POTHOLE DETECTION

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CANDIDATE'S DECLARATION

I, Deepraj Arya, Roll No. 2K21/MSCMAT/14 , student of M.Sc. Applied Mathematics , hereby declare that the project Dissertation titled "Pothole Detection" which is submitted by me to the Department of Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Science, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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I hereby certify that the Project Dissertation titled "Pothole Detection" which is submitted by Deepraj Arya, Roll No 2K21/MSCMAT/14 [Department of Applied Mathematics], Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Science, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: Delhi **Ms. Sumedha Seniaray**

Date: **SUPERVISOR**

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My supervisor, Ms. Sumedha Seniaray, has my deepest gratitude for all of her time, effort, and patience in assisting me in achieving academic success. Her depth of knowledge and breadth of expertise have motivated me throughout my academic career.

I want to thank everyone who has helped me on this trip. It has been a wonderfully great experience for me to study and live in Delhi because of their kindness and encouragement. I'd like to thank my parents before I end. Without their unfailing support, I would not have been able to complete my education.

ABSTRACT

Roads are the most important form of nation's transportation system. It is extremely crucial to maintain them in good situation. Potholes are a type of road problem that can harm vehicles and have a detrimental impact on drivers' ability to drive safely, which can result in traffic accidents. Potholes that develop on the road must be filled to keep the roadways in excellent condition. It is essential that you keep them in good shape. It can be difficult to locate potholes in the road, particularly in India where there are millions of km of roadways. In a complicated road environment, effective and proactive management of potholes is crucial for ensuring driver safety. Driver safety is significantly improved by effective and proactive treatment of potholes in a complex road environment. Additionally, it is anticipated to help maintain traffic flow and assist to the reduction of traffic accidents. To get around this problem, a number of strategies have been developed, including manual reporting and government initiatives to help auto-detect pothole zone. There have been several strategies created to get around this problem, from human reporting to authorities to take action for automatic detection of pothole zones. Automated methods for spotting potholes have recently been developed, and these systems include a number of fundamental technologies, including sensors and signal processing. Considering the technology used in the process of identifying potholes, three different types of automated pothole detection systems can be categorized- methods based on vision, vibration, and 3D reconstruction. Building an autonomous model of pothole detection is the major goal of this endeavour, which aims to find potholes as soon as possible. Therefore, it is necessary to automate pothole detection with high speed and real-time accuracy. Our major objective is to train and analyze the YOLOv5, YOLOv7, and YOLOv8 model for pothole identification. These models are trained using a collection of data for potholes images, and the results are examined by assessing the model's accuracy, computational speed, recall, and size, which are then contrasted with those of previous YOLO algorithms. The methodology used in this paper will greatly aid in road maintenance by decreasing expenses and speeding up the detection of potholes. In this article, 84.6%, 87.1% and 85.4% accuracy has been achieved for yolov5, yolov7 and yolov8 model respectively.

CONTENTS

Candidate's Declaration	ii
Certificate	iii
Acknowledgement	iv
Abstract	v
Contents	vi
List of Tables	vii
List of Figures	vii
CHAPTER 1 INTRODUCTION	1
1.1 Introduction	1
CHAPTER 2 LITERATURE REVIEW	3
2.1 Literature survey	3
CHAPTER 3 METHODOLOGY & IMPLEMENTATION	4
3.1 Methodology	4
3.2 Implementation	7
CHAPTER 4 RESULTS	12
4.1 Model's Results	12
4.2 Conclusion	20
References	20

LIST OF TABLES

1. Comparison Table among yolo v5, v7, v8 12

LIST OF FIGURES

1. Bounded Boxes on Pothole Images 5
2. Coordinates of the bounding box 5
3. Flow Chart 7
4. Sample of Pothole Images from Data Collection 8
5. Labelled Images 9
6. Training for yolov5 model 10
7. Training for yolov7 model 11
8. Training for yolov8 model 11
9. Model Accuracy / Epoch for yolov5 12
10. Precision / Epoch for yolov5 13
11. Loss / Epoch 14
12. Results of YOLOv5 model 15
13. Results of YOLOv7 model 16
14. Graph of Accuracy, Precision & Loss / Epoch for yolov8 17
15. Results of YOLOv8 model 18
16. Confusion Matrix 19

