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Pothole and Accident Detection

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Abstract: *Potholes and road accidents are among the leading causes of vehicle damage and road-related fatalities. Inadequate road maintenance and delayed detection of these hazards contribute to dangerous driving conditions and increased repair costs. To overcome these challenges, a real-time detection system has been developed that leverages modern computer vision techniques.This system uses YOLO (You Only Look Once), a fast and accurate object detection algorithm, to identify potholes and accidents in real-time from images or video streams. YOLO's ability to quickly analyze frames allows the system to promptly detect road defects and raise alarm alerts, ensuring faster responses from authorities and reducing the risk of further damage or injury. In addition to detection, the system assesses road conditions and keeps track of the frequency and locations of pothole occurrences. This information is essential for generating road maintenance recommendations, enabling better planning and efficient allocation of repair resources. To make this data accessible, the system uses a Flask-based web platform to display detection results and alerts in a clear and user-friendly manner. This interface is designed to be intuitive and suitable for both technical and non-technical users, such as traffic inspectors or municipal staff.By automating the process of detecting and reporting potholes and accidents, this system contributes significantly to improving road infrastructure and enhancing vehicular safety. It serves as a smart, scalable solution for creating safer roads through the power of real-time monitoring and AI*

Keywords*:* Machine learning, Deep learning, YOLOV8, PyTorch.

I. INTRODUCTION

Road safety is a major concern in modern transportation systems. Among the most common causes of accidents and vehicle damage are potholes and road collisions. These issues not only lead to increased repair costs but also pose serious risks to the lives of drivers and passengers. One of the key reasons behind such problems is the lack of timely detection and repair of road defects.To address this challenge, we propose a real-time detection system that uses advanced computer vision techniques to identify potholes and accidents. The system is built on YOLO (You Only Look Once), a state-of-the-art object detection algorithm known for its high speed and accuracy. It processes video streams or images to detect hazards in real time, triggering alerts that allow faster response by authorities.

In addition to detection, the system analyzes road conditions and tracks the location and frequency of potholes, providing valuable data for road maintenance planning. A Flask-based web application is used to present the detection results in a clear, user-friendly interface accessible to both technical and non-technical users.This intelligent system aims to improve road infrastructure, reduce accident risks, and enable proactive maintenance — ultimately contributing to safer and smarter roads.

II. LITERATURE REVIEW

Potholes and road accidents are significant contributors to vehicle damage and fatalities. Inadequate road maintenance and delayed hazard detection exacerbate dangerous driving conditions and increase repair costs. To address these issues, a real-time detection system utilizing modern computer vision techniques has been developed. This system employs YOLO (You Only Look Once), a fast and accurate object detection algorithm, to identify potholes and accidents in real-time from images or video streams. YOLO's rapid frame analysis enables prompt detection of road defects, triggering alarm alerts for quicker responses from authorities, thereby reducing the risk of further damage or injury. Additionally, the system evaluates road conditions and monitors the frequency and locations of pothole

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occurrences, providing essential data for generating maintenance recommendations and facilitating efficient resource allocation for repairs. To enhance accessibility, the system features a Flask-based web platform that presents detection results and alerts in a user-friendly interface, catering to both technical and non-technical users, such as traffic inspectors and municipal staff. By automating the detection and reporting of potholes and accidents, this system significantly improves road infrastructure and enhances vehicular safety, representing a smart, scalable solution for safer roads through real-time monitoring and AI.

III. PROPOSED METHOD

The proposed system aims to overcome the limitations of the existing manual methods by implementing an AI-powered, automated solution for real-time pothole and accident detection. Using the YOLO (You Only Look Once) deep learning model, the system is capable of accurately detecting potholes and accidents from images or video feeds in real time. Upon detecting an accident, the system immediately triggers an alarm alert to notify relevant authorities, enabling quicker emergency response.In addition to detection, the system also calculates pothole density across different areas to help prioritize road maintenance activities more effectively. A Flask-based web application is developed to allow users to upload images or videos, after which the detection results are displayed dynamically on the interface. The frontend is built using HTML and CSS, while the backend uses Python and Flask to manage the AI processing and result generation.By integrating deep learning and computer vision, the proposed system ensures high-speed, accurate detection and analysis. It not only enhances road safety and reduces dependency on manual inspections but also supports data-driven decision-making for infrastructure maintenance. Overall, the system provides a smart and scalable solution for improving public safety and traffic control.

