Roadway Impairment Identification in Asphalt Road Using YOLOv8

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ABSTRACT

Roads connect distant rural areas to urban areas, offering a quick and easy means of transportation. In Bangladesh, most highways and inner roads of rural and urban areas are damaged at various times throughout the year. Nowadays, road damage detection is an emergency crisis. Manual or traditional road damage detection is a very time-consuming and costly method. In this study, we propose an automated process to identify road potholes and cracks by applying deep learning techniques. YOLOv8, a cutting-edge object detection algorithm, has demonstrated encouraging results in several object detection tasks, but its use in road defect detection has not received much attention. We employed the YOLOv8 model to determine the different cracks, including rutting, potholes, travelling, mending, and shoving. We trained the model and tested it using a dataset of 655 photos of roads with cracks labelled. This study demonstrates YOLOv8's ability to detect road damage. The study's findings can be put into soar the effectiveness of the procedures for inspecting roadware defects. To confirm the efficacy, we also contrasted the YOLOv8 model with other models that are currently in use. The outcomes of the trial verified the efficiency with which the enhanced YOLOv8 performance. There is a 3.85% improvement in AP when compared with others.

CCS CONCEPTS

• **Computing methodologies → Machine learning approaches**.

KEYWORDS

Roadway damage detection, Object Detection, YOLOv8, YOLOv5.

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1 INTRODUCTION

The economic development of a country depends on its road network. Effective, dependable, and safe highways and other transportation networks facilitate trade, industry, and mobility needs, which are critical to economic blooming. However, with time, the population is growing, infrastructure is deteriorating and the escalated cost of building new roads presents challenges for maintaining a high-yielding road. If the country is to proceed with its economic momentum infrastructure in the transportation sector should be refined whenever it is required. Road damage, a recurring problem, has negative impacts on driving conditions and road safety. It is critical to identify road cracks as soon as possible to prevent damage to the road and maintain traffic safety. Both manual and multi-functional road inspection vehicles are used to detect road defects. However, manual inspection requires a lot of time and labor and depends on the inspector's subjective assessment. Nevertheless, ground-penetrating radars, GPS, cameras, and laser profilers are just a few of the integrated sensors used by multi-functional road inspection vehicles to accurately and conveniently detect road imperfections. Moreover, Roadware has developed vehicles for the detection of road damage that are capable of night time operation. Nevertheless, road inspection vehicles are currently unsuitable for widespread promotion due to their high construction costs which can amount to USD 500,000 [1]. Therefore, there is a strong need in practice for the development of quick, accurate and efficient crack detection technologies.

Our research aims to study the following:

1. Existing damage detection procedures for roads.
2. Efficiency of these approaches in detecting damage.

To address these questions, we design a solution that can identify and pinpoint road damages on Bangladeshi road images. To do this, we evaluate the YOLOv8 model's performance. Although high accuracy is crucial. Another important factor is the model's speed. The primary goals of this research are given below:

1. To properly recognize various types of road damage including fractures and craters.
2. To enable real-time performance in detecting road damage.
3. To ensure the reliability of detection in various real-world scenarios such as weather, shadows and different types of road materials.

Furthermore, to adapt the model for various road types and conditions without experiencing a noticeable drop in performance. This generalization guarantees the model's efficacy in various settings and situations, making it convertible for broad implementation. To achieve our goals, firstly, we collected photographs of roads having damage from both pastoral and urban settings and labelled the images. So that we can contribute a road damage dataset where images were captured by mobile phones in two districts (Cumilla and Tangail) areas of Bangladesh namely Salmanpur, Kalirbazar, Chandina and Tangail. The objects in these pictures are then labelled through annotation, helping to educate the model on what each object looks like. Three sets of pictures have been annotated for training, validation, and testing. Training photographs are accustomed to educate the model while testing shots are used to assessing its execution. Then for roadware potholes detection and sorting tasks we used the YOLOv8 model alongside associated techniques including regulated attention and label smoothing processes with the output consisting of bounding boxes surrounding discovered instances of road damage and the corresponding confidence scores. From the literature we know that YOLOv8 is a version of the YOLO family of real-time object detection algorithms. Road damage detection is one of the many computer vision applications that make use of YOLO algorithms. YOLOv8 can be applied in object detection, efficiency, training on datasets, integration with GIS Systems, monitoring and maintenance, automation, and alert systems. Experimenting with YOLOv8 approaches using our dataset, we get a Precision score of 60.1%, AP@50 of 45.9% and a Recall of the system of 46.9%.