CHAPTER 1 INTRODUCTION

1.1 INTRODUCTION

A significant large structural road collapse is a pothole. Currently, potholes are forming mostly as a result of vehicle movement, extremely wet weather, and other factors. Traumatic accidents and loss of human life result from this. It is created as a result of water and traffic both and water being present. Water seeps into the earth underneath the surface of the road, weakening it. As a result, the traffic cracks the worn-out road surface, resulting in the removal of some of it. The pothole, which is characterised by a portion of the pavement that is fashioned like a bowl, is one of the most apparent kinds of road damage. It's smallest depth is 150 mm in size [1]. Pothole regions develop as a result of ageing structures, heavy traffic volumes, inadequate drainage, substructures with thin asphalt layers, and unstable substructures. Consequently, internal or external factors can cause a pothole to form [2]. The pavement material's resilience, reactivity, and degradation to climate variations such heavy rain and snowfall are the internal causes. Many problems, such as traffic flow, accident reduction, and road safety measures, are given substantial importance internationally as a result of the growing demand for vehicles. In addition to being annoying, road potholes represent a major risk to vehicle performance and traffic safety. According to reports, more than 40k people died in road crashes in the USA in 2017 while operating a vehicle [3]. Similar to this, some 25,000 people died on European Union roads as a result of serious traffic accidents, and about 1 lakh 35,000 people were hurt [4]. In order to decrease the risk of road accidents occurring, it is essential to plan and maintain a road effectively [5]. For instance, the Chicago Sun-Times reported that 11,706 complaints about potholes on the roadways were made by drivers in the first two months of 2018. A third of the 33,000 traffic fatalities, according to The Pothole Facts, were caused by potholes that occur each year in the US are caused by dangerous road conditions. Similar to other countries, India relies heavily on its road infrastructure for transportation [6]. Road transport is used by almost 90% of countrywide passengers, 65% of whom are goods carrying the same passengers. In addition, India's dense population forces the construction of narrow, congested roads with poorer surface quality and maintenance [7]. As a result, the road infrastructure does not meet expectations. Considering that driving is a risk to one's life and causes breath holding, this issue occurs not just in India but all across the world [8]. Therefore, it is essential and vital to evaluate roads time to time and fix potholes. There have been numerous instances in recent years where forty thousand people in the US died in traffic accidents while operating motor vehicles. Similar to this, around 25,000 people died on European Union roads as a result of serious accidents, and about 1 lakh 35,000 people were hurt. Similar to this, India's primary means of transportation are its roads. Road transportation is used by almost 90% of countrywide passengers, 65% of whom are freight carrying the same passengers. In addition, India's roads are built in a narrow, congested style with poorer surface quality due to the country's high population density. The number of vehicles is rapidly rising daily in comparison to earlier eras. Currently, the primary method of finding potholes in the road is manual visual inspection. Road potholes are frequently found and reported by structural engineers and professional inspectors. This procedure is costly, risky, and inefficient. Because of these issues, monitoring the road surface is now essential to the government in order to speed up repair and the discovery of potholes. In the past, the goal of locating and fixing potholes was to improve driving conditions and to minimize traffic accidents, so saving both human and vehicular lives. As a result, those who choose to travel by the side of the road do so in comfort. Self-driving cars have been developed recently, and it is crucial to spot potholes on the road in order to prevent accidents and vehicle damage when automobiles are operated only by technology without the use of human eyesight for driving decisions. Data-driven technologies have been tested by some automakers. With the help of this technology, drivers are alerted to pothole locations and given cautions to reduce vehicle speed. While Clear Motion created an intelligent suspension system that anticipates, absorbs, and counteracts the shocks and vibrations brought on by road potholes using a combination of hardware and software. As a result, this study offers a thorough examination of pothole-filled damaged roads and their detection methods and suggests a detection strategy in real time for dangerous obstructions on open pothole roads that can cope with the challenging environment. The following are this paper's key contributions:

1) This work presents a real time identification approach for negative impediments on roadways in open pothole using a dataset of potholes on roads that have been gathered. With the help of this technique, potholes can be quickly, effectively, and extremely reliably detected so that autonomous cars can get an early warning.
2) It is suggested to use an enhanced Yolov5 object detecting algorithm. To further enhance the capability of feature representation, we employ dynamic convolution.
3) Yolov7 technique, a new improved object detection algorithm, is later introduced. It effectively fixes the problem of challenging detection when the targets overlap and has greater detection accuracy than the preceding yolov5 algorithm.
4) Yolov8 is a new member of the yolo series that offers real-time detection and increased accuracy. Compared to previous yolo series methods, this one produced extremely excellent accuracy in a shorter amount of time. When used for real-time pothole identification, this is extremely quick.

CHAPTER 2 LITERATURE REVIEW

2.1 LITERATURE SURVEY

Deep CNNs and YOLO series have recently emerged as the most popular methods for detecting road potholes in machine/deep learning. Typically, semantic segmentation, object detection, and image classification networks —three separate types of methodologies—are utilised to construct data-driven systems for identifying potholes in the road. In order to detect road potholes, researchers in this sector have mostly integrated several image classification networks into the SSD. Road pothole recognition uses R-CNN and YOLO series more commonly than SSD. The YOLO series object identification techniques are the major subject of this article. [9] has made an effort to predict where potholes would appear on the road surface. For this categorization, regular road-based photos and photographs of speed bumps are necessary. Convolution Neural Network (CNN) ResNet-50 classification of surface of road based on these photos was provided. Images are initially manually categorised, and the classifications are used to train a neural network. The picture is then run through an object identification neural network to determine the object's precise position. It employed the YOLO approach for recognition of objects, and it was enhanced to create a warning for suspension adjustment and improved ride comfort based on road preview. The YOLOv1 (original version of YOLO) [10], launched in 2015 and authored by Joseph Redmon and Ali Farhadi.

This YOLO basic model was able to handle 45 frames per second of real-time image processing. It outperforms other detection techniques, like DPM (Deformable Parts Model) [11] and R-CNN, in terms of speed [12]. YOLOv2 [13] was published in 2017 after YOLOv1's training and performance were enhanced. In 2018, the book YOLOv3 [14] by Joseph Redmon and Ali Farhadi was published. Small item detection, precision, and real-time functionality have all been enhanced over version 2. YOLOv4 [15] was released by Alexey Bochkovskiy et al. in April 2020. They improved its suitability for single GPU training by integrating cross-iteration batch normalisation and a route aggregation network. The network's backbone, CSP Darknet, which combines CSP Net and Darknet, helps the convolutional layer train more effectively while also using less storage space. By utilising the YOLOv4 method for multiple object identification applications, the researchers were also able to enhance their pothole detecting system. Different YOLOv4-based pothole detection methods have been presented [16]–[18].

