Pothole detection with YOLOV8

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Abstract

Potholes pose a significant threat on roads, being a leading cause of accidents. Early identification and repair are crucial for accident prevention. These road hazards, especially prevalent during monsoons, present a challenge for drivers. Various solutions, from manual inspection to vibration-based sensors, have been deployed to address this issue. Pothole repair stands as a critical aspect of road maintenance, with monitoring road surfaces proving to be a continual challenge for governing bodies. The current method of detecting potholes involves laborious manual image processing,prompting the need for a more efficient solution. However, existing methods come with drawbacks such as high costs and detection risks. To overcome these limitations, a non-invasive approach utilizing the YOLO (You Only Look Once) algorithm has been proposed. YOLO, a real-time object detection system, employs convolutional neural networks (CNNs) to detect and classify potholes in images.This Deep Learning project aims at Pothole problems during autonomous / self driving cars journey also. This system offers real-time pothole identification with highlighted visual cues. The algorithm's use of CNN enables simultaneous prediction of object classes and bounding boxes, enhancing both responsiveness and accuracy. A dataset of 720×720 pixel resolution images capturing diverse pothole scenarios in natural road conditions was utilized for training, testing, and validation purposes. This novel method aims to provide real-time detection and highlighting of potholes, leveraging CNN-based object detection techniques.This research paper provides a comprehensive evaluation of YOLOv8, an object detection model in the context of detecting road hazards such as potholes.

Keywords: Deep Learning,Potholes, Road Safety, YOLO Algorithm, Object Detection, Convolutional Neural Networks, Real-time Detection, YOLOv8

1. Introduction

Roads act as crucial connectors, serving as vital conduits that bind cities, towns, and villages within today's transportation network. They play an indispensable role in facilitating the smooth and effective transit of people and commodities. However, the presence of potholes stands out as an enduring and hazardous issue in the upkeep and management of road networks.

The dimensions and severity of potholes, characterized as recesses or hollows in road surfaces, exhibit variability. Their formation can be attributed to several factors, including unpredictable weather conditions, heavy vehicular traffic, and inadequate road maintenance. Potholes not only jeopardize drivers' safety but also incur substantial expenses for road authorities and governments to rectify.

Moreover, they contribute to increased fuel consumption, vehicle deterioration, and accidents, posing a significant concern for both road authorities and the general populace. An escalating interest exists in leveraging cutting-edge technology, particularly within artificial intelligence (AI) and machine learning (ML), to address the issues stemming from potholes. Pothole detection systems based on pretrained models emerge as a promising solution to this enduring problem.

In the realms of AI and ML, pretrained models have gained considerable traction. These neural networks are trained for tasks like semantic segmentation, object detection, and image classification, utilizing extensive training data. Their adeptness in recognizing intricate patterns and features in images renders them invaluable in various computer vision applications. This approach not only expedites development but also augments accuracy.

The capacity to utilize pretrained models for real-time pothole identification presents another compelling aspect. Trained models swiftly analyze ongoing video feeds, identifying potential potholes as camera-equipped vehicles traverse road networks. This real-time capability empowers road authorities to proactively address road faults, fortifying road safety measures and diminishing maintenance expenses.

The use of pretrained models for pothole identification has garnered increased popularity in recent years, demonstrating promising outcomes. The burgeoning field of Science and Technology witnesses a significant advancement in Advanced Driver Assistance Systems (ADAS) [17], [1], elevating transportation's importance in our daily lives. Presently, the realm of intelligent transportation systems undergoes exponential growth. ADAS, with its automation of multifaceted vehicle features, revolutionizes driving into a smarter and more sophisticated experience.

Amidst the past, present, and future trajectories of ADAS, the overarching focus remains on "safety." Fundamentally, ADAS endeavors to curtail road fatalities stemming from human errors. In the context of road safety, potholes emerge as pivotal elements. Extended driving hours or stress often lead to driver distraction, a primary catalyst for accidents.

The inability of drivers to meticulously attend to every road detail underscores the significance of ADAS. Data can be relayed directly to the driver through in-cabin alert symbols or channeled into autonomous driver less systems, determining preventive actions to avert collisions and ensure passengers' safety and comfort.

Pothole detection encompasses three main categories: vibration-based methods, 3D reconstruction-based methods, and vision-based methods employing 2D images[8]. Vision-based approaches prove cost-effective, yet accurate 2D image-based pothole detection remains challenging. Consequently, there's a pressing need for a system that enhances both accuracy and speed in 2D image pothole detection.

