AI-Based Speed bumps, Potholes Detection and Alert System Using YOLOv8 Model.

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***Abstract*: The rising incidence of accidents brought on by bad road conditions including potholes and unmarked speed bumps has raised serious concerns about road safety. These road irregularities frequently result in collisions and car damage, particularly when traveling at night or in bad weather. Road dangers cannot be tracked in real time using manual road inspection techniques, which are ineffective. In this research, a deep learning-based AI-based pothole and speed bump detection system is proposed. The system detects road dangers in real time using OpenCV image preprocessing and the YOLOv8 object detection model. The deep learning algorithm analyzes road photos taken by a car-mounted camera to find speed bumps and potholes. The technology informs the driver with both visual dashboard indicators and auditory cautions when it detects a hazard. Python, OpenCV, PyTorch, and Flask are used in the system's implementation. The suggested system can efficiently identify road risks and deliver real-time notifications, enhancing driver awareness and road safety, according to experimental results.**

Keywords: *YOLOv8, Deep Learning, Computer Vision, Pothole Detection, Smart Transportation, Road Hazard detection*

INTRODUCTION

Road infrastructure is crucial to the security of transportation. However, common issues that often result in collisions and car damage include potholes and poorly posted speed bumps. Drivers frequently have trouble identifying these risks, particularly at night or during periods of severe rain when visibility is poor. Transportation authorities undertake manual surveys as part of traditional road inspection methods. These approaches are ineffective and time-consuming, and they are unable to give drivers real-time information about potential hazards.

Automated systems that can evaluate road photos and automatically identify risks have been made possible by recent advancements in computer vision and artificial intelligence (AI). In image classification and object recognition tasks, deep learning methods like Convolutional Neural Networks (CNN) and objectdetection models have demonstrated encouraging outcomes.

The YOLOv8deeplearning model is used in this project's AI-based speed bump and pothole detection systemto identify irregularities in the road in real time. In order to alert drivers to potential risks on the road, the system analyzes pictures taken by a camera mounted on a car.

I. BACKGROUND STUDY

Road infrastructure is essential for safe and efficient transportation. However, damages like potholes, cracks, and speed bumps can cause accidents and vehicle issues if not spotted and fixed promptly. With improvements in artificial intelligence and computer vision, automated road damage detection has become a key research area. Deep learning methods, especially convolutional neural networks (CNNs) and object detection models, are commonly used to find road surface problems in images and videos. These techniques can automatically pull visual features from road images and classify various types of road damage with high precision.

Kumar et al. (2024) proposed a pothole detection system using the YOLOv5 object detection model. They trained their system on a custom dataset of Indian road conditions. The model achieved about 85% accuracy in detecting potholes and 83.8% accuracy in identifying speed bumps. The study showed that real-time detection with deep learning models could enhance road safety. However, the system's performance was influenced by different lighting conditions and weather.

Arya et al. (2020) studied road damage detection using CNNs and deep learning methods. Their approach used road images taken with smartphone cameras and vehicle-mounted cameras. The experiments showed that several CNN models reached detection accuracy above 90%. The research pointed out the potential of deep learning for automated road monitoring systems, although the models needed large labeled datasets and substantial computational power.

Zhang et al. (2024) introduced a new detection framework called POT-YOLO, which integrates the YOLOv8 architecture with edge segmentation techniques to improve pothole detection accuracy. The model was trained on datasets from road video frames and achieved 99.10% accuracy. The system proved to be highly reliable for real time detection. However, it required extra preprocessing and powerful GPU hardware for effective use.

Eriksson et al. (2021) took a different approach to road anomaly detection using smartphone sensors like accelerometers and GPS data. Their system identifies potholes based on sudden vehicle vibrations while driving. The study showed a cost-effective way to monitor roads in smart city settings. However, the system can only detect potholes after the vehicle drives over them and cannot visually identify road damage ahead of time.

Sevčík et al. (2023) conducted a comparative study with various deep learning object detection models, including Faster R-CNN, Sparse R-CNN, and YOLOv7, for road damage detection. Their tests were on a Slovakia road image dataset. The results revealed that the YOLOv7 model performed best with a mean average precision (mAP) of 88.4%. The study underscored the effectiveness of YOLO-based architectures for spotting potholes in real-world road images. However, the dataset was confined to a specific geographic area.

