A HYBRID APPROACH TO DETECT POT-HOLES

Prof. D.G. Harkut
HOD CSE Department at Prof Ram Meghe College of Engineering and Management, Badnera
Yash Haramkar, Gaurav Gimonkar, Yuvraj Kothe, Sejal Mankar
(Students at Prof Ram Meghe College of Engineering and Management, Badnera)

ABSTRACT
Potholes are a persistent problem in transportation infrastructure, causing vehicle damage and hazards for drivers. Manual detection methods are time consuming and costly. Computer vision and machine learning offer potential solutions for automating pothole detection. These technologies can improve road maintenance and safety by accurately identifying potholes. This paper presents an integrated approach for pothole detection and classification using YOLOv7, SVM, and segmentation techniques. A user- friendly web application is developed using Stream-lit for easy interaction. The YOLOv7 model accurately detects and classifies potholes based on annotated training datasets.
Segmentation techniques refine pothole regions, enabling precise boundary extraction for accurate analysis. The model is trained on labeled pothole images to classify different pothole types.
The web application allows users to upload images, detect and classify potholes, and visualize results. It aids road authorities and maintenance crews in identifying problematic areas and planning repairs, contributing to safer road conditions.

INTRODUCTION
Efficiently detecting and classifying potholes on roadways is vital for ensuring road safety and effective maintenance. This paper presents an integrated approach that utilizes the YOLOv7 object detection model for accurate pothole detection and classification. Additionally, a user-friendly web application is developed using Stream-it to provide an intuitive interface for interaction and result in visualization. The detection process relies on the YOLOv7 model, which is trained on annotated datasets to precisely locate and classify potholes in road imagery. The model's robust object detection capabilities make it well-suited for identifying potholes with high accuracy. To enhance user experience and facilitate result visualization, a web application is built using Stream-lit. Application allows users to easily upload road images and applies the YOLOv7 model to detect and classify potholes. The detected potholes are then presented to the user in an accessible and user-friendly format. By combining the YOLOv7 object detection model and the Stream-lit-based web application, our integrated approach provides an efficient solution for accurate pothole detection and classification. This empowers road authorities and maintenance crews to swiftly identify and address potholes, ultimately contributing to safer road conditions and more effective maintenance practices.

LITERATURE SURVEY
In a study conducted [1], various image pre-processing and segmentation methods were explored to improve the accuracy of pothole detection. The study specifically implemented the difference between Gaussian-Filtering and clustering-based segmentation methods and compared their results. The findings revealed that the K-Means clustering-based segmentation method was the most efficient in terms of computing time, while edge detection-based segmentation was the most accurate. The study aimed to identify a superior method for pothole detection compared to traditional methods, and this objective was achieved by using performance measures to evaluate the different techniques reviewed.
Their research paper [2] discussed a pothole detection model using computer vision and machine learning. The study involved collecting road images from BMC Mumbai and applying various computer vision operations such as pre-processing, morphological operations, canny edge detection, and decision tree algorithms to detect potholes. The proposed model aimed to identify potholes and report them to relevant authorities while utilizing machine learning techniques to enhance prediction accuracy. Despite the availability of smart technologies like IOT, machine learning, and artificial intelligence,