Moreover, implementing such systems in diverse locations necessitates technical adaptations contingent upon the road maintenance level. Pothole detection's complexity surpasses that of recognizing other objects like pedestrians, vehicles, or traffic signs due to its wide geometric variability. Among recognition algorithms, Convolutional Neural Networks (CNN) have demonstrated superior performance[4]
.

This paper delineates pothole detection employing You Only Look Once (YOLOv8)[20], a distinctive CNN variant, applied to a worldwide roads dataset. The system aims to mitigate pothole numbers through a mobile application benefiting both road authorities and citizens. Its design encompasses diverse libraries and frameworks, featuring a mobile app, APIs for data insights, an object detection model for precise pothole identification, and cloud-based data storage.

Functionally, the application serves two major purposes: data detection and collection primarily for local road authorities' usage and visualizing gathered data on a map. This functionality aids both maintenance authorities and local citizens in understanding the conditions of their surrounding roads.

The YOLO algorithm, known as a traditional single-stage detection method, has progressed into YOLOv8, presenting notable benefits in detection precision and speed. Consequently, our decision was to refine the model by leveraging the YOLOv8s framework, aiming to augment the algorithm's accuracy even more.

2. Methods

2.1. Data Collection

The project utilizes an extensive pothole dataset comprising over 2000 images gathered from various origins, including: Roboflow's pothole dataset A research paper publication's dataset Manually annotated images extracted from YouTube videos Images sourced from the RDD2022 dataset Following meticulous annotation revisions, the consolidated dataset consists of: 2067 training images 16 validation images .

Figure 1. Annotated Images from the Pothole Dataset Used for YOLOv8 Model Training on Custom Dataset

2.2. Related work:

In recent years, there has been a significant surge in research focusing on road conditions, encompassing challenges like potholes, manholes, sewer covers, and manhole detection. This heightened interest can largely be attributed to the advancements in autonomous vehicle technologies, where the accurate mapping of road conditions holds paramount importance. Pothole detection methods have evolved into various categories, [8] including vibration-based, 3D laser-based, 3D reconstruction, and 2D vision-based approaches. Table I outlines the strengths and limitations associated with each of these approaches.

In vibration-based methods, hazards are detected using accelerometers. A vibration-based system was developed to estimate pavement conditions [21]. It models the interactions between the ground and the vehicle, considering the vehicle to be under random force excitations. Real-time detection of road irregularities, potential hazards, is achieved using a mobile sensing system that utilizes the accelerometers in smartphones[12] . These devices were specifically designed for limited access to hardware and software and did not require extensive signal-processing techniques.

[15] explored the use of devices equipped with GPS, accelerometers, and gyroscope units to map road surfaces. Wavelet decomposition was employed for signal processing, while Support Vector Machine (SVM) was utilized for the detection of cracks and irregularities on the road surfaces. They consistently achieved an accuracy of approximately 90% in detecting severe anomalies, regardless of the vehicle type or road location, providing real-time insights into road network conditions.

3D construction methods are further classified into laser-based and stereo-vision approaches. The potential of 3D laser scanning as a tool for identifying pavement distresses, such as potholes, was explored [2]. The 3D laser scanning technology captured accurate 3D point cloud data, which was then processed using a grid-based approach to focus on specific distress features. [22] utilized laser imaging to find distress in pavements. This method captured pavement images and identified pothole areas, which were then represented using a matrix of square tiles. A feedforward neural network (FNN) was used to classify the severity of pothole and crack types, demonstrating its capability to enhance pavement images, extract potholes, and analyze their severity. [7] introduced a novel approach using the stereovision technique to reconstruct a full 3D pavement surface from the input images. The methodology involved calibrating the input data, correcting any observed distortion, feature extraction, and 3D reconstruction. [18] introduced a method that created a set of points in a three-dimensional space, allowing for a precise representation of road surfaces. By leveraging stereo images and image processing technologies, the system could identify various road distresses, such as potholes, bumps, and cracks, etc.