Our primary contributions are as follows:

1. We create a custom dataset of local areas of two districts in Bangladesh including both rustic and urban settings, by considering various lighting conditions.
2. We took the appropriate steps to adjust the model parameter and performance in a balanced way so that we ensure appropriate accuracy by considering model speed.
3. We modified the model to perform in real time.
4. We achieved 3.85% improvement in terms of AP.

The remaining portion of the paper is structured as: The paper's introduction is given in Section 1. Related Work, which explains the various other connected works and theoretical background which is described in Section 2. Section 3 elucidates the process, datasets and methodology. Section 4 narrates the experimental outcomes. This paper's summary is given in Section 5.

2 RELATED WORKS

Significant advancements in object detection have been made recently due to the deep learning algorithms' rapid expansion. There are two basic categories which object detection can be generally divided. The first strategy is two-stage, region-based type of detection, which entails two different procedures. Firstly, a list of possible locations with the capacity to hold things is put out. These suggested regions are then subjected to classification network deployment to identify the object categories present in each region. In 2022, using YOLOv7 [2] road damages detection and classification, authors achieved an F1 score of 81.7% on road damage data obtained from the US utilizing Street View from Google and 74.1% on all test photos in this dataset. Region-based fully Convolutional Networks [3], Mask R-CNN [4], and Fast R-CNN [5] are popular two-stage techniques that are based on areas with masks. The second tactic consists of regression-based one stage detection methods that specifically classify certain groups and estimate their boundaries. Although approaches handled information more quickly than the two-stage approach, their accuracy was typically a little bit worse. Several well-known algorithms in this area include Single Shot MultiBox Detector [7], the You Only Look Once [8] series, and Single Shot MultiBox Detector (SSD) [9]. Deep convolutional neural networks are currently being used by a growing number of academics to identify and categorize road fractures [9]. Notably, the transportation industry stands to benefit greatly from the rapid advancement and dissemination of deep learning technologies, particularly in the area of road damage identification. One well-liked deep learning method in this area is Faster Region-Based Convolutional Neural Networks (Faster R-CNN**)** [10] which introduced a road defect identification technique that combines adversarial networks with generative algorithms and partially-supervised learning to achieve an average recognition accuracy of upto 81.54%. Additionally, it was suggested to use EfficientDet-D7[11] to identify and categorize photos of asphalt roads, placing it in 7th place in IEEE Big Data, Roadway Impairment Identification in Asphalt Roads using YOLOv8 Challenge in the year 2020. However, EfficientDet-D7 [12] has shortcomings like a slow detection speed and large parameter size, making it inappropriate for real-time applications. It employed several data augmentation methods in conjunction with the Cascade R-CNN model. In the 2020, global road damage detection challenge, they received an F1-score of 0.635[13]. But even with the contributions made by the previously mentioned research to tasks involving finding damage to the road, there is still a great deal of space for enhancement regarding precision and speed of detection. The YOLO algorithm, a traditional one-step detection method, has developed into YOLOv8 [14], which provides notable benefits in terms of speed and detection accuracy. Consequently, to increase the algorithm's accuracy even further, we decided to optimize the model using the Ultralytics YOLOv8 framework.

