SAFE DRIVE: ADVANCED POTHOLE DETECTION SYSTEM FOR ENHANCED ROAD SAFETY IN RAINY CONDITIONS

Kowshikaa.k.s[1]

[1] *Post graduate M.Tech ,M.Tech (dual degree) in Computer Science Engineering with Business Analytics, Vellore Institute of Technology, Tamil Nadu, India*

ABSTRACT

In rainy weather, the presence of potholes on road surfaces constitutes a formidable hazard to vehicular safety. These potholes, formed through the synergistic effects of wear and tear alongside rain-induced erosion, precipitate accidents, inflict vehicle damage, and cause significant traffic disruptions. This project seeks to harness the power of deep learning techniques to develop an advanced object detection system with the specific aim of identifying potholes obscured beneath accumulated rainwater. The inherent challenge in this endeavor is the paucity of image data depicting potholes under turbid rainy water conditions. Current imaging technologies fall short in acquiring clear images in such turbid environments, necessitating an innovative approach.

To overcome this limitation, we propose the generation of synthetic images based on sophisticated physical models of underwater scenes. These generated images will serve as the training data for a YOLOv8 model, enabling real-time detection of submerged potholes. The endeavor will not only focus on creating a robust training dataset but will also involve a meticulous comparison of the detection capabilities of the YOLO model when trained with conventional images versus those generated for underwater conditions.

This project, therefore, represents a confluence of advanced machine learning, image generation techniques, and practical application in road safety. By enhancing the real-time detection capabilities of potholes under rainy conditions, we aim to mitigate the risks posed by these hazards, thereby contributing to safer driving experiences and reducing the incidence of traffic accidents and vehicle damage. The ultimate goal is to create a reliable and efficient system that can be deployed in real-world scenarios, ensuring enhanced road safety even in adverse weather conditions.

Keyword : *Pothole detection, Rain-induced road hazards, Real-time pothole alerts,YOLO*

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1. INTRODUCTION

India's extensive road network plays a vital role in connecting the country's diverse regions, but it also presents challenges due to varying conditions. The annual monsoon season, in particular, exacerbates these challenges, causing waterlogging. Due to this, many accidents are caused because potholes on roads are hidden underwater. To counter this, IoT and AI systems can be used. However, training these systems requires images that can capture the potholes even in muddy rain waters. Though research is being done to improve the hardware, as of now it still is unsolved.

Rainwater accumulated on roads is muddy and has a brownish color attenuation. This can make the pothole detection systems trained on surface potholes less efficient in detecting ones underwater, as the system would be trained on clear images. Works to tackle these problems typically go in the multi-modal direction and employ several sensor technologies to calculate the depth of potholes and detect them. But these don’t have the advantage of being able to detect potholes before coming into the vicinity of the pothole that vision technologies have.

1.1 PROBLEM APPROACH

YOLO, or You Only Look Once, is an object detection algorithm that rapidly identifies objects within an image or video frame. Unlike traditional methods that scan the image multiple times, YOLO divides the image into a grid and makes predictions for the whole grid simultaneously. For each grid cell, it predicts bounding boxes (representing object locations) and class probabilities. After predictions, it uses non-maximum suppression to refine the bounding boxes, keeping only the most confident ones. This method enables YOLO to process images in real-time, making it popular in various applications requiring swift and accurate object detection, such as autonomous vehicles and video surveillance systems.

1.2 CONTRIBUTIONS

Introduction Improving pothole detection to work in rainy conditions by training with artificially generated underwater images.
Using a physical image model to simulate pothole images under rainy water.
Using the latest YOLO architecture to perform the pothole detection task.

2. PREVIOUS WORK

These categories encompass the different approaches and methodologies used in previous research related to pothole detection, highlighting the diversity of techniques from thermal imaging to deep CNN networks and anomaly detection using various CNN architectures. Adjustments can be made based on specific findings and details from previous research .

2.1 Thermal Imaging and Deep Learning Approaches

Uses thermal imaging for pothole detection. This work also takes advantage of the applicability of deep learning approaches on thermal images and uses CNN approach for the detection of potholes. Using pre-trained CNN models increases the accuracy of detection significantly. Thermal imaging has been used as an alternative for other high-cost setups for night vision. By using thermal imaging, the captured images are able to represent potholes in areas which are not well lit or have weather conditions like fog and rain.

