior results in detecting longitudinal cracks, transverse cracks, and alligator cracks in various lighting and weather conditions [17]–[20]. Moreover, recent research has considered intelligent road monitoring solutions that involve UAV images, LiDAR sensors, GPS localization, and multimodal data fusion in order to provide large scale monitoring and smart city applications [21]–[25]. In spite of recent progress in this field, most of the existing solutions concentrate on damage detection accuracy and benchmarked datasets, whereas very few solutions have considered real-time implementation along with GPS-enabled visualization for infrastructure management. Thus, this work considers a solution based on YOLOv8 in order to detect various kinds of road damages and provides real-time GPS-enabled visualization.

## 2. RESEARCH METHOD

This study utilizes the YOLOv8 deep learning framework to enable real-time identification of road surface problems, including potholes, cracks, and surface irregularities. YOLOv8 is a sophisticated convolutional neural network (CNN) architecture engineered to attain elevated precision and minimal latency in object detection, rendering it exceptionally appropriate for real-time surveillance of roadway conditions. Figure 1 shows in detail how the suggested system is built.

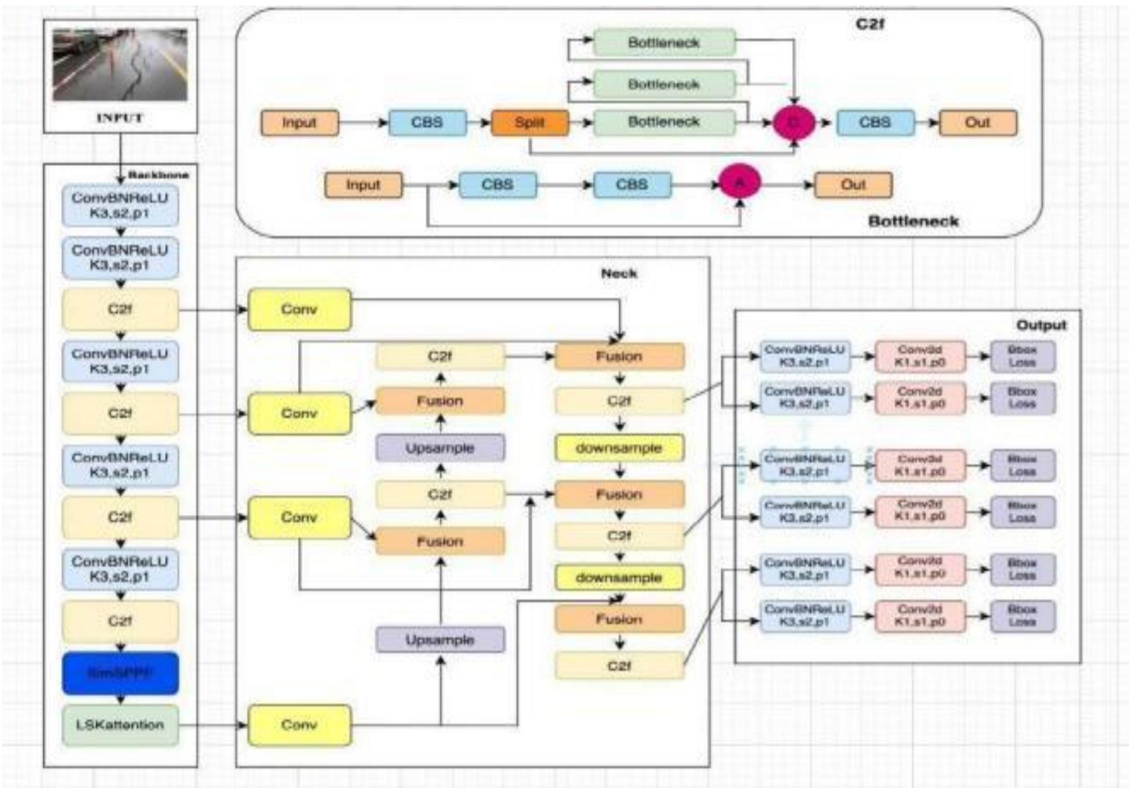


Figure 1. Block diagram of proposed system

### 2.1. Dataset collection

A dataset consisting of 3,178 real-world images was gathered from the NH-44 spur road (Hyderabad–Nizamabad–Nagpur segment). These images show problems with the road surface in many kinds of light and weather. To make the dataset more diverse, further annotated examples from the crowdsensing-based road damage detection challenge 2022 were added. The combined dataset was carefully labeled to show the many kinds of road damage.

