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Research Article

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YOLOv8 for Road DamageRecognition: Deep Learning-Based Segmentation and Detection System

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Abstract

Road surface detection is critical for improving traffic safety and reducing road maintenance costs. Because traditional methods are time-consuming and costly, deep learning-based image processing techniques offer an important alternative in this field. This study aims to develop a model that automates the detection and segmentation of road surface defects such as potholes, manhole covers, and culverts using deep-learning-based image processing techniques. In this study, a dataset previously used in the literature was preferred. It was observed that object detection was performed using a dataset from the literature. In this study, both object detection and object segmentation were performed using different parameters. To prove the success of object segmentation, both object detection and segmentation were performed using the YOLOv8 algorithm, which has previously obtained successful results. AdamW optimization and Auto Batch parameters were selected for this study. With these parameters, object detection was first performed with the YOLOv8s model, which is one of the variances of the YOLOv8 algorithm with the most successful results in the literature, and a successful 92.8% mAP@50 performance value was obtained according to the sources in the literature. In this study, the YOLOv8n, YOLOv8s, YOLOv8m, and YOLOv8l variance models of the YOLOv8 algorithm were used with the preferred parameters, and segmentation was performed. In object segmentation, a map@50 performance value of 90.9% in all classes and 99.1% in culverts was obtained using the YOLOv8l model. A map@50 performance value of 89.1% for pothole segmentation and 88% for manhole cover segmentation was obtained using the YOLOv8s model. The results of the analyses showed consistency in precision and recall values. These findings contribute significantly to improving road safety, reducing maintenance costs, and supporting sustainable urban infrastructure. Future research could explore integrating multiple data sources and adapt these models to more complex road conditions.

Keywords YOLOv8 · pothole detection · road damage segmentation · image preprocessing · surface cracks

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Introduction

In the last few years, research into artificial intelligence (AI), particularly deep learning, has been very active. It has been widely applied in image processing and object detection technologies. Deep learning is a subset of general AI. It has enabled computers to use large amounts of data with exceptional accuracy, inspired by the neural networks of the human brain. It has applications in agriculture, automotive, commerce, economics, finance, agriculture, gaming, entertainment, and marketing (Han et al., 2008). Going beyond the traditional pattern recognition algorithms used in vision systems, deep learning has helped transform autonomous driving, surveillance, and retail. With this revolutionary approach to image processing, they are now equipped for real-time perception and decision making (Chen et al., 2023; Li et al., 2024). The combination of AI, deep learning, and image processing has a significant impact on various industries worldwide. This is an opportunity that business people cannot afford to miss, helping everyone work more efficiently with information. Rapid developments in this field will influence the way in which we live and the entire global economy in the future.

Image processing is an important area in the transition to deep learning. These networks, extended on Neural Networks (NN) such as Convolutional Neural Networks (CNN) and Recurrent neural networks (RNN), offer successful performance from object detection to tabular data. CNN, as well as RNN, holds a significant position in the area of deep learning. RNNs may be used to process sequential data, making them suitable for solving a variety of data analysis problems (Kumar et al., 2023). CNNs are commonly preferred deep learning architecture for image processing and object recognition tasks. The key benefit of CNNs is that they can learn image data features automatically. According to Kilic et al. (2019) CNN can achieve high success rates in image classification problems. This characteristic has made it a popular choice worldwide, such as in medical imaging, agriculture, and biomedicine. Another common approach for sequential data and time-series forecasting is RNN. Due to their ability to remember information about past events, they are often used in tasks like natural language processing and time series forecasting.

Future studies can expand visualization and analysis methods to handle more complex datasets. In this context, You Only Look Once (YOLO) is a powerful real-time object detection tool. The efficiency of the proposed method stems from requiring only one forward pass for object detection, which makes it significantly faster and more accurate than traditional methods. Chang and Kim (2023) outline the process of creating a real-time object detection system using YOLO, focusing on its impact on both object detection and segmentation. The broad coverage and faster processing rates further highlight the wide application of YOLO in various fields. One of the areas of work mentioned above is to include applications that will increase the level of life of the society and the potential of the service by applying computer vision (Diwan et al., 2022). For example, the automatic detection and segmentation of potholes, bumps, and drainage systems is crucial for maintaining modern city infrastructure. Such applications are essential for improving traffic safety and reducing infrastructure maintenance costs. These algorithms, which are based on advances in real-time object detection, are highly effective in specialized applications, such as pothole detection. In this context, Babulal (2022) investigated the effect of deep learning-based object detection on image segmentation and used the YOLO algorithm to identify bounding boxes and segment objects such as wires and shaded trees. It has been stated that acceptable error rates can be achieved in object detection with appropriate parameter start.

YOLO is also very efficient in object detection, especially in noisy environments. Ghanem and Bakour (2023) examined the object detection ability in noisy images using the YOLO v5 algorithm and found that the performance in noisy images significantly decreased when the added noise ratio changed. In addition, it stated that image quality is important for complex tasks. In conclusion, in image processing and object detection, in addition to the benefits of the YOLO algorithm, the effects of noise and other ambient conditions should also be considered in terms of accuracy.In the literature, Faster R-CNN, YOLO, and U-Net models are the most widely used deep learning-based models. These models enable easy detection of potholes and road area segmentation, which is vital for monitoring and managing urban infrastructure. The following sections introduce various mean-variance neural network technologies, datasets, and pothole detection applications. The methods developed for the detection of road surface defects range from deep learning-based models to hybrid 2D/3D approaches (Rastogi et al., 2020; Arjapure and Kalbande, 2021; Ragab, 2021; Jakubec et al., 2023).

- **Deep learning-based models** like YOLO, Faster R-CNN, and U-Net are mostly used for pothole detection. In some studies, special network architectures were developed to improve efficiency, i.e., MVGG16-based Faster R-CNN (Safyari et al., 2024; Ghanam and Khaled, 2023)
- **2D/3D Hybrid Approaches** enable classical image processing techniques along with 3D point cloud data and deep learning algorithms. (Safyari et al., 2024)
- **Special Dataset (Data and Metrics):** Very few pothole datasets are available, and even fewer give in to the creation of high-quality diverse datasets. To address this issue, several datasets have been created based on stereo camera images, drones, and crowdsourcing techniques (Bello et al., 2020).
- **Application Areas:** These areas accelerate road surface maintenance and repair activities while lowering costs. Applications for mobile phones and drone-assisted systems can be used to gather data on the status of potholes, bumps, and drainage systems.