2.2 Classification of Potholes for Autonomous Driving

Discusses classification of potholes for scene understanding for Autonomous driving cars. The model proposed uses a deep CNN network that works as a feature extractor. The extracted features are further given as input to a random forest classifier. Performance of the model is boosted with advanced mutation and dipper throated optimization for parameter learning.

2.3 CNN Networks and Anomaly Detection on Roads

Employs CNN networks like Alex net, ReNet18, and Squeeze Net and categorizes the anomalies detected on roads including potholes. The study seeks to increase the capability of supervised and unsupervised crack detection through categorizing the detected anomalies on roads. Performance comparison of the three models was performed in which ResNet18 gave the highest accuracy of 85.20%.

2.4 Gaps in Literature

Most of the real-time models, implemented mostly for ADAS (Advanced Driver Assistance Systems), use IoT and sensing technologies. There is a lack of exploration of real-time implementation for computer vision-based techniques, which can provide more advantages like richer features, less preprocessing (relative to other sensing technologies), and better suitability for real-time implementations. Existing vision-based methods for pothole detection mostly focus on using transfer learning techniques and two-shot detectors like Faster R-CNN and Mask R-CNN. We wish to implement YOLO architectures such as YOLOv7 and YOLOv8, which are advanced and proven faster and more efficient for object detection in real-time. Most of the models proposed consider cracks and road deformities in general and not specifically potholes. We would like to address the specific case of potholes to cover different types and shapes, not just generic potholes. Additionally, many studies focus on dry or water-filled potholes captured on roads after rain but which are dried. In reality, people do drive during rains and immediately after despite the hazards. Pothole detection systems would be very useful in such scenarios. Hence, we aim to explore shallow underwater image processing for identifying not only water-filled potholes but also underwater potholes.

Research Gap	Outcome
Lack of real-time implementation for computer vision-based techniques	Implement YOLOv7 and YOLOv8 architectures for real-time pothole detection
Focus on general cracks and road deformities, not specific potholes	Develop a model specifically for pothole detection to cover various types and shapes
Emphasis on dry or water-filled potholes, not rainy or underwater potholes	Explore shallow underwater image processing for identifying underwater and rain-filled potholes

Table-1 This table summarizes the identified gaps in the literature and the corresponding outcomes that your research aims to achieve. Adjust the specifics as per your detailed findings and research objectives.

3. MUDDY UNDER WATER IMAGE GENERATION

The proposed methodology for pothole detection in flooded conditions has two parts. Due to most of the work on pothole detection using computer vision is on the surface, there is no available dataset for potholes under muddy / rainy waters. To make the model better at identifying underwater potholes we aim to train it with images that are simulated to represent those taken under rainy waters. We achieve this by applying an attenuation mask based on ocean water type coefficients that best represent muddy waters.

3.1 UNDERWATER IMAGE FORMATION MODEL

Introduction To generate images of potholes under rainy waters, we use this underwater image degradation model that has been widely used in traditional underwater restoration methods[9]:

$$U_\lambda(x) = I_\lambda(x) \cdot T_\lambda(x) + B_\lambda \cdot (1 - T_\lambda(x)) \qquad (1)$$

Here x refers to a point in the image. U is the degraded underwater image, I_λ is the original image, the scene radiance, B_λ is the homogeneous background light, λ is the wavelength for the R,G,B channels. $T_\lambda(x)$ is the energy ratio of the light wave which causes the color cast. Which can be interpreted as the normalized energy ratio, which depends on the depth of the point x.

3.2 DEPTH ESTIMATION

The depth map required for the transformation was calculated using MIDAS, a monocular depth estimation model[7]. The model computes inverse depth from a single image.

MiDas Monocular Depth Estimation is a depth estimation model that is robust and can be trained across multiple datasets.The success of monocular depth estimation relies on large and diverse training sets. Due to the challenges associated with acquiring dense ground-truth depth across different environments at scale, a number of datasets with distinct characteristics and biases have emerged. It enables mixing multiple datasets during training, even if their annotations are incompatible. It proposed a robust training objective that is invariant to changes in depth range and scale. It also advocated the use of principled multi-objective learning to combine data from different sources, and highlighted the importance of pretraining encoders on auxiliary tasks.

