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Pothole and Road Hump Detection using Deep Learning

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"border" is usually impossible to determine. we can give them

***Abstract* — Every vehicle, whether manual or automatic, relies on the quality of the roads they travel on to reach their destination safely. Damage to vehicles and even death can result from imperfections in the road, such as speed bumps and potholes. Consequently, accidents and vehicle damage can be lessened by identifying and describing these outliers. Due to large quantities of duplicated data and significantly polluted measurement noise, street photographs are inherently multivariate, making the identification of street irregularities more challenging. Using a YOLO Deep learning model, this research provides automated color image processing of road potholes from video frames or smartphone images. In order to make training and usage go more smoothly, a lightweight architecture was selected. It has seven interwoven layers that work together well. With no scaling at all, each and every pixel of the source image is utilized. To acquire the maximum amount of data possible, we employed the standard stride and pooling processes. Because of this, the created model can detect potholes better and warn drivers to be careful. The proposed method gathers vital data for pothole detection by reviewing previous studies in this area.**

Keywords: *Deep learning model, YOLO neural network, Pothole detection, Road hump detection.*

I INTRODUCTION

Worldwide, poor road conditions are a major contributor to accidents, but distracted driving, speeding, and other driver mistakes also play a major role. Flooding, rain, damages (e.g., from overloaded large vehicles), and lack of physical maintenance are only a few of the many reasons why a road might become unsafe. When evaluating the state of a road, it is important to look for and identify specific signs of surface distress, such as cracks, potholes, or changes in texture, that warrant repair. Being traffic-relevant is the defining characteristic of macro-scale road characteristics. As an additional traffic-relevant feature, speed bumps necessitate identification in order to facilitate driver assistance.

In the context of road hardship, a pothole is unique. The road's geometry is determined arbitrarily, and its exact

a general idea, but we can be more specific about how deep they go. Cars, people, cyclists, dogs, and cats all have clearly defined shapes that can be identified using deep learning's appearance properties. In contrast, a pothole's complex geometric structure and random shape make it a difficult object-detection task.

Automated systems have emerged in many different industries in recent years, and technology has been crucial to their development. Life has gotten much easier for humans since the introduction of autonomous technology. A lot of good has come out of automating transportation and surveillance systems. When it comes to transportation, highways are crucial because they make up the largest network. Autonomous systems must operate without endangering their users, and potholes are a major problem for transportation networks on roads. There were 4,869 fatal incidents in 2015 due to potholes, according to official statistics given by the Indian government. This highlights the critical nature of keeping roads in good repair.

The COVID-19 epidemic has hit the globe hard. Road maintenance is one of several industries hit hard by the lockdowns. Road conditions have worsened as a result of this. Therefore, a system that can monitor road conditions autonomously is needed. This research presents a method for pothole identification and dimension estimate that utilizes Deep Learning and Image Processing. There have been a slew of new object detection methods created recently that rely on Convolutional Neural Networks to glean features. The YOLO (You Only Look Once) principleis suggested as a method for detecting potholes in this article. Intersection over Union (IoU) and mean average precision (mAP) are used to evaluate the outcomes after training multiple iterations of the YOLO algorithm using a bespoke dataset that includes both dry and waterlogged craters of different shapes and sizes. With respectable precision, the model can identify numerous types of potholes. In addition, the suggested pothole size estimator, which is based on image processing, uses triangular similarity to provide somewhat precise dimensions of the discovered potholes, significantly lowering the total time needed for road maintenance.

[1] In this paper, P. A. Chitale et al. hope to lessen the reliance on human labor for road maintenance, particularly in the event of a pandemic. The study demonstrates that in terms of accurate pothole detection, the YOLOv4 based model performs better than the YOLOv3 based model. Pothole dimensions are computed with high precision and a significantly low error rate. As YOLOv4 improves its IoT, it offers an accurate estimate of the potholes' proportions. Subsequent efforts will involve expanding the system to include surveillance vehicles so that exact automated road condition monitoring is possible. Additionally, a GPS module would be installed in these surveillance trucks so that the precise location of the potholes could be noted. The estimated dimensions of the potholes would be useful in determining the amount of road damage as well as the amount of raw materialsneeded to fill them. As a result, most planning and inspection can be completed remotely.