### 2.2. YOLOv8 architecture

The YOLOv8-s model was chosen to attain an optimal equilibrium between detection precision and computational performance. The architecture comprises three primary components: the backbone, neck, and head networks.

#### 2.2.1. Backbone network

The backbone network of YOLOv8 plays a crucial role in feature extraction by means of convolutional layers directly applied to the input image. This procedure is expressed as follows mathematically:

$$F(i,j) = \sum\sum I(m,n) \cdot K(m,n) \tag{1}$$

The pixel value at (m,n) in the input image is represented by the notation where I(m,n), K(m,n), and F(i,j) respectively stand for the kernel weight, the output feature at (i,j) of the second layer and so on.

$$\mathrm{ReLU}(x) = \max(0,x) \tag{2}$$

Upgrading the feature extraction in YOLOv8 is realized with cross stage partial fusion (C2f), which is a next-generation architecture that unites shallow and deep features in an effective manner. Rather than dealing with all feature maps at each layer. The following equation describes this merging method:

$$\mathrm{Fmerged} = \mathrm{Fshallow} + \mathrm{Fdeep} \tag{3}$$

#### 2.2.2. Neck network

The neck module of the YOLOv8 architecture is responsible for refining and improving the extracted features before they reach the detection head. The neck does this by the use of two powerful architectures: feature pyramid network (FPN) and path aggregation network (PAN), this process can be represented as:

$$\mathrm{Fcombined} = \mathrm{Flow} + \mathrm{Up}(\mathrm{Fhigh}) \tag{4}$$

The path aggregation network (PAN) further refines the feature fusion process by enabling bidirectional information flow across multiple scales.

$$\mathrm{Ffinal} = \mathrm{Down}(\mathrm{Fcombined}) + \mathrm{Up}(\mathrm{Fcombined}) \tag{5}$$

where Down(Fcombined) refers to the process of downsampling, which extracts more contextual information from the lower layers while Up(Fcombined) is the process of upsampling that allows the refined features to be propagated back to the higher resolutions.

#### 2.2.3. Head network

In YOLOv8, the head network is crucial to the process of obtaining the final object detection predictions based on the refined feature maps that have been passed on. The bounding boxes are defined by the four parameters: the center coordinates (x,y) of the box and its width w and height h. When depicted mathematically, the bounding box is as follows:

$$B = (x,y,w,h) \tag{6}$$

The confidence score is calculated based on the Intersection over Union (IoU) metric, which indicates how much the predicted box overlaps with the actual box. The formula for the confidence score is as follows:

$$C = \mathrm{Po} \times \mathrm{IoU} \tag{7}$$

In this context, Po refers to the likelihood of an object being present within the bounding box predicted, while IoU signifies the ratio of the overlap area to the combined area of the predicted and actual bounding boxes.

### 2.3. Model training

The model was trained over 100 epochs using a group size of 16 and an input resolution of 640 × 640 pixels. The Adam optimizer was employed with a learning rate of 0.001. The trained model attained an overall detection accuracy of 91.2%, assessed across confidence thresholds spanning from 0.60 to 0.95.

### 2.4. Real-time deployment and spatial mapping

People could upload pictures, movies, or watch live webcam streaming through a web app made with Streamlit. The trained YOLOv8 model is used to evaluate each frame in real time to find and classify objects. GPS integration makes it possible to automatically find road flaws, and an interactive interface shows information about the sort of damage, how sure you are about it, and where it is on a map.

### 2.5. Performance evaluation metrics

Assessing the performance of an object detection model like YOLOv8, evaluation metrics play a crucial role. The metrics used in this study are:

#### 2.5.1. Precision

Precision and recall are fundamental metrics used to evaluate object detection performance. It is defined as:

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

True positives (TP) represents correctly identified objects, and false positives (FP) represents incorrectly detected objects that do not correspond to actual objects in the image.

#### 2.5.2. Recall

It measures the proportion of correctly detected objects out of all actual objects present in the ground truth. Recall is given by:

$$Recall = \frac{TP}{TP+FN} \quad (9)$$

where false negatives (FN) represents objects that were present in the image but not detected by the model.