Mednis et al. (2021) suggested a machine learning-based pothole detection system using Random Forest and K Nearest Neighbor

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(KNN) algorithms. Their method classified road anomalies through vehicle vibration sensor data. The model reached 94.44% accuracy in detecting potholes. While the system effectively identified road irregularities, it had limitations in differentiating between various types of road damage. Efficient object detection frameworks like YOLOv8 have gained attention for road damage detection due to their ability to offer high accuracy while ensuring real-time processing speed. These models can detect multiple road defects at the same time using image or video input. Despite the advances in automated road damage detection, several hurdles remain. Many models face challenges due to changes in lighting, weather, and different road conditions. Additionally, some systems require significant computational resources or large annotated datasets for proper training. These issues emphasize the need for efficient and lightweight models that can deliver accurate real . time road damage detection for practical use..

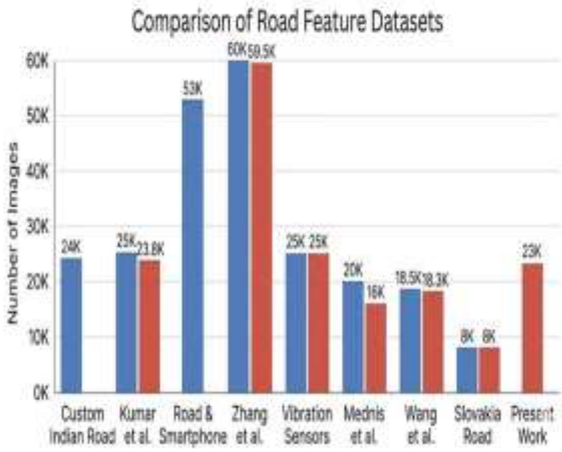
Authors & Year	Model Architecture	Dataset Used	Performance	Result	Limitations
R. Kumar et al., 2024	YOLOv5 Deep Learning Model	Custom Indian road dataset	85% pothole detection, 83.8% speed breaker detection	Real-time detection for autonomous vehicle safety	Performance affected by lighting and weather conditions
S. Arya et al., 2020	CNN and Deep Learning Models	Road images, smartphone sensor, camera data	Many models achieved >90% accuracy	Demonstrates effectiveness of deep learning in road condition monitoring	Requires large labeled datasets and high computation
M. Zhang et al., 2024	YOLOv8 with Edge Segmentation (POT-YOLO)	Road video frame dataset	98.10% accuracy	Highly accurate real-time pothole detection	Needs preprocessing and powerful GPU hardware
J. Eriksson et al., 2021	Machine Learning with Smartphone Sensors	Accelerometer and GPS data from vehicles	Effective anomaly detection	Low-cost smart city road monitoring system	Cannot visually detect potholes before vehicle contact
A. Mednis et al., 2021	Random Forest and KNN	Vehicle vibration sensor dataset	Effective anomaly detection	Low-cost smart city road monitoring system	Cannot visually detect different road damages
L. Wang et al., 2025	CNN and YOLO-based Computer Vision	Image-based road datasets	Up to 100% accuracy in reviewed works	Comprehensive analysis of road obstacle	Lack of unified benchmark datasets
P. Ševčík et al., 2025	Faster R-CNN, Sparse R-CNN, YOLOv7	Image-based road datasets	YOLOv7 achieved 88.4% mAP	Road Comprehensive analysis of road obstacle	Dataset limited to specific geographic region
Y. Chen et at al., 2025	Multimodal Trans- + Hybrid Deep Learning	Camera and sensor fusion dataset	YOLOv7 achieved 88.4% mAP	Reliable pothole detection in real-world road	Dataset limited to specific geographic region
P. Ševčík et al., 2024	YOLOv5 with image Processing	Road and UAV image dataset	Road and UAV image dataset	Reliable pothole detection in real-world road	Complex architecture with high computational
K. Sharma et al., 2024	YOLOv5 with image Processing	Road and UAV image dataset	Augment road image dataset	Cloud based smart monitoring application	Dependent on internet/ cloud connectivity
T. Li et al al., 2025	DD-CNN-23Layers	Road damage image dataset	97.54% mAP	Detects potholes, cracks, speed bumps and manholes	High computational cost due to deep network

II. Analysis of Datasets

The performance of the proposed road damage detection system was evaluated using image datasets that feature various types of road surface conditions, including potholes, speed breakers, and normal roads. These datasets consist of road images collected from different environments such as urban areas, highways, and rural locations. The images are sorted into different categories so that the deep learning model can learn the visual traits of road damages. Using labeled datasets helps the system identify and classify road defects accurately.