[2] A. Fox along et al. Explains With the increasing ubiquity of smart automobiles, it is now possible to identify environmental road elements (potholes, road inclination angle, etc.) from embedded sensor data. Crowdsourcing can be used to more accurately detect environmental information by combining data from several cars. The author focuses on locating and identifying potholes on multi-lane roads using such data. Undersampling sensors, sensor mobility, asynchronous sensor operation, sensor noise, vehicle and road heterogeneity, and GPS position error make it difficult to extract information from aggregated vehicle data. Since GPS position error is typically greater than standard lane widths, it is especially problematic in multi-lane situations. In this study, the authors look into these problems and create a crowdsourced system that uses accelerometer data from embedded vehicle sensors to locate potholes in multi-lane situations.

[3] The techniques described by A. Dhiman et al. for identifying potholes on road surfaces are intended to helpoffline data gathering for road maintenance or real-time control of a vehicle (for driver assistance or autonomous driving) by providing strategies for the offline or real-time detection of potholes. For these reasons, pothole detection techniques have been thoroughly investigated in studies conducted globally. This report divides developed strategies into multiple categories after providing a quick overview of the area. Next, author showcase the author's contributions to this subject by putting tactics for pothole identification that are automatically detected into practice. The author constructed two models for deep learning-based pothole detection and researched and produced two methods based on stereo-vision analysis of road conditions ahead of the car. These four created strategies are evaluated experimentally, and specific advantages of these methods are concluded.

Section 2 of this paper reviews relevant prior work, whereas Section 3 describes in depth the current implementation of the idea utilizing the phrase proposed technique. Examine the outcomes in Section 4 of the Results and Discussions section. This study endeavor concludes withthe conclusions and future scope contained in section 5.

II RELATED WORKS

[4] B. Hosking et al. explain One of the most crucial parts of road maintenance is finding potholes. Generally speaking, computer vision techniques are predicated on either 3D road surface modeling or 2D road image analysis. These two groups are, nevertheless, always applied separately. Additionally, the precision of pothole detection is still far fromacceptable. As a result, the authors of this work provide a reliable pothole detecting technique that is effective in terms of computing. Initially, a detailed disparity map is created to help distinguish between sections of damaged and undamaged roads. Golden section search and dynamic programming are used to estimate the transformation parameters in order to obtain higher disparity transformation efficiency. The possibleundamaged road areas are then extracted from the altered disparity map using Otsu's thresholding technique. Using least squares fitting, the differences in the extracted areas are represented by a quadratic surface.

[5] An effective stereo vision-based road surface 3-D reconstruction and pothole detection system was demonstratedby R. Fanet al. The PT algorithm [4] was originally made more broad by the author by using the stereo rig roll angle in the PT parameter calculation procedure. The potholes were clearly visible from the intact road surface thanks to DT. The modified discrepancies were clustered by SLIC into a set of super pixels. Ultimately, by identifying the super pixels—pixels with values below an adaptive threshold established by k-means clustering—potholes were found. Using an RTX 2080 Ti GPU, the suggested pothole detecting method was constructed using CUDA. The experimental findings demonstrated the 98.7% successful detection rate and 89.4% F-score that the author's method is capable of achieving.

[6] According to Dharneeshkar J. et al., When compared to other item detections, such human, automobile, airplane, and so forth, pothole detection is distinct. Potholes are not shaped like other objects are. It is harder to detect as a result. Because of the aforementioned constraint, it is challenging to increase the mean average precision for pothole identification. This research uses different versions of YOLO to train a newly produced dataset of 1500 images. Furthermore, appropriate architectural modifications improve the mean average precision. In the future, a raspberry pi with a camera will be used to implement the system in real-time in a car's dashboard.The road repair crew can greatly benefit from the system's ability to trace the position of potholes that are recognized thanks to an inbuilt GPS.

[7] The pothole detection system, which has excellentaccuracy and enhances the bounding box's precision for

pothole representation, was proposed by C.-W. Kuan et al. and improved the deep reinforcement learning-based pothole avoidance system, which is capable of successfully avoiding potholes. Furthermore, these systems may be operated in real time and are installed on an energy-efficient edge platform.

