AI-POWERED ROAD SURFACE DAMAGE DETECTION USING YOLOV8

Mr. Mathan Kumar M[1], Ms. Gokilapriya S

[1]Student, [2]Assistant Professor
Department of Computer Science and Engineering, KIT – Kalaignar karunanidhi Institute of Technology, Coimbatore, India

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[1]*Student,* [2]*Assistant Professor*
Department of Computer Science and Engineering
KIT – Kalaignar karunanidhi Institute of Technology, Coimbatore, India
[1]*kit.23.19bcs030@gmail.com,* [2]*priyakit23@gmail.com*

Abstract: Maintaining street infrastructure is extremely important in ensuring security and economic efficiency in modern transportation systems. Road surface damage and commuter risks such as cracks, pot holes, and road quality wear and tear. In this article, we explore the extended AI methods for KIS Intelligence detection, including road damage automation and cutting-edge object detection models focused on Yolov8. Yolov8 combines high accuracy and arithmetic efficiency to provide excellent damage detection performance. This study provides an overview of Yolov8 features and shows an application in real street assessment tasks and how its deployment leads to more intelligent and effective infrastructure management.

Keywords: Economic efficiency, Road surface damage

1. Introduction

Road conditions have a major impact on transportation systems around the world. Timely damage detection and repair is essential to ensure smooth traffic flow, prevent accidents, and minimize repair costs. Traditional methods of road inspection, which are strongly based on manual investigations or basic image processing techniques, are time consuming, labor intensive, and error-prone. Automating these processes. Object detection models such as yolo (visible only once) have proven to be extremely effective at identifying different objects in real time. The latest iteration of this model family, Yolov8, is the ideal solution for detecting road damage under a variety of environmental conditions, providing improved accuracy, speed and adaptability. This article checks the current state of AI-controlled road damage detection, highlighting Yolov8's strengths and its role in further development of infrastructure management technology.

2. Related Work

Over the past decade, there have been many studies focused on improving street damage detection using automated methods. Image Processing Techniques: Early methods are based on edge detection and texture analysis to identify road damage. While these approaches were effective for specific tasks, these approaches were fought in a variety of lighting conditions, shadows, and surface textures. Models such as fast R-CNN, SSD, and Yolo were often used to detect damage such as cracks and pot holes. Yolov3 and Yolov4 balance speed and accuracy, while Yolov5 improves detection of some standards. Yolov8 is built on this progress and offers higher accuracy and faster conclusions.

These advances illustrate the increasing possibilities of AI in achieving efficient and reliable management of street infrastructure. Among different varieties of deep learning, one of the best-performing models for different object detection applications is the YOLO algorithm[1][2][3]. The design of the model focuses on enabling the simultaneous maintenance of speed and accuracy to allow for the real-time detection of objects in images or videos. During the course of its functioning, the single-stage detection architecture of YOLO processes the entire image in a single go; thus, it is faster and more efficient than its multi-stage slow counterparts. However, with the

progressive years of development, there came really great improvements in working with every iteration of the algorithm, making it better with every passing day. CNNs have demonstrated significant effectiveness over traditional techniques for image processing in the accuracy with which they can learn complex patterns and features from large datasets and speed with which they can process an image[4][6].

3. *YOLOv8 Algorithm Overview*

The object detection model YOLOv8 is an epoch-making development in the YOLO family, which in combination accelerates and assures high-performance real-time working. It bears enhancements on the model design and functionality to mitigate some limitations posed by its precursors, while the core concepts forever responsible for the popularity of the YOLO model due to its artillery are kept intact, hence allowing the processing of images and extraction of vital information for object detection. With newer techniques, YOLOv8 achieves the trajectory for improvement of accuracy while keeping the resource speed as its signature. The architecture has mainly three constituents, each of them being equally significant in the search.