CHAPTER 3 METHODOLOGY & IMPLEMENTATION

3.1 METHODOLOGY

You only look once known as YOLO algorithm is in charge of accurately and instantly identifying various kinds of items in a given image. In yolo, regression is used to identify objects, and it gives classes a likelihood of the items in the processed pictures. Yolo algorithm is essential because of its speed, high accuracy, and learning capabilities. Yolo technique, which uses real-time detection, can increase the speed at which objects are detected for various models. It provides very high and good object detection accuracy in the photos. The YOLO (You Only Look Once) algorithm functions primarily with three parts. In order to capture and learn complicated visual characteristics, it first uses residual blocks, which are neural network architectural building pieces. These building pieces improve the model's capacity to glean relevant information from the incoming information. In order to estimate the coordinates of the bounding boxes surrounding objects of interest, YOLO also uses bounding box regression. The goal of YOLO is to precisely localise and highlight the objects in a picture by regressing the bounding box coordinates. The overlap between predicted bounding boxes and ground truth boxes is assessed using the IoU (Intersection over Union) measure, which is employed by YOLO. By assessing the degree of overlap between the anticipated and real bounding boxes, the IoU score aids in determining the accuracy of the object detection.

3.1.1 Residual blocks

A crucial architectural element known as residual blocks facilitates the extraction of intricate and significant properties from input data. Within the framework of the neural network, residual blocks are a sort of building block that facilitate the effective exchange of information and deal with the issue of disappearing gradients during training. The goal of residual blocks is to identify and learn residual characteristics, or the discrepancy between the desired output and the network's actual state. Skip connections, sometimes referred to as shortcut connections, enable the direct flow of information from one layer to a subsequent layer in the network, and they are used to accomplish this. The YOLO method effectively captures both low-level and high-level properties of objects in a picture by including leftover blocks. The skip connections let the network to keep track of crucial gradients and information from prior layers, preventing them from fading or disappearing during training. This solves the vanishing gradient issue and makes it easier to learn intricate patterns and representations of objects. In YOLO, residual blocks help to improve its capacity to quickly and effectively recognise and categorise items. These building pieces improve the network's ability to recognise small features and manage objects of different sizes and complexity levels inside a picture. For instance, it functions for object detection when it falls into the centre of the grid, in which case the grid is accountable for object detection.

3.1.2 Bounding Box Regression

The important element known as bounding box regression is in charge of forecasting the precise coordinates of the bounding boxes surrounding identified objects. The initial bounding box suggestions are improved using a technique called bounding box regression, which moves them closer to the real items in the picture. The YOLO algorithm learns to predict a collection of parameters that characterise the location, scale, and form of the bounding boxes during the training phase. The coordinates of the box's top-left and bottom-right corners are normally included in these parameters, along with any others that pertain to the box's size or aspect ratio. An illustration of a bounding box may be seen in the image below. You may think of the bounding box as an outline.

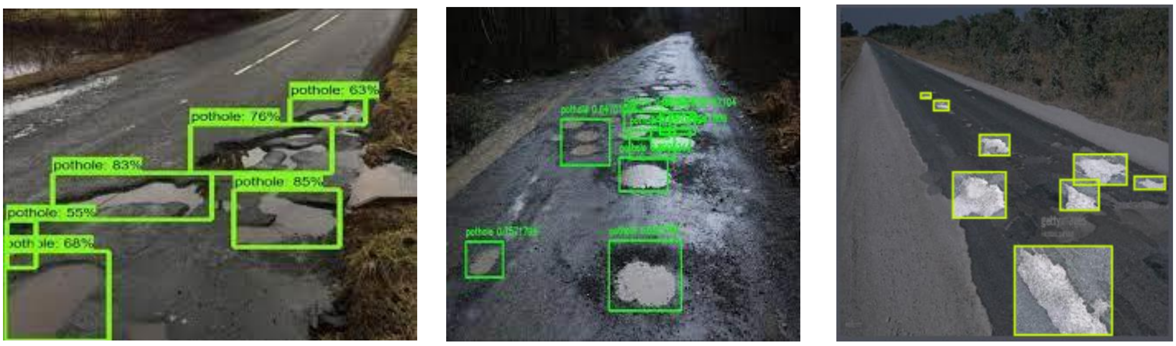
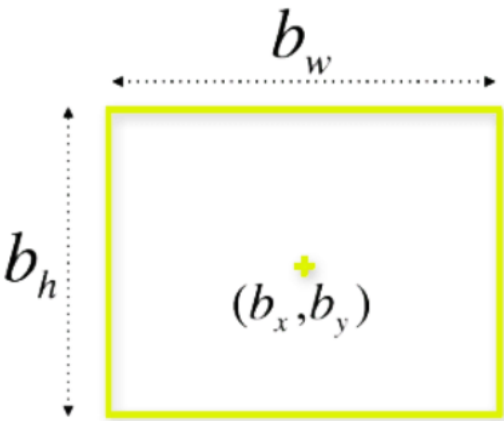


Fig.1 Bounded Boxes on Pothole Images



$$y = (p_c, b_x, b_y, b_h, b_w, c)$$

Fig.2 Coordinates of the bounding box

The original bounding box suggestions are modified during the bounding box regression procedure depending on these discovered parameters. The algorithm adjusts the placements and dimensions of the bounding boxes to more accurately include the items of interest by applying the anticipated alterations to the initial recommendations. Bounding box regression in YOLO aims to increase object localization's accuracy and precision. YOLO seeks to align the predicted bounding boxes as closely as feasible to the ground truth boxes, which reflect the real objects in the image, by repeatedly modifying the bounding box suggestions using learnt parameters.