[8] Extracting accurate features from the input image is the first stage in creating a successful machine learning model for image segmentation, according to H. K. I. S. Lakmal et al. The research that is being presented focuses on the application of computer vision as a driver aid device for water-filled pothole detection. In order to identify the water surfaces and segment the water region in an input image, this study presents a number of different attributes. In addition, the author trained a model for the segmentation of the water surface using the Random Forest Classifier and ranked features. Authors were able to get testing accuracy of 0.877 and training accuracy of 0.998 with the suggested design.

[9] M. Omar et al. explain how the YOLOv4 algorithm, which is based on deep learning, is the primary tool used in the Intelligent Transport system paradigm for pothole detection. This work achieves an average IoU of 38.38% by training a dataset of roughly 200 photos for pothole identification. Video samples are also successfully used to detect potholes using the trained model based on picture datasets. This idea may be usedin the future by the auto industry and road maintenance organizations to identify different types of road damage.

[10] In order to enable autonomous driving under unstructured road conditions, M. Rasib et al. introduce a unique pipeline com binning deeplabV3 based road region recognition and steering angle estimation mechanism for the self-driving automobile. To accomplish the generalization, the author also created a sizable road-based dataset with 15,000 photos and pixel-by-pixel annotations. After that, using a dataset that they had created themselves, the author conducted tests to assess the performance of the suggested pixel level segmentation road identification and steering angle estimation approach. As a result, the technique the author has suggested improves the ability of level-5 autonomous vehicles to maneuver in unstructured road environments without lane lines or in areas where they have faded over time.

[11] According to A. A. Alhussan et al., An essential component of traffic intelligence implementation is the self-driving car. The safety and comfort of self-driving cars are significantly impacted by the smoothness of the road in front of them. Potholes in the roadway can cause a number of issues, such as crashes and vehicle damage. As a result, autonomous vehicles ought to have the ability to adjust their driving style in response to the real-time identification of potholes in the road. This issue is being addressed in a number of ways, such as by reporting findings to the relevant authorities, utilizing vibration-based sensors, and 3D laser imaging. However, these approaches were limited by issues including high setup costs and the risk of detection. As a result, the identification of potholes must be done quickly and precisely by automation. This work presents a novel approach for feature selection and optimization of the random forest (RF) classier, based on adaptive mutation and dipper throated optimization (AMDTO).

[12] Storytelling by D. Chen et al. For smart cities, vehicle- road collaboration is crucial, and one of the key pillars of this collaboration is the detection of potholes. Road pothole detection accuracy has increased recently due to advancements in mapping and surveying technologies. Unfortunately, the convenience of use and real-time observation capabilities of the historical detection technologies prevent the timely mapping of potholes in the road. The author suggested a reflectometry method with vibration signal analysis and spatial-temporal trajectory fusion to provide real-time pothole spotting in order to address this important problem. The author went on to construct a number of prototype gadgets for testing. These prototype devices use geminal processing and spatiotemporal formation fusion. They measure the acceleration signal that is mounted on the wheel steering lever.

[13] A novel virtual environment was created by J.-C. Tsai et al. to train pothole identification. The author's system incorporates a number of contemporary VR and simulation techniques, such as deep learning interface, 3D modeling, VR simulation, and automobile simulation. The author proved thatvirtual images can in fact improve the accuracy of a realpothole detector through a series of tests done on real pothole datasets. under subsequent study, the author plans to experiment with deep reinforcement learning using Carim and train an artificial intelligence agent to automatically modify the suspension system of a car under a variety of weather and road situations.

[14] B.-h. Kang et al. created a pothole detecting system with a camera and 2D LiDAR. A large portion of the road surface can be more precisely scanned by employing two LiDARs. The author then created an algorithm for detecting potholes that included line extraction, gradient of data function, filtering, and clustering. The pothole detecting system's error rate provides insight on the system's developed performance. The author also demonstrated how 2D LiDAR may be usedfor 3D pothole detection. When 2D LiDAR and video data are integrated, pothole identification utilizing the combined data performs more accurately.