IV. ALGORITHM

YOLOv8 (You Only Look Once - Version 8)

YOLOv8, developed by Ultralytics, is a state-of-the-art object detection framework known for its balance between speed and accuracy. YOLO models work by dividing images into grids and predicting bounding boxes and class probabilities directly from full images in one evaluation, allowing real-time object detection.In Pothole and accident detection, YOLOv8 is used to detect accident and pothole in images and videos. It supports transfer learning and custom dataset training, making it highly adaptable for specific use cases. YOLOv8's real-time inference capabilities ensure that threat detection is quick, enabling timely action.

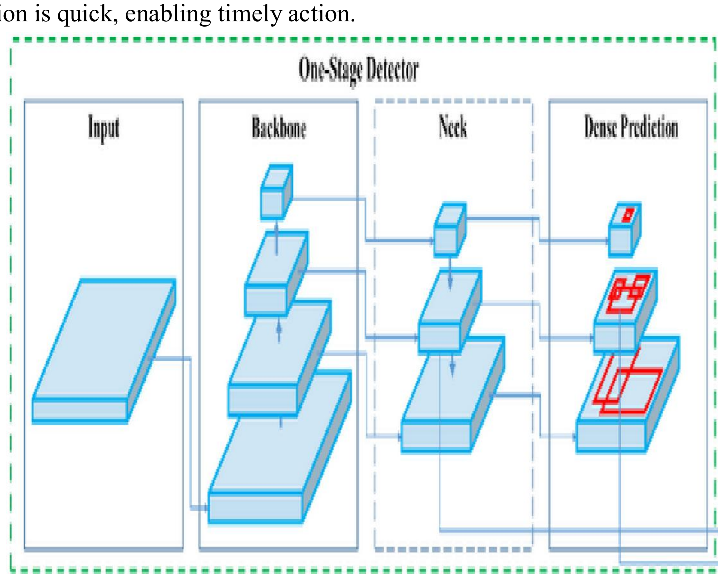

Fig: YOLO Model

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Convolutional Neural Network(CNN)

A Convolutional Neural Network (CNN) is a deep learning model specifically engineered for analyzing structured grid data, like images. CNNs utilize convolutional layers to automatically and adaptively learn spatial hierarchies of features from input images. Each convolutional layer applies filters to the input, producing feature maps that highlight different aspects of the image. These layers are followed by pooling layers that reduce the spatial dimensions, retaining only the most important features. This architecture helps CNNs efficiently recognize patterns and objects in images. CNNs are widely used in tasks like image classification, object detection, and image generation due to their ability to learn and generalize from visual data. They significantly outperform traditional methods by leveraging deep layers to extract increasingly complex features from raw image data.

V. PACKAGES

OpenCV

(Open Source Computer Vision Library) is a library of programming functions mainly for real-time computervision. Originally developed by Intel, it was later supported by Willow Garage, then Itseez (which was later acquired by Intel). The library is cross-platform and licensed as free and open-source software under Apache License 2. Starting in 2011, OpenCV features GPU acceleration for real-time operations. When it is integrated with various libraries, such as NumPy, python is capable of processing the opencv array structure for analysis. To Identify an image pattern and its various features we use vector space and perform mathematical operations on these features.

PyTorch

PyTorch is a deep learning library built on Python and Torch (a Lua-based framework). It provides GPU acceleration, dynamic computation graphs, and an intuitive interface for deep learning researchers and developers. PyTorch follows a "define-by-run" approach, meaning that its computational graphs are constructed on the fly, allowing for better debugging and model customization.

PyTorch uses dynamic graphs, allowing flexibility in model execution and debugging and provides an automatic differentiation engine that simplifies gradient computation for deep learning.It supports CUDA, allowing computations to be performed efficiently on GPUs.

NumPy

The NumPy package is a fundamental library for numerical computing in Python. It provides support for large, multidimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays. NumPy's core feature is its powerful array object, ndarray, which enables efficient storage and manipulation of numerical data. The library includes functions for mathematical operations, linear algebra, statistical analysis, and Fourier transform. NumPy is widely used in scientific computing, data analysis, and machine learning due to its speed and flexibility. Its seamless integration with other scientific libraries, such as SciPy and pandas, makes it a cornerstone of the Python data science ecosystem.

