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Pothole Detection System

Sagar Haryani*,Pradyumna Arun**,Adarsh Bhatia***, Uma Ade****

*(Department of Computer Engineering, Watumull Institute of Electronics Engineering and Computer Technology, UlhasnagarEmail:sagarharyani@gmail.com)

**(Department of Computer Engineering, Watumull Institute of Electronics Engineering and Computer Technology,Ulhasnagar, Email:arunpradyumna@gmail.com)

***(Department of Computer Engineering, Watumull Institute of Electronics Engineering and Computer Technology,Ulhasnagar, Email:adarshbhatia.98@gmail.com)

****(Assistant Professor, Department of Computer Engineering, Watumull Institute of Electronics Engineering and ComputerTechnology,Ulhasnagar, Email: umakishorade878@gmail.com)

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Abstract:

Roads are connecting lines between different places and are used in our daily life. Roads' periodic maintenance keeps them safe and functional. Detecting and reporting the existence of potholes to responsible departments can save the roads from getting worse. This study deployed and tested different deep learning architectures to detect the presence of potholes. Various object detection algorithms are employed to detect potholes in the road images. Real-time Deep Learning algorithms with several configurations like YOLOv3-Darknet53, and YOLOv4- CSPDarknet53 are used to compare their performances on pothole detection. YOLOv4 achieved a high recall of 81%, high precision of 85% and 85.39% mean Average Precision. The proposed method can help in reporting road potholes to government agencies, increasing the safety of drivers by detecting potholes timeahead, and improving the performance of self-driving cars to ensure safe trips for passengers in the future.

Keywords-**Pothole detection, Deep Learning Architectures, YOLO, Darknet, TensorFlow.**

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IV. INTRODUCTION

The size of roads varies based on their functionality. For instance, highways are large enough to contain many lanes designed for massive traffic. However, roads inside towns are constructed to be smaller and made up of one or two lanes. Roads are vital in people's daily life, so periodic maintenance shall be made to keep them functional and safe. The many roads that exist within a given country make it difficult to have a continuous assessment of roads; therefore, one can't predict the formation of potholes. Pavement distress is the main cause of defects of roads. Pavement distress can be classified into three classes [1]: Pavement distortion (shoving, corrugation, and rutting), fracture (fatiguing, spalling, andcracking), and disintegration (raveling and stripping).

This work focuses on potholes which are considered the worst pavement distress, and their creation is unpredictable. The main reason behind such distortions can be related to a combination of environmental conditions and traffic pavement stresses. Potholes are a worldwide problem as they cost governments and citizens billions of dollars yearly [2, 3]. 1.25 million people die each year because of road traffic accidents, 34% of which are related to road potholes [4]. A pothole detection system made up of Raspberry Pi, camera, 3G mode, and Micro SD card was proposed to be affordable and simple [5]. The authors made use of OpenCV and the system is installed in a stationary manner to report potholes in real-time. The method is based on collecting different frames and convert the picture into a blurring grayscale image. Finally, and after applying some morphological functions, edge detection is employed to define the contours which are fed to Hough transform.

V. LITERATURESURVEY

Pothole detection can be categorized into three approaches [5]: Vibration-technique approach [6, 7, 8], 3D reconstruction technique approach (with laser scanner method, stereo vision method, and Kinect sensor method) [9, 10], and Vision technique approach. Table 1 summarizes and compares different pothole detection approaches based on technology used, response and sense time, processing, cost, pothole characterization, and accuracy of detection [9]. Traditionally, a group of employees was performing the pothole detection through reviewing recorded digital videos captured from roads. This method is costly and time-consuming. The authors used Sobel operators on original images and the vector of edges is then detected using the Fuzzy Inference System (FIS). The usage of FIS type 1 remarkably improves results with a neural network. FIS type 2 improved the training cost of neural network provides a deep review and comparison of the existing pothole detection methods.

