Paving the Way: AI-Driven Pothole Detection with Computer Vision

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Problem Statement and Motivation

Potholes are a major issue that affect road safety and leads to accidents, vehicle damage, and traffic issues. It is the need of hour to efficiently detect and timely maintain the potholes to ensure smoother traffic and prevent hazards. The goal of the project is to address the need for a reliable pothole detection. By combining insights from past research with modern techniques, we seek to develop a more accurate solution that can help authorities identify and repair potholes.

Literature Review and Limitations

Hu et al. (HZ10) introduces a simple method for detecting cracks using Uniform Local Binary Patterns (ULBP). Their method achieves scale and rotation invariance by classifying local patterns into five sub-classes and merging non-uniform patterns into uniform ones. They also incorporated a roughness measure to estimate local variance, effectively detecting cracks as small as 1 mm. A lookup table and post-processing steps helps reduce noise and eliminate false positives.

In contrast, Maeda et al. (MSS+18) uses a more advanced approach using the SSD algorithm to develop a mobile app for road damage detection. They create a dataset of over 9,000 images captured in diverse conditions using a mobile camera mounted on a car. Training the SSD model on MobileNet and Inception V2 frameworks, Maeda's team achieved high precision and recall, while MobileNet outperformed Inception V2 in terms of efficiency and accuracy. Their dataset and mobile app are now available as open-source tools.

Similarly, Thompson et al. (TRB+22) focuses on semantic segmentation in the SHREC2022 competition to identify road damage. They worked with a dataset of over 4,000 images from public sources, using deep learning-based models to achieve high pixel accuracy. PUCPUnet++ and HCMUS-CPS-DLU-Net emerged as top-performing models, showcasing effective segmentation in road crack detection.

Other research has applied classical image processing methods. Salman et al. (SMKR13) studies Gabor filters with multi-orientations to detect cracks by combining responses from filters applied to pre-processed images. This approach reached an impressive precision of 95%. Nienaber et al. (NBK15) utilizes Canny edge detection and contour detection on greyscale images, followed by convex hull algorithms to improve segmentation. Their technique achieved precision and recall values of 81.8% and 74.4%, respectively.

Jo et al. (JR15) took a black-box camera approach, detecting potholes through image processing methods like grayscale conversion and thresholding. They applied a cascade detector to eliminate irrelevant objects such as tires and shadows, achieving 88% precision.

More recently, Shaghouri et al. (SAB21) explores real-time pothole detection using SSD and YOLO models (YOLOv3 and YOLOv4). They trained these models on images of Lebanese roads using Google Colab, achieving the best results with YOLOv4. Their work demonstrated the effectiveness of deep learning for rapid pothole detection, setting a new standard for real-time applications in road safety.

Dataset and Preprocessing

We will use the data set available on *Kaggle* and *Roboflow* universe for training the models.

The data is preprocessed to have the distribution: train 1390, validation 133 and test 67 images. The raw images are resized to 640×640 to maintain the uniformity. Moreover, the following geometric augmentation are made:

- **Flip:** Horizontal and Vertical
- **90° Rotate:** Clockwise, Anti-Clockwise, Upside Down
- **Rotation:** Between -15° to 15°

Implementation and Discussion

Based upon the literature review we plan to use three techniques: (i) simple edge detection, (ii) YOLO based model and (iii) AutoML model using Roboflow 3.0. We use confidence interval of 20% for all the methods.

Edge Detection: We use Canny Edge Detection algorithm for detecting the potholes. The edge detection approach performed the worst. Parameters had to be tuned per image, and many times, it would detect potholes in locations where they were not present. While it determines the general location of the potholes pretty well, the individual potholes are not separated, and some false positives are also present. Figure 1 showcases the detections.

Roboflow 3.0 is an end-to-end platform to building and deploy computer vision models that simplifies the dataset management and model training process. For pothole detection, it can significantly reduce the time and complexity

Figure 1: Canny Edge Detector

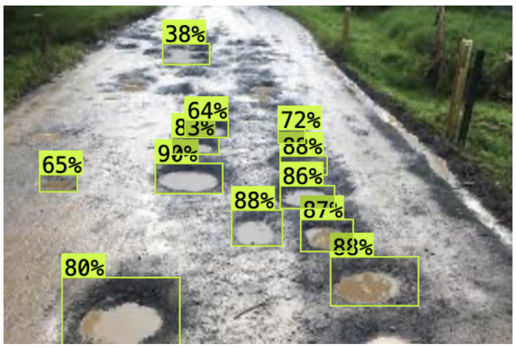

Figure 2: Roboflow 3.0

of creating a functional model. However, the flaw with the model is that it is a black box, i.e. the hyperparameters or even the approach utilised by the model is not fully known. As such, any modifications that may be needed later would be difficult to implement. Figure 2 demonstrates the detection following Roboflow 3.0. Note that the potholes in the back are not recognized and also one pothole present in the fron is missed. It may be due to the dataset used.

You Only Look Once (YOLOv11) is a state-of-the-art real-time object detection model. Its advantage lies in speed and accuracy which makes it ideal for pothole detection, where the system needs to process a lot of data in real-time. Figure 3 illustrates detection by the YOLOv11 approach. Note that more potholes in the front are recognized compared to the Roboflow approach.

Results

Figure 4 depicts pothole detection in one of the 67 images from test set. Table 1 provides the performance of all the models at confidence of 20%. The reports and codes can be accessed through the *GitHub repository*.

Models	Precision (%)	Recall (%)	mAP (%)
YOLOv11	76.8	**75.9**	**82.5**
Roboflow 3.0	**82.9**	69.1	80.2
Canny Edge	-	-	-

Table 1: Performance of YOLOv11 and Roboflow 3.0

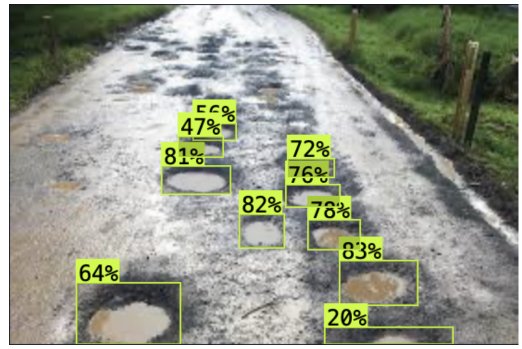

Figure 3: YOLOv11

Figure 4: Pothole Detection using YOLOv11

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