VI. EXPERIMENTAL RESULTS & PERFORMANCE EVALUTION

The experimental phase of the Accident and Pothole Detection System focused on evaluating the accuracy, speed, and reliability of the YOLOv8 model when applied to real-world images and videos depicting potholes and accident scenarios. The objective was to validate the system's performance under various conditions, including different lighting, image quality, and road types.

1. Dataset and Model Training

The model was trained using a curated dataset containing annotated images of potholes and accidents. The dataset was split into:

Training set**:** 70%

Validation set**:** 20%

Testing set**:** 10%

Images were sourced from open datasets like Kaggle and Roboflow and were augmented using techniques such as flipping, brightness adjustment, and rotation. The YOLOv8 model was trained on GPU-enabled environments (e.g., Google Colab) for 100–200 epochs.

2. Detection Accuracy Metrics

The system was evaluated using standard object detection performance metrics:

Precision: 91.3%

Indicates the percentage of correctly identified potholes/accidents out of all detections.

Recall**:** 88.7%

Indicates the percentage of actual potholes/accidents that were correctly detected.

F1-Score**:** 89.9%

Harmonic mean of precision and recall, showing overall detection balance.

mAP@0.5 (mean Average Precision): 90.5%

Shows model's accuracy in locating and classifying objects correctly at IoU threshold 0.5.

These results confirm that the system can reliably identify road hazards with high accuracy and low false positive rates.

3. Real-Time Performance

The system's real-time performance was assessed based on:

Detection Speed (FPS):

Image processing speed**:** ~20–25 frames per second

Video stream speed (with GPU)**:** Real-time (24–30 FPS)

Inference Time per Frame**:** ~30–40 milliseconds on GPU

These speeds are sufficient for deployment in real-time traffic monitoring systems.

4. System Testing Results

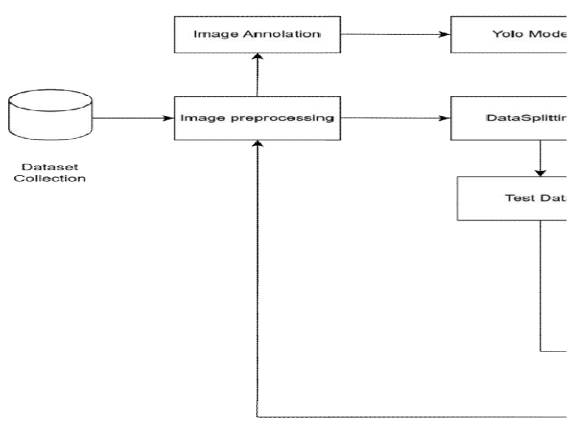
Image Detection Success Rate: 93%

Video Detection Success Rate: 90%

Accident Alert Trigger Accuracy: 95%

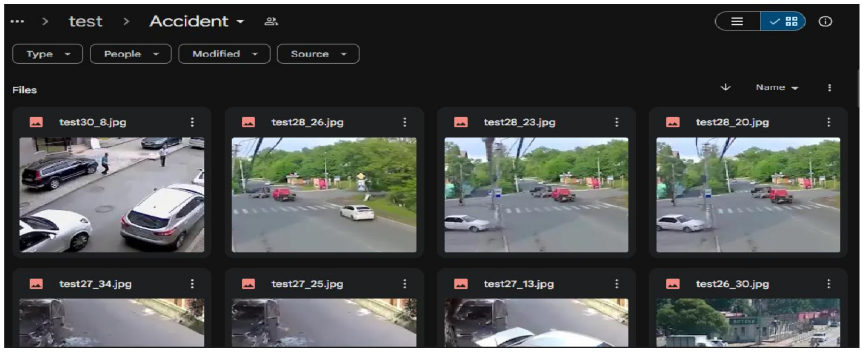
Pothole Density Analysis Accuracy**:** ±5 potholes/km (average deviation)