[15] According to M. Omar et al., the YOLOv4 algorithm, which is based on deep learning, is the primary tool used in the Intelligent Transport System paradigm for pothole detection. This work achieves an average IoU of 38.38% by training a dataset of roughly 200 photos for pothole identification. Video samples are also successfully used to detect potholes using the trained model based on picture datasets. This idea may be used in the future by the auto industry and road maintenance organizations to identify different types of road damage.

III PROPOSED METHODOLOGY

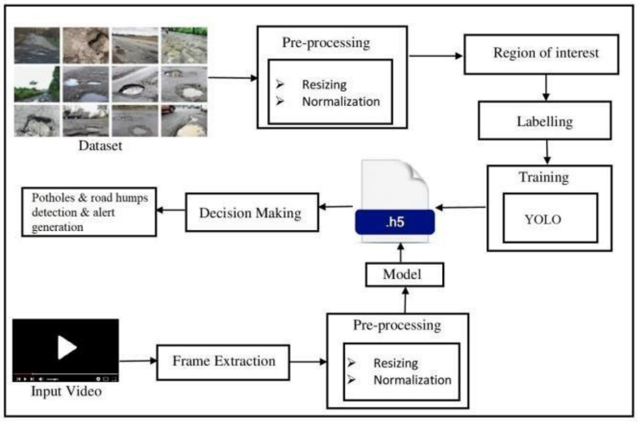

Figure 1: Overview of the proposed model

The method that has been proposed to successfully implement Yolov8's pothole detection capabilities is shown in figure 1. What follows is a detailed description of the many stages that make up the offered method.

Step 1: YOLO V8 Pothole Image Training — In order to successfully identify the pothole in the image, the system is using the image. In order to generate an alert, the initial phase of the approach is to identify the pothole in the image. In order to successfully identify potholes, the pothole identification module employs the Yolov8 method. Prior to using this model for pothole recognition, it must be trained.

Downloading the roboflow dataset and installing the Yolov8 model's ultralytics are the first steps in the training process. To link Roboflow to your API key, go to https://public.roboflow.com/object-detection/pothole and get the dataset for pothole recognition. It efficiently scans the downloaded dataset to retrieve the directory's file list. After that, we may find out how many files are in the directory by using the file list. In all, 465 files will be used for training purposes. After sorting the files alphabetically, the 46 files are transferred to the destination directory and jumbled. Recalculating the number of files in the directory yields 419 for training and 179 for the other directory.

We can start the yolov8 model for the yolo object identification challenge after you've successfully integrated the roboflow data and effectively shuffled the potholes dataset. With a batch size of 32 and an image size of 640, the detection model is trained for 200 epochs using the trained weights. After training the yolov8 model, the project runs are saved as a zip file in the provided directory.

A Convolutional Neural Network (CNN) variant, the YOLOv8 is its offspring. It achieves object identification with improved accuracy by using the CNN technique components in a unique and effective manner. To prevent overfitting and regularize the model, the Yolo design uses 24 convolutional layers with different parameters, a max pooling layer, and a number of dropout and batch normalizations. Two fully connected layers are the model's apex.

The channels are max-pooled after the first convolutionallayers decompose and reduce them; the kernel size is 2x2 andthe stride is 2. All of the model's layers use the same maxpooling algorithm. To handle the increase in data, the kernelsizes of the succeeding convolutional layers get progressivelylarger. This layer architecture makes use of the ReLUactivation function. With the exception of the fully connectedlayers, which use a linear activation function to generate the.ptfile—Yolo8's trained data file—all of the layers' activationfunctions are same. In the following steps, this.pt file will beutilized to notify the presence of the pothole. The sameprocedure is applied on the road humps dataset also which isobtained from the URL https://universe.roboflow.com/detection-system/humps- bumps-potholes-detection/dataset/8. Table 2 provides detailsabout the Yolov8 model.