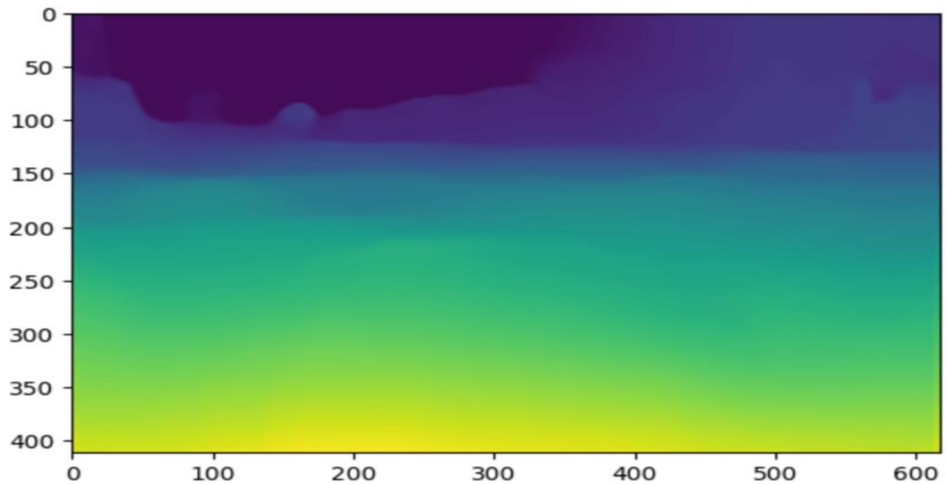

Fig1: Depth estimation

3.3 IMAGE GENERATION METHOD

The attenuation coefficient of the degraded image Nλ, is chosen based on type 7 of jerlov's water types which best represent muddy water[10, 12]. Water types , I, IA, IB, II, and III for open ocean waters, and 1, 3, 5, 7, and 9 for coastal waters. Since coastal water best represents the turbidity in the rainwater on road, we choose type 7's coefficients[12] to generate our images.

TYPE	RED	BLUE	GREEN
7	0.620	0.610	0.500

Table 2 Nλ Values for synthesizing underwater images

FIG2: original image vs generated image

4.OBJECT DETECTION WITH YOLO V8

YOLOv8 [13]is one of the most advanced object detection models available today. It has several advantages over other models, such as:

1.Speed and accuracy: YOLOv8 is faster and more accurate than previous versions of YOLO, as well as other popular models like Efficiently and Faster R-CNN. It can achieve real-time performance on various devices, while maintaining high precision and recall.
2.Unified framework: YOLOv8 can perform not only object detection, but also instance segmentation and image classification. It provides a consistent and easy-to-use API for training and deploying models for different tasks.
3.Extensibility: YOLOv8 is compatible with all previous versions of YOLO, and supports various export formats for different platforms. It also allows users to customize the model architecture, backbone network, loss function, and data augmentation techniques.

Improvement over previous models : Yolov8 builds on its previous versions, with slight changes in its architecture. The backbone module is C3 instead of the usual Cf2 ,the number of block per stage in the new version is [3, 6, 6, 3] and the Anchor Base was replaced by anchor free[14] all of which makes the above mentioned advantages possible

5. EXPERIMENTS AND EVALUATION

The Yolo v8 model was trained and evaluated on the original images and the generated images to see if the model trained with generated images are able to perform better on turbid underwater conditions. The mAP50 and mAP50-90 scores of the different training experiments are given in table 3.

Fig 3: Yolo detecting potholes

Train	Test	mAP50	mAP50-90
Original images	Original images	0.379	0.204
Original images	Generated images	0.238	0.106
Generated images	Generated images	0.452	0.236