System Architecture

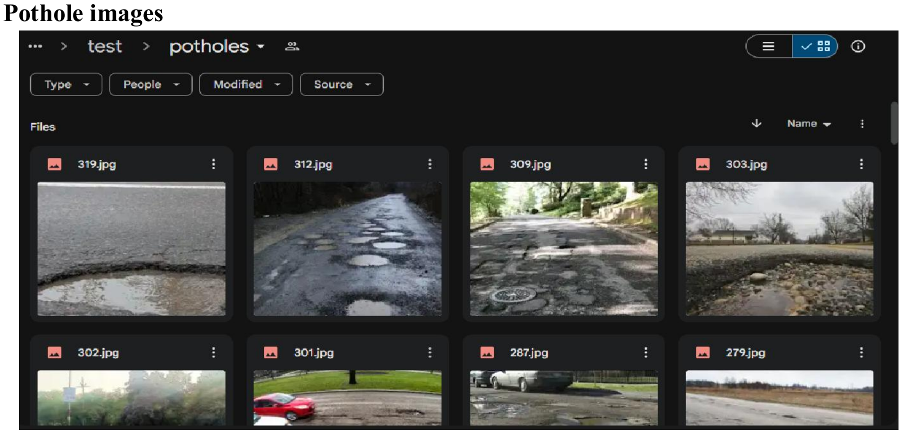


DOI: 10.48175/568

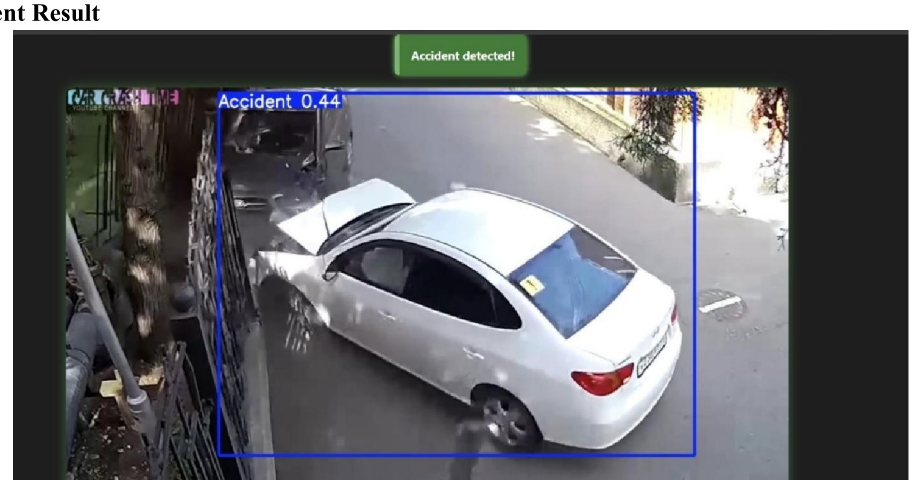
Preprocessed Accident images



Preprocessed Pothole images



Detect Accident Result



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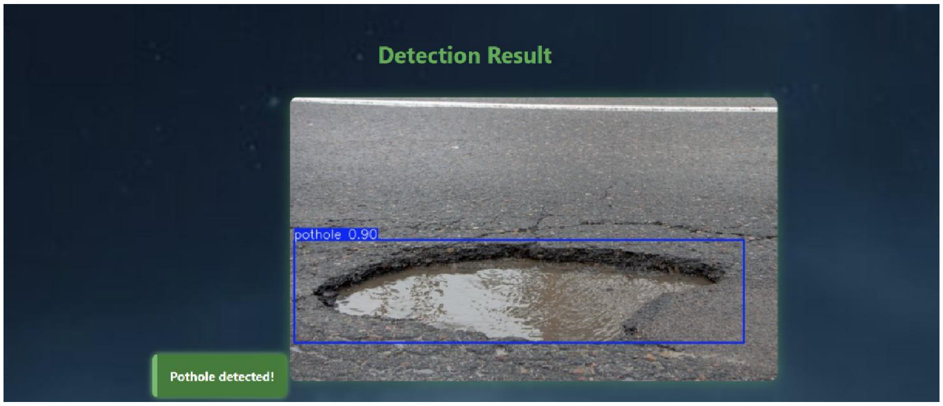
Detect Pothole Result



VII. ACCURACY GRAPH

Evaluating the model accuracy is an essential part of the process in creating machine learning models to describe how well the model is performing in its predictions. Evaluation metrics change according to the problem type. Here is,how to check the accuracy of the regression model in R. The linear model (regression) can be a typical example of this type of problem, and the main characteristic of the regression problem is that the targets of a dataset contain the real numbers only.