3.1.3 Intersection Over Union (IoU)

The overlap between predicted bounding boxes and the ground truth boxes is measured using the intersection over union (IoU) metric. IoU is a crucial metric for determining how closely the two bounding boxes agree or differ, and it is used to evaluate object detection accuracy. The approach computes the intersection area between the anticipated bounding box and the actual ground truth bounding box to determine the IoU. The region where the two boxes overlap is represented by the intersection area. The area covered by the anticipated and ground truth boxes combined is then calculated as the union area. By dividing the intersection area by the union area, the IoU is calculated. As a consequence, a number between 0 and 1 is generated, with 1 denoting a perfect overlap between the anticipated and ground truth boxes and 0 denoting no overlap at all. YOLO assesses whether a prediction is a genuine positive or a false positive by comparing the IoU of each predicted bounding box with a predetermined threshold (e.g., 0.5). The predicted box is regarded as a legitimate detection if the IoU is greater than the threshold. For testing the precision of object identification algorithms like YOLO, IoU is a crucial statistic. It is useful for assessing the accuracy of bounding box predictions and is important for jobs like non-maximum suppression, which gets rid of redundant or duplicate detections by comparing the IoU values between different bounding boxes.

3.1.4 FPS, Precision and Recall

As the final assessment indicators, the F1 score and mAP produced in accordance with the precision and recall rate are utilised to calculate the model's recognition accuracy. The primary indicators are the recall rate and accuracy. The complexity of the model or method is measured in GFLOPs, while the size of the model is measured in Params. Generally speaking, the less processing power necessary to represent the model, the less hardware performance needed, and the simpler it is to incorporate low-end devices, the lower the Params and GFLOPs.

$$\text{Precision} = \frac{tp}{tp+fp}$$

$$\text{Recall} = \frac{tp}{tp+fn}$$

$$\text{F1} = 2\,\frac{precision \times recall}{precision + recall}$$

$$\text{AP} = \sum_{n=1}^{N} (R_n - R_{n-1})\, P_n$$

$$\text{mAP} = \frac{1}{N}\sum_{i=1}^{N} \text{AP}_i$$

3.2 IMPLEMENTATION

On a unique dataset, we are now running an end-to-end item identification project, utilising the YOLOv5, YOLOv7 & YOLOv8 implementation.

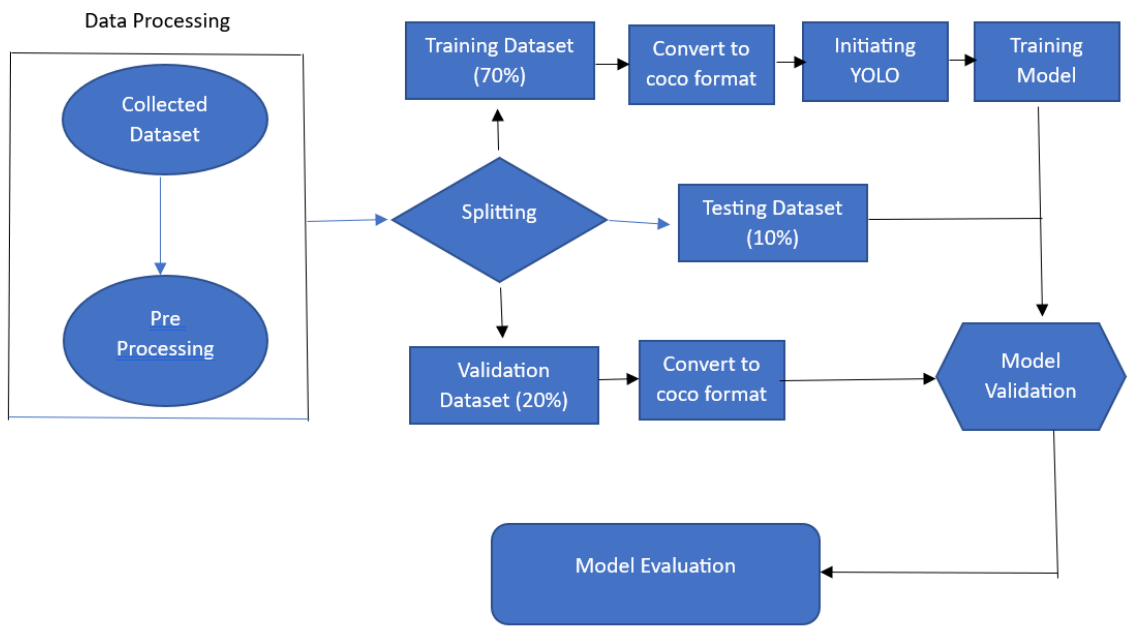


Fig.3 Flow Chart

To train our own model, assess its effectiveness, use it for inference, and We will even convert it to various file formats like ONNX and TensorRT by using transfer-learning strategies. The actions listed below, continuing with methodology, will yield the desired outcomes.