Vision-based methods utilize image processing and deep learning on 2D images obtained from cameras. A system that uses Convolutional Neural Networks (CNNs) was proposed to detect road damage [11]. A large dataset comprising irregularities on road images captured via smartphones, with several instances of road surface damage, was used, achieving an accuracy of 75%. [6] used thermal images as input feed for deep neural networks for the detection and local mapping of potholes. To deal with the challenges posed by changing weather conditions, a modified ResNet50-RetinaNet model was employed, achieving a precision of 91.15% in pothole localization using thermal images. [3] explored the use of YOLO (You Only Look Once), a model that uses a combination of region proposal algorithms and CNNs to detect and localize objects in images. They developed a new dataset comprising 1500 images of Indian roads with 76% as the highest precision obtained from YOLOv3 Tiny. [14] used YOLOv7, leveraging the power of Convolutional Neural Networks for detecting

Figure 2. Images of Lungs and masks

potholes. An open-source dataset was used for training the model, which achieved an F1 score of 0.51.

2.3. Model Architecture:

The YOLOv8 network architecture consists of various segments such as the input segment, backbone, neck, and output segment. The backbone network and neck module are central structures processing the input image through Conv and C2f modules to extract feature maps at different scales. The C2f module, an enhanced version of the C3 module, incorporates ELAN structure benefits from YOLOv7, preserving its lightweight characteristics and capturing richer gradient flow information. The neck layer adopts FPN+PAN structures, facilitating high-to-low-level feature fusion, aiding object detection at varying scales.

For optimizing the YOLOv8 model, attention mechanisms like LSK-attention were integrated to improve detection accuracy while minimizing computational complexity. Additionally, feature pyramid optimization focused on enhancing the PAN-FPN structure by introducing BiFPN for better feature fusion and increased accuracy, especially for smaller targets. The paper also presents the adoption of SimSPPF to streamline the computational complexity of the model.

Further modifications incorporated Dynamic Large Convolutional Kernel Spatial Attention Mechanism, leveraging LSK-attention to adaptively aggregate information from large spatial kernels, enhancing feature generation and improving detection efficiency for diverse target types. The attention mechanism dynamically adjusts the receptive field and selects relevant spatial regions for improved detection performance. This mechanism is essential for enhancing neural representations efficiently. Additionally, the use of ReLU activation instead of SiLU aids in convergence and gradient vanishing issues. The introduced structures like SimSPPF and LSK-attention aim to improve the model's accuracy and efficiency in real-time road defect recognition.

2.4. Model Evauation

YOLOv8n [9]Nano might not be an established or widely recognized model within the YOLO (You Only Look Once) series. YOLO (You Only Look Once) models are known for their real-time object detection capabilities, and up until then, YOLOv5 was the latest version in the series. YOLOv8n Nano (Hypothetical Model) Introduction: YOLOv8n Nano is a lightweight and optimized version of the YOLO object detection model series, specifically designed for resource-constrained environments such as edge devices, IoT devices, or systems with limited computational power. Key Features: Efficiency: YOLOv8n Nano