DifferentTypes of Road Damage

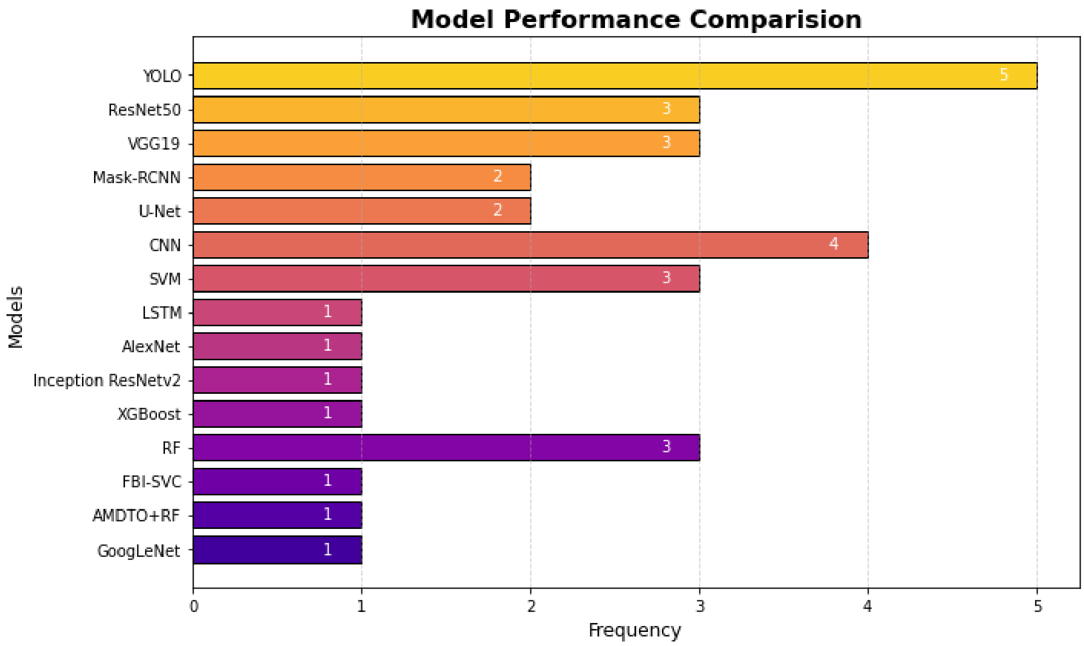
Weather conditions, traffic density, the type of vehicles in use, and the conditions of the road pavement can all lead to road damage. There are many different types of road damage: cracks, potholes, sinkholes, wiped-out lanes, and pedestrian crossings. Potholes become more dangerous the deeper (or bigger) they become. Least of all, small potholes that are often ignored can be fatal, while large potholes cause vehicle tires to burst and get stuck, as well as causing serious accidents. Thus, the features of the pothole need to be extracted and addressed. Detection was performed along with the edge of the pothole, and its size was estimated for this purpose. An edge is a line that separates two different light regions. There are four main types of edges: loop, line, step, and ramp edges. A loop edge is a place in an image where the brightness changes gradually and then returns to its normal value at a certain point. A line edge is an area where the brightness transition occurs abruptly and fades over time. The step edge is an area where the brightness change is abrupt. Here, an edge is a region where the brightness transition is rapid. Edge detection is a technique used to obtain the pixel that corresponds to the edge; this process gets the gradient through a partial differentiation process. This method uses the first differential to detect edges in images by identifying the presence of edges. The sign of the graph gradient indicates the location of bright and dark pixels in the edge pixels, as determined by the second differential. Potholes in the road damage image data are darker than the adjacent environment. Thus, edge detection can extract features in real-time.

Literature Review

It has been mentioned that the detection of various damages on roads is usually performed using deep learning algorithms. Automatic detection of damage such as potholes, bumps, and culverts is based on studies in which image processing and computer vision techniques are at the forefront. Deep learning algorithms work effectively to classify and segment road surface damage and become even more efficient when real-time data processing is performed.

Figure 1

Frequency Distribution of Models in Literature



According to the data in Figure 1, the YOLO model stands out as the most frequently preferred algorithm, being used 5 times, highlighting its strong performance and widespread use in computer vision problems such as object detection. The CNN model ranked second with 4 uses, indicating that traditional CNNs are still popular in the literature. ResNet50, VGG19, SVM, and RF (Random Forest) models can be counted among the widely preferred methods with 3 uses. In particular, ResNet50 and VGG19 are deep learning-based architectures, which suggests that these methods are preferred for complex image classification tasks. The Mask-RCNN and U-Net models are used in detailed operations, such as segmentation with 2 uses. In contrast, algorithms such as LSTM, AlexNet, Inception ResNetv2, XGBoost, FBI-SVC, AMDTO+RF, and GoogleNet were used only once. This suggests that there are areas of use for more niche or specific problems. In general, it has been observed that fast and effective object detection models such as YOLO have a dominant usage trend, and classical CNN and deep learning methods continue to have a strong presence in the literature.

Research conducted by Kim and Ryu (2014) revealed that various pothole detection methods have been developed in recent years to improve road safety and maintenance processes. The first study aimed to develop a decision support system to prevent pothole-related accidents, which are increasing because of climate change. This system aims to create pothole classification guides from the data collected from video recordings, integrate these guides into a 2D database, and accelerate the repair process. Using the YOLO algorithm, Baek and Chung (2020) achieved good accuracy with edge detection algorithms, having previously converted RGB images to grayscale. In 3D laser data, the highest accuracy, precision, and recall rate on the "watershed" method were achieved by Tsai and Chatterjee (2018), which resulted in 94.97%, 90.80%, and 98.75%, respectively. Hoang et al. (2021) obtained a classification accuracy of 94.833% on publicly available roads using texture-based descriptors to automatically detect patched and unpatched potholes on asphalt road surfaces. With a deep learning-based approach, Saisree and Kumaran (2023) found the VGG19 model to be 97% and 98% accurate for the detection of potholes on highways and muddy roads, respectively.

Image-based, vibration-based, and three-dimensional reconstruction methods for automatic pothole detection were studied by Zhang et al. (2022), who compared their advantages and disadvantages. The road conditions were classified with 93% accuracy using a mobile application developed by Thiruppathiraj (2020). Li et al. (2017) achieved an accuracy of 80% by applying machine learning techniques to pothole detection using smartphone sensors and camera images. These studies propose novel approaches for enhancing road infrastructure and improving traffic safety. Chen et al. proposed a sublimate approach to the road pothole detection problem and proposed an algorithm for object detection in road images based on neural network Net CIFAR 10 classification boundary area identifications; it outperformed another existing detection method. Alhussan (2022) suggested that road potholes should be detected in real time to improve the safety of autonomous cars, namely, an adaptive mutation and dip-throated Optimization (AMDTO)-based Random Forest (RF) classifier as a new feature selection algorithm with an accuracy rate over 99%. Agrawal (2021) proposed a CNN-based model for pothole detection and classified potholes with 88% accuracy and road types with 96% accuracy by evaluating a subset of road images in two groups: paved and unpaved. Kim and Ryu (2014) highlighted the need for deep learning-based studies, emphasized that manual methods are expensive and time-consuming, and outlined future directions to improve the efficiency and accuracy of automated systems.

Ma et. al. (2022) investigated classical image processing, 3D point cloud modeling, and deep learning algorithms for pothole detection using 2D and 3D data collection systems. The study predicts that classical methods are insufficient, CNN-based approaches provide successful results, and multimodal semantic segmentation with self-supervised learning will develop in the future. Rehana and Remya (2022) proposed automatic detection and classification of road damages using the YOLOv5 algorithm and reported that the model achieved 92% accuracy. Al Haqi and Hidayat (2022) developed a system with supervised learning methods to support users' visual assessments and showed that these results depend on human factors.

Considering the studies conducted in 2024 and 2025, Overall, these studies highlight the effectiveness of deep learning-based YOLO models, particularly YOLOv7 and YOLOv8, in detecting and classifying potholes under various conditions, improving road safety, and aiding autonomous navigation and accessibility solutions. Bhavana et al. (2024) introduced a YOLOv8-based pothole detection framework with image preprocessing using Contrast Stretching Adaptive Gaussian Star Filter and Sobel edge detection, achieving 99.10% accuracy, outperforming Faster R-CNN, SSD, and Mask R-CNN. Omar and Kumar (2024) compared YOLOv5, YOLOv6, and YOLOv7 for pothole detection in Intelligent Transportation Systems (ITS), concluding that YOLOv7 achieved the highest precision of 93%. Khan et al. (2024) proposed a YOLOv8-based system (2024) for autonomous vehicles and demonstrated superior pothole detection performance, showing promise for real-time applications in self-driving technology.