Unlike many previous studies that depend on limited datasets, using a diverse dataset in this proposed system improves the model's strength and detection accuracy. The dataset includes images taken in various lighting conditions, weather situations, and road textures. This variety allows the model to learn a broad range of visual patterns related to road damages, which enhances detection performance in real-life situations. In this project, a road damage image dataset sourced from public resources was used for training and evaluation.

The dataset contains thousands of annotated images showing potholes and speed breakers. After preprocessing and filtering, the dataset was split into 80% for training and 20% for testing to ensure proper model training and unbiased evaluation. Preprocessing steps such as resizing images, normalizing data, and formatting annotations were applied to make the dataset compatible with the object detection framework used in this system.



III. Methodologyof ProposedSystem

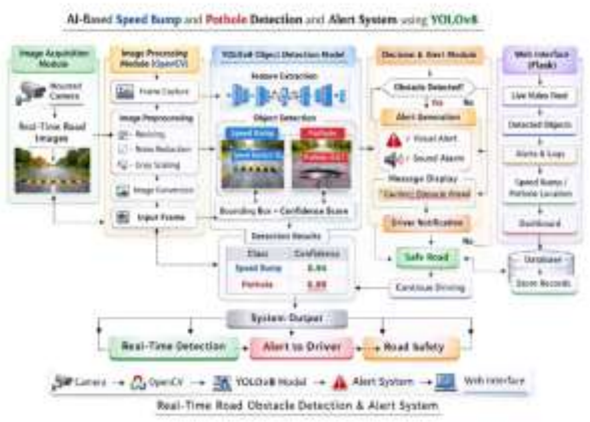
. The system uses a deep learning object detection method to identify road anomalies such as speed bumps and potholes. The goal focuses on road safety. The system detects these obstacles in real time and sends alerts before a driver reaches them. The process starts with dataset collection. The dataset contains images of speed bumps and potholes. Each image includes labels for two classes. Speed bumps and potholes. The images show different road conditions, lighting levels, and viewing angles. This variation helps the model learn useful visual patterns.

The dataset split follows an 80 to 20 ratio. Eighty percent of images support training. Twenty percent support testing. This split supports fair performance evaluation. Image preprocessing prepares the data for the deep learning model. Each image undergoes resizing to a fixed resolution. The resolution matches the input requirement of the detection model. Normalization and formatting also occur during preprocessing. These steps improve data consistency and training efficiency. The prepared dataset moves to the training stage. The system uses the YOLOv8 object detection model.

YOLO stands for You Only Look Once. The model detects multiple objects in a single image. The model analyzes spatial features and visual patterns. Training helps the model learn surface irregularities, shape patterns, and texture differences linked with speed bumps and potholes. During real time operation, a camera mounted on the vehicle captures continuous road images. The system processes these images with the OpenCV library. OpenCV handles frame extraction, preprocessing, and format conversion. Each frame then moves to the trained YOLOv8 detection model.

The model scans the frame and identifies speed bumps or potholes. Detection appears through bounding boxes around the objects. The model also outputs a confidence score. This score shows the probability of the detected object belonging to a specific class. When the system detects a road obstacle, an alert module activates. The module displays a warning message and plays an audible alert. The alert informs the driver about the obstacle ahead. This warning helps the driver reduce speed and take action.