#### 2.5.3. F1-score

The F1-score represents the harmonic mean of both precision and recall which guarantees one measure of model performance. The formula for calculating it is as follows:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (10)$$

The F1-score ranges from 0 to 1, with higher values indicating a better balance between precision and recall.

#### 2.5.4. Mean average precision

Mean average precision (mAP) is the main measure for comparing object detection models and is determined by adding up the precision-recall curve at various confidence thresholds. Initially, the average precision (AP) for each category is found as the area under the precision-recall curve:

$$AP = \int_0^1 Precision(Recall)\ d(Recall) \quad (11)$$

where precision is measured at different recall levels, and the integral represents the sum of precision values over varying recall thresholds.

$$mAP = 1/C \sum_{i=1}^{C} AP_i \quad (12)$$

where C is the total number of object classes, and APi is the Average Precision for class iii. A higher mAP value signifies that the model performs well across different object categories.

## 3. RESULTS AND DISCUSSION

The outcome shows that the efficacy of the proposed YOLOv8-based road surface damage detection framework in precisely identifying multiple categories of road defects, such as potholes, longitudinal cracks, transverse and alligator cracks. The trained model attained an overall detection accuracy of 91.2%, with confidence scores primarily falling between 0.60 and 0.95, demonstrating strong and dependable performance across diverse road textures and illumination environments. The robust performance of the YOLOv8 model can be ascribed to its anchor-free detection approach, it uses the FPN–PAN architecture to combine features at different scales and has a cross stage partial-based backbone instead. All of these traits help it find fissure patterns that are microscopic, irregular, and hard to see. These architectural features make it easier to find things even when the real world is hard to deal with. The recommended system is better at finding things and making generalizations than other systems that have been released, like YOLOv5, Faster R-CNN, and traditional CNN-based methods. This is especially true when the technology is used on real-world roads with different types of pavement and wear patterns. The proposed system maintains high accuracy while facilitating real-time deployment, contrasting with earlier techniques that occasionally encounter issues with real-time inference.

### 3.1. Result analysis

Figure 2 illustrates the main interface of the GPS-enabled YOLOv8 road damage detection system. Images (.png, .jpg), videos (.mp4), and live camera streams may be provided to facilitate flexible real-time analysis. Bounding boxes, confidence levels, and positional metadata are allocated to each road defect and Figure 3 illustrates the real-time online interface developed with Streamlit. This interface enables automated detection and geolocation of road damage, facilitating straightforward fault visualization. Users have the ability to dynamically adjust confidence thresholds to optimize the trade-off between false positives and missed detections.