Saranya et al. (2024) evaluated real-time pothole detection. They found that it was more efficient than CNN models, with a successful deployment potential in edge devices. Reddy et al. (2024) focused on real-time pothole detection to mitigate traffic congestion and accidents and reported improved detection rates using YOLO. Paramarthalingam et al. (2024) applied YOLO for visually impaired individuals by integrating an auditory feedback system for safer navigation and achieved 82.7% accuracy. Zanevych et al. (2024) incorporated YOLOv11, Grad-CAM++, and Feature Pyramid Networks and demonstrated significant advancements in nighttime pothole detection, achieving 0.88 mAP50, improving detection under low-light conditions.

Pothole detection research in 2024-2025 has mainly focused on the benchmarking and optimization of advanced deep learning models such as YOLOv7 and YOLOv8. The studies aimed to improve accuracy through image pre-processing techniques, improve detection capabilities at night and in low light conditions, implement real-time applications in autonomous vehicles, provide accessibility solutions for visually impaired individuals, and the applicability of the systems on edge devices. This research has led to significant advances in road safety and intelligent transportation systems.

Therefore, road damage prediction is an important tool in the detection and management of road damages. The integration of deep learning and machine learning methods increases the effectiveness of the proposed technology and accelerates road maintenance processes. In the future, further research in this area will be critical to ensure the sustainability and safety of road infrastructure.

Table 1

Pothole Detection Methods and Their Performance Metrics: A Comprehensive Overview

Year	Authors	Method	Success rate/advantages
2011	Yu and Salari,	CCD image sensors and laser imaging	High precision and efficiency
2017	Li et al.	Machine learning	%80.1 accuracy
2018	Tsai and Chatterje	Watershed method	%94.97 accuracy
2020	Baek and Chung	YOLO, edge detection	%80 above accuracy
2020	Thiruppathiraj	RF, XGBoost, and ANN	%93 accuracy
2020	Dhoundiyal	İmage processing	Fast and economical solutions
2021	Hoang et al.	Texture-based descriptors	94.833% accuracy
2021	Agrawal	CNN	%96 road-type accuracy
2022	Alhussan	AMDTO+RF classifier	%99.795 accuracy
2022	Rehana and Remya	YOLOv5	%92 accuracy
2022	Lin et al.	Field-compatible methods	Data compatibility in different countries
2022	Saha et al.	YOLO	
2023	Saisree and Kumaran	VGG19	97% on motorways and 98% ACC on muddy roads
2024	Bhavana et al.	YOLOv8 with Contrast-Stretching Adaptive Gaussian Star Filter	99.10% accuracy
2024	Omar and Kumar	YOLOv5, YOLOv6, and YOLOv7 comparative analysis	%93.00 accuracy with YOLOv7
2024	Khan et al.	YOLOv8-based system	YOLOv8 significantly outperformed
2024	Saranya et al.	Evaluation of pothole detection by YOLOv7	YOLOv7 is more efficient than the CNN model
2024	Reddy et al.	Real-time pothole detection	YOLOv7 outperformed
2024	Paramarthalingam et al.	Detect potholes using YOLOv5	82.7% accuracy
2024	Zanevych et al.	YOLOv11, Grad-CAM++, and Feature Pyramid Networks	0.88 mAP50

Research breakthroughs have been made in detecting damage to road surfaces, especially potholes, bumps, and culverts, and other automatic detection of depressions is given in Table 1. When the researches in Table 1 are examined, deep learning based algorithms have been applied especially in road surface analysis. In fact, object detection and segmentation algorithms can be particularly beneficial for road maintenance and driver safety by rapidly and accurately identifying these damages. For the classification of road surface deteriorations like potholes, algorithms like YOLO and Mask-RCNN can be used, while models such as CNN and U-Net are also very effective for performing surface segmentation. Using image processing and computer vision methods, these technologies improve traditional manual detection processes with increased efficiency and speed up maintenance processes. At the same time, such applications enable real-time road analysis by processing images collected from vehicles or drones, thus being a part of the growing trend of automation of maintenance and repair work. Although popular algorithms, such as YOLO, ResNet50, SVM, and CNN, are used more frequently, studies have intensively preferred deep learning-based methods, segmentation, and machine learning methods. Machine learning methods (SVM) and deep learning methods (CNN) are superior to these data with various criteria such as accuracy, segmentation, etc.

Dataset

This study aims to automatically detect and segment potholes, culverts, and manholes on roads. Deep learning-based image processing technologies were used in this study. To perform experimental analyses in the image processing process, a dataset containing potholes, culverts, and manhole covers was required. For this study, previously conducted datasets were investigated in this context to obtain the dataset. Khare et al. (2023) used a dataset comprising 3770 images. This dataset was used in the study by Khare et al. as 3033 training data, 491 validation data, and 246 test data. To measure the performance of the dataset accurately, the same separation values were used in this study. Figure 2 shows examples of the classes contained in the dataset.

Figure 2

Sample Images from Different Categories

Data Collection andPre-Processing

Image pre-processing is critical in the first step of our study because it can improve the data quality and relevance to object detection. This project used a dataset that contained road surface anomalies (potholes, bumps, and drainage covers) in high-resolution images. These images were taken from real-life environments and cover a variety of lighting, weather, and road surface conditions. The bounding boxes indicating the locations of the anomalies in the dataset are also fed into this dataset, allowing them to be labelled, which is used as the ground truth by the object detection model.

For the dataset to be pre-processed for object detection, the following methods were used:

- **Resize Process:** Images are resized to the same resolution to facilitate their passing as input to the detection model.
- **Normalization:** All pixel values were normalized to be between 0 and 255, adjusted according to the chosen model architecture, which helped the model converge faster during training.
- **Data Augmentation:** Depending on the variety of road conditions on which the model will be implemented, data augmentation in terms of rotation, flipping, and color jittering will be performed. Therefore, this approach expands the dataset and helps prevent overfitting.
- **Noise Reduction:** Some images in the dataset are noisy, which can result from environmental conditions. In the data preparation process, noise reduction techniques (e.g., Gaussian blurring, median filtering) are employed to maintain the salient features while removing the noise.
- **Bounding Box Adjustment:** Bounding boxes are adjusted as necessary. This can be helpful in situations where initial annotations may have minor deviations due to human error.

All these pre-processing measures are crucial to enhance the model's capacity to precisely identify and categorize potholes, bumps, and drainage covers during the final detection stage, resulting in more reliable outcomes in practical environments.

In the study where the dataset was obtained, various pre-processing operations were performed on the existing data;

- **Image Flip:** Horizontal flipping of images
- **Image Scaling:** The scaling process of images was performed and 640x640 image size.
- **Motion Blurring:** The motions in the images are blurred.
- **Color Manipulation:** RGB color adjustment to adapt images to low ambient conditions
- **Fog addition:** This step adds fog to images.

In this study, unlike the current study, not only horizontal orientation but also Auto-Orient, that is, automatic orientation, was applied. Because of this pre-processing process, the dataset size was increased by 43. Finally, the dataset included 3076 training, 491 validation, and 246 test data.

Implementation and Evaluation of Model

This work poses the performance of road damage with a mixed dataset on an NVIDIA P100 on Google Colab Plus. In this dataset, the input image sizes contain different image sizes. But, 640x640 image size was applied to the dataset for the YOLO algorithm. The dataset was split into 70% training, 20% validation, and 10% test sets to prevent overfitting. Edge detection is performed for pothole classification, and the performance of the model is evaluated based on image data corruption and repair rates, classification results obtained during the final test stage, and the efficiency of the suggested approaches. Results were reported by considering the mAP, precision, and recall metrics. Those metrics; mAP (mean average precision), precision, and recall are used to evaluate the model's accuracy and performance. Precision measures the ratio of correctly predicted objects or segmentations to all predictions, which indicates the accuracy of the model. Recall calculates the ratio of correctly detected objects or segmentations to the total number of real objects, indicating the comprehensiveness of the model. mAP summarizes the model's performance at different thresholds by combining the precision and recall values; it is a metric that evaluates the overall performance of the model. These metrics are critical for understanding the model's ability to perform accurate detection and segmentation while balancing false positives and missing detections.