	Vision-based	Vibration-based	Laser-based	Stereo imaging
Device used	Camera	Accelerometer	Laser	Cameras
Technology used	2D imaging	Force and rotation and orientation	3D reconstruction of the image using light reflection	3D reconstruction using multiple cameras
Response time	High	Low	Low	High
Sensing time	While approaching the pothole	While going through a pothole	While approaching the pothole	While approaching the pothole
Processing	Complex image processing algorithms	Readings are directly used	Collection of 3D point cloud with their elevations.	A complex process of 3D image constructic combining image from different camera pe
Cost	High because of delicate parts like lens	Low	High	High
Characterization of pothole	Based on size	Based on vibrations	Based on 3D image constructed	Based on 3D image constructed
Detection at night time	Difficult due to poor lighting	Can detect	Can detect	Difficult due to poor lighting
Accuracy	Depends on the algorithm used	High	High	Depends on the alignment of cameras and algorithms used

Table. 1.
Pothole Detection Approaches

The vibration method, which is based on an accelerometersensor, can't predict potholes ahead of time. This is because the vehicle should pass over the pothole for detection. This method cannot differentiate between potholes and other artifacts on the road like bridge joints and road reflectors. Laser scanning systems are classified among the 3D reconstruction methods.

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Detection of potholes using CNN Convolutional Neural Networks (CNNs) have the ability to learn the art of extracting relevant features from an Image. We have created a dataset of 1500 images datasets of pothole. The dataset is annotated and trained using YOLO (You Only Look Once).

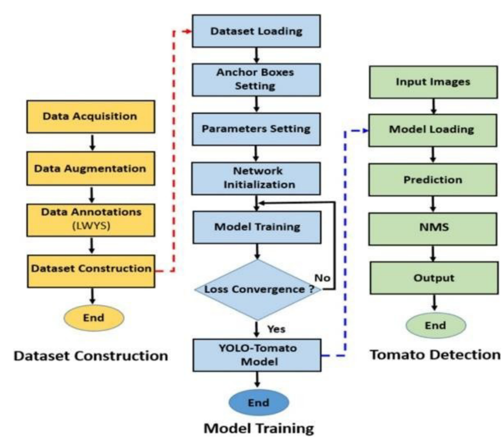

Fig.1. Block Diagram forYOLO Model training.

VI. METHODS

D. Applied Object Detection:

Object detection process served under different variations inposes, occlusions, viewpoints, and lighting conditions of the input data. The pipeline object detection model can be divided into three parts:informative region selection, feature extraction, and classification. At the informative region selection, the objects that may present in an image have different sizes, aspect ratios, or specified positions. A multi- scale sliding window is, therefore, used to scan the whole image. Due to limitless redundant candidate windows, its computation is viewed to be expensive. On the other hand, unsatisfactory regions can be detected if only a fixed number of sliding window templates are applied. At the feature extraction, one should extract visual features with robust and the second type is regression at which is based on adopting a unified architecture to achieve results directly. The best two known examples from this group are the SSD (Single Shot Multi-box Detector) and YOLO (You Only Look Once) family algorithms.

E. Datasets:

In this study two datasets are used: the first database is available online and made up of 431 different images with potholes. The second dataset is a combination of images collected from Lebanese roads (with 344 images with potholes) and 312 images were collected from different sources on theinternet. Most of them are from videos that were recorded via dashboard camera for people driving their car. Asa result, 1087different images with more than 2000 potholes are used in thisstudy.

F. Architecture and Techniques:

1)FRCNN:

FRCNN is a machine learning algorithm with an end-to-end open source. It is based on Classification, and it uses two-stage methods. Firstly, interested regions are selected. Secondly, they are classified using Convolutional Neural Networks by running predictions.

2) Darknet Framework:

Darknet is an open-source framework like TensorFlow and written in C/CUDA, and it is used to train neural networks and serves as the basis for YOLO.

3) You Only Look Once Detector Version 3 (YOLOv3):

YOLO can produce decent boxes for detected objects. YOLO is an abbreviation of "You Only Look Once", and its name is inherited from the fact that: you only look once at the input image to predict what objects present in addition to their position in an image. Unlike other models which require a scan of an image several times. YOLO is an increment work started in 2015 with YOLOv1, YOLOv2 in 2016, YOLOv3 in 2018, and YOLOv4 in 2020. The dig. plots the accuracy vs speed of YOLOv3 against RetinaNet-50 and RetinaNet-101. Clearly, YOLOv3 brings a significant advantage over other detection models in terms of speed [3].