there is a lack of effective techniques for detecting and preventing road anomalies such as potholes. The model also utilized GPUs to
Accelerate deep learning processes, albeit at the cost of significant power and energy consumption. Additionally, data from vibration and GPS sensors were utilized to evaluate road surface quality. By leveraging image processing techniques, the system successfully detected potholes from input images, enabling effective identification of such road hazards.
In their study [3], researchers aimed to develop a pothole detection method using a combination of pothole and normal road image data. The study involved collecting and preprocessing the data by resizing and rescaling the images. MobileNetV2 was utilized for feature extraction, and dimensionality reduction techniques such as PCA, LDA, and t-SNE were applied to reduce the feature dimensions. Five machine learning classification algorithms were employed to train the system, including Support Vector Machine (SVM), Logistic Regression, Random Forest, Elastic Net, and Decision Tree. The results were analyzed, and it was observed that Logistic Regression, Elastic Net, and SVM performed better than the other algorithms. A comparison of the top- performing algorithms concluded that Support Vector Machine (SVM) achieved the highest accuracy, reaching 99%.
In their research [4], the focus was on detecting potholes to prevent road accidents by utilizing a combination of hardware and software technologies. The researchers employed a Pi Camera for capturing images, benefiting from its high clarity and the ability to connect it to the Raspberry Pi for remote access. An interface was developed to facilitate remote access to the Pi Camera. The system architecture involved taking input from the Pi Camera, sending it to the processing unit via a TCP server for networking, and utilizing a Neural Network Model for pothole detection. Once potholes were detected, the direction of an RC car would be modified accordingly. The study also employed Image Threshold segmentation for visualizing the potholes and Canny Edge Detection for detecting the edges of the images. The images were initially converted into grayscale and Open-CV libraries were utilized for edge detection.
In their study [5], researchers aimed to design and develop an Automatic Pothole Detection and Alert System that incorporates an ultrasonic sensor, accelerometer, stereo camera, and Global Positioning System (GPS) integrated with Raspberry Pi. The system's primary objectives were to detect potholes, alert riders, and create a location database of existing potholes. By enhancing rider awareness, the system has the potential to reduce accidents and vehicle maintenance costs. Experimental results demonstrated a 90 percent accuracy rate in pothole detection. The estimated cost of the system is approximately 8000 INR, and it can lead to a reduction of 35-50 percent in average vehicle maintenance expenses. The system is capable of promptly sending GPS location information to the database and alerting the rider within 4 seconds. The database generated by the system is organized on a city- wise basis and has the potential for future expansion to cover the entire nation.
In their study [6], researchers focused on developing an algorithmic approach for pothole detection that does not rely on machine learning. Unlike traditional methods that utilize simulated pothole models or footage from advantageous vantage points, this study utilized an image library, a pothole model, and basic image processing techniques to detect potholes from within a vehicle. The algorithm aimed to identify various road features, including lane markings, road signs, and potholes, with the goal of enhancing road safety. The study aimed to improve pothole detection capabilities and make a contribution to overall road safety improvement.
Vibration-based method uses accelerometers in order to detect potholes. Considering the advantages of a vibration-based system, these methods require small storage and can be used in real-time processing. However, vibration-based methods could provide the wrong results, for example, that the hinges and joints on the road can be detected as potholes and that potholes in the center of a lane cannot be detected using accelerometers due to not being hit by any of the vehicle’s wheels (Eriksson et al.)
3D laser scanner methods can detect potholes in real time. However, the cost of laser scanning equipment is still significant at the vehicle level,

and currently these works are focused on the accuracy of 3D measurement. Stereo vision methods need a high computational effort to reconstruct pavement surfaces through matching feature points between two views so that it is difficult to use them in a real-time environment.

Recently, Monza et al. [17] used a low-cost Kinect sensor to collect the pavement depth Also, the obtained pothole information is provided to the Road Management System, and the repair time and maintenance quantities are determined according to the severity and location of the pothole. Also, the obtained pothole information is provided to the Road Management System, and the repair time and maintenance quantities are determined according to the severity and location of the pothole.

Other methods besides deep learning—such as support vector machines (SVM) and nonlinear SVM have been explored for extracting potholes from images. Gao et al. [18] employed texture features from grayscale images to train an SVM classifier to distinguish road potholes from cracks in the pavement.

In addition to the aforementioned machine-learning-based techniques, other approaches have been developed. Penguin et al. [19] used morphological processing in conjunction with geometric features from pavement images to detect pothole edges. Koch et al. [20] used histogram shape-based threshold to detect defective regions in road surface images and subsequently applied morphological thinning and elliptic regression to deduce pothole shapes; texture features within these shapes were compared with those from surrounding non-pothole areas to determine if an actual pothole was present. Enhanced deep SR network (EDSR) [21] introduces the idea of performing object detection on SR images in the remote sensing field for some of the popularly used architectures. The ESRGAN [22] architecture improved on the existing super-resolution GAN networks to provide more realistic SR images. The authors employed residual-in-residual dense block (RRDB) with adversarial and perceptual loss to achieve this. The authors achieved a considerable improvement in a subsequent study regarding real-ESRGAN [23] with the use of only synthetic data with high-order degradation modeling, which were close to the real-world degradations. [24] Addressed the issue of small object detection with SR data by proposing a transformer that had three parts: a shallow feature extraction step, a deep feature extraction step, and a high-quality image reconstruction step using the residual Swim transformer blocks (RSTB). This transformer produced good results on the DIV2K dataset and the Flickr2K dataset.

Zhang et al. [25] proposed a model called BSRGAN to address degradation issues of SR models that often affect the performance of such models. They proposed that BSRGAN uses random blue shuffle, down sampling, and noise degradation techniques to produce a more realistic degradation of LR images.