Method

Object detection is a popular computer vision task, and one of the most successful solutions is YOLOv8 (You Only Look Once) model. This model is notable because it handles images in one network while simultaneously completing the classification and location estimation (bounding box) tasks. YOLOv6 and YOLOv7 increased the object detection speed and improved the model accuracy. The model splits the input image into a grid of cells (in fact using k-means clustering) and, for each cell, returns whether an object is present in that cell according to the confidence/threshold. Instead of using regression to classify and locate objects, the proposed YOLOv8 uses direct linear classification methods. This eliminates the need for a model to predict accurately in advance, which makes it a much faster model.

Lidar-based models have been used in the literature. The Lidar-based model uses the laser method. Laser beams are sent parallel to the target area, and gaps are detected. In this study, it is aimed to detect road defects using image processing technology. Road defects can be detected using these two methods. When road defects are to be detected by a moving highway vehicle, the use of image processing technologies is expected to provide more efficient operation and results, considering that the process of sending laser beams parallel to the road will cause various problems. For this reason, image processing was preferred in this study.

In the proposed YOLOv8, CNN (Convolutional Neural Network) is the primary network. The new version of the network is deeper but has fewer parameters, which decreases the training time and computational burden. YOLOv8 can work in real-time, which is one of the most significant innovations of the proposed model. Then, for each cell, it is calculated whether there are objects in a certain area of the image. One of the four parameters is estimated: class probability, center coordinates, width, and height. Yolov8 also refines regression strategies to improve localization results. The neural network learns the estimated bounding boxes and class probabilities using this model.

In the Yolov8 model, an input image is split into an S×S grid, and B bounding boxes are predicted for each cell, with each class being a C class predicted for every class. This can be represented as the estimated outputs for each cell in Formula 1:

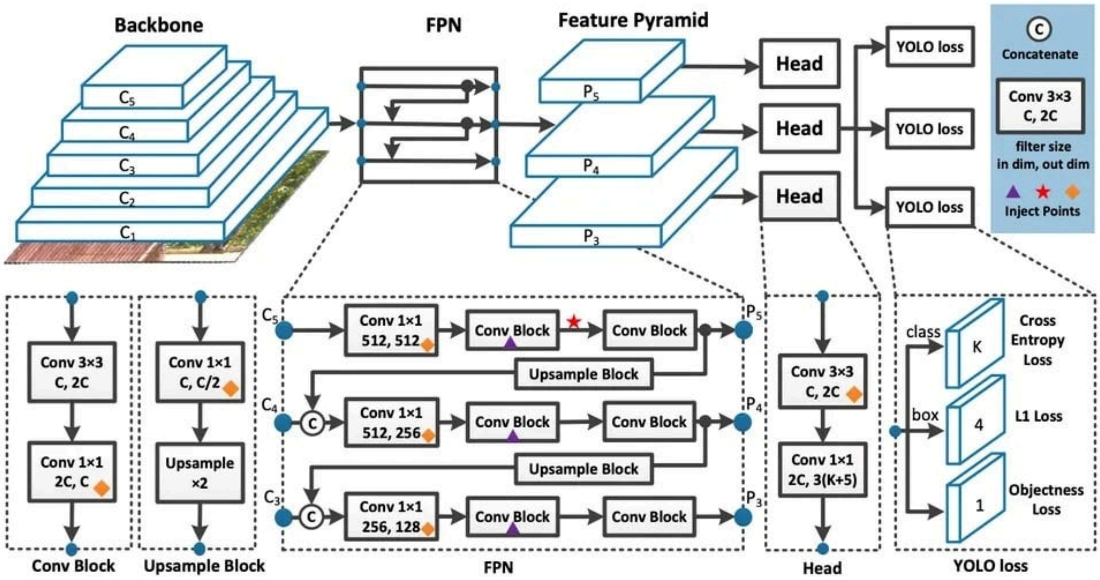
$$p_{cell} = (x, y, h, p_1, p_2, ..., p_c) \tag{1}$$

where x and y are the center coordinates of the object; w and h are the width and height of the object; p1, p2, p(c) are the probability values of each class. For this purpose, it employs a certain loss function, focusing on the predictions. The loss function is responsible for optimizing the class and location accuracy in YOLOv8. Therefore, the loss can be expressed as follows in Formula 2:

$$\mathcal{L} = \lambda_{coord}\Sigma_i\mathcal{L}_{coord}(i) + \lambda_{obj}\Sigma_i\mathcal{L}_{obj}(i) + \lambda_{coord}\Sigma_i\mathcal{L}_{noobj}(i) + \lambda_{cls}\Sigma_i\mathcal{L}_{cls}(i) \tag{2}$$

This combination of components helps improve the model's accuracy. There are many optimizations in Yolov8, which are now also used to obtain better and quicker results. The success of this model stems from the new generation of structures that offer context awareness and optimized training strategies. Yolov8 is one of the most powerful steps influencing the future of deep learning object detection and segmentation (Figure 3).

Figure 3
Algorithmic Schema of Yolov8



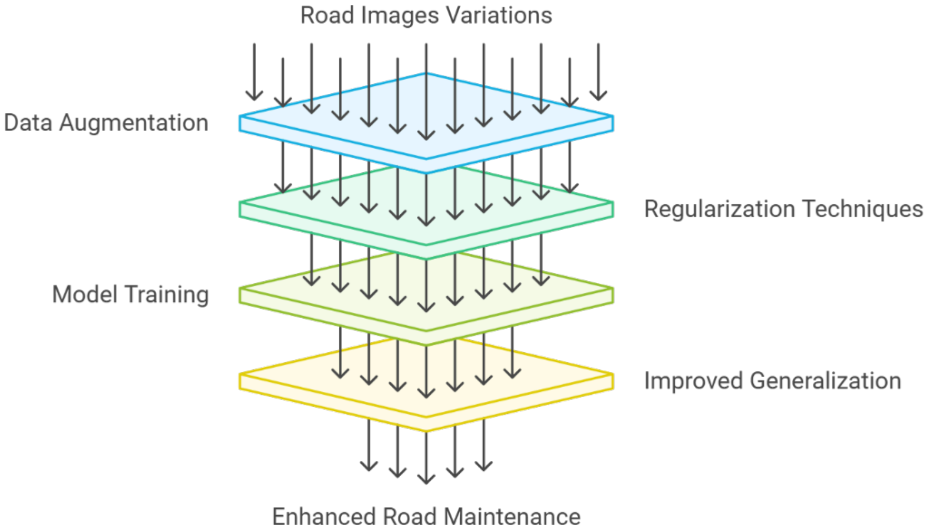
Detecting road damages is an important task because it helps improve road safety by avoiding accidents caused by potholes and cracks (Fan et al., 2021; Nawale et al., 2023). However, conventional classification models that primarily determine the presence of potholes, segmentation, and detection are designed to find and classify the exact location and contours of potholes in road images (Atluri&Bandi, 2022; Fan, Wang, Wang, Liu, & Pitas, 2021). In fact, this step is very important because it involves not only identifying the existence of a pothole but also determining its exact position and size, which are necessary for maintenance and repair planning (Fan, Wang, Bocus, & Liu, 2020; Fan et al., 2021). Segmentation involves determining which pixels of the image belong to the pothole (i.e., that represent the pothole in the image), while detection describes only the localization of the pothole, that is, predicting bounding boxes or masks around the damaged area.