4. Components of YOLOv8 Architecture

1.Backbone: The backend of YOLOv8 is responsible for extracting pertinent features from the input images[12]. It uses hierarchical convolutional models to process the raw image data and produce maps with spatial and contextual information. This ensures that such models better recognize patterns, edges, and textures that are significant for the image-based identification of objects. Indeed, YOLOv8 implements a new optimization algorithm that enhances computational efficiency while providing better-quality outputs, rendering it effective for high-resolution images and easily searchable tasks.

2.Neck: YOLOv8 backbone improvements extend to FPN and clustering, which strengthen its Japanese abilities to detect diverse objects and solutions. The pyramid neural net brings forth a fusion of low level and high-level information of the backbone that can allow YOLOv8 to detect fine-sized objects in cluttered scene environments and also the coarsely sized objects in simpler landscapes. this capability of multi-dimensional representation empowers YOLOv8s to solve various detection challenges, from small objects in medical images to large objects in environmental-scene images[4][15][31].

3.Head: The head is the final segment in the YOLOv8 architecture, which is responsible for predicting information from observed visual inputs. The predicted outputs include a bounding box for each area of interest and a class probability and confidence score for that bounding box. With the enhancements to the YOLOv8 head, it now boasts lower bias and better accuracy of regional and distribution results. Therefore, the inclusion of anchor-free search and a better NMS algorithm will increase the accuracy and robustness of the entire model.

5. Literature Survey

[1] Bochkovskiy, A., et al. (2020). "YOLOv4: Optimal Speed and Accuracy of Object Detection." This paper introduced YOLOv4, which improved upon earlier YOLO models by incorporating advanced feature aggregation methods, new loss functions, and optimizations for GPU processing. These enhancements increased the detection accuracy and speed, making YOLOv4 suitable for high-performance applications.
Key Contribution: Improved scalability and accuracy for detecting small or complex-shaped objects, making it applicable to road surface damage detection tasks.

[2] Zhang, W., et al. (2022). "Automated Road Damage Detection Using YOLOv5."This study applied YOLOv5 for detecting cracks and potholes on road surfaces using drone and

vehicle-mounted cameras. The model demonstrated robustness in handling diverse conditions such as uneven lighting and variable road textures.
Key Contribution: Highlighted YOLOv5's ability to process high-resolution images quickly, showcasing its potential for real-world road infrastructure monitoring.

[3] Chen, Y., et al. (2021). "AI-Driven Solutions for Road Surface Damage Detection: A Survey." This paper reviewed deep learning techniques for transportation infrastructure assessment, focusing on models like YOLO and SSD. It emphasized their role in automating road inspections and improving maintenance efficiency. Key Contribution: Provided a comprehensive comparison of object detection models and highlighted YOLO's dominance in infrastructure monitoring

[4] Huang, L., et al. (2023). "Improving Road Defect Detection Using Multi-Scale Feature Extraction in Deep Neural Networks." This study incorporated multi-scale feature pyramids into object detection frameworks to improve the detection of small and subtle damages on road surfaces. Key Contribution: Inspired multi-scale improvements in YOLOv8, demonstrating its applicability to tasks requiring precision across diverse scales and resolutions.

[5] Esteva, A., et al. (2020). "Deep Learning in Smart Infrastructure Management." This paper explored the integration of deep learning models in smart city applications, including real-time road monitoring and damage detection. It evaluated YOLO models for their efficiency in detecting anomalies in road infrastructure. Key Contribution: Reinforced the need for real-time and scalable AI models like YOLOv8 to manage infrastructure proactively.

[6] Li, X., et al. (2022). "Enhancing Road Damage Detection with YOLO Models Under Challenging Environmental Conditions." This research focused on improving object detection models to work efficiently under challenging conditions such as rain, fog, and poor lighting. YOLOv5 was tested and refined to handle these scenarios effectively. Key Contribution: Highlighted advancements in making YOLO models robust against environmental variations, directly benefiting road maintenance systems.