3 METHODOLOGY

Roadway impairment identification has shown promise when using object detection algorithms like YOLO. This system detects damage to the road. YOLO is a cutting-edge object recognition program that recognizes and categorizes things in pictures and videos using deep learning methods. Cracks, potholes, and other types of damage in roadways may all be identified and classified by YOLO when it is trained using a dataset of photographs of village roads and pavement. Using a grid of cells to represent an image, the YOLO object detection system forecasts bounding boxes and class probabilities for individual cell. To calculate a job synchronization measure based on the regression coordinates and sorting scores, YOLOv8 uses a task-aligned assigner. YOLOv8 is employed in the inspection of road degradation; the output usually consists of bounding boxes surrounding instances of road damage that have been found, along with the corresponding confidence scores. Below is a summary of the usual results:

1. YOLOv8 produces bounding boxes on road damage to represent the detected objects. Every bounding box has four coordinates defined: (x, y) for the upper-left quadrant and (width, height) for the box's measurements.
2. Every detected object in YOLOv8 is given a class label in addition to bounding boxes. The classes in the context of detecting road damage may include different kinds of damage like cracks, potholes, bumps, or any other predetermined categories.
3. Each detection is given a confidence score by YOLOv8, which represents the model’s level of assurance in its prediction. Greater confidence scores signify the model's increased assurance in the detection's accuracy.

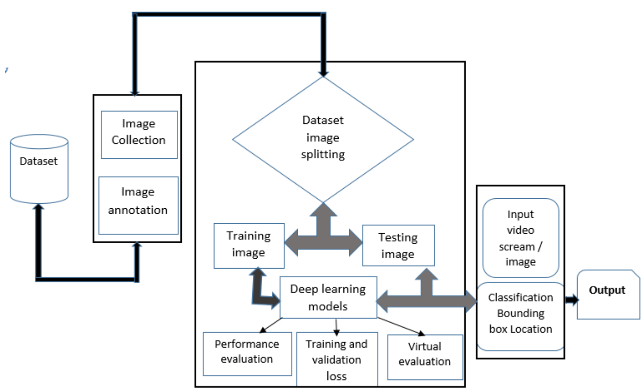

Figure 1: Workflow Diagram

Figure 1 shows a workflow diagram to recognize and categorize items in photos and video streams, and then to use the mode to locate and sort objects in photos or video streams. It is necessary to first compile a dataset of various photos to train the model. The objects in these pictures are then labelled through annotation, helping to educate the model on what each object looks like. The training, validation, and testing sets of photographs are the three sets of annotated photos. A deep learning system is taught using the training images. It picks up characteristics and trends connected to every object with a label. Continuous performance evaluation is carried out. Performance evaluation is a continual process that tracks measures such as validation loss and training loss to see how effectively the model is learning. Custom weights that are optimized to precisely recognize and classify items in the provided context are obtained after adequate training. These weights can be used for virtual evaluation before being used in real-time applications. Next, fresh input video streams or photos are fed into the trained model with customized weights. It locates things in these inputs by classifying them and putting bounding boxes around each object that is recognized.

3.1 Data Collection

The initial pace of the procedure is creating a database of damaged road images, which has 655 examples of different issues such as potholes, cracks, and rutting. Various methods, such as manual inspection and automated imaging systems can be employed to collect the images. Here the images were taken from Bangladeshi rural and urban areas (Chandina, Kalirbazar, Salmanpur and Tangail Sadar). The resolution of the original images ranges from 0.07 megapixels to 16.04 megapixels with an average size of 640 x 640 pixels. Figure 2 shows the data distribution.