Segmenting and detecting roads also have an additional challenge in background noise analysis like cracks or other road defects, which are not of immediate concern (A Review of Vision-Based Pothole Detection Methods Using Deep Learning, 2023; Fan, Wang, Bocus, & Liu, 2020). Also, we had to filter out these non-pothole objects, as we wanted the model to only pay attention to the pothole regions (Atluri&Bandi, 2022; Nawale et al., 2023). This is done by pre-processing the images by detecting only non-pothole objects using the YOLO algorithm and edge detection to detect the pothole boundaries to ensure that only the right boundaries of the potholes are preserved (Khare et al., 2023, Fan et al., 2021). As the background can be standardized to a white background, it increases the visibility of segmentation and detection, thus helping the model to separate potholes even better from other features.

Finally, data augmentation and regularization are often used to increase the robustness and accuracy of segmentation and detection models. This approach of feeding new variations of road images will help the model generalize through multiple types of potholes and road conditions. Techniques such as dropout and batch normalization may be applied at the training stage to avoid overfitting and ensure that the model is not biased toward the examples used for training, which may not necessarily be representative. In summary, in relation to road maintenance, pothole segmentation and detection using edge detection and modern object detection algorithms like YOLO serve as a crucial methodology for detecting and localizing road deterioration, enhancing road maintenance operations, and ultimately bolstering road safety.

Figure 4

Road Damage Image Analysis Process for Our Work



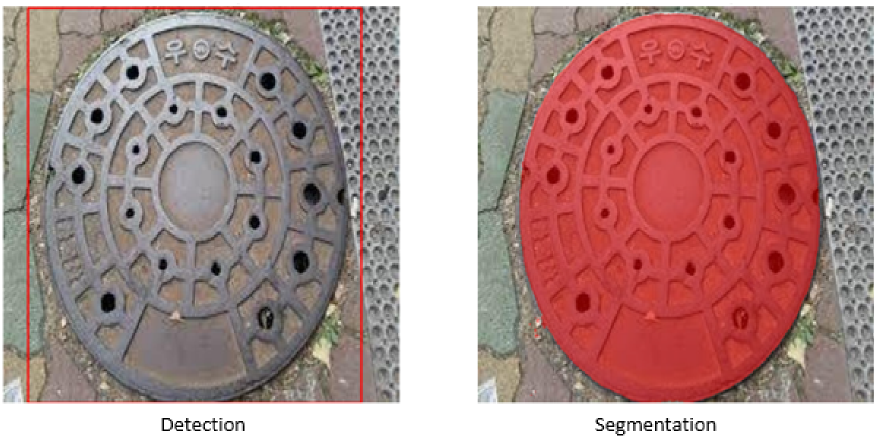
According to the model shown in Figure 4, in the first step, Data Augmentation, allows the model to learn different situations by creating variations in the road images. In the second step, the risk of overfitting is reduced using regularization techniques. In the third step, Model Training is performed, and the generalizability of the model is increased by the techniques developed in this process. In the last step, this improved model improves the efficiency of field operations by providing Enhanced Road Maintenance. This structure shows a systematic progression from data to real-world applications. The dataset used in this study consisted of images taken from wet and dry ground. In particular, for the pothole data, images with dry and water-filled potholes were selected.

Findings and Performance Evaluation

In this study, the detection and segmentation of potholes, culverts, and manhole covers on roads were carried out. In the detection of images using image processing technologies, the target area is enclosed in a rectangle. However, if segmented, the images enclosed in a rectangle are limited to two dimensions. In this way, the target is revealed more clearly. Figure 5 shows the sample detection and segmentation outputs.

Figure 5

Samples of Detection and Segmentation



Training processes were performed on the experimental YOLOv8s, YOLOv8s, and segmentation datasets and YOLOv8m datasets. Some hyper-parameters were used in the experimental training process. The values of these parameters are given in the Table 2 compared with those of the study from which the dataset was taken.

Table 2

Hyper-parameters and Values on Our Implementation

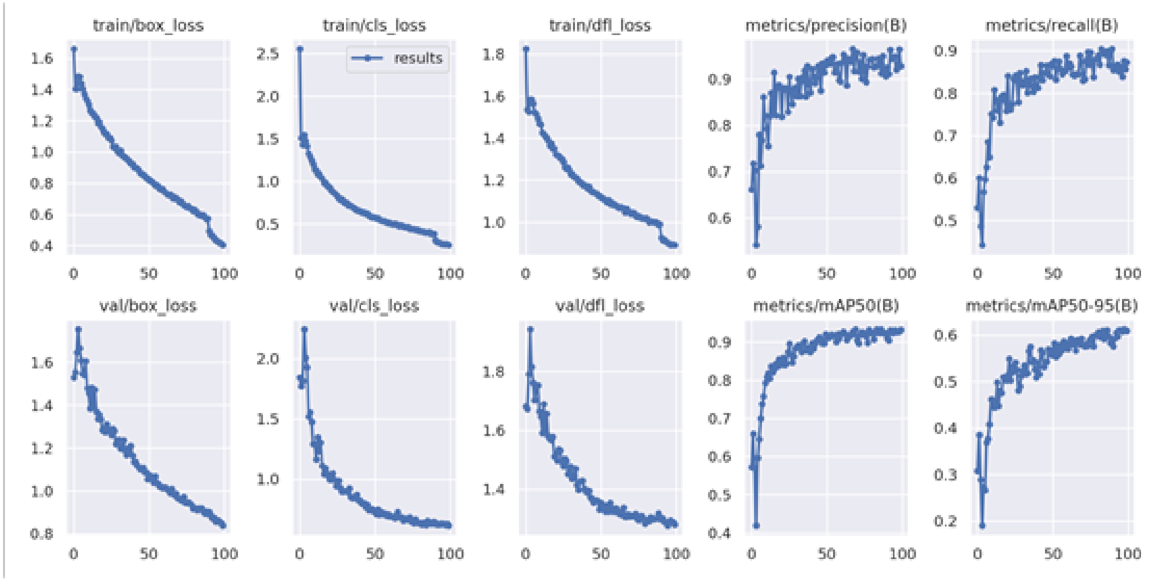
Hyperparameter	Kharevd. (2023) Value	Our Value
Epoch	250	**100**
Batch Size	16	**Auto**
Learning Rate	0.01	0.01
Weight Decay	0.0005	0.0005
Optimizer	Adam	**AdamW**
Momentum	0.937	0.937

Unlike the study of Khare et al. (2023), the epoch value was 100, and the batch size value (-1), that is, automatic, and AdamW was used for optimization. Because of the experimental training process, the performance values obtained from the models are given in Table 2.

YOLOv8s Detection: YOLOv8s and the parameters given in the hyperparameter table, 87.6% recall, 92.7% precision, and 92.8% mAP50 performance values were obtained in the detection process of images. In the present study, the detection process was performed only at this stage. The results of this detection process were compared with those of an experimental study using the dataset. Thus, the success of the hyperparameters used in this study was tested. The detection and segmentation processes were continued according to their success. In addition, the performance outputs of this model are presented in the visual below.

Figure 6

Graphs from Training Process of Our YOLO Model



Graphics from the traning process of our YOLO model are shown in Figure 6. The graphs obtained during the training process of the proposed YOLO model demonstrate that the model's performance improved steadily. The bounding box loss (box_loss), classification loss (cls_loss), and distribution focal loss (dfl_loss) values in the training and validation sets have decreased regularly; this proves that the model is successful in correctly detecting object coordinates and class prediction. In particular, the similar decrease in training and validation losses indicates that the model avoids the overfitting problem and exhibits strong generalizability.

In terms of performance metrics, precision increased to 90% and recall increased to 85%. In addition, the mAP@50 and mAP@50-95 values have shown a steady increase during the training process, revealing that the model made high-accuracy predictions even at different IoU thresholds. These results demonstrate that the proposed YOLO model increases the true positive prediction rate and reduces the number of missed objects in the object detection task, indicating that the model is trained successfully and reliably. The performances obtained in the study of Khare et al. (2023) are comparatively given in the Table 3.