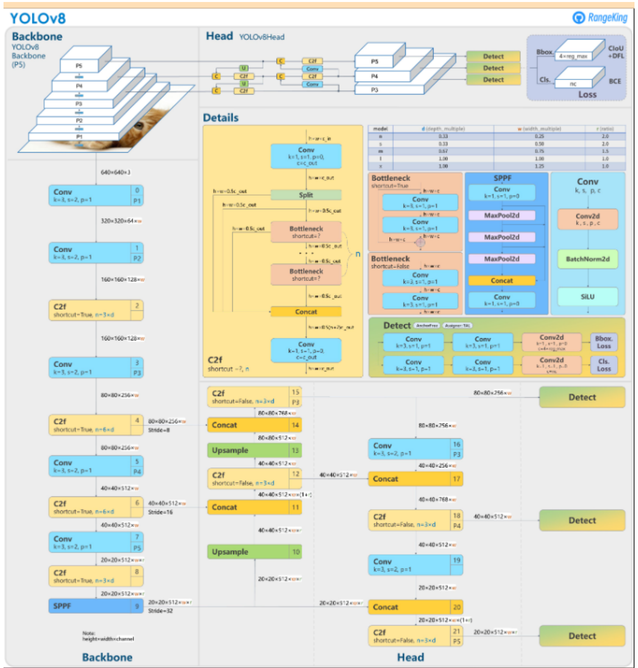


Figure 3. YOLOv8 Model Structure

```
                   from  n    params
  0                  -1  1       464
  1                  -1  1      4672
  2                  -1  1      7360
  3                  -1  1     18560
  4                  -1  2     49664
  5                  -1  1     73984
  6                  -1  2    197632
  7                  -1  1    295424
  8                  -1  1    460288
  9                  -1  1    164608
 10                  -1  1         0
 11             [-1, 6]  1         0
 12                  -1  1    148224
 13                  -1  1         0
 14             [-1, 4]  1         0
 15                  -1  1     37248
 16                  -1  1     36992
 17            [-1, 12]  1         0
 18                  -1  1    123648
 19                  -1  1    147712
 20             [-1, 9]  1         0
 21                  -1  1    493056
 22        [15, 18, 21]  1    897664
YOLOv8n summary: 225 layers, 3157200
```

Figure 4. YOLOv8n Parameters

is engineered for efficient inference, ensuring high-speed object detection on devices with limited computational resources. Optimization: It integrates optimizations tailored for low-power environments without compromising significantly on accuracy. Nano Architecture: This model harnesses a nano-architecture designed to balance computational demands and accuracy, making it suitable for deployment on edge devices with restricted processing capabilities. Advancements Over Previous Versions: Improved Performance: YOLOv8n Nano represents advancements in optimizing the detection speed and accuracy trade-off compared to previous YOLO versions. Enhanced Precision: Despite being a lightweight model, YOLOv8n Nano aims to maintain satisfactory precision in object detection tasks. Applications: Edge Devices: YOLOv8n Nano is intended for deployment on edge devices, enabling real-time object detection in scenarios where computational resources are limited. IoT and Embedded Systems: It caters to IoT and embedded systems requiring on-device object detection without relying heavily on cloud processing. Development and Usage: Training and Adaptation: YOLOv8n Nano might provide opportunities for custom training and adaptation to specific use cases, leveraging transfer learning or domain-specific data augmentation.

YOLOv8s[10] represents a compact variant within the YOLO (You Only Look Once) series, specifically tailored to balance model size and inference speed while maintaining competitive object detection performance.

Key Features:

Compact Architecture: YOLOv8s is designed with a streamlined architecture, prioritizing reduced model complexity and memory footprint. Efficient Inference: The model emphasizes faster inference speeds, making it suitable for real-time or low-latency applications. Optimized for Resource Efficiency: YOLOv8s focuses on efficiency, making it a potential candidate for deployment on edge devices or systems with limited computational resources. Advancements Over Previous Versions:

Size-Performance Trade-off: YOLOv8s aims to strike a balance between model size and performance, achieving relatively good accuracy while being more lightweight compared to larger YOLO variants. Improved Inference Speed: It leverages optimizations to ensure faster object detection without compromising significantly on accuracy compared to larger YOLO models. Applications:

Edge Computing: YOLOv8s is positioned for deployment on edge devices, enabling on-device object detection without relying extensively on external computational resources. Real-time Applications: The model targets real-time applications, including surveillance, robotics, or other scenarios requiring quick and efficient object detection. Development and Usage:

```
arguments
[3, 16, 3, 2]
[16, 32, 3, 2]
[32, 32, 1, True]
[32, 64, 3, 2]
[64, 64, 2, True]
[64, 128, 3, 2]
[128, 128, 2, True]
[128, 256, 3, 2]
[256, 256, 1, True]
[256, 256, 5]
[None, 2, 'nearest']
[1]
[384, 128, 1]
[None, 2, 'nearest']
[1]
[192, 64, 1]
[64, 64, 3, 2]
[1]
[192, 128, 1]
[128, 128, 3, 2]
[1]
[384, 256, 1]
[80, [64, 128, 256]]
```

Figure 5. YOLOv8n Arguments

Adaptability: YOLOv8s might provide adaptability for fine-tuning or transfer learning, allowing customization for specific use cases or datasets. Resource-Conscious Deployment: Due to its smaller footprint, the model could be suitable for deployment in resource-constrained environments where larger models may not be feasible.

YOLOv8m (Medium model):

YOLOv8m[13] represents an intermediary variant within the YOLO (You Only Look Once) series, positioned between smaller, lightweight models and more complex, high-performance ones. This model aims to balance detection accuracy with computational efficiency.