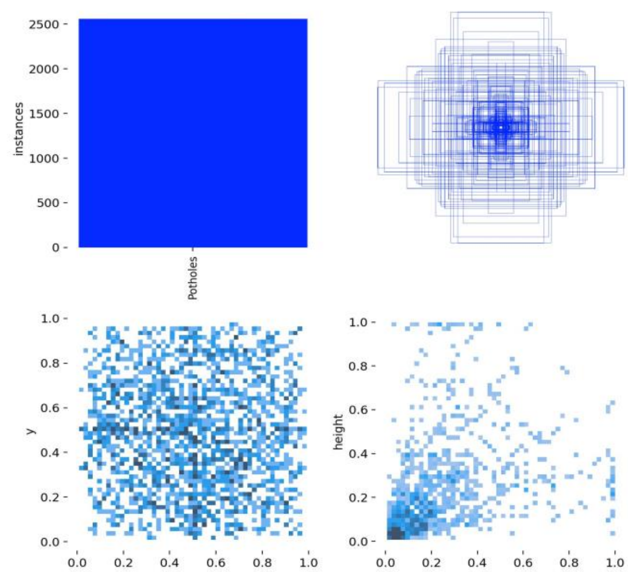

Figure 2: Distribution of data

3.2 Data processing

The process of preparing the data can determine whether an object detection system succeeds or fails. Enhancing the object recognition system's capacity to identify things from various angles and expanding the training data source are the goals of data preprocessing. The damaged road photographs are preprocessed to prepare them for use with the YOLOv8 object detection method.

This could involve reducing the size of the images, enhancing the data, rotating, flipping, blurring, converting to grayscale, and applying filters to boost contrast and reduce noise. Six hundred and fifty-five images to guide the models. Figure 3 shows the samples of each data set.

Figure 3: Sample images of road defects with multiple types of damages in various conditions.

It involves cropping the photographs, resizing them to the required resolution (640x640)pixel and converting them to a common format such as JPG or PNG. Augmentation involves applying various distortions and transformations to the photos including rotations, flips (horizontal and vertical) and random cropping to increase the diversity and resilience of the data set. We labelled every dataset of road site damages using the labellmg tool (Roboflow)[15].

3.2 Dataset Folder Structure

One of the three folders in YOLOv8 will contain a dataset collected from construction workers. These are validation, testing and training. There are two subfolders called images and labels in every folder. Within the folder containing images.

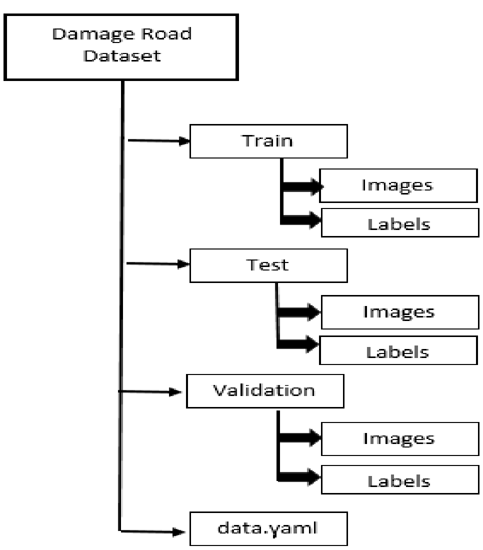

Figure 4: Folder structure of the dataset

Every image is preserved and every labelling image is preserved in the label folder. A configuration file called "data.yaml" holds details about the dataset that is employed to train the model. Usually, this file can be found in the YOLOv8 project's "data" directory. The paths to the training and validation sets, class names, and other parameters about the data set are defined in the data.yaml file. Figure 4 represents the folder structure of the dataset.

3.3 Training the YOLOv8 model

The damaged road approximately 655 picture dataset must be used to train the YOLOv8 object detection algorithm. Optimize the system's ability to recognize and classify road defects, this involves feeding the algorithm with the pictures and adjusting the weights of the neural networks. The popular object detection and picture segmentation model known as YOLO (was developed by Redmon et.al. and YOLO has gained popularity since its inception in 2015 because of its remarkable speed and precision. The breakthrough Ultralytics YOLOv8 object detection model builds on the successes of previous YOLO iterations. To improve performance and flexibility, it includes new features. YOLOv8 is intended to be quick, precise and simple to use. It is a great option for a variety of tasks, including image classification, pose estimation, object tracking and segmentation.