The dual regression network (DRN) [26] mapped LR images to HR ones and provided a corresponding degradation mapping function. The authors also found that their method achieved better performance in terms of PSNR (peak signal-to-noise ratio) and the number of parameters.

NLSN for non-local sparse network [27] uses a non-local sparse attention (NLSA) to address the problem of image SR. The method divides the input into hash buckets that contain relevant features, which prevents the network from providing noise or attention to areas of the image with less information during training.

As deep learning technology has developed rapidly, these machine-learning-based limitations have been overcome with the development of object detection techniques in computer vision. These object detection techniques are classified mainly into two-stage detectors and one-stage detectors. The two-stage detector extracts numerous candidates in the area where the object exists and sequentially processes the classification and localization processes; thus, the accuracy is high, but the computation speed is slow. However, as the one-stage detector processes the classification and localization processes simultaneously, the accuracy is low, but the computation speed is fast. YOLO has the fastest computation speed among existing one-stage detector-type object detection models, and most researchers are currently developing YOLO-based 2D pothole detection algorithms. U et al. attached a camera for road surface detection to the rear of a vehicle to capture road surface images in East Java

Province [28] and trained YOLOv3, YOLOv3 tiny, and YOLOv3 SPP using selected 448 images. As a result of training various YOLO models, each model achieved MAP of 83.43%, 79.33%, and 88.93%, respectively. Through this result, the author argued that the YOLOv3 SPP combined with SPP achieved the highest accuracy. Park et al. split a 665-pothole image dataset into training, validation, and test datasets by selecting 70%, 20%, and 10% of the total sample, respectively, then trained 598 pothole image datasets to YOLOv4 [26], YOLOv4 tiny , and YOLO v5s models. As a result of the performance evaluation of the model, YOLOv4, YOLOv4 tiny, and YOLOv5s achieved 77.7%, 78.7%, and 74.8% m AP (I o U = 0.5), respectively. In conclusion, the author noted that YOLOv4 tiny achieved the highest accuracy, and there is a need to extend the backbone network of YOLOv4 tiny to improve accuracy. Bucko et al. trained 1052 images collected differently under clear, rainy, sunset, evening, and night weather conditions. Especially under clear weather conditions, YOLOv3, YOLOv3 SPP, and Sparse R-CNN achieved 77%, 79.1%, and 72.6% m A P (I o U = 0.5), respectively. Dharma al. [29] trained a dataset of 1500 Indian road images collected from Coimbatore, Idukki, and KY mil on the YOLOv2, YOLOv3, and YOLOv3 tiny models, achieving m AP (I o u = 0.5) 45.33%, 38.41%, and 49.71%, respectively. Assad et al. [30] trained 665 pothole datasets on the YOLOv4 tiny, YOLOv4, and YOLOv5 models, and verified the real-time detection possibility in a low-end embedded system. An OAK-D camera with a single main board (Raspberry Pi) was used to detect potholes. One of the limitations was that only a YOLOv4 tiny model achieved real-time detection of 31.76 FPS among various YOLO models. However, although the existing computation speed of the YOLOv4 tiny model is fast, this model needs to extract richer object features to be detected. Therefore, in this study, we attempted to improve the accuracy by combining multi-scale feature networks, such as SPP and FPN, with the YOLOv4 tiny architecture to extract rich object features. The multi-scale feature networks are used to improve the detection performance. SPP extracts pothole features of various sizes by applying multiple max-pool filters to compensate for the spatial information loss of the image that occurs during max-pooling, which is a part of the convolutional neural network process [31]. The FPN compensates for spatial information loss by combining high-level feature maps generated in deep convolutional layers with low-level features generated in shallow convolutional layers [32]. This mechanism of combining various feature maps makes greater use of the spatial information of the image by extracting the rich features of the object, thereby improving the overall performance of the deep learning model. Below mention table 1 summarizes selected studies on pothole detection and shows their contribution, models, hardware systems, FPS, and m AP (Io U = 0.5).