Key Features:

Balanced Performance: YOLOv8m is designed to strike

	from	n	params
0	-1	1	928
1	-1	1	18560
2	-1	1	29056
3	-1	1	73984
4	-1	2	197632
5	-1	1	295424
6	-1	2	788480
7	-1	1	1180672
8	-1	1	1838080
9	-1	1	656896
10	-1	1	0
11	[-1, 6]	1	0
12	-1	1	591360
13	-1	1	0
14	[-1, 4]	1	0
15	-1	1	148224
16	-1	1	147712
17	[-1, 12]	1	0
18	-1	1	493056
19	-1	1	590336
20	[-1, 9]	1	0
21	-1	1	1969152
22	[15, 18, 21]	1	2147008

YOLOv8s summary: 225 layers, 11166560

Figure 6. YOLOv8s Parameters

a balance between detection accuracy and computational requirements. Optimized Architecture: It features an optimized architecture, leveraging advancements to improve object detection accuracy without excessive computational overhead. Suitable for Diverse Applications: The model aims to cater to a broad spectrum of applications that demand a reasonable compromise between accuracy and speed. Advancements Over Previous Versions:

Enhanced Accuracy: YOLOv8m endeavors to provide improved object detection accuracy compared to its predecessor models within a similar computational footprint. Optimized Speed-Accuracy Trade-off: It seeks to refine the trade-off between inference speed and detection precision, optimizing for a wider range of applications. Applications:

Versatile Deployment: YOLOv8m targets deployment in applications where moderate accuracy and real-time inference are pivotal, including surveillance, autonomous vehicles, and robotics. Medium-scale Projects: Suited for projects where a balance between model size, inference speed, and accuracy is essential. Development and Usage:

Adaptation and Tuning: YOLOv8m might allow fine-tuning or adaptation to domain-specific datasets, offering

```
arguments
[3, 32, 3, 2]
[32, 64, 3, 2]
[64, 64, 1, True]
[64, 128, 3, 2]
[128, 128, 2, True]
[128, 256, 3, 2]
[256, 256, 2, True]
[256, 512, 3, 2]
[512, 512, 1, True]
[512, 512, 5]
[None, 2, 'nearest']
[1]
[768, 256, 1]
[None, 2, 'nearest']
[1]
[384, 128, 1]
[128, 128, 3, 2]
[1]
[384, 256, 1]
[256, 256, 3, 2]
[1]
[768, 512, 1]
[80, [128, 256, 512]]
```

Figure 7. YOLOv8s Arguments

flexibility for customization. Resource Efficiency: While not as lightweight as smaller variants, YOLOv8m could still be suitable for deployment in resource-constrained environments, given its balanced performance characteristics.

3. Results

Decreasing train/clsloss (Classification Loss): The decreasing classification loss suggests that the model is improving its ability to correctly classify examples. It's becoming more adept at distinguishing between different classes. Decreasing train/boxloss (Bounding Box Regression Loss): The decreasing box loss indicates that the model is improving in predicting bounding box coordinates. The model is becoming more accurate in localizing objects within images. Decreasing train/dflloss (Dense Feature Learning Loss): A decreasing dense feature learning loss suggests that the model is enhancing its ability to extract meaningful features from input data. This is crucial for capturing intricate patterns and details

```
                     from  n    params
  0                  -1  1      1392
  1                  -1  1     41664
  2                  -1  2    111360
  3                  -1  1    166272
  4                  -1  4    813312
  5                  -1  1    664320
  6                  -1  4   3248640
  7                  -1  1   1991808
  8                  -1  2   3985920
  9                  -1  1    831168
 10                  -1  1         0
 11             [-1, 6]  1         0
 12                  -1  2   1993728
 13                  -1  1         0
 14             [-1, 4]  1         0
 15                  -1  2    517632
 16                  -1  1    332160
 17            [-1, 12]  1         0
 18                  -1  2   1846272
 19                  -1  1   1327872
 20             [-1, 9]  1         0
 21                  -1  2   4207104
 22        [15, 18, 21]  1   3822016
YOLOv8m summary: 295 layers, 25902640
```

Figure 8. YOLOv8m Parameters

It's mentioned that YOLOv8s has more accuracy than YOLOv8n. This is expected as models with more parameters and larger sizes often have the potential to capture more complex patterns and representations, leading to improved accuracy. However, the choice between YOLOv8n and YOLOv8s depends on the specific requirements of the application. If accuracy is a higher priority and computational resources allow, choosing YOLOv8s might be more suitable