S. no	Layer Type	Parameters
1	Convolutional Layer	7x7x64 Stride-2
2	Maxpool Layer	2x2 Stride 2
3	Convolutional Layer	3x3x192
4	Maxpool Layer	2x2 Stride 2
5	Convolutional Layer	1x1x128
6	Convolutional Layer	3x3x256
7	Convolutional Layer	1x1x256
8	Convolutional Layer	3x3x512
9	Maxpool Layer	2x2 Stride 2
10	Convolutional Layer	1x1x256
11	Convolutional Layer	3x3x512
12	Convolutional Layer	1x1x256
13	Convolutional Layer	3x3x512
14	Convolutional Layer	1x1x256
15	Convolutional Layer	3x3x512
16	Convolutional Layer	1x1x256
17	Convolutional Layer	3x3x512
18	Convolutional Layer	1x1x512
19	Convolutional Layer	3x3x1024
20	Maxpool Layer	2x2 Stride 2
21	Convolutional Layer	1x1x512
22	Convolutional Layer	3x3x1024
23	Convolutional Layer	1x1x512
24	Convolutional Layer	3x3x1024
25	Convolutional Layer	3x3x1024
26	Convolutional Layer	3x3x1024 Stride 2
27	Convolutional Layer	3x3x1024
28	Convolutional Layer	3x3x1024
29	Fully Connected Layer	
30	Fully Connected Layer	

Figure 2: Model Summary for YOLOv8

Step 2: Testing the model for pothole: Here, we've provided the video input for the pothole and are extracting frames to feed in real-time. To find the pothole in the live streaming frames, we use the trained model file.pt. We get their upper left rectangular locations from this file. At this vantage point, we can see the frames' stability being monitored; we can also see the red and white markings of road humps and potholes. The confidence values of red potholes imply that they are more extensive, while those of white potholes indicate that they are shallower.

IV RESULTS AND DISCUSSIONS

To test the developed model, we use a Windows PC with an Intel (... n expresses the confusion matrix's accuracy score parameter, which is uti ... d Road humps. The following equation shows the values of Precision and R ...

$$Precision(P) = \frac{TP}{TP + FN} \qquad -(1)$$

$$Recall(R) = \frac{TP}{TP + FP} \qquad -(2)$$

Here, TP is True positive cases, TN is True Negative cases, FP is False positive cases and FN is False Negative cases. Below we can see the precision and Accuracy graphs that we obtained during the process of training the model in figure 3 and 4 along with the snaps of obtained results in figure 5 and 6.