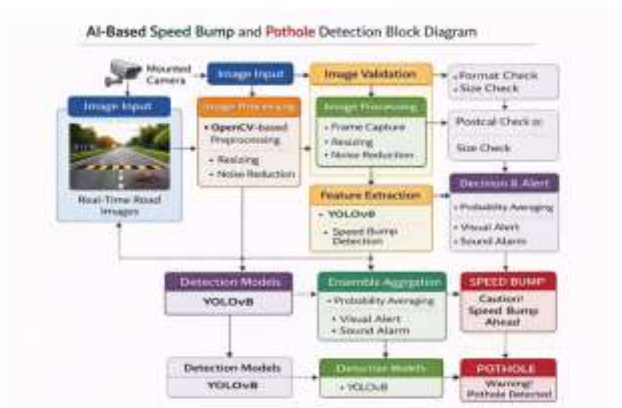
The system reduces the risk of vehicle damage and improves road safety. A web interface supports user interaction. The system builds this interface with the Flask framework and Python libraries. The interface allows image upload and result viewing. The screen displays processed images with bounding boxes, labels, and confidence scores. The full system combines camera image capture, OpenCV preprocessing, YOLOv8 detection, and a Flask web interface. Tests show accurate detection of speed bumps and potholes under different road conditions. The system supports intelligent transportation and driver assistance applications.



The figure shows the system architecture for the AI based speed bump and pothole detection and alert system. Amounted camera captures road images. The system processes these images through several modules. These modules include image acquisition, preprocessing with OpenCV, object detection with the YOLOv8 model, and an alert generation module.

The system analyzes each frame and detects road obstacles such as speed bumps and potholes in real time. The image acquisition module collects continuous road images from the mounted camera. The system sends these images to the image processing module. OpenCV performs preprocessing steps such as frame extraction, image resizing, and noise reduction. These steps prepare the images for the detection stage.

The YOLOv8 model works as the main detection module. The model extracts visual features from the processed images. The model identifies patterns linked with speed bumps and potholes. The system then places bounding boxes around detected objects. The model also produces confidence scores which show the accuracy of each detection. After detection, the decision and alert module activates. The system displays a warning message on the screen. The system also produces a sound notification. This alert informs the driver about the obstacle ahead.



IV. Implementation

The system uses an AI model to detect speed bumps and potholes on roads. A deep learning model works with a web interface to monitor the road in real time and send alerts. Development used Python. Key libraries include YOLOv8 from Ultralytics, OpenCV, NumPy, and Flask. Model training ran on Kaggle and Google Colab with GPU support. GPU access reduced training time and improved training efficiency. The first step involved collecting a dataset. The dataset includes images of speed bumps and potholes from public sources. Each image contains labels for road conditions and obstacle types.

The dataset went through sorting and preparation before training. Data split followed a simple rule. Eighty percent of the images went into training. Twenty percent went into testing. This split helped measure model performance aftertraining. An image preprocessing pipeline prepared the data for the model. Each image went through resizing to match the input resolution required by YOLOv8. Normalization and formatting steps followed. These steps produced consistent input data. Consistent data improves model accuracy and training stability.

The YOLOv8 object detection model performs the main detection task. The model focuses on two classes. Speed bumps. Potholes. Training helps the model learn visual patterns on road surfaces. These patterns include irregular shapes, edges, and texture differences between smooth roads and obstacles. Training used a defined batch size and several epochs. Each epoch allowed the model to improve pattern recognition. During training the model generated bounding boxes around detected obstacles. Each box carried a confidence score. Higher scores indicate stronger detection confidence.

After training, the saved model moved into the live detection system. The real time system uses a camera mounted on a vehicle. The camera captures road frames continuously. OpenCV handles frame capture and initial processing. Processed frames move into the trained YOLOv8 model for analysis. When the model detects a speed bump or pothole, the system triggers alerts. The system shows a visual warning and plays an audio notification for the driver. A web interface built with Flask displays the detection results. The interface shows captured images and detected obstacles. Alert messages appear on the screen when the system detects road hazards.