3.2.1 Data collection

First, from several public sources, including Google and Kaggle, pothole images dataset has been gathered. Totally user-friendly and completely free Roboflow software has been used, which took a very few hours. After this step, these pictures has been uploaded to Roboflow as well. Now, training of pothole photos per class is advised to produce a robust YOLOv5 model. It is also encouraged to use up to 10% additional background images to reduce false-positive rates. Following images are some examples of used pothole dataset in this article.

Fig.4 Sample of Pothole Images from Data Collection

3.2.2 Image labelling

There is not much annotated data readily available for objrct detection. That might be a problem. Many free tools are available to annotate the any kind of dataset.

In this article, roboflow is used to lebel images. There are different bounding box formats like “YOLO”, “albumentations” and “coco”. Bounding box coordinates are represented differently by each format. Two files with the identical name are used by YOLO series networks, but the files’ extensions are different. One file is a jpeg file, and other is a text file (.txt) that contains data about the labels that are present in the image. Currently, only a limited subset of annotated data is accessible for object detection. That might be an issue. There are numerous bounding box formats, including coco, YOLO, albumentations, and Pascal voc. Bounding box coordinates are represented differently by each format. YOLOv5 and other YOLO networks employ two files with the same name, although they all have different file extensions. A text file (.txt) containing details about the labels that are included in the image and a jpeg image file are both present. The annotations vary from 0 to 1 and are normalised to the picture's pothole's size. These are displayed in the following format: Box width, Box height, object-class-ID, X and Y centres. The text in the YOLO annotations file might read as follows if there are two items in the image. Following are some sample of labelled images from pothole dataset.

Fig. 5 Labelled Images

Fig. 5 displays the images with labels. Roboflow is used for labelling the images in the dataset with bounded boxes format.

3.2.3 Configuration

The repository includes 3 YAML files with training setups. We may change these files to suit our needs depending on the task. The data-configurations file format is used to describe the dataset's parameters. Due to the fact that we are using our own unique potholes dataset, the directories for the training, validation, and testing datasets, the classes' names in accordance with their index order, together with the number of classes (nc), will all be added to this file by editing. Our project consists of just one class, which is called Pothole. We placed the data.yaml file, which contains the customised data configurations under the data directory. Configurations file of the model dictates the model architecture. The YOLOv5n (nano), YOLOv5s (small), YOLOv5m (medium), YOLOv5l (large), and YOLOv5x (extra large) architectures are supported by ultralytics. When employing 640x640 pixel images for training, these architectural layouts perform well. Supplementary series known as P6, are created to train with 1280*1280-pixel images and YOLOv5n6, YOLOv5s6, YOLOv5m6, YOLOv5l6, and YOLOv5x6 are their respective names. For detecting larger things, P6 models come with an extra output layer. These benefit the most and perform better when they train at greater resolution. Ultralytics provides an integrated model for each of the aforementioned architectures, model configuration files in the model's directory. The model-configurations YAML file should be selected that corresponds to the appropriate architecture age if you are starting from scratch with training. This project makes use of YOLOv5s6.yaml. To make your custom data's class count accurate, simply modify the number of classes (nc) option after that.

3.2.4 Training and Validation

After the data has been labelled, the dataset has been divided into train and validate sets. Datasets for train, validate, and test may be separated in roboflow. The pothole image dataset collection in this example has been divided into 70-20-10 percentage for Train, Validate and Test. Depending on your unique requirements, dataset can be divided as desired ratio. This will divide the custom dataset directory and place the information in the folders for training and confirming. The system is very effective when it is completely trained from start on a sizable dataset. Initial randomization of the weights is used when the weights option is set to an empty string (' '). Training is induced upon receiving the order. An impartial assessment of a model fitted to the training data while fitting the model's hyper-parameters is provided by the validation dataset. In a neural network, for instance, layers and layer widths are examples of hidden units.

```
[ ]  !python train.py --img 416 --batch 16 --epochs 250 --data {dataset.location}/data.yaml --weights yolov5s.pt --cache
```

Fig. 6 Training for yolov5 model

```
[ ] %cd {HOME}

    !yolo task=detect mode=train model=yolov8s.pt data={dataset.location}/data.yaml epochs=25 imgsz=800 plots=True
```

Fig. 7 Training for yolov7 model

```
[ ] %cd {HOME}

    !yolo task=detect mode=train model=yolov8s.pt data={dataset.location}/data.yaml epochs=25 imgsz=800 plots=True
```

Fig. 8 Training for yolov8 model

The use of validation datasets for early stop regularisation, or terminating training as soon as the error in the validation dataset rises, is possible. In this case, regularisation indicates that the training dataset has been overfit. Despite the fact that they all seek to provide stability by anticipating the behaviour of a predictive model. It is also possible to modify the hyperparameters, or the values used to control the entire procedure. Some experts believe that ML models without tuning options or hyperparameters do not require a validation set.

CHAPTER 4 RESULTS

4.1 Models's Results

	Yolov5	Yolov7	Yolov8
Image	123	100	100
Instances	269	221	221
P	0.823	0.813	0.847
R	0.763	0.846	0.778
mAP50	0.843	0.871	0.854
epoch	250	55	25
Time (Hour)	0.373	0.396	0.150
Speed(s/it)	1.56	1.11	1.35

TABLE 1 : Comparison Table among yolo v5, v7, v8

In table 1, the relationship between yolov5, yolov7, and yolov8 is seen. Here, yolov5's accuracy was 84.3, with a 0.823 p score and 0.763 r score, and yolov7's accuracy was 87.1, with a 0.813 p score and 0.846 r score. Yolov8 has achieved a similar 85.4 accuracy with a 0.847 p and 0.778 r score. Here, the table for the yolov5, yolov7, and yolov8 methods also includes the number of images, epoch, time, and speed.