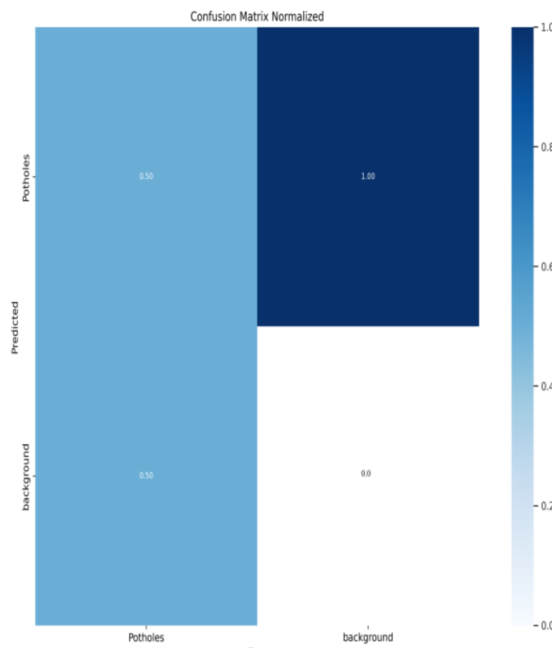

Figure 5: Confusion Matrix

3.4 Evolution of the Model

The YOLOv8 model is evaluated using measures including F1 score, recall, and precision after training. These scores provide insight into the model's accuracy and efficiency in locating and classifying pavement defects. An indicator of a classification model's accuracy is the F1 score. The proportion of true positives to all expected positives is known as precision. A true positive is an occurrence that can be appropriately classified as positive. The proportion of genuine positives to all actual positives is known as recall. A real positive is an incident that is genuinely positive, regardless of how the model categorizes it. The details of the parameters are as follows:

1. A damage occurrence in an image is deemed to be a true positive (TP) when the intersection over union (IoU) score of the model's projected presence and location is more than 0.5.
2. When the model forecasts the presence of damage inaccurately, it produces a false positive (FP). for example, when the IoU value is greater than 0.5 in a photograph. This may occur if the model forecasts a damage case in the absence of any damage instances or if the model forecasts a damage instance with a label that is not consistent with the actual world.
3. When an image's IoU score of less than 0.5 suggests that a damage instance is absent from the model, this is known as a false negative (FN). This could happen if the model predicts a harm instance with a smaller bounding box than the ground truth or if it ignores a damage instance discovered in the ground truth.

4 EXPERIMENTAL RESULTS

A chart used to describe the outcomes of a classification method is a confusion matrix. The achievement of a classification algorithm is outlined and illustrated using a confusion matrix. We can see the confusion matrix in Figure 5.

Accuracy, precision, recall and F1-score are among the performance measures of an algorithm. The accuracy of an algorithm is measured by the ratio of correctly identified data points to all data points. Precision (P), Recall (R), and Average Precision (AP) are used to measure the detecting tasks. One of them referred to as precision,which is computed as follows: It quantifies the ratio of expected positive cases to all positive examples.

$$P = \frac{TP}{TP + FP}$$

$$P = \frac{65}{65 + 49} = 0.5701$$

Where, respectively P, TP, and FP stand for precision, true positives and false positives. Recall, which is expressed where FN denotes false negatives,which is used to describe how many of the positive samples were found in the prediction.

$$R = \frac{TP}{TP + FN}$$

$$R = \frac{65}{65 + 65} = 0.50$$

Calculated from the area under the precision-recall curve, Average Precision combines P and R and can be given by:

$$AP = \frac{TP + TN}{TP + TN + FN + FP}$$

$$AP = \frac{65 + 0}{65 + 0 + 65 + 49} = 0.3631$$

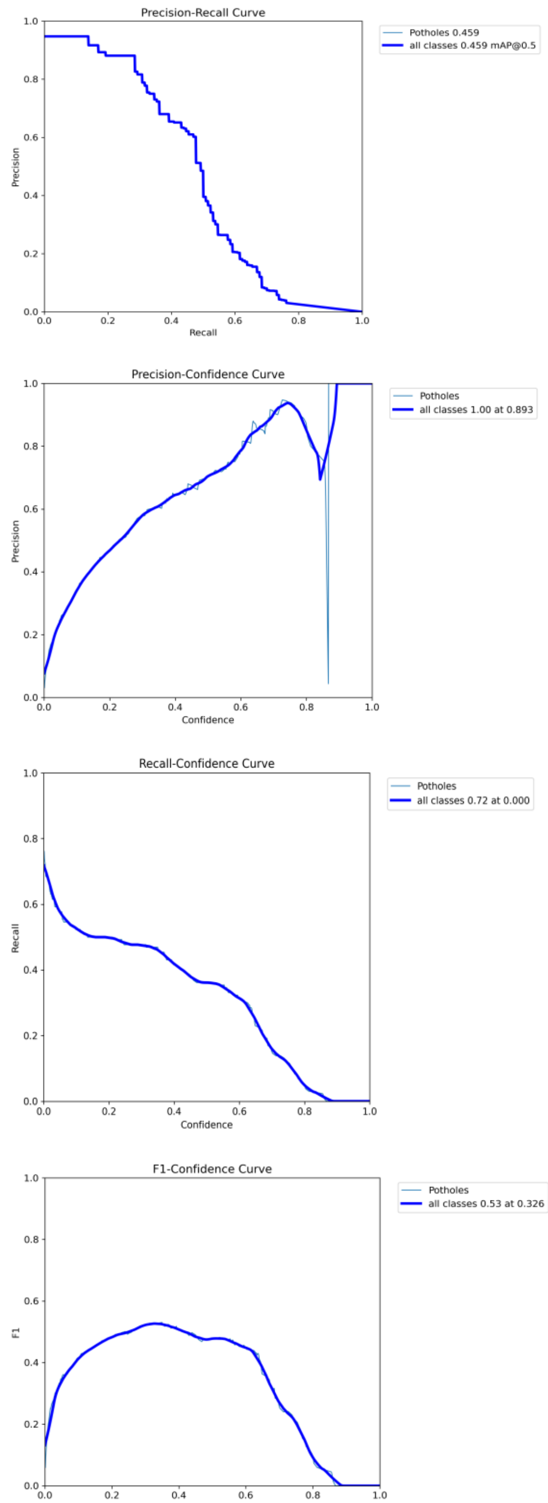

Figure 6: PR curve, P curve, R-curve, F1-curve metrics simulation.

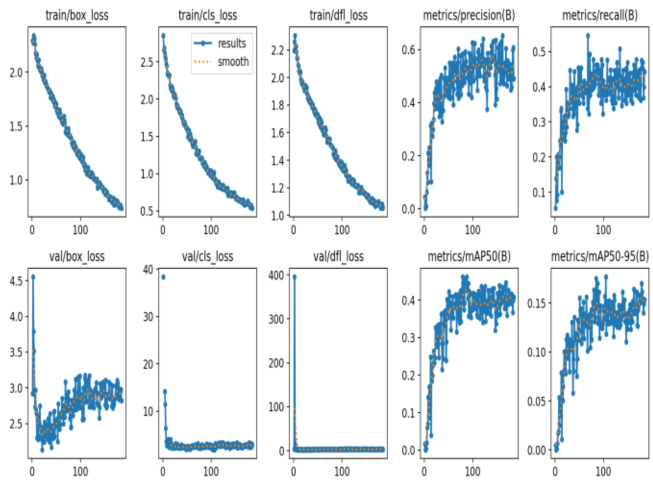

Figure 7: Loss Precision-Recall Curve.

We have calculated the loss function of precision and recall. The discrepancy between expected and actual results in a machine learning model is quantified by a loss function. It's a method of evaluating how well the model performs in our dataset. The loss function of precision and recall is illustrated in Figure 7.