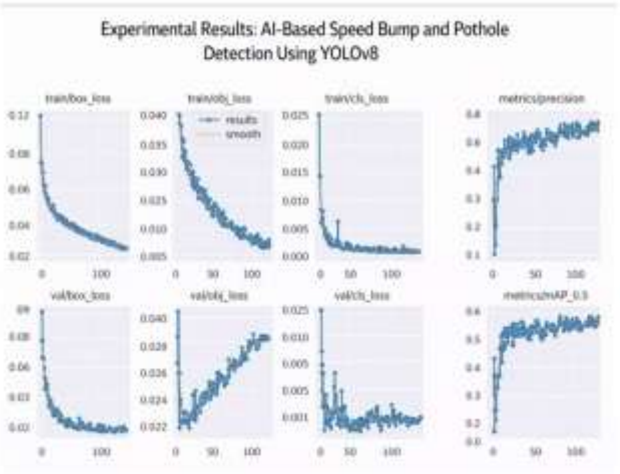
This setup combines deep learning detection, live image processing, and a web interface. The result supports better driver awareness and road safety

V. ExperimentalResults

The proposed AI system detects speed bumps and potholes. Evaluation used training and validation metrics from the YOLOv8 training process. Graphical plots present the results. The plots show changes in training loss, validation loss, precision, recall, and mean Average Precision across multiple training epochs. Training losses include box loss, object loss, and classification loss. These losses decrease as training epochs increase.

This pattern shows successful learning of visual features related to speed bumps and potholes. Validation losses remain stable during training. Stable validation results indicate good generalization on unseen data and low overfitting. Precision and recall measure detection performance. Precision shows the proportion of correct detections among all predicted detections. Recall measures the ability to detect all obstacles present in the dataset. Both metrics increase during training. The increase indicates improved detection performance.

Mean Average Precision metrics provide overall detection evaluation. The metrics include mAP@0.5 and mAP@0.5:0.95. These values increase during training. Higher values indicate improved accuracy in detecting and locating speed bumps and potholes under different intersection over union thresholds. The experimental results show effective learning of road obstacle features by the YOLOv8 detection model. The graphs show clear convergence of the training process. Detection accuracy improves across training epochs



This figure shows pothole detection results using the YOLOv8 model. The system identifies potholes on road surfaces and marks them with bounding boxes along with confidence scores, demonstrating accurate detection under different road conditions.

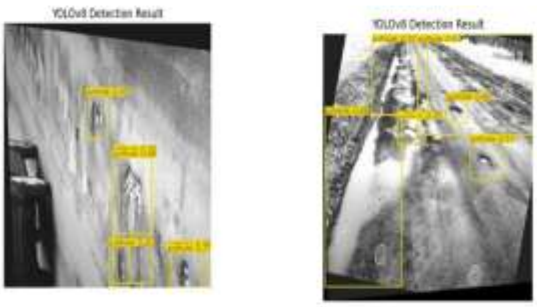


Fig. 3.2: Pothole Detection using YOLOv8 Model
This figure shows pothole detection results using the YOLOv8 model. The system identifies potholes on road surfaces and marks them with bounding boxes along with confidence scores, demonstrating accurate detection under different road conditions.

VI . GAPS IDENTIFIED IN EXISTING RESEARCH

Deep learning improves road obstacle detection, yet limitations remain. Many models train on limited datasets with specific road and lighting conditions. This limits performance in real environments such as low light, shadows, or uneven roads. More diverse data and reliable real time systems improve detection accuracy and road safety

Gaps Identified in Road Obstacle Detection Research

GAP AREA	SUMMARY OF GAP	IMPLICATIONS
Dataset Diversity and Conditions	Many datasets mainly include specific road conditions and weather scenarios	Limits detection accuracy in diverse driving environments.
Environmental Variability	Existing models struggle with varying lighting, weather and road surface conditions.	Reduces reliability in poor lighting, shadows, rain, or uneven roads.
Offline Detection Focus	Some systems focus on offline image detection rather than real-time analysis.	Limits practical use for real-time driver assistance.
Limited Generalization Ability	Models trained on limited, region-specific data struggle to detect diverse obstacles.	Causes failure to accurately detect speed bumps and potholes in new regions.

Gap Identification for existing models

The proposed system addresses these gaps through an object detection approach based on the YOLO model. The model trains on road obstacle datasets and uses image preprocessing techniques. This approach improves detection accuracy, system robustness, and real time performance under different road and environmental conditions.