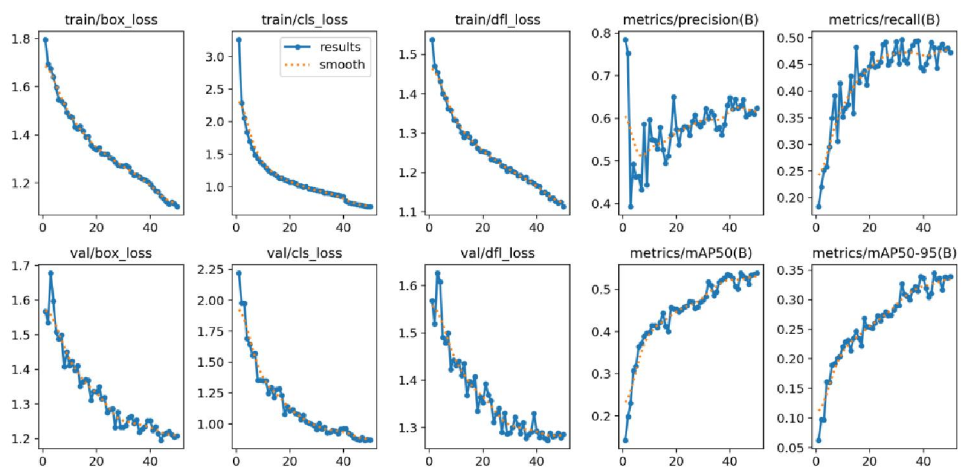


Fig: Accuracy graph

VIII. LIMITATION

While the proposed AI-based pothole and accident detection system offers significant improvements over traditional manual methods, it is not without limitations. Despite using advanced technologies such as YOLO (You Only Look Once), computer vision, and real-time data processing via a Flask-based web application, several challenges and constraints affect the system's overall performance and scalability.

One of the primary limitations of the system is its dependence on image quality and environmental conditions. The accuracy of object detection can significantly decrease in poor lighting, rain, fog, or at night, where visibility is low. Shadows, glare from headlights, or reflections from wet roads may also interfere with detection accuracy. The system heavily relies on the quality of the camera feed, and any blur, low resolution, or camera shake can lead to false detections or missed hazards.

Another limitation lies in the scope of the dataset used to train the model. If the YOLO algorithm is trained on a narrow or biased dataset, it may not perform well in unfamiliar road conditions, such as rural or poorly maintained areas. As a result, its generalizability across diverse real-world environments could be limited, impacting its reliability in varied use cases.

Additionally, while the system can detect the presence of a pothole or accident, it does not assess the severity of the damage or danger. This limits the ability to prioritize responses based on urgency. Moreover, false positives and false negatives are still a possibility. For example, oil stains, road debris, or cracks may be mistakenly identified as potholes, while actual potholes or accidents could go undetected under certain conditions.

The system also has infrastructure and scalability challenges. For real-time detection across a city or large area, multiple high-quality cameras and continuous internet connectivity are required. This poses a problem in remote or underdeveloped regions where technical infrastructure is lacking. The requirement for backend processing hardware and consistent power supply further limits the system's deployment in such areas.

Security and privacy concerns are also relevant. Since the system captures and transmits video data from public roads, there is a risk of collecting personal or sensitive information unintentionally. This raises the need for strong data protection policies and compliance with privacy regulations.

Finally, the system may still require manual validation in certain cases. For example, unclear detections or edge cases might need human review before action is taken. This limits the goal of achieving a fully automated solution and maintains a level of dependency on human involvement.