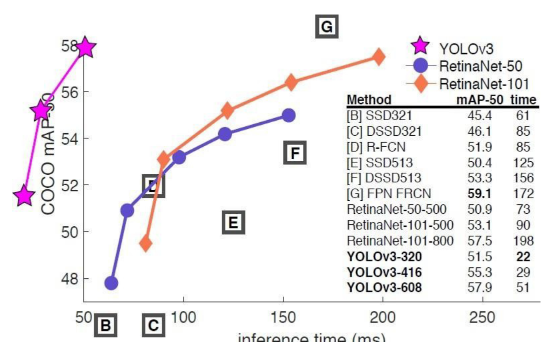

Fig. 2 Detection Models Performance

4) You Only Look Once Detector Version 4 (YOLOv4):

YOLOv3 is known to be a strong detector that can produce decent boxes for objects detected in real-time. YOLOv4 comes as an improvement of YOLOv3. [46] claims that YOLOv4 is10% better than the YOLOv3 in AP, and 12% for the speed. YOLOv4 is a recently released architecture by April 2020.

G. Training and Preparation:

In this work, Darknet is the framework used to build a real-time model that can detect potholes. The images of the first dataset are annotated before loadingthem into the framework. Image annotation is the process oflabeling the objects to be detected. The software used to labelthe data is called "LabelImg", an abbreviation of Label Image[49]. The labeling process can be done by drawinga boundingbox around the potholes. The position of each pothole is thenconverted into a text file with the coordinates ofthe boundingbox having the following format (Xmin; Ymin; Xmax; Ymax).This is the procedure used to prepare the YOLOv3 and YOLOv4 training, the frame work used is Darknet. To start training, the hardware accelerator option is enabledby selecting the GPU option. GPUs are known to be much faster than Central Processing Unit(CPU) for our deep learning application. There are libraries to optimize the use ofGPUs in deep learning as the NVIDIA CUDA Deep Neural Network Library (cuDNN), known as a GPU-accelerated library for deep learning[10]. This procedure is used to prepare the YOLOv3and YOLOv4 training, the framework used is Darknet. To start training, a new note book was created and the hardware accelerator option is enabled by selecting the GPU option.GPU sare known to be much faster than Central Processing Unit (CPU) for our deep learning application. There are libraries to optimize the use of GPU sin deep learning as the NVIDIACUDA Deep Neural Network Library (cuDNN), known as a GPU- accelerated library for deep learning.

VII. EXPERIMENTS

Given that all preparations of data and training are done on COLAB with a GPU hardware accelerator, the following experimentation sare done:

A. YOLOv3-Darknet53 for Pothole Detection :

The format of the bounding box in YOLO is given as (class, Xcenter of Bounding box, Ycenter of Bounding box, width of the bounding box, height of the bounding box). YOLO is also known as a fast object detectionarchitecture and darknet is its framework. Six different training scenarios are conducted.

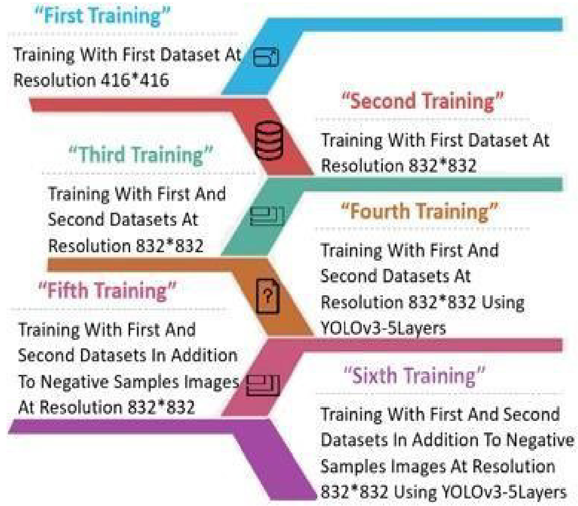

Fig. 3. Different Training Scenarios

The trainings scenarios in Error! Reference source not found. would actually help in finding the best configurations for YOLOv3 detector in our pothole detection application. To check the performance and robustness of the model at each scenario, four different configurations of confidence and IoU thresholds were used at every 250 iterations:

- Test 1: confidence threshold 25% and IoU threshold 50%
- Test 2: confidence threshold 25% and IoU threshold 10%
- Test 3: confidence threshold 25% and IoU threshold 1%
- Test 4: confidence threshold 50% and IoU threshold 1%

B. YOLOv4-Darknet53 for Pothole Detection

YOLOv4 is a new architecture released in April 2020 and this work is the first of its kind to use YOLOv4 for pothole detection applications. Two pieces of training were done to evaluate YOLOv4 in potholes detection. The first training contains the first and second datasets and trained like the YOLOv3, and the second training contains an additional 941 negative images. Negative images are images that don't contain potholes. The two training scenarios were used to find the best configuration for YOLOv4 pothole detection as illustrated below.