VII. Future Enhancements Suggested in the Literature

Research on road obstacle detection shows several ways to improve system performance and reliability. One key improvement involves the use of larger and more diverse road datasets. Many studies rely on limited data with specific road conditions or lighting environments. Expanding datasets with images from different weather, lighting, and road situations improves the generalization ability of detection models. Another improvement involves advanced deep learning architectures such as improved YOLO models and hybrid CNN based frameworks. These models learn complex road features and detect obstacles such as speed bumps and potholes with higher accuracy. Researchers also focus on improving model robustness through data augmentation, transfer learning, and improved training methods. These techniques help models learn diverse road patterns and perform better in new environments. Future systems also focus on real time detection integrated with smart transportation and driver assistance systems. These systems provide alerts to drivers and help reduce accidents caused by road obstacles.

VIII.Conclusion

Artificial intelligence and deep learning enable intelligent solutions for transportation problems. Road obstacle detection plays an important role in improving road safety. Speed bumps and potholes create risks for drivers and vehicles. Computer vision systems help identify these obstacles early. This work presents an AI based road obstacle detection system. The system identifies speed bumps and potholes from road images. A deep learning object detection model performs the detection and classification task.

Training uses labeled datasets containing images of these obstacles. The model learns visual patterns which help distinguish obstacles under different road conditions. The system applies image preprocessing and effective training methods to improve detection performance. The trained model detects road obstacles with good accuracy and reliability. Early detection reduces the risk of accidents caused by unnoticed speed bumps or potholes

Experimentalresults show strong detection performance.Evaluationmetrics andtraining graphs indicate stablelearning and reliable predictions during testing. The proposed approach offers an automated solution for road obstacle detection.

The system supports safer driving environments. Future integration with smart transportation systems, driver assistance technologies, and real time road monitoring improves practical use

IX.References

[1]. P. C. Nissimagoudar, S. R. Miskin, V. N. Sali, A. J, R. S. K, D. S. K, G. H. M, R. S. Hongal, S. V. Katwe, B. Basawaraj, and N. C. I,"Detection of Potholes and Speed Breaker for Autonomous Vehicles," Procedia Computer Science, vol. 237, pp. 675–682, 2024.