Table 3

mAP@50, processing time, and model size in different works

Authors	Model	mAP@50 (%)	Processing Time	Size of Model
Kharevd (2023)	YOLOv5n	0.84	28 ms	14.8 mb
	YOLOv5s	0.86	38 ms	15.1 mb
	YOLOv7	0.90	35 ms	74.8 mb
	YOLOv8n	0.911	8.8 ms	6.3 mb
	YOLOv8s	0.92	11 ms	21.5 mb
Our Model	YOLOv8s	**0.928**	5.9 ms	21.5 mb

In this study, the dataset of Khare et al. (2023) was used. Table 3 compares this study with the previous study. In our study, the best performance and success values were obtained using the YOLOv8s model. The primary purpose of our study was to perform segmentation. However, to observe the performance of the most appropriate parameters during segmentation, the appropriate parameters were first selected, and the most successful model in Khare et al. (2023) was tested. When the selected parameters and the YOLOv8s model were used, the most successful result was obtained, as shown in Table 3. This indicates that the proposed parameters yield successful results. These parameters were used in the partitioning process, which is the main objective of this study. The reason why the object detection Map@50 values are different in Table 3 and Table 4 is that Table 3 shows the one-time object detection result, and Table 4 shows the simultaneous object detection value of this segmentation process.

Instance Segmentation (Detection and Segmentation): At this stage of the study, dataset training was performed using image processing technologies to detect and segment potholes, culverts, and manhole covers from road defects. The YOLOv8s and YOLOv8m models were used from the image processing models. The performance values of the YOLOv8s and YOLOv8m models are given in Table 4.

Table 4

Performance metrics on YOLOv8s, YOLOv8m, YOLOv8n, and YOLOv8l

		Detection (%)				Segmentation (%)			
Model	Class	Precision	Recall	mAP@50	mAP@50-95	Precision	Recall	mAP@50	mAP@50-95
YOLOv8n	All	88.7	85.6	**91.1**	59	87.8	84.8	90.3	56.8
	Manhole	93.5	90.7	98.4	63	93.5	90.7	98.4	61.7
	Sewer Cover	92.1	85.1	**89.3**	54.2	89.4	82.7	86.8	52.6

		Detection (%)				Segmentation (%)			
	Pothole	80.6	81	85.7	59.7	80.6	81	85.8	56.1
YOLOv8s	All	89.4	84	88.7	57.3	88.5	83.2	87.9	54.7
	Manhole	86.6	80.8	86.5	48	86.6	80.8	86.5	49.4
	Sewer Cover	91.2	87.8	90.3	55.2	88.7	85.4	88	49.8
	Pothole	90.3	83.3	**89.5**	68.7	90.3	83.3	89.1	64.7
YOLOv8m	All	91.1	84.3	90.8	61.3	90.2	83.5	89.3	58.8
	Manhole	93.3	87.4	93.9	59.7	93.3	87.4	93.9	59.6
	Sewer Cover	89.5	83.5	89.4	56.1	87	81.3	85.8	51.8
	Pothole	90.4	81.9	88.9	68	90.3	81.8	88.3	63.9
YOLOv8l	All	93.9	78.7	91	59.8	93.9	78.7	90.9	58.2
	Manhole	1	83.8	**99.1**	64.5	1	83.9	99.1	64.3
	Sewer Cover	88.8	82.9	86.8	52.6	88.6	82.9	86.8	51.3
	Pothole	92.8	69.3	87	62.4	92.9	69.4	86.7	59

According to the results, when the four models are compared, it can be seen that the YOLOv8l model produces more successful results in the All and Manhole classes than the thermal models. The YOLOv8s model produces more successful results in the Sewer Cover and Pothole classes than the thermal models. In general, when all classes are considered, it is concluded that the YOLOv8l model produces more successful results. When looking outside the YOLOv8l model, it can be seen that the YOLOv8n model produces more successful results than the thermal models in the All and Manhole classes. According to Table 4, when interpreting the results of the analysis, on average, the most successful models in all classes are the YOLOv8l and YOLOv8n models.

In the study by Khare et al. (2023), where the dataset was obtained, detection was performed. In this study, detection and simultaneous detection and segmentation were performed. The difference between our work and that of Khare et al. (2023) is that we used AdamW optimization, automatic batch (-1) and epoch 100 parameters, as shown in Table 2. With these parameters, we applied detection to the same dataset as the YoloV8s model, which achieved the most successful 92% mAP@50 performance in the study by Khare et al. With the parameters applied in this study, it has been shown that successful results can be obtained by obtaining 92.8% mAP@50 performance according to the data presented in Table 3. In this study, in addition, segmentation was performed with the existing data set and the parameters that we have pre-tuned, which we think will contribute to the literature. In the segmentation process, different variances of the Yolov8 model, which has the most successful results in Khare et al. (2023), were used. Table 4 presents the results of these variance models. Detection is also performed by the system during the simultaneous training process for the experimental training of segmentation. The detection process given in Table 4 is performed within the segmentation training; thus, it differs from the detection training results shown in Table 3. The most successful segmentation experimental result was obtained with the Yolov8l model, which extracts the Yolov8 variances.

Figure 7

YOLOv8n performance metrics

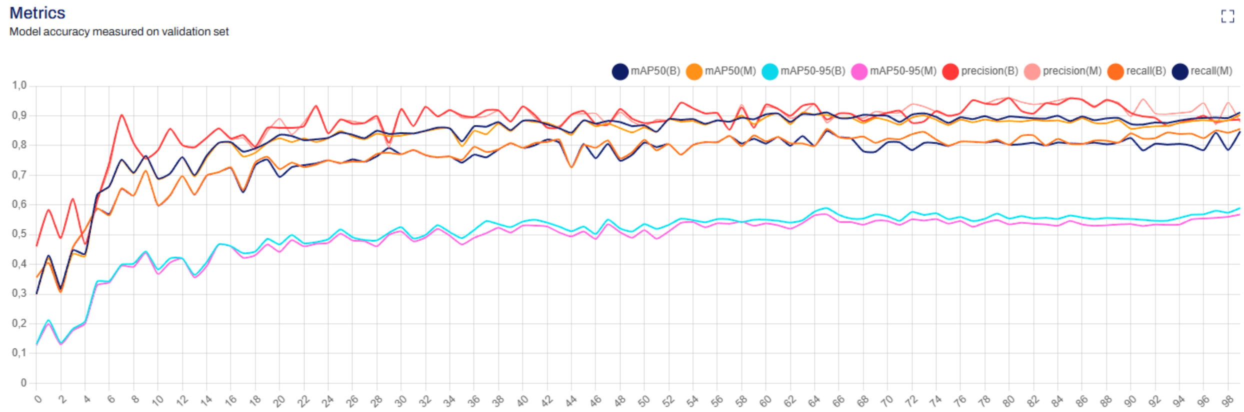
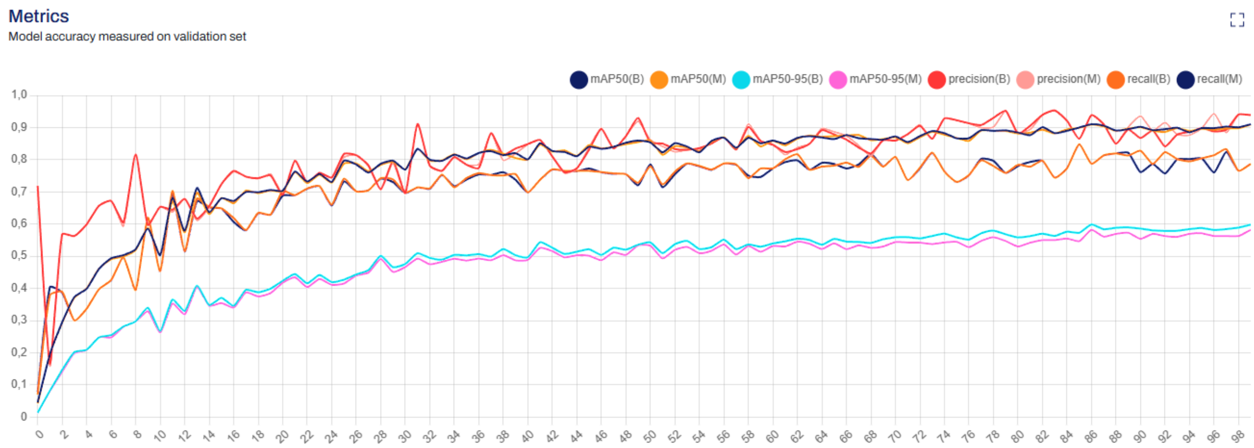


Figure 8

YOLOv8l performance metrics



Looking at the visualization of the performance metrics of YOLOv8n and YOLOv8l models, it can be seen that the YOLOv8n model has a parabolic distribution similar to YOLOv8l model. It can be seen that there is no memorization error in either model in Figure 7 and Figure 8.