4.1.1 Yolov5

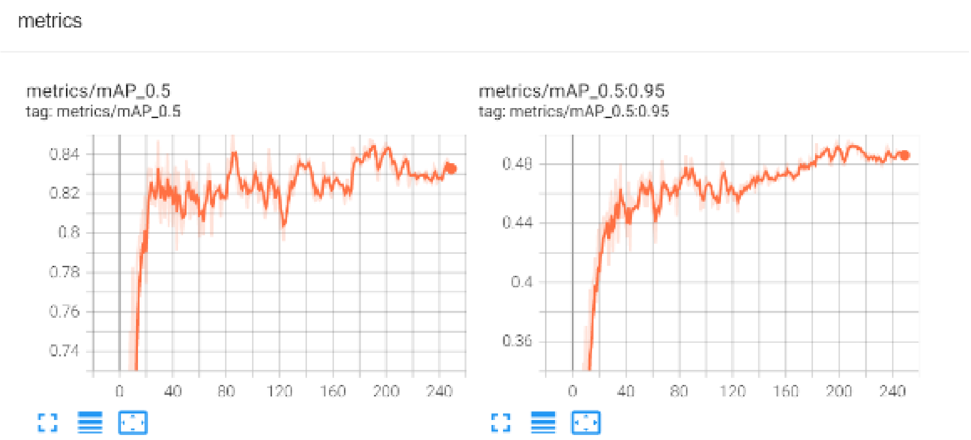


Fig.9 Model Accuracy / Epoch for yolov5

Fig 9 graphically represents the results of yolov5 model. In which the mAP50 score is represented by the y axis and the epoch by the x axis, this experiment has produced a result of 84.3% mAP50. In this context, accuracy measures the percentage of accurate forecasts to all predictions in the training data, and epoch is how many times the data was trained in total.

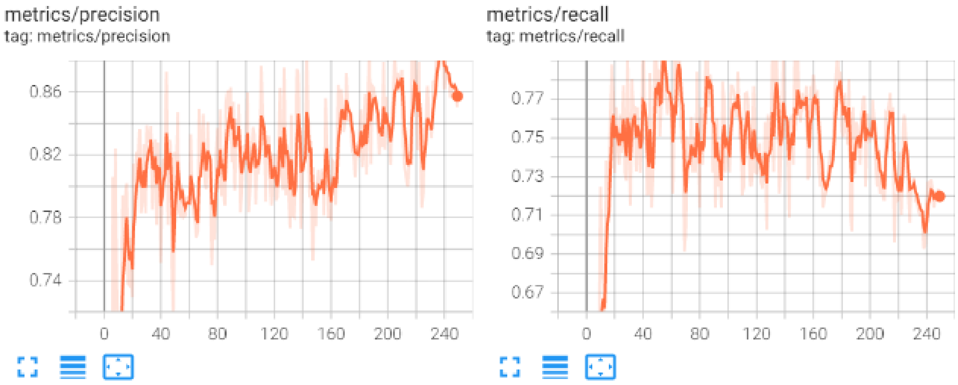
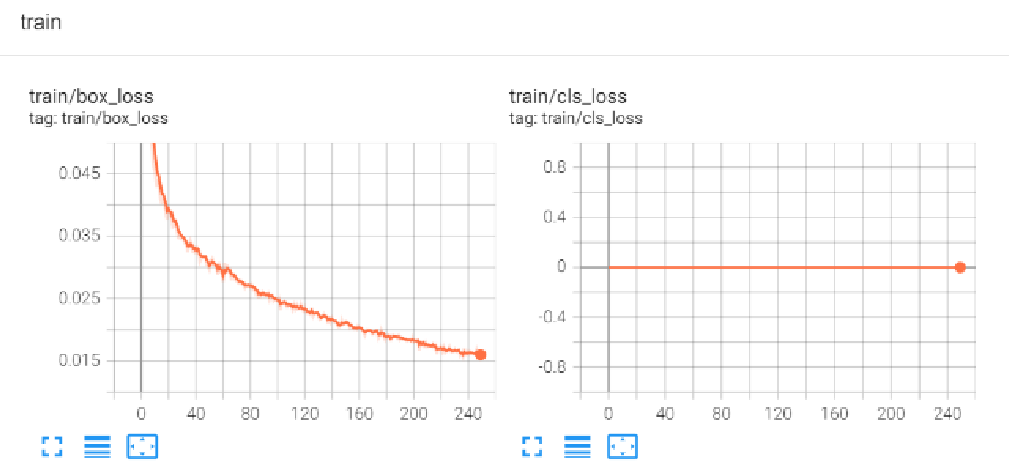


Fig.10 Precision / Epoch for yolov5

In fig 10, the relationship between the Yolov5 model's metrics and precision is visually depicted. In which the mAP50 score is represented by the y axis and the epoch by the x axis, this experiment yielded a p score of 82.3%. Here, accuracy is challenged by the percentage of affirmative identifications that were accurate.