Fig. 4. The two training scenarios on YOLOv4-CSPDarkner

IV. RESULTS AND DISCUSSION

Compared results of YOLOv3 and YOLOv4 can be summarized.SDD is not included since SDD exhibited inferior performance in comparison with YOLO. YOLOv4 proved to be a robust object detector architecture. It can work with real-life conditions and at a high speed of processing. The proposed system achieved high recall 81%, high precision 85%, and 85.39% mAP. Moreover, this pothole detector attained a processing speed up to 21 FPS using Colab GPU, NVIDIA Tesla P100-PCIE. This system can work with raw data collected from dashboard Cameras for roads. In other words, our system can work without the need to cropping and deleting non-pothole data from the input images. Additionally, the proposed pothole detector can detect a pothole from a distance reaching 100 meters.

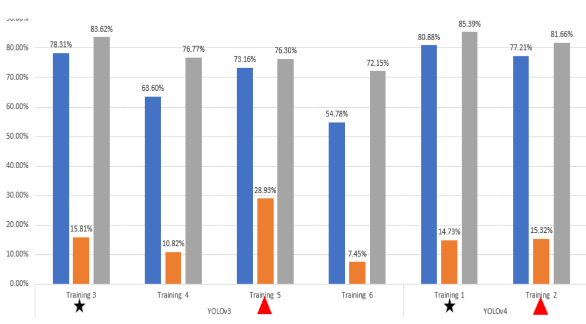

Fig. 5. YOLOv3 VS YOLOv4 training results

Systems such as "Pothole Detection System Using A Black-box Camera". However, the system has a short range of pothole detections in comparison with the tested YOLOv3 andYOLOv4 models. Furthermore, the system needs to have a clear view of the car path which is not practical in real life. "Deep Learning-Based Detection of Potholes in Indian Roads Using YOLO" [32] has a good range of detection, but the evaluation metrics were better in our model.

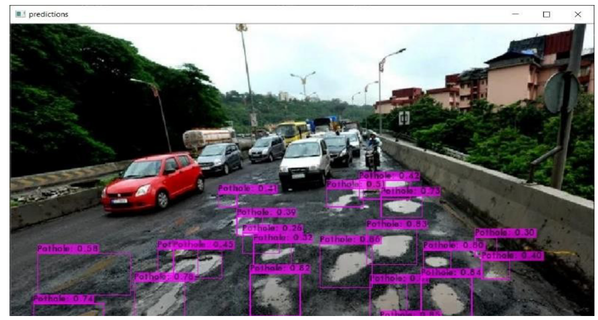

Fig. 6. Testing YOLOv4 on real life scenario

V. CONCLUSION

The potholes detector using YOLOv3 achieved high recall 78%, high precision 84%, and 83.62% mAP. YOLOv4achieved high recall 81%, high precision 85%, and 85.39% mAP. YOLOv3 and YOLOv4 have a speed of processing of around 20 FPS and this can be considered high enough for our real-time application. Therefore, our potholes detector using YOLOv4 can be considered as a robust and real- time system that can be used in real-life scenarios.

Our future work will include a larger dataset, more than 2000images, for training and it has more images for potholes from different roads, with several severities and different lighting and weather conditions. Any other researchers emphasized using alarge dataset with more than 2000 images for training to get a robust object detector that can work under any conditions and circumstances.

Moreover, in our future work, we will include manholes in the training of our system. Manholes and potholes have common features and this important improvement to be done into our current system to differentiate between manholes as a pothole. Knowing that the current system was able to differentiate between manholes andpotholes in most of the cases. Moreover, we aim to deploy oursystem into several cars to analyze the road condition in a live and real-time manner by adding GPS to get the coordinates of the pothole for maintenance.

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