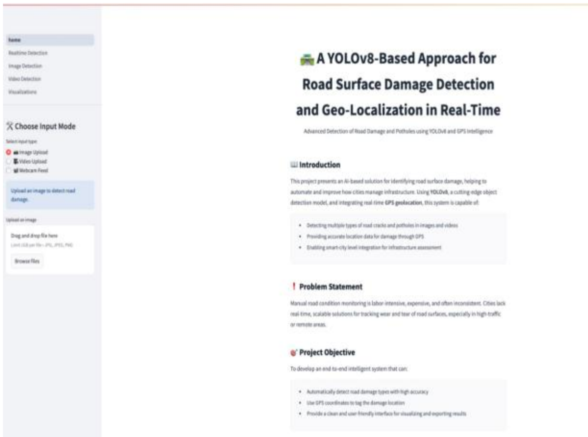


Figure 2. Home page screen 1

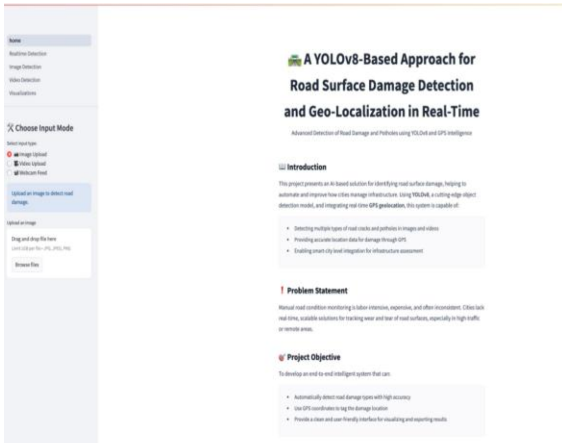


Figure 3. Home page screen 2

Figure 4 illustrates the video-based detection module, wherein uninterrupted video streams are examined frame by frame for real-time identification of road damage. Location identification, real-time preview, and machine-driven processing enhance the efficiency of road inspection footage analysis with this module. The analytical interface depicted in Figure 5 summarizes the detection outcomes. A bar chart indicates that potholes constitute the most prevalent form of road damage, followed by longitudinal, transverse, and alligator fissures. This statistical representation facilitates the assessment of damage prevalence and supports data-driven maintenance planning.

Geolocation-based visualization of road damage is presented in Figure 6. The interactive map displays defect locations, types of damage, and confidence scores for spatial analysis. Visualization helps you figure out which road repairs are the most important and makes it easier to plan maintenance. Finally, Figure 7 shows pictures of damage to the road, as well as graphs that show how often different types of damage happen and how the confidence scores are spread out. Most of the time, the detection model's confidence scores are between 0.6 and 0.9, which means it is likely correct.