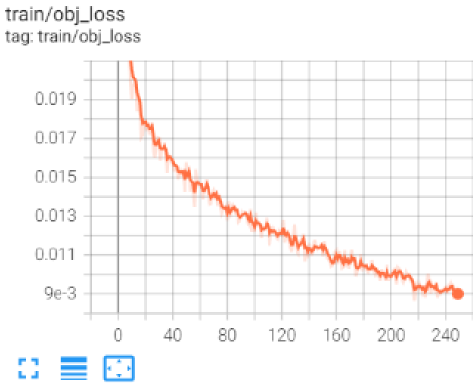
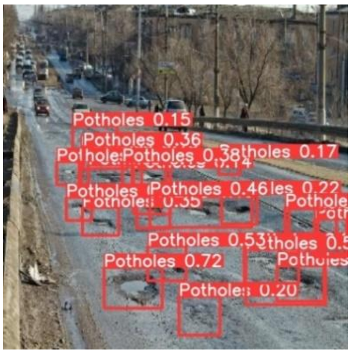
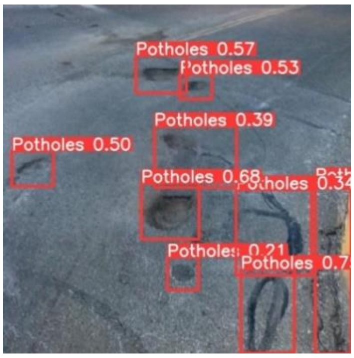
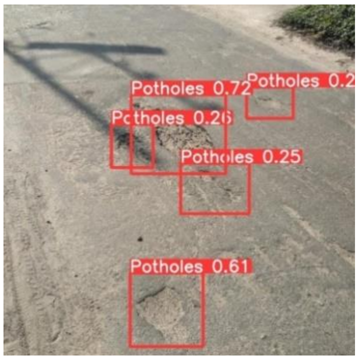


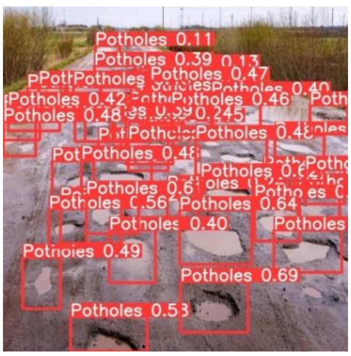
Fig.11 Loss / Epoch

Fig 11 graphically represents the training performance of yolov5 model where it is represented by the Yolov5 train/box_loss of mean squared error. As the epoch increases and the graph decreases, box loss also decreases.









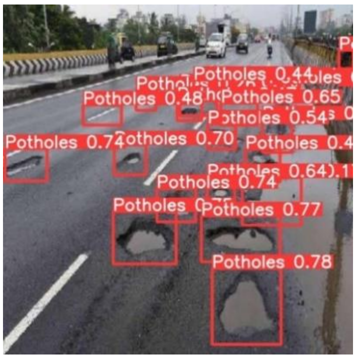


Fig.12 Results of YOLOv5 model

Fig 12 shows the final result after detecting the potholes with the mAP score. These are a few of the images that represent the results of the Yolov5 model. Yolov5 has a very high accuracy of 84.3 in identifying potholes.

4.1.2 Yolov7

Fig.13 Results of YOLOv7 model

Following the use of the mAP score to identify potholes, Fig.13 displays the final outcome of Yolov7. Here are a few of the yolov7 model's final results. Yolov7 has a very excellent accuracy of 87.1 and has a great ability to identify potholes. In terms of accuracy, this approach outperforms yolov5 significantly.

4.1.3 Yolov8

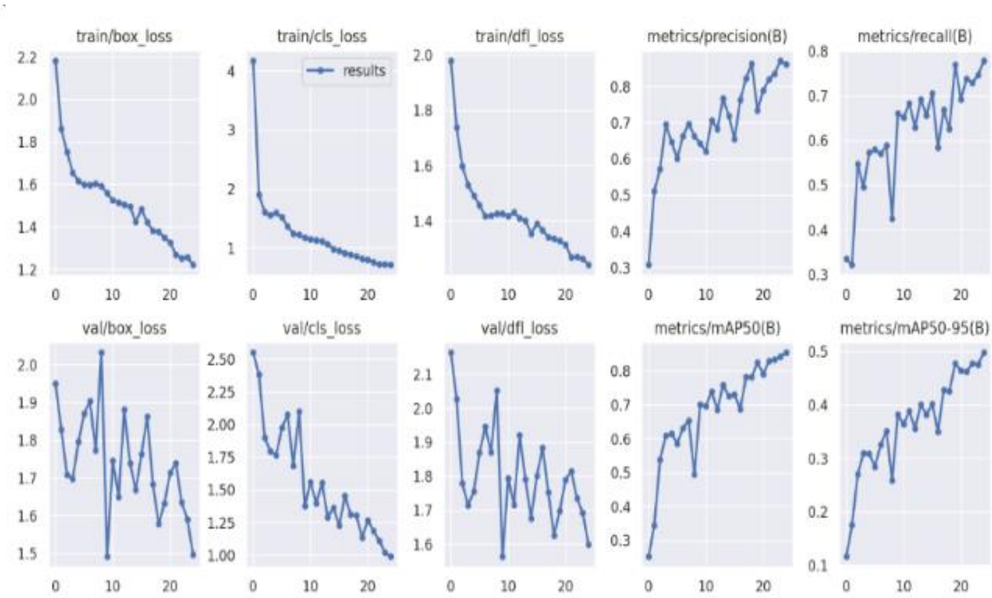


Fig.14 Graph of Accuracy, Precision & Loss / Epoch for yolov8

In fig 14, the relationship between the model's mAP50 score, accuracy, recall, and box_loss and epoch are graphically depicted. This experiment obtained 85.4% mAP50 and finished 221 instances in 0.150 hours.