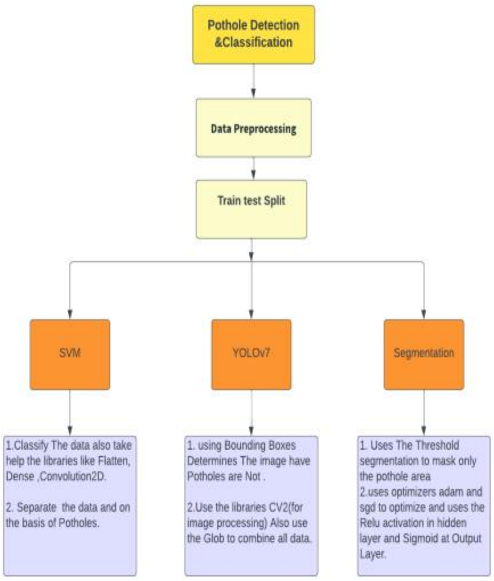
Table 1. A summary of recent road pothole detection algorithm performance Yolo

References & Year	Contribution	Model	CPU	GPU	FPS	mAP(IoU@0.5)
Ukhwah et al. [21], 2019	Detection of potholes and area estimation	YOLOv3 YOLOv3 tiny YOLOv3 SPP	Intel ® Xeon (R) CPU@2.30GHz	Tesla T4 (13 GB)	0.4	83.43% 79.33% 88.93%
Park et al. [25], 2021	Comparison with various YOLO models	YOLOv4 YOLOv4 tiny YOLOv5s	-	Tesla K80 (12 GB)	-	77.7% 78.7% 74.8%
Asad et al. [30], 2022	Detection of pothole using Raspberry Pi 4	YOLOv2 YOLOv3 YOLOv4 YOLOv4 tiny YOLOv5	ARM Cortex-A53@1.4GHz	-	3.20 2.39 1.98 31.76 18.25	81.21% 83.60% 85.48% 80.04% 95.00%
Bucko et al. [2], 2022	Detection potholes under adverse weather condition	Sparse R-CNN YOLOv3 YOLOv3-SPP	-	-	- 28.57 27.78	72.6% 77.1% 79.1%
Dharneshkar et al. [29], 2020	Detection potholes of the India road	YOLOv2 YOLOv3 YOLOv3 tiny	-	GeForce GTX 1060	-	45.33% 38.41% 49.71%

In [33] the accelerometer data collected from mobile phones are normalized by Euler angle computation which is fed to a combination algorithm of Z-THRESH and G-ZERO approaches. Then, spatial interpolation is used to locate the pothole. Results revealed a 100 % accuracy in detecting potholes without false positives. Another work presented a real time system for inspecting and detecting road distresses [34]. The system used a high-speed 3D transverse scanning method. Structured light triangulation formed the base of the characterization and dynamic generation of the 3D pavement profile. The detection system is made up of a GigE digital camera and an infrared laser (810 nm) line projector. The system is mounted on the rear side of the vehicle. To make the laser stripe covers a full lane of pavement transversely, an 80 degree angle laser projector has been used. The camera catches continuous images for the lines of the laser to compute 3D transverse profile. Based on the triangulation principle, the elevation of a specific point can be found. Another work employed laser imaging for pavement distress inspection [35]. Several features are then captured including the total number of distress tiles and the depth index which are given to a three-layer neural network for classifying the type of the crack and to estimate its severity.

METHODOLOGY

For a system that can find potholes in real-time, the suggested method looks for potholes with a custom trained YOLOv7 model, SVM machine learning algorithm, and image segmentation. Like the other modules, YOLOv7 gets information from the webcam or live camera and sends the pictures through the trained model. Each picture is annotated after the dataset has been collected. Before giving it to deep learning models like the YOLO family to train custom models, the labeled data is split into training and testing data.



Proposed Model

DATA COLLECTION AND PRE-PROCESSING

How well the models work and how reliable they are based on the dataset used to train them. The data set must have pictures of real potholes. So, the most recent pothole image dataset that is open to the public is used. This dataset has 700+ images with real-world effects like shadows, moving vehicles, and different lighting. The pictures in the dataset come from online sources, which means that they are noisy and of low quality. Selected images to create training datasets would be laborious. Therefore, we approach existing datasets as benchmarks for training deep learning models to automatically detect road damage from the collected videos. There are some datasets available. However, the one provided in the IEEE 2020 Big Data Challenge Cup by Sekilab2 is considered practical. This benchmark dataset consists of one training set (train) and two test sets (test1 and test2). The training set contains 4,041 images (829, 1706, and 1,506 for Czech, India, and Japan, respectively). The two test sets contain 631 and 664 images, correspondingly. The training set has 4,041 ground truth labels (bounding boxes and damage types). There are four damage considered: longitudinal cracks (D00), traverse cracks (D10), alligator cracks (D20), and potholes (D40). Data is cleaned to archive error-free data set. After cleaning the data set, all the images were annotated with the relevant labels.