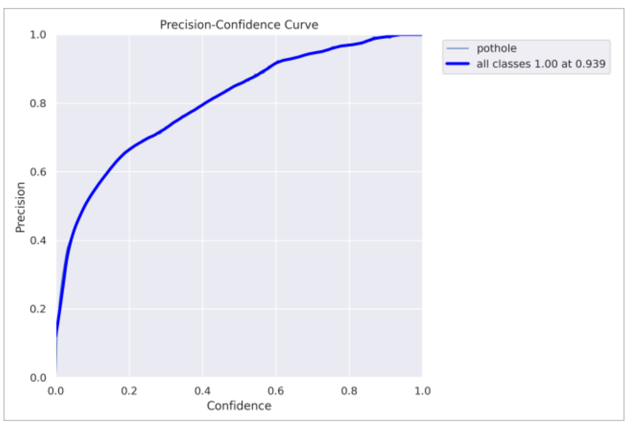

Figure 3: Precision Curve

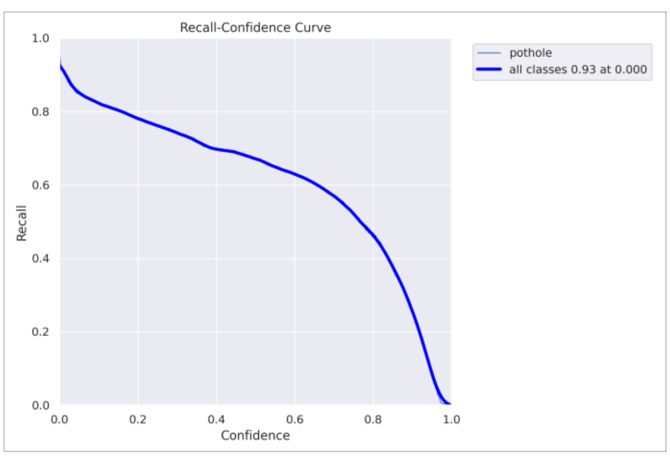

Figure 4: Recall Curve

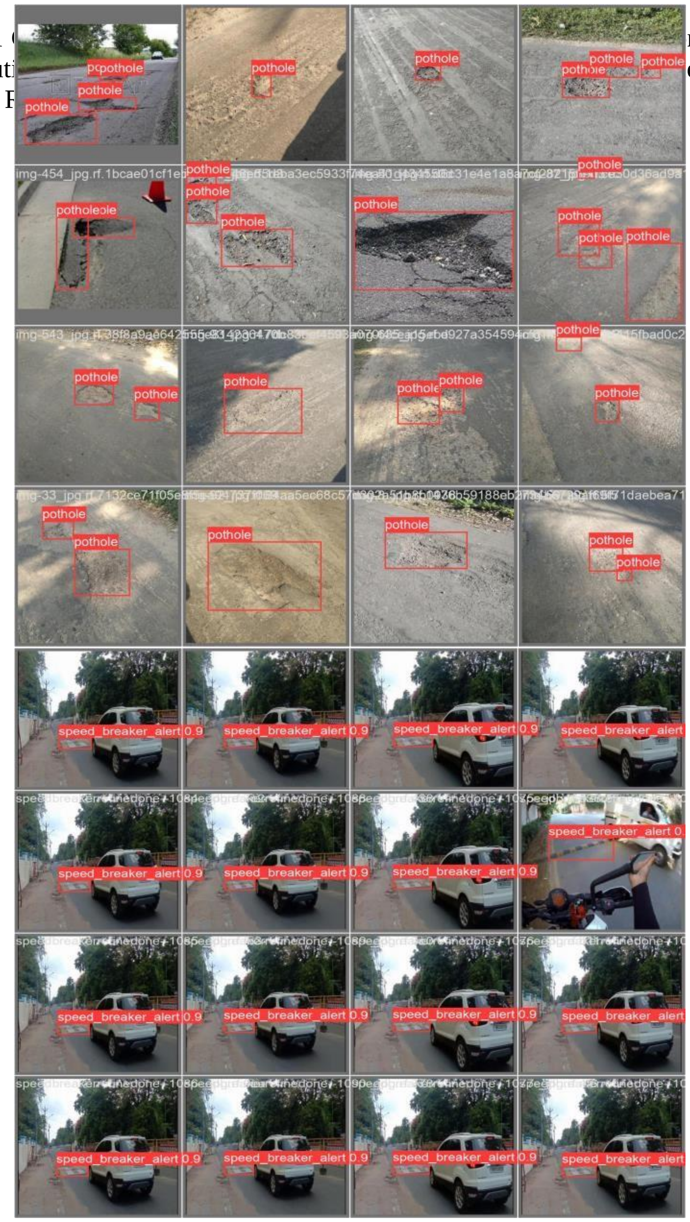

Figure 5: Obtained results for Road humps detection

The obtained graphs in figure 3 and 4 indicates that system is yielding good precision of almost 100% and recall of 93%, this eventually indicates the model is deployed in best way to detect potholes and road humps.

V. CONCLUSION AND FUTURE SCOPE

In order to train the YOLO model, the first step of the process is to realize the input dataset. Following its creation, the dataset will undergo shuffling program. The input images are resized and normalized by the YOLO module to expedite the training of the neural network model. After they've been preprocessed, these images are utilized to assess potential areas of interest that can be labeled to extract potholes from the original images. Prior to providing the model with the images to train on, they will be efficiently tagged with the regions of interest. Training is taking place on the YOLO network, while testing is taking place in real-time input video to detect the potholes and road humps efficiently. Less dense potholes and road humps are denoted as white color, on the other hand bit heavy potholes and road humps are shown in red color to distinguish both of them clearly.

A future expansion of the system will include surveillance cars, allowing for precise autonomous road condition monitoring. Additionally, these monitoring vehicles would have GPS modules installed so that they could pinpoint precisely where the potholes and roadhumps were. By estimating the sizes of the holes, we can estimate the amount of road damage and the quantity of raw materials needed to repair the potholes. As a result, most inspections and planning may be done remotely.

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