Figure 9

YOLOv8n performance parameters

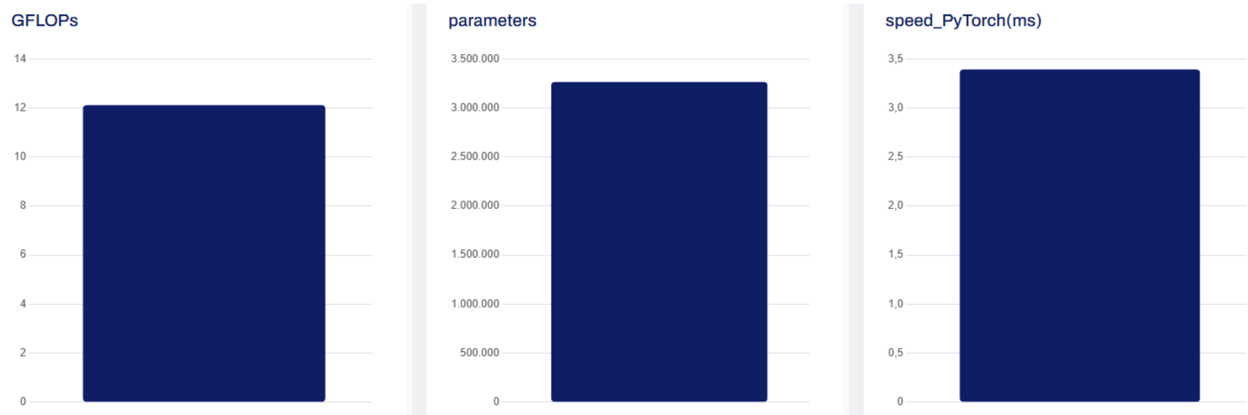
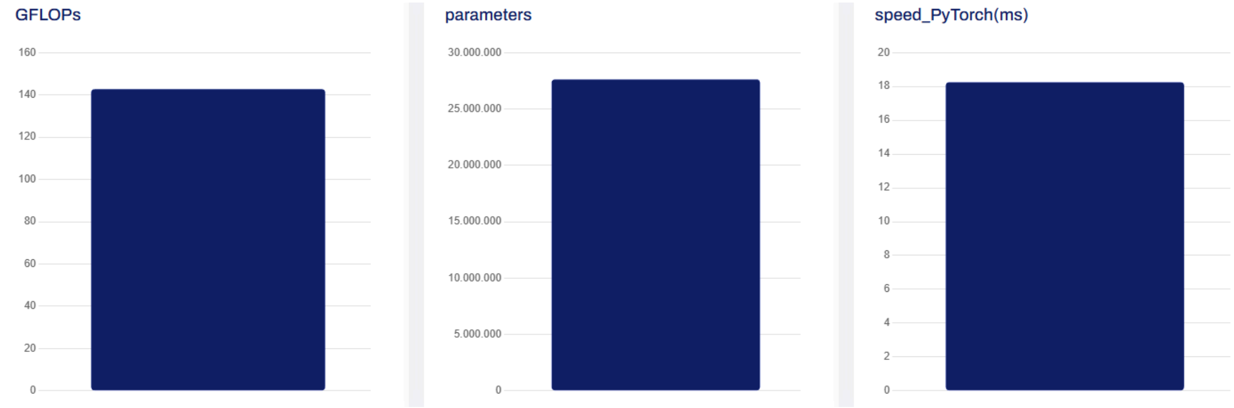


Figure 10

YOLOv8l performance parameters

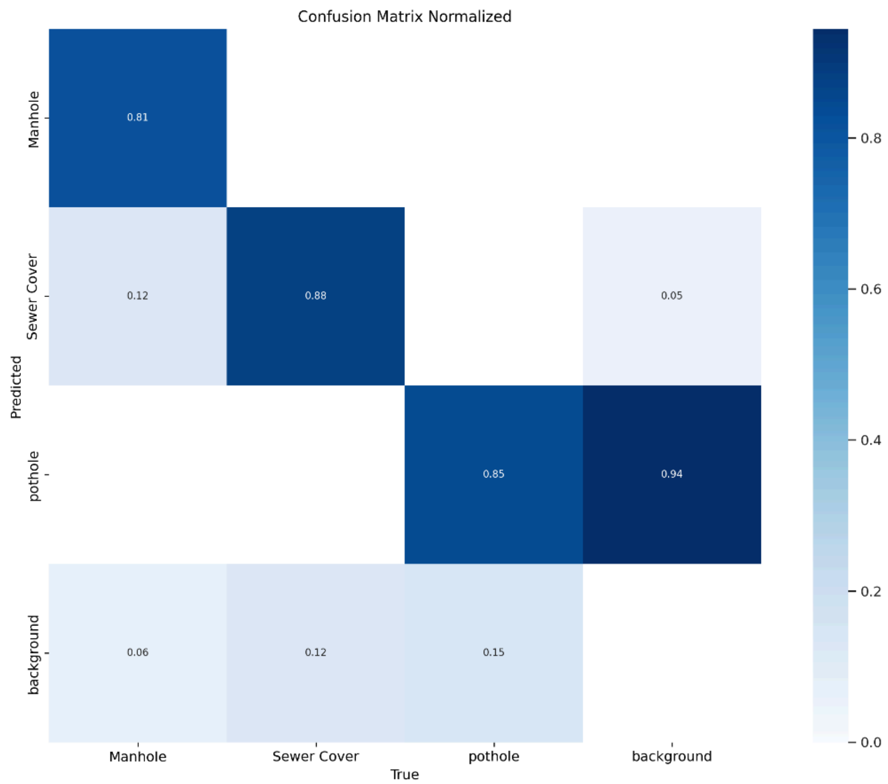


According to the graphs shown in Figure 9 and Figure 10, When the parametric performances of the YOLOv8n and YOLOv8l models are examined, it is seen that YOLOv8l model works with higher hyperparameters and is faster. The YOLOv8n model also works with a processing time of 3.7 ms and a size of 6.48 mb/s. It is observed that YOLOv8l model works with 17.2 ms processing time and 53.3 mb/s size of 53.3 mb/s. According to these data, the YOLOv8l model was more successful with its data read speed per second.

An analysis of the hyperparameter and Yolov8 variance models used in this study and the data obtained because of training shows that the Yolov8l model was the most successful. The confusion matrix values obtained from training the dataset using the Yolov8l model are shown in Figure 9 and Figure 10.