MODEL TRAINING AND TESTING

The Machine Learning model is developed with YOLO v7 architecture, SVM machine learning algorithm, and segmentation algorithm. The Training and Testing ratio is 80:20

POTHOLE DETECTION USING DEEP LEARNING MODEL DEEP CONVOLUTION NEURAL NETWORKS

Have shown that they can do a lot of things to find objects. Deep learning lets you train on several object recognition models, such as the region-based convolution neural network family and the YOLO family. But the R-CNN family is hard to compute, which leads to low delay. On the other hand, YOLO is being consider the computational resources available for deployment. Faster R-CNN and R-FCN may be computationally intensive, while SSD and YOLO are designed to be more efficient and suitable for real-time applications on resource-constrained devices.

The choice of the algorithm may also depend on the availability and size of the pothole dataset. Some algorithms may require larger datasets for effective training, while others, like SSD and YOLO, can perform well with smaller datasets. Potholes can have irregular shapes, and algorithms like YOLO, with their grid-based Approach, may be better at handling objects with diverse shapes and aspect ratios.

Fig- Segmented Image Using YOLO

Once (YOLO) are known for their efficiency and speed. They perform detection in a single pass, making them suitable for applications where low latency is critical.

YOLOv7

YOLO, which stands for "you only look once," was first used by Red in 2016. The YOLO architecture can find objects by using three key terms. It is important to understand these three tactics to fully understand why this model works so quickly and accurately compared to other object identification algorithms. The YOLO approach starts with the implementation of the remaining blocks. In the first step of the architectural plan, grids were made in the specific picture using the remaining 7 × 7 blocks. These grids act as center points, and a different prediction is made for each grid based on what it shows. In a second way, the bounding boxes are made by taking each of a forecast's central points into account. Although the classification jobs are successful for each grid, it is more difficult to separate the bounding boxes for each forecast. The intersection of union (IOU) is the third and final approach. It is used to find the best bounding boxes for a given object identification job.

SEGMENTATION

Segmentation is used to highlight the specific part of any image in this we used to highlight the pothole area for better understanding. we used threshold segmentation in this Project first we have to convert the images into greyscale images for better observation we used the sigmoid and re activation in this Canny edge detection model there are a total of 119 layers we used the re used in the background and the sigmoid issued for the front end for flatten the output.

Original Image

Edge Image

EVALUATION METRICS

Different experiments result in different models. Thus, we need to have a robust metric to select the best models out of all experiments. There are two common evaluation metrics used in this area. The first one is the Average Precision (m AP) calculated at I o U (Intersection over Overlapping) threshold of 0.5 (mAP@0.5). The second one is the F1 score. The m AP is a good measurement when we need to ensure the model is stable across different confidence thresholds (robust) while the F1 score is computed for a specific confidence threshold. The common practice is to use mAP@0.5 on the validation set to select the best model and use the F1 score to report the model performance on the test dataset. This project also follows this common practice (using mAP@0.5 to select the best models and report F1 scores on the test sets). These fine-tuning techniques improve prediction accuracy with a slight trade-off of the inference time compared to the standard YOLOv7 inference time. However, this trade-off is insignificant because standard YOLOv7 with standard configuration (used in this project) is reasonably fast (≈ 40 114 frames per second). These techniques are highly recommended and help boost prediction accuracy if time requirements are insignificant.

ADDITIONAL ACCURACY FINE-TUNING TECHNIQUES

We build three models for each dataset folder with a test set. One model is the default YOLOv7 configuration with the modified image augmentation options, one model is the configuration with three additional coordinate attention layers in YOLOv7's head, and one model is the configuration similar to the second one and three more Coordinate Attention layers in the YOLOv7's backbone. We use the ensemble method to combine the results from the three best models for each folder and improve the accuracy.

WEB-APPLICATION

Web application developed using Stream-lit, a popular Python framework for building interactive data applications. The purpose of this web app is to detect and address potholes on Roads. The user interface is designed to be user-friendly and intuitive, allowing users too easily Interact with the application. The web app built with Stream-lit provides a platform for users to upload images or videos of roads containing potential potholes. It incorporates a backend algorithm, and we also try to get some dashboard to present information of pothole.

CONCLUSION

An approach is presented for analyzing the images with potholes and performing operations on them and labeling them as pothole or non-pothole images as well as creating the bounding boxes for better visualization. His system is efficiently designed to fulfill two main criteria:

1. Detecting potholes on the road
2. Implement Web Based Application for detection purpose.

This Project will help many peoples to detect Potholes in the Future this Software can be implemented in the Car as an in-build so the speed of detection will increase.

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