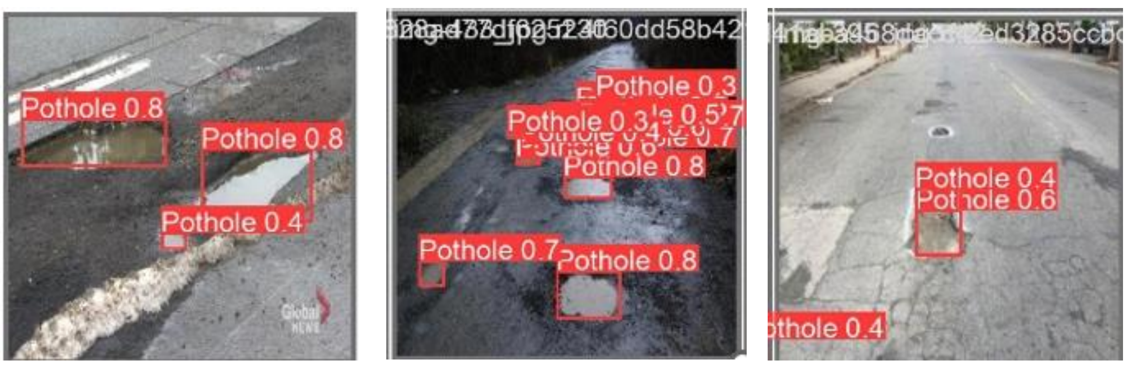


Fig.15 Results of YOLOv8 model

Fig. 15 shows the results of Yolov8 after the usage of the mAP score to locate potholes. Several of the yolov8 model's final results are shown below. Yolov8 is incredibly accurate (85.4%), and it can spot potholes pretty well. It performs better than both the Yolov7 and Yolov5 in terms of the speed of pothole identification.

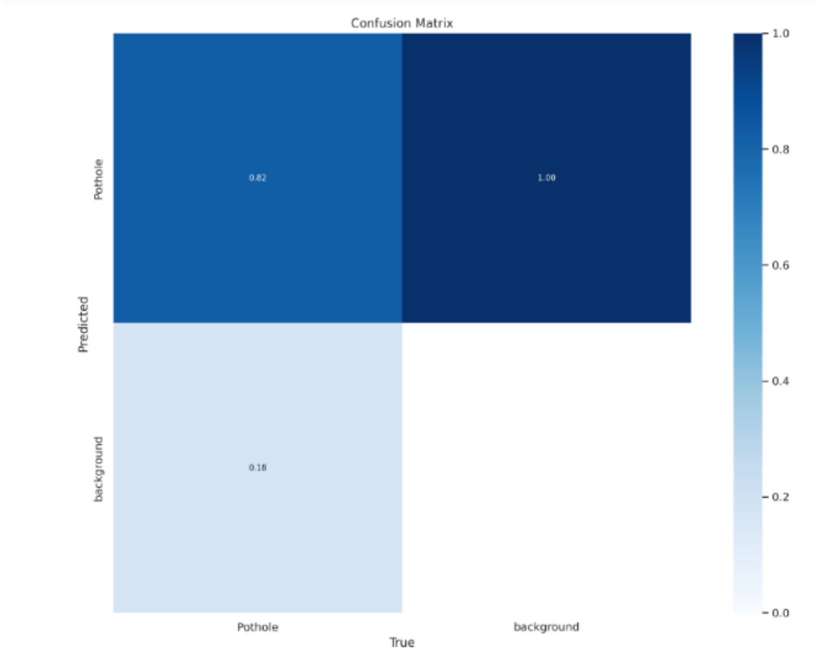


Fig. 16 Confusion Matrix

In Fig.16 confusion matrix displays how well the model did on the test set. It aids in comprehension of how well the YOLO algorithm detects potholes and distinguishes them from other items. With the use of the test set's ground truth labels, this confusion matrix predicts labels from the model and this confusion matrix tracks the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) based on comparison.

4.2 Conclusion

There have been numerous studies of all kinds carried out to overcome the difficulty of detecting road damage, which is a significant issue. We identified road damage using a YOLO-based approach using an open-source dataset to train the algorithm. Yolov5 model in this instance uses a dataset of 613 photos, whereas Yolov7 and Yolov8 models utilize a dataset of 500 images. The inference time for our YOLO-based approach is really quick. When it comes to problems with real-time road damage diagnosis, FPS might be a far more important aspect. Of course, accuracy is important, but so is the speed of inference. This yolov5 model's pace is faster than any other functioning model, as it completes 250 epochs with 84.3% accuracy in just 0.373 hours. Yolov8 had an accuracy of 85.4% and completed the model in 0.150 hours, but Yolov7 had an accuracy of 87.1% and completed the model in 0.396 hours. These techniques might thus be helpful for autonomous cars to utilize detecting road degradation in real-time. Improving accuracy is still major challenge for researchers in future.

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