Table 3 mAP50 and mAP50-90 of the Yolov8 model

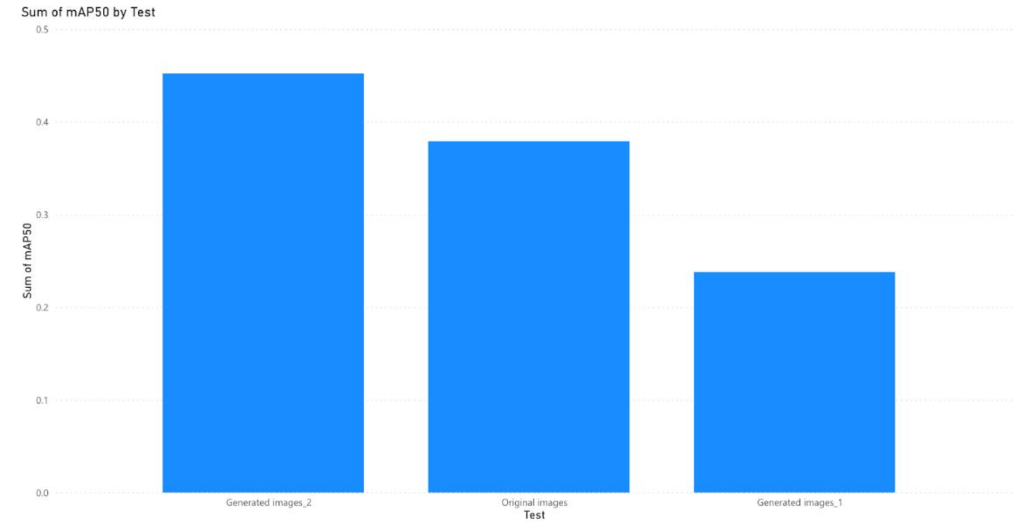

Fig 4 mAP50 for Different training data

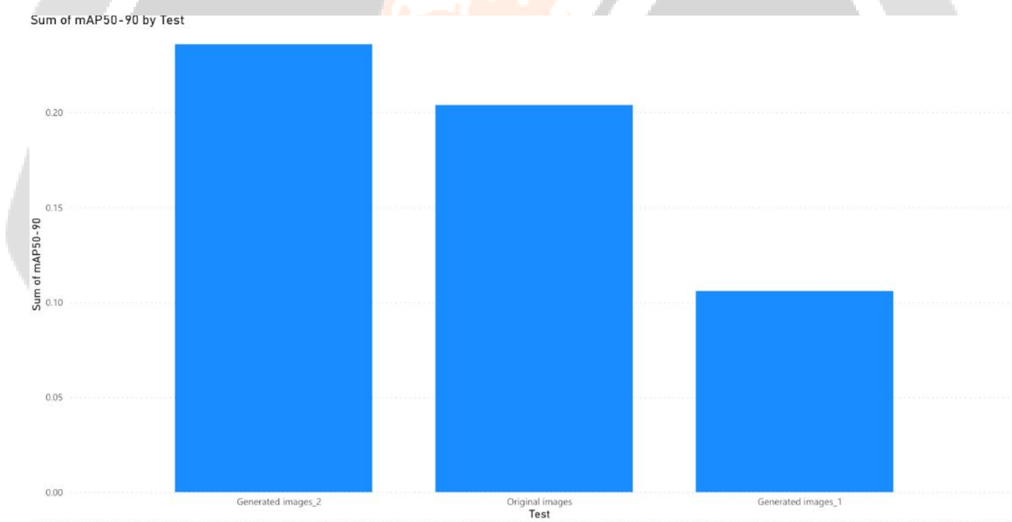

Fig 5 mAp50-90 for different training data

As we can see the model trained with generated underwater images performs better than the original model. From this we can say that training with simulated images improves the pothole detection for rainy conditions.

6. CONCLUSIONS

Though there is ongoing research to develop cameras that can capture under turbid water environments there is still no way to effectively do that. We propose using synthetic image generation using existing underwater physical image formation models so we can try and tackle the challenge of underwater potholes by improving our software solution with the help of Artificial Intelligence. Our work as of now only captures the color attenuation issue of turbid rainy waters. We aim to further improve our work to tackle other degradation issues and improve the accuracy of the pothole detection system.

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BIOGRAPHIES

Author Photo-1 	Description about the author1 "I am a enthusiastic machine learning and business analyst, and passionate about leveraging data-driven insights to solve complex problems. My expertise lies in applying advanced machine learning algorithms to extract meaningful patterns from data, driving informed business decisions. With a keen interest in problem-solving, I thrive on tackling challenges and optimizing processes to enhance efficiency and achieve strategic goals."