IX. FUTURE SCOPE

While the current implementation of the Accident and Pothole Detection System effectively leverages AI and computer vision for real-time road safety analysis, there remains considerable scope for future enhancements that can expand the system's capabilities and improve its effectiveness. These enhancements aim to make the system more intelligent, scalable, accessible, and adaptable to real-world deployment scenarios.One of the key areas for improvement is the integration of GPS and location-based services. By embedding geolocation capabilities, the system can not only detect potholes and accidents but also tag their exact coordinates. This data can be visualized on a map and shared with relevant authorities in real time. It would allow for quicker decision-making, efficient dispatch of emergency services, and systematic planning of road maintenance activities based on affected zones.Another major enhancement involves developing a mobile application to increase accessibility. A mobile app would enable drivers and pedestrians to capture road conditions directly through their smartphones and submit them to the central system. This crowd-sourced data can enhance detection coverage and keep the model updated with diverse real-time inputs. In addition, users could receive alerts about accident-prone areas or pothole-heavy roads along their planned routes, thereby enhancing public safety.The use of IoT (Internet of Things) sensors and smart cameras can further enhance the system's automation. For example, cameras embedded in vehicles or mounted on traffic poles can continuously capture road footage and transmit data to the detection engine in real-time. Integration with traffic control systems can help redirect traffic dynamically in case of detected accidents or severe road damage, thus minimizing congestion and secondary incidents.

X. CONCLUSION

Road safety is a pressing issue that affects millions of people around the world. With the rise in vehicle density and deteriorating road infrastructure, accidents and potholes have become common threats to commuters. This project, Accident and Pothole Detection for Public Safety and Traffic Control, provides a practical, AI-powered solution to address these challenges through the use of deep learning and real-time computer vision technologies.By leveraging the power of the YOLO (You Only Look Once) model, the system is capable of detecting accidents and potholes in real-time with high accuracy. It processes input from images and videos to not only detect but also analyze road conditions. The model is trained on annotated datasets of potholes and accident scenarios, enabling it to make intelligent predictions even in complex environments. In addition, it computes pothole density, providing data that can be used to prioritize road maintenance and infrastructure improvement efforts.The implementation of this system through a Flask-based web interface ensures accessibility and usability. Users can upload media files and instantly receive detection results, including accident alerts and road condition reports. The system also integrates an alarm mechanism to notify authorities immediately in the event of an accident, enhancing response time and potentially saving lives.Throughout the development of this project, key aspects such as system design, module integration, dataset preparation, testing, and deployment were carefully addressed. The choice of tools like Python, OpenCV, Flask, and YOLOv8 contributed to the robustness and performance of the final system. Security features and backup mechanisms were incorporated to maintain data integrity and system reliability.In conclusion, this project demonstrates the effective application of artificial intelligence in the field of public safety and transportation management. It showcases how technology can be harnessed to detect critical road issues, prevent accidents, and guide timely infrastructure maintenance. While the current system serves as a strong prototype, future enhancements such as GPS integration, mobile app support, and IoT sensor connectivity can further increase its practical value and scalability. This project not only contributes to smart city initiatives but also promotes safer, smarter, and more sustainable transportation systems.

REFERENCES

[1]. Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). *You Only Look Once: Unified, Real-Time Object Detection*. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 779–788.

[2]. Bochkovskiy, A., Wang, C. Y., & Liao, H. Y. M. (2020). *YOLOv4: Optimal Speed and Accuracy of Object Detection*. arXiv preprint arXiv:2004.10934.

[3]. Badrinarayanan, V., Kendall, A., & Cipolla, R. (2017). *SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation*. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(12), 2481–2495.

[4.] Jadhav, R., & Pande, S. (2021). *Real-Time Pothole and Accident Detection Using Deep Learning Techniques*. International Journal of Innovative Research in Science, Engineering and Technology, 10(4), 10654–10660.

[5]. Patel, P., Patel, R., & Prajapati, S. (2020). *Pothole Detection System Using Machine Learning and Computer Vision*. International Research Journal of Engineering and Technology (IRJET), 7(5), 2135–2139.

[6]. Sahu, N., & Singh, D. (2022). *Accident Detection Using YOLO and Deep Learning on Surveillance Videos*. International Journal of Computer Applications, 184(3), 25–30.

[7]. Tiwari, R., & Agrawal, A. (2020). *Road Damage Detection Using Convolutional Neural Networks*. Procedia Computer Science, 167, 2554–2562.

[8]. Yao, X., & Zhou, X. (2021). *Deep Learning-Based Real-Time Object Detection for Traffic Surveillance*. IEEE Transactions on Intelligent Transportation Systems, 22(11), 6853–6865.