Table 1 : Analyzing the Performance of Several Object Detection Models

Reference	Author/(s) Name	Method/(s)	F1-Score (%)
[11]	Naddaf-SH et.al.	Deep Learning	56%
[16]	Pham et.al.	Faster R-CNN	51.0%
[4]	Jeong et.al.	[used 12 Yolov5x method] Ensemble	67.44%
[17]	Guo et.al.	Faster R-CNN and Detectron2	51.0%
[17]	Guo et.al.	YOLOv5+MobileNetV3+ KMeans + CA + Conv-BN	55.9%

Table 1 provides a comprehensive comparison of the F1-Score achieved by different object detection systems. The model, leveraging YOLOv8, outperforms its counterparts with an impressive F1 score of 63.66%. On the contrary, the existing methods, for instance, Faster R-CNN by Wang et al. [16] and YOLOv5 by Guo et al. [17], Zhang et al. demonstrated an F1-score of 62.5% and 61.86% respectively. Additionally, the Deep Learning method[11] by Long et al. achieves an accuracy of 78.3% while YOLOv3[5] by Naddaf-SH et al. lags with a comparatively lower F1-score of 56% while YOLOv5X [4] by Jeong et al. have a comparatively higher F1 score of 67.44%. This comparison analysis demonstrates how much better the suggested YOLOv8 based system is in object detection accuracy by F1-score in contrast to alternative cutting-edge techniques.

Table 1: Performance Comparison of Various Road Damage Detection Models

Reference	AP	AP@50	Method
[3]	27.8	49.1	R-FCN
[18]	27.2	48.4	Faster R-CNN
[18]	34.9	55.7	Faster R-CNN++
Ours	38.75	0.459	YOLOv8

Table 2 provides a specific comparison of various road crack detection procedures in terms of AP and AP@50, Where our models perform better than other existing approaches.

Table 2: Simulation Information of Our Dataset

Parameter	Our Dataset
Inference time	11.8 ms
Preprocess	0.2 ms
Postprocess per image	1.0 ms
Number of images	655
Precision metric	0.601
Recall metric	0.469
mAP50-95	0.172
mAP50	0.459

Table 3 provides the simulation information regarding our custom dataset.

4.1 Sample Outputs

Multiple photos were utilized to test the model. Here, Figure 8 and Figure 9 display a representation of the road assessment output.

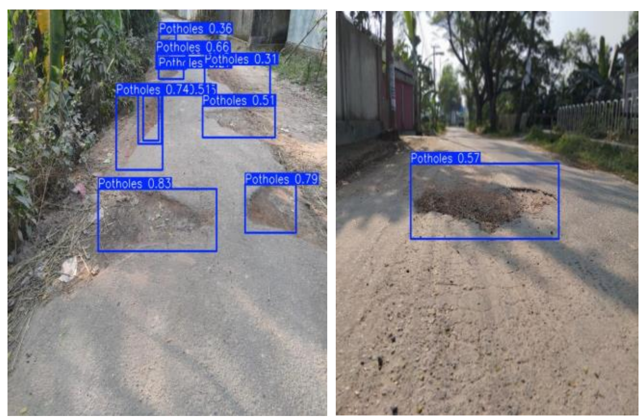

Figure 8: Sample outcomes of our system.

4.2 Discussion

Our road fault detection system is more accurate than the original YOLOv8 model. But there are still some faults on the route due to the factors mentioned below. The initial rationale pertains to the attributes of the images. Different kinds of road issues can be brought on by various road conditions and weather patterns. Moreover, long shooting distances and small cracks may result in hazy road images which would complicate the identification problem. The complexity of road conditions, wherein information about the road obstacles, cars, and pedestrians all are included in the images that were taken. As such, these conflicting factors make it more difficult to identify road fractures. The third rationale is pertinent to the YOLOv8 concept. Even though the YOLOv8 model can now recognize small targets more accurately.