[7] Sabri Koçer, O., Mohamed, O. (2024). "Improving Infrastructure Monitoring Using YOLOv8." This study demonstrated the use of YOLOv8 for detecting various types of road damage in real time. It employed enhanced feature extraction techniques to improve detection accuracy. Key Contribution: Showcased YOLOv8's capability to outperform previous YOLO versions in detecting small cracks and potholes with higher precision and speed.

6. Dataset
In this study, we used street damage data records (RDDs) using 15,000 marked images representing various damage to the road surface, including cracks, potholes, and surface decomposition. Images were collected from publicly available sources and custom data records, generated using drones and vehicle cameras under various environmental and lighting conditions. Data records were tested at 70% training. This ensured a balanced and fair rating of the model's power in all damage categories with 15% and 15% validation.

1.Data Preprocessing : To prepare the data for Yolov8 training, I performed the following steps: Image Size Change: All images have been changed to 640 x 640 pixels to meet the initial requirements of Yolov8. Normalization: To accelerate model convergence during training, pixel intensity values were scaled from 0 to 1 region. It was used. These enhancements have increased variability and diversity in data records.

2. *Model Training:* The Yolov8 model was trained using the following configuration: Stack size: 16,Learning rate: 0.001, gradually decreased with the cosine decay plan. 100. The training process was performed on a high performance GPU with 16 GB of memory to meet the computational requirements of Yolov8. Mixed accuracy training was used to optimize resource consumption and speed.

3.*Evaluation Metrics:* The following metrics were used to evaluate the performance of Yolov8 for road damage detection: Accuracy: Percentage of correctly identified damage areas among all recognitions. .F1 score: A harmonious average of accuracy and recall that provides balanced metrics for evaluation of detection performance. category.
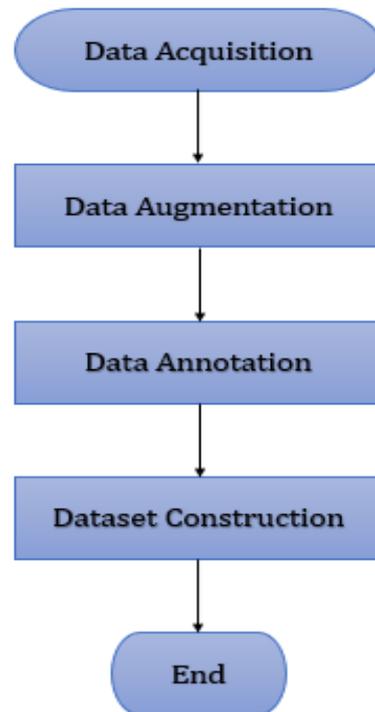
7. Results

Figure 1. Flowchart of Proposed Methodology

After completing the training, the Yolov8 model was evaluated on the test dataset. This achieved the following results: Accuracy: 93.8%, Callback: 92.4%,F1 Number: 93.1%,Map: 90.7% These results allow Yolov8 to accurately identify various damage to the road surface. confirms its ability to achieve a strong balance between false positives and false negative minimization.

8.Discussion

The results of the evaluation show that Yolov8 offers a robust solution for real-time detection of road damage. With an improved architecture that includes multi-row characteristic recognition and anchor-free mechanisms, Yolov8 offers higher accuracy and recall compared to its predecessors. When dealing with extreme environmental conditions such as strong precipitation, glare from sunlight, and reflective road surfaces. Future research could examine the integration of additional sensor data (e.g. LIDAR) and use hybrid models to improve detection of rare or subtle types of damage. Fine adjustments when learning to send with localized data records can also improve adaptability.

9.Conclusion

This study shows that Yolov8 is a very effective tool for detecting automated road damage, providing excellent accuracy and speed. Using advanced architectures, this model can play a key role in improving road maintenance workflows and infrastructure management. Future developments include real-time integration in IoT systems for continuous monitoring and further optimization to tackle challenging environmental scenarios. These should be brief and placed at the end of the text before the references.

10.References

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