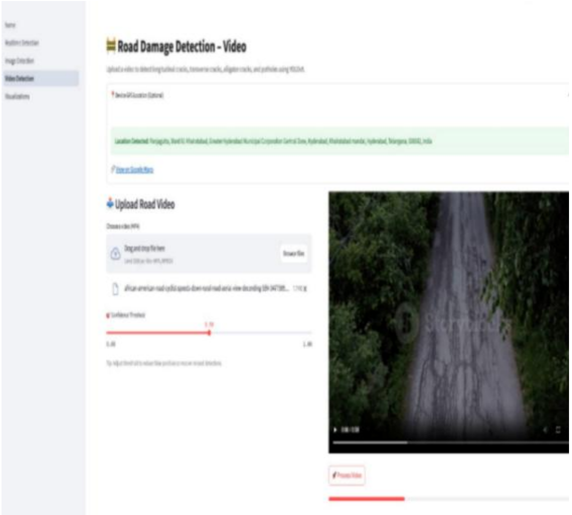


Figure 4. Video detection screen

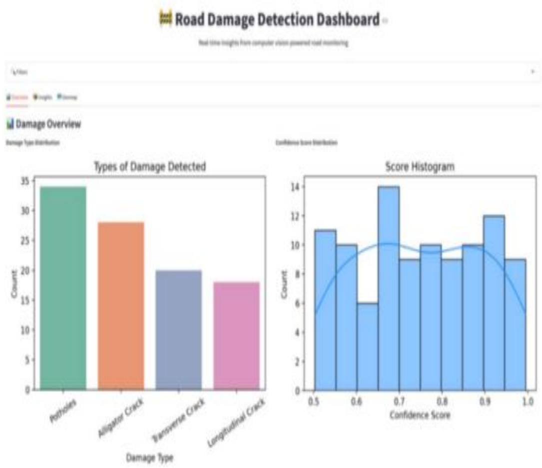


Figure 5. Road damage detection analytics dashboard

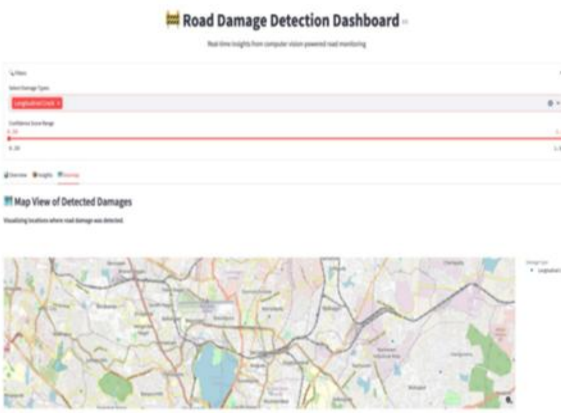


Figure 6. Geo location visualization

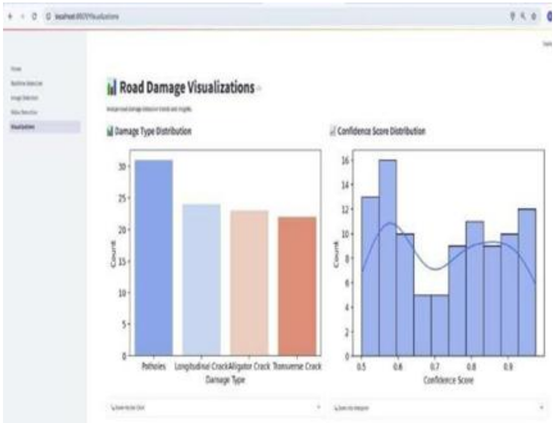


Figure 7. Road damage detection visualization

## 4. CONCLUSION

This study developed a YOLOv8-based system for real-time road damage recognition and mapping that can accurately identify potholes, longitudinal fractures, transverse cracks, and alligator cracks. The suggested system had 91.2% detection accuracy across road and illumination conditions, proving its reliability. Practical implementation is possible since the framework processes pictures, video feeds, and live camera inputs in real time. An interactive visualization tool with GPS-enabled geolocation makes road damage mapping and monitoring easier. Scalable, user-centric, and cost-efficient, the suggested system may automate road condition assessment, maintenance prioritization, and smart city infrastructure management.

Future study will integrate semantic segmentation and multimodal sensory data to improve detection robustness. Long-range damage detection, real-time road hazard notifications, and connection with big navigation platforms may improve route planning and road safety.

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**AUTHOR CONTRIBUTIONS STATEMENT**

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

**CONFLICT OF INTEREST STATEMENT**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors state no conflict of interest.

**DATA AVAILABILITY**

The data that support the findings of this study are available from the corresponding author upon reasonable request.

**REFERENCES**

[1] C. Wu *et al.*, "An automated machine-learning approach for road pothole detection using smartphone sensor data," *Sensors*, vol. 20, no. 19, p. 5564, Sep. 2020, doi: 10.3390/s20195564.

[2] B. Varona, A. Monteserin, and A. Teyseyre, "A deep learning approach to automatic road surface monitoring and pothole detection," *Personal and Ubiquitous Computing*, vol. 24, no. 4, pp. 519–534, Aug. 2020, doi: 10.1007/s00779-019-01234-z.

[3] W. Zhang, J. Qu, W. Wang, J. Hu, and J. Li, "Geo-location method for images of damaged roads," *Electronics*, vol. 11, no. 16, p. 2530, Aug. 2022, doi: 10.3390/electronics11162530.

[4] G. Guo and Z. Zhang, "Road damage detection algorithm for improved YOLOv5," *Scientific Reports*, vol. 12, no. 1, p. 15523, Sep. 2022, doi: 10.1038/s41598-022-19674-8.

[5] N. Ma *et al.*, "Computer vision for road imaging and pothole detection: a state-of-the-art review of systems and algorithms," *Transportation Safety and Environment*, vol. 4, no. 4, Nov. 2022, doi: 10.1093/tse/tdac026.

[6] M. H. Asad, S. Khaliq, M. H. Yousaf, M. O. Ullah, and A. Ahmad, "Pothole detection using deep learning: a real-time and AI-on-the-edge perspective," *Advances in Civil Engineering*, vol. 2022, no. 1, p. 9221211, Jan. 2022, doi: 10.1155/2022/9221211.

[7] D. Arya *et al.*, "Deep learning-based road damage detection and classification for multiple countries," *Automation in Construction*, vol. 132, p. 103935, Dec. 2021, doi: 10.1016/j.autcon.2021.103935.

[8] D. Arya, H. Maeda, S. K. Ghosh, D. Toshniwal, and Y. Sekimoto, "RDD2022: A multi-national image dataset for automatic road damage detection," *Geoscience Data Journal*, vol. 11, no. 4, pp. 846–862, Jun. 2024, doi: 10.1002/gdj3.260.

[9] M. Anandhalli, A. Tanuja, V. P. Baligar, and P. Baligar, "Indian pothole detection based on CNN and anchor-based deep learning method," *International Journal of Information Technology*, vol. 14, no. 7, pp. 3343–3353, Dec. 2022, doi: 10.1007/s41870-022-00881-5.

[10] K. R. Ahmed, "Smart pothole detection using deep learning based on dilated convolution," *Sensors*, vol. 21, no. 24, p. 8406, Dec. 2021, doi: 10.3390/s21248406.