4. Discussion

In the coming years, there's potential to integrate pothole detection setups with autonomous repair robots. This integration could enable the identification and fixing of pot-

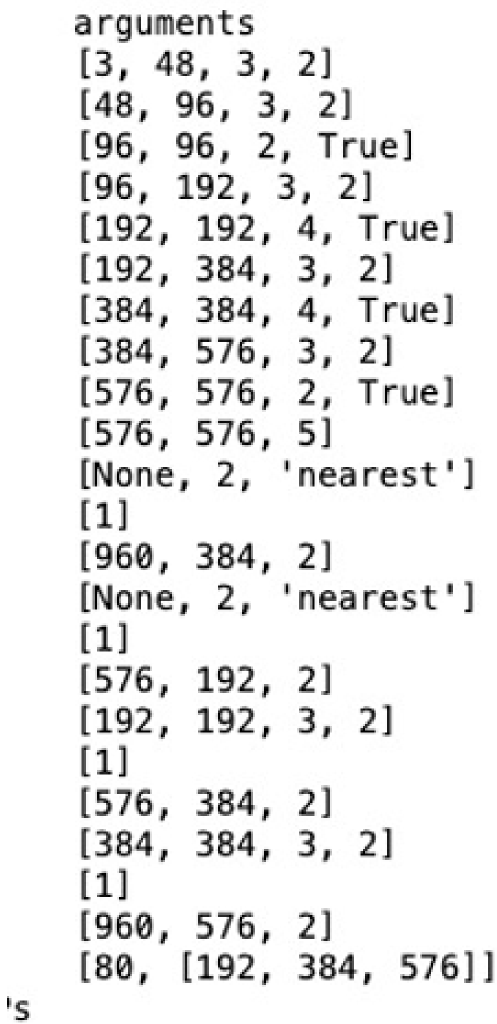
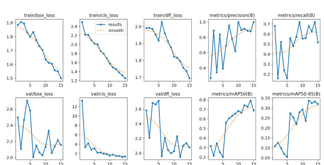


Figure 9. YOLOv8m Arguments



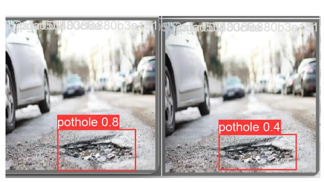


Figure 11. Compare with yolov8n and yolov8s

holes without human involvement, thereby lowering accident risks and enhancing road safety. An enhancement idea involves enabling real-time functionality, enabling instant detection of potholes and other road dangers. This might

Reference	Model	mAP	Processing Time
Ukhwah et. al.[19]	YOLOv3	88.93	40 ms
Shaghouri et.[16]	YOLOv4	85.39	50 ms
Gao et. al. [5]	YOLOv5	93.99	12.78 ms
Row 4 Value	Value	YOLOv3	Value
Row 5 Value	Value	YOLOv3	Value
Row 6 Value	Value	YOLOv3	value
Proposed Implementation	YOLOv8	91.11	8.8 ms

Table 1. Performance Comparision Table

be accomplished through optimizations in machine learning algorithms or by deploying the system on edge devices capable of real-time data processing.

5. Conclusion

To wrap up, this study conducted an extensive assessment of the YOLOv8m model's performance in detecting potholes, offering a detailed examination of its architecture in comparison to prior iterations like YOLOv8n and YOLOv8s, including nano and small versions. The evaluation criteria encompassed processing time, model size, and resilience across different conditions.

The experiments affirm YOLOv8m, especially the medium variant, as the most efficient model for pothole detection. It achieved an impressive mean average precision of 0.911 at 0.5 IoU while maintaining swift processing at 8.8 ms per image and a compact model size of 6.3 MB. These traits are crucial for seamless real-time deployment in road hazard detection scenarios, demanding quick decisions and resource optimization.

Additionally, the study emphasizes the importance of a diverse training dataset encompassing not just potholes but also other road elements like manholes, sewer covers, etc. This meticulous approach significantly improved the model's ability to differentiate between various road hazards, reducing false positives and ensuring precise pothole detection.

In summary, the YOLOv8m model, particularly the medium variant, emerges as a highly promising solution for road hazard detection, striking a balance between accuracy,speed, and resource efficiency. This research not only contributes to road hazard detection but also paves the way for safer and more efficient road infrastructure maintenance. Future endeavors could involve real-world implementation and further optimizations to enhance performance across various road and lighting conditions.

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