Figure 11

Yolov8l Confusion Matrix Chart



As shown in Figure 11, the confusion matrix elucidates the classification efficacy of the road defect detection model. The analysis of the normalized values reveals exceptional performance across the primary categories. The model demonstrated high accuracy in identifying manholes with a classification rate of 0.89, while sewer covers and potholes exhibited robust detection rates of 0.88 and 0.85, respectively.

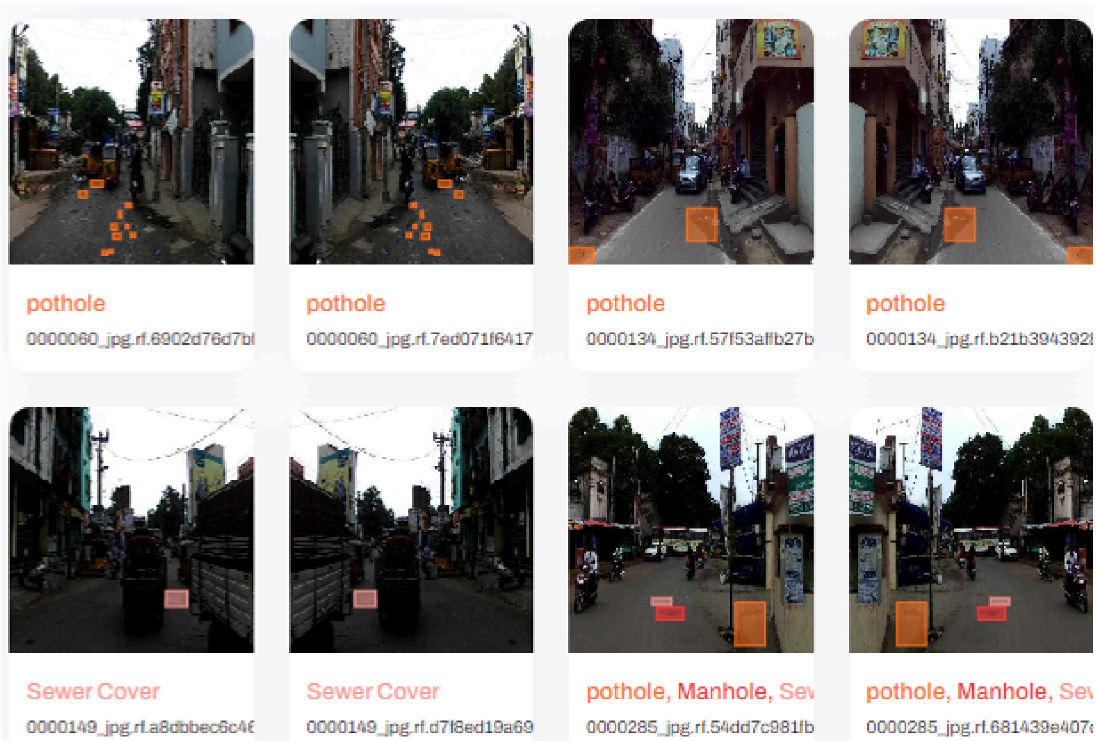
Examination of the error distribution indicates minor classification challenges between categories. Specifically, the model occasionally misclassifies sewer covers as background elements (0.12 misclassification rate) and confuses potholes with sewer covers in approximately 10% of cases. Similarly, manholes are erroneously identified as sewer covers in 8% of the cases. These metrics substantiate the model's high discriminative capability for critical road safety features. The pronounced diagonal values in the confusion matrix affirm the algorithm's reliability in distinguishing various road defects. In infrastructure maintenance applications, accurate identification of potentially hazardous road conditions is paramount.

The minimal cross-category confusion demonstrates the model's refined feature extraction capabilities and suggests effective hyperparameter optimization. The classification outcomes documented in this confusion matrix represent a significant advancement in automated road defect detection systems, with potential applications in preventive maintenance planning and road safety enhancement initiatives.

An experimental study was performed with the YOLOv8m algorithm and sample test data is shown in Figure 12.

Figure 12

Samples of YOLOv8m Test Data



Results and Discussion

According to the results of this study, the detection and segmentation of road surface defects were successfully performed using the YOLOv8-based model. In the detection of road defects, the success of the parameters was demonstrated by adding hyperparameters to the dataset and model in the study by Khari et al. (2023) and achieving a success value of 92.8% for mAP@50. Segmentation was performed on the same dataset using the parameters that demonstrated successful object detection. In the segmentation process, unlike single-object detection, the variances of the YOLOv8 model were used. The YOLOv8n, YOLOv8s, YOLOv8m, and YOLOv8l variances of the YOLOV8 model were used.

In addition, segmentation analyses were performed with the YOLOv8n model with 98.4% manhole, 86.8% sewer cover, 85.8% pothole, and 90.3% mAP@50 performance value. With the YOLOv8s model, segmentation analyses were performed using 86.5% manhole, 88% sewer cover, 89.1% pothole, and 87.9% mAP@50 performance value. With the YOLOv8m model, manholes were 93.9%, sewer covers were 85.8%, potholes were 88.3%, and all classes were 89.3% with the mAP@50 performance value. With the YOLOv8l model, 99.1% manhole, 86.8% sewer cover, 86.7% pothole, and all classes with a performance value of 90.9% mAP@50 were performed. In the segmentation analysis processes, the most successful Manhole 99.1% mAP@50 performance value was obtained with the YOLOv8l model, Sewer Cover 88% mAP@50 performance value was obtained with the YOLOv8s model, Pothole 89.1% mAP@50 performance value was obtained with the YOLOv8s model, and the average 90.9% mAP@50 performance value in all classes was obtained using the YOLOv8l model.

Furthermore, analyses on test data showed that the YOLOv8n, YOLOv8s, YOLOv8m, and YOLOv8l models showed significant detection and segmentation performance, but the YOLOv8l model had higher data processing capacity (Tang, Li, & Wang, 2023; ultralytics, 2024). These findings support the usability of the developed model under real-life conditions and show that it is an important step to accelerate road maintenance processes. In future, studies can be conducted on the integration of the model with drone-based data collection systems and adaptation to different geographical conditions.

During the study, we observed that image preprocessing techniques significantly affected model performance. The noise reduction and data augmentation methods enabled the model to generalize better in noisy environments; this increased the accuracy of the data obtained, especially in outdoor conditions. In addition, the fast-working capacity of the YOLOv8 algorithm confirmed its suitability for real-time road analysis.

In comparison with previous studies, this study achieved higher mAP@50 values through hyperparameter optimization. While Khare et al. (2023) reported 91.1% mAP using YOLOv5, our implementation with YOLOv8 reached 92.8% mAP, demonstrating the superior detection and segmentation capabilities of YOLOv8's optimized architecture. Our research used the model variants from Khare et al. (2023) with parametric presets applied to the existing dataset, allowing us to evaluate the effectiveness of the parameter adjustments while maintaining a comparable framework.

As a result of the study by Khare et al. (2023), a detection process was performed and contributed to the literature. In this study, the dataset used in Khare et al. (2023) was used, and more successful results were obtained by proposing a different method. It has been shown that more successful results can be obtained using hyperparameters in such studies. In addition to detection, segmentation was performed. The use of segmentation systems in road-defect detection and similar studies can be a successful method for detecting defects and marking their boundaries. It has been shown that different performance values can be obtained by using different variances of the models commonly used in the literature.

Future work may focus on feature fusion techniques and integration with different deep learning architectures to further improve the performance of the proposed YOLOv8 algorithm. In addition, the generalization capability of the model can be increased by using larger and more diverse datasets; in particular, the success of the model can be tested under harsh weather conditions, such as extreme lighting, shadow, or precipitation. However, the development of models with low hardware requirements will increase the efficiency of real-time applications. Finally, building on the current achievements of YOLOv8, detailed analyses, such as multi-class detection and grading of different road defects, can be added to provide more comprehensive solutions for maintenance prioritization systems.

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