[11] F. Wan, C. Sun, H. He, G. Lei, L. Xu, and T. Xiao, "YOLO-LRDD: a lightweight method for road damage detection based on improved YOLOv5s," *EURASIP Journal on Advances in Signal Processing*, vol. 2022, no. 1, p. 98, Oct. 2022, doi: 10.1186/s13634-022-00931-x.

[12] A. A. Sami, S. Sakib, K. Deb, and I. H. Sarker, "Improved YOLOv5-based real-time road pavement damage detection in road infrastructure management," *Algorithms*, vol. 16, no. 9, p. 452, Sep. 2023, doi: 10.3390/a16090452.

[13] M. Ren, X. Zhang, X. Chen, B. Zhou, and Z. Feng, "YOLOv5s-M: a deep learning network model for road pavement damage detection from urban street-view imagery," *International Journal of Applied Earth Observation and Geoinformation*, vol. 120, p. 103335, Jun. 2023, doi: 10.1016/j.jag.2023.103335.
[14] S. V. H. Pham and K. V. T. Nguyen, "Productivity assessment of the YOLO v5 model in detecting road surface damages," *Applied Sciences*, vol. 13, no. 22, p. 12445, Nov. 2023, doi: 10.3390/app132212445.
[15] J. Zeng and H. Zhong, "YOLOv8-PD: an improved road damage detection algorithm based on YOLOv8n model," *Scientific Reports*, vol. 14, no. 1, p. 12052, May 2024, doi: 10.1038/s41598-024-62933-z.
[16] Y. Li, C. Yin, Y. Lei, J. Zhang, and Y. Yan, "RDD-YOLO: Road damage detection algorithm based on improved You Only Look Once version 8," *Applied Sciences*, vol. 14, no. 8, p. 3360, Apr. 2024, doi: 10.3390/app14083360.
[17] Y. Jiang, "Road damage detection and classification using deep neural networks," *Discover Applied Sciences*, vol. 6, no. 8, p. 421, Aug. 2024, doi: 10.1007/s42452-024-06129-0.
[18] T. Li and G. Li, "Road defect identification and location method based on an improved ML-YOLO algorithm," *Sensors*, vol. 24, no. 21, p. 6783, Oct. 2024, doi: 10.3390/s24216783.
[19] A. Karukayil, C. Quail, and F. Auat Cheein, "Deep learning enhanced feature extraction of potholes using vision and LiDAR data for road maintenance," *IEEE Access*, vol. 12, pp. 184541–184549, 2024, doi: 10.1109/ACCESS.2024.3512783.
[20] Y. Zhang and C. Liu, "Real-time pavement damage detection with damage shape adaptation," *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 11, pp. 18954–18963, Nov. 2024, doi: 10.1109/TITS.2024.3416508.
[21] N. Shakhovska, V. Yakovyna, M. Mysak, S.-A. Mitoulis, S. Argyroudis, and Y. Syerov, "Real-time monitoring of road networks for pavement damage detection based on preprocessing and neural networks," *Big Data and Cognitive Computing*, vol. 8, no. 10, p. 136, Oct. 2024, doi: 10.3390/bdcc8100136.
[22] W. Wang *et al.*, "YOLO-RD: A road damage detection method for effective pavement maintenance," *Sensors*, vol. 25, no. 5, p. 1442, Feb. 2025, doi: 10.3390/s25051442.
[23] S. H. Abdelwahed, B. K. Sharobim, B. Wasfey, and L. A. Said, "Advancements in real-time road damage detection: a comprehensive survey of methodologies and datasets," *Journal of Real-Time Image Processing*, vol. 22, no. 4, p. 137, Aug. 2025, doi: 10.1007/s11554-025-01683-1.
[24] S. Zhang, Z. Liu, K. Wang, W. Huang, and P. Li, "OBC-YOLOv8: an improved road damage detection model based on YOLOv8," *PeerJ Computer Science*, vol. 11, p. e2593, Jan. 2025, doi: 10.7717/peerj-cs.2593.
[25] W. Chen, J. S. Yang, C. Xia, Y. Li, and X. Xiao, "Road surface damage detection based on enhanced YOLOv8," *Computers in Industry*, vol. 173, p. 104363, Dec. 2025, doi: 10.1016/j.compind.2025.104363.


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