4.3 Future work

The system can be used with a real-time dashboard camera in the future. In addition, a GPS module that marks the coordinates after the dashboard module detects a pothole which can be used to activate the system. When maintenance personnel work on the damaged road, they can use the coordinates to find the potholes. The model can also be trained on a specific dataset that contains images taken from the mobile camera to increase accuracy.

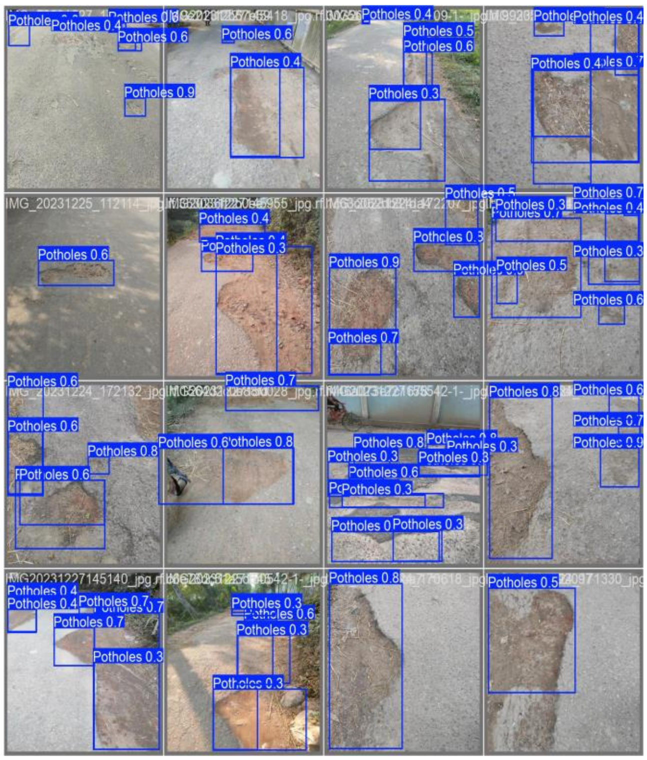

Figure 6: Roadway Impairment Identification in Asphalt Road Using YOLOv8.

Additionally, using calibrated stereo cameras or a variety of image processing techniques, the width and size of the detected potholes can be measured. Some of the photographs in the dataset were captured under various lighting circumstances because of the existence of dimness. Additionally, some of the pictures were captured from various camera angles. These elements might have had an impact on the model's analysis of the test dataset's performance. The process of detecting potholes becomes more challenging when they are smaller and farther away and the accuracy of detection declines with these smaller potholes. The research also does not address the accuracy of crack detection in roads. Future research can address these problems and further refine this model. We will investigate the possibility of using a smartphone-based road damage detection application to either partially or completely replace manual road damage inspections. We have a plan, to create an app, so the organizations in charge of keeping an eye on the roads can obtain information about damage to the roads from common users, improving their capacity to keep an eye on and fix Bangladeshi roads.

5 CONCLUSION

The idea of this project is to gather and categorize road damage data using mobile phones. This method of gathering data is effective as images and videos contain a vast number of pictures of highways and rural and urban areas. This research investigates various cutting-edge object identification techniques and how well they operate for tasks involving roadway damage detection and classification. The YOLOv8 model showed remarkable accuracy in identifying and pinpointing many types of road damage including cracks, potholes, and abnormalities. The model showed stability under a range of environmental circumstances, overcoming obstacles like shifting lighting, bad weather and uneven roads. Another important factor in the model performance was the caliber and variety of annotated datasets. YOLOv8's real-time processing skills have shown to be useful in the rapid and efficient detection of road damage, allowing for the timely formulation of maintenance program decisions. Preventing maintenance of infrastructure is made easier by the automated identification of road damage, which enables focused repairs according to the extent and location of the damage. By reducing the expenses and increasing the effectiveness of repair operations, the project provides a framework for road maintenance resource allocation that is optimized.

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