[2]. L. Manoni, S. Orcioni, and M. Conti, "Recent Advancements in Deep Learning Techniques for Road Condition Monitoring: A Comprehensive Review," IEEE Access, vol. XX, pp. XX–XX, Oct. 2024, doi: 10.1109/ACCESS.2024.3481649. [3]. B. N., M. M. Kodabagi, M. Kumar B., A. P., Muthukumar N., and A. A., "POT-YOLO: Real-Time Road Potholes Detection using Edge Segmentation based YOLOv8 Network," IEEE Sensors Journal, vol. XX, no. XX, pp. XX–XX,2022024, doi: 10.1109/JSEN.2024.3399008. [4]. Assemlali, H., Bouhissini, S., and Sael, N., "Computer Vision-Based Detection and Classification of Road Obstacles: Systematic Literature Review,"IEEE Access, vol. XX, no. XX, pp. XXXX–XXXX, 2025, doi: 10.1109/ACCESS.2025.3588668 [5]. O. A. Egaji, G. Evans, M. G. Griffiths, and G. Islas, "Real-time Machine Learning–Based Approach for Pothole Detection," Expert Systems with Applications, vol. 184, Art. no. 115562, 2021, doi: 10.1016/j.eswa.2021.115562 [6]. Lieskovská, E., Jakubec, M., Bučko, B., and Zábovská, K., "Automatic pothole detection," Transportation Research Procedia, vol. 74, pp. 1164–1170, 2023, Elsevier. [7]. Palwe, S., Gunjal, A., Jindal, S., Shrivastava, A., Deshmukh, A., & Navlakha, M., "An Intelligent and Deep Learning Approach for Pothole Surveillance Smart Application," Procedia Computer Science, vol. 235, pp. 3271 3282, Elsevier, 2024. [8]. Nissimagoudar, P.C., Basawaraj, Gireesha, H.M., Kulkarni, A., Bhat, S., Iyer, N.C. (2023). Pothole Detection and Road Condition Updation on Google Maps. In: Choudrie, J., Mahalle, P.N., Perumal, T., Joshi, A. (eds) IOT with Smart Systems. ICTIS 2023. Lecture Notes in Networks and Systems, vol 720. Springer, Singapore. https://doi.org/10.1007/978-981-99-3761-5 [9]. B. Bučko, E. Lieskovská, K. Zábovská, and M. Zábovský, ''Computer vision based pothole detection under challenging conditions,'' Sensors, vol. 22, no. 22, p. 8878, Nov. 2022, doi: 10.3390/s22228878. [10]. A. K. Pandey, R. Iqbal, T. Maniak, C. Karyotis, S. Akuma, and V. Palade, ''Convolution neural networks for pothole detection of critical road infras tructure,'' Comput. Electr. Eng., vol. 99, Apr. 2022, Art. no. 107725, doi: 10.1016/j.compeleceng.2022.107725 [11]. K. Gajjar, T. V. Niekerk, T. Wilm, and P. Mercorelli, ''Vision-based deep learning algorithm for detecting potholes,'' J. Phys., Conf. Ser., vol. 2162, no. 1, Jan. 2022, Art. no. 012019, doi: 10.1088/1742 6596/2162/1/012019. [12]. Q. Li, Y. Shi, Q. Liu, and G. Liu, ''Deep learning-based pothole detection for intelligent transportation: A YOLOv5 approach,'' Int. J. Adv. Comput. Sci. Appl., vol. 14, no. 12, pp. 408–415, 2023, doi: 10.14569/ijacsa.2023.0141242. [13]. D. K. Dewangan and S. P. Sahu, ''PotNet: Pothole detection for autonomous vehicle system using convolutional neural network,'' Elec tron. Lett., vol. 57, no. 2, pp. 53–56, Jan. 2021, doi: 10.1049/ell2.12062.. [14]. R. Bharat, A. M. Ikotun, A. E. Ezugwu, L. Abualigah, M. Shehab, and R. A. Zitar, ''A real-time automatic pothole detection system using convo lution neural networks,'' Appl. Comput. Eng., vol. 6, no. 1, pp. 750–757, Jun. 2023, doi: 10.54254/2755-2721/6/20230948 [15]. H. Samma, S. A. Suandi, N. A. Ismail, S. Sulaiman, and L. L. Ping, ''Evolving pre-trained CNN using two layers optimizer for road damage detection from drone images,'' IEEE Access, vol. 9, pp. 158215–158226, 2021, doi: 10.1109/ACCESS.2021.3131231 [16]. G. Guo and Z. Zhang, ''Road damage detection algorithm for improved YOLOv5,'' Sci. Rep., vol. 12, no. 1, pp. 1–12, Sep. 2022, doi: 10.1038/s41598-022-19674-8. [17]. S.M. Sangve, M. Kulkarni, K. Chawade, G. Marathe, and P. Pawar, ''Advanced driver assistance system (ADAS),'' in Proc. Int. Conf. Emerg. Smart Comput. Informat. (ESCI), Mar. 2024, pp. 1–6, doi: 10.1109/esci59607.2024.10497387. [18]. T. S. Brisimi, C. G. Cassandras, C. Osgood, I. C. Paschalidis, and Y. Zhang, "Sensing and Classifying Roadway Obstacles in Smart Cities: The Street Bump System," IEEE Access, vol. 4, pp. 1301–1313, 2016, doi: 10.1109/ACCESS.2016.2529562 [19]. M. K. Tripathi, D. Baswaraj, S. Deshmukh, K. Misal, N. P. Bhosle, and S. M. Sangve, ''Pothole detection in bituminous road using con volutional neural network with transfer learning,'' Indonesian J. Electr. Eng. Comput. Sci., vol. 33, no. 3, pp. 1950–1957, Mar. 2024, doi: 10.11591/ijeecs.v33.i3.pp1950-1957. [20]. A. Hassan, T. Rahim, and S.-Y. Shin, ''An improved deep con volutional neural network-based autonomous road inspection scheme using unmanned aerial vehicles,'' Electronics, vol. 10, no. 22, p. 2764, Nov. 2021, doi: 10.3390/electronics10222764