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Minor Project on

**“Pothole detection and Dimension estimation**

**using Deep Learning”**

*Submitted in partial fulfilment of the requirements for the degree of*

### Bachelor of Technology

Department of Computer Science & Engineering

#### Submitted By

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# Declaration of Academic Integrity

#### We declare that this written submission conveys our ideas in our own words. We have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/date/fact/source in our submission.

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#### This is to certify that “Amey Patil, Drashya Sodha, Danish Rehman, Karka Rohan , Kirtan Dhinoja” have satisfactorily completed their minor project on “Pothole detection and Dimension estimation using Deep Learning” during the academic term 2023-24 and their report is approved for final submission.

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# CERTIFICATE

#### This is to certify that the minor project entitled “Pothole detection and Dimension estimation

#### using Deep Learning” is a bonafide work of “Amey Patil , Drashya Sodha , Danish Rehman, Karka Rohan , Kirtan Dhinoja” submitted to the Amity School of Engineering and Technology, Amity University Mumbai in partial fulfilment of the requirement for the degree of B. Tech Computer Science & Engineering.

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We perceive this opportunity as a big milestone in our career development. We shall strive to use the gained skills and knowledge in the best possible way and shall continue to work on their improvement, to attain the desired objectives.

## ABSTRACT

The world is advancing towards an autonomous environment at a great pace, and it has become a need of an hour, especially during the current pandemic situation. The pandemic has hindered the functioning of many sectors, one of them being Road development and maintenance. Creating a safe working environment for workers is a major concern of road maintenance during such difficult times. This can be achieved to some extent with the help of an autonomous system that will aim at reducing human dependency. In this project, one of such systems, pothole detection and dimension estimation, is proposed. The proposed system uses a Deep Learning based algorithm Resnet50 for pothole detection. Further, an image processing based triangular similarity measure is used for pothole dimension estimation. The proposed system provides reasonably accurate results of both pothole detection and dimension estimation. The proposed system also helps in reducing the time required for road maintenance. The system uses a custom-made dataset consisting of images of water-logged and dry potholes of various shapes and sizes.

Results from our experiments indicate that the ResNet50 model achieves a detection accuracy of over 75%, significantly outperforming traditional methods. The dimension estimation algorithm demonstrates remarkable precision, with a mean absolute error of less than 5%, ensuring the accurate assessment of pothole size and severity. This high level of performance ensures that the proposed system is both reliable and efficient, making it a valuable tool for modern road maintenance and safety management. Furthermore, the system's ability to rapidly and accurately detect and measure potholes can lead to substantial cost savings and improved road safety by facilitating timely repairs. Overall, the proposed system represents a significant advancement in the field of autonomous road maintenance, offering a practical solution to one of the most pressing infrastructure challenges

## TABLE OF CONTENTS

**CHAPTER NO. TITLE PAGE NO.**

**1. INTRODUCTION 9**

**1.1** Background

**2. LITERATURE SURVEY 11**

**2.1** Introduction

**2.2** Existing Methodologies

**2.3** Comparative Analysis

**3. PROBLEM STATEMENT 16**

**4. SYSTEM ANALYSIS 18**

**5. SYSTEM DESIGN 21**

**5.1** Design Model – Use case Diagram/

Class Diagram (Detailed Design)

Function Specifications (Data flow diagrams)

**6. PROJECT TIMELINE 22**

**6.1** Gantt chart

**7.** **IMPLEMENTATION, RESULTS AND TESTING 23**

**7.1** Details of Hardware and Software

**7.2** Result and Discussion

**8.** **CONCLUSION AND FUTURE SCOPE 29**

**8.1** Conclusion

**8.2** Future Scope

**REFERENCES 31**

**PUBLICATIONS AND CERTIFICATES**

**LIST OF FIGURES & IMAGES**

|  |  |  |
| --- | --- | --- |
| **Sr. No.** | **Figure/Image Title** | **Page No.** |
| **1** | **System Workflow** | **18** |
| **2** | **Dataflow Diagram** | **21** |
| **3** | **Class Diagram** | **21** |
| **4** | **Gantt Chart** | **22** |
| **5** | **Results** | **25** |
| **6** | **Dimension Estimation (Result)** | **26** |
| **7** | **Streamlit Deployment (Result)** | **27** |
| **8** | **Comparative Analysis** | **28** |

**LIST OF TABLES**

|  |  |  |
| --- | --- | --- |
| **Sr. No.** | **Figure/Image Title** | **Page No.** |
| **1** | **Comparative Analysis** | **29** |

**CHAPTER 1**

**INTRODUCTION**

* 1. **Background**

Technology has played an essential role in the development of automated systems in various sectors in the past few years. With the advent of Autonomous systems, human lives have become more convenient. Transportation and surveillance systems have significantly benefited from the incorporation of automation. Specifically for transportation, roads are of foremost importance as roads constitute the most extensive network. It is important for an autonomous system to function without compromising the safety of its users and for road transportation systems, potholes pose a great threat. According to the official data released by the Government of India, 2015 people lost their lives in 4,869 accidents caused by potholes last year. This makes road maintenance of paramount importance. Road infrastructure plays a pivotal role in modern society, facilitating transportation networks essential for economic activities and societal well-being. However, maintaining roadways in optimal condition presents an ongoing challenge for transportation authorities worldwide. Among the myriad of road hazards, potholes stand out as a ubiquitous and disruptive menace. These depressions in road surfaces not only compromise driving safety but also inflict costly damages on vehicles, posing significant concerns for both public safety and infrastructure maintenance.

Traditionally, the detection and repair of potholes have relied on manual inspections conducted by road maintenance crews. This labor-intensive and time-consuming process often results in delayed repairs, leading to increased risks for road users and heightened maintenance costs. Moreover, manual inspections are inherently subjective and prone to human error, limiting their efficacy in accurately identifying and prioritizing pothole repairs. To address these challenges, there has been a growing interest in leveraging technological advancements, particularly in the fields of computer vision and deep learning, to automate pothole detection and assessment. By harnessing the power of artificial intelligence (AI) and machine learning, researchers and engineers seek to develop robust and efficient systems capable of autonomously identifying potholes and quantifying their dimensions with precision.

The objective of this project is to contribute to this emerging field by designing and implementing a novel deep learning-based solution for pothole detection and dimension estimation. By harnessing state-of-the-art deep learning models(CNN), the proposed system aims to analyze road images captured by cameras mounted on vehicles or infrastructure and identify regions indicative of potholes. Furthermore, the system will estimate the dimensions of detected potholes, providing valuable insights into their severity and prioritizing maintenance efforts accordingly.This project builds upon existing research and methodologies in computer vision, deep learning, and road maintenance. By conducting a thorough literature review, we aim to identify the strengths and limitations of previous approaches, informing the design and implementation of our solution. Through systematic analysis and experimentation, we seek to demonstrate the efficacy and reliability of our system in real-world scenarios, thereby advancing the state-of-the-art in pothole detection and road infrastructure management.

In addition to its immediate practical implications, this project holds broader significance within the context of smart cities and intelligent transportation systems. By automating pothole detection and assessment, our system has the potential to enhance the efficiency of road maintenance operations, reduce traffic disruptions, and improve overall road safety. Moreover, the insights gained from this project can inform the development of integrated infrastructure monitoring systems capable of proactively identifying and addressing various road hazards, contributing to the sustainable development of urban environments. There is a need for an autonomous system that can monitor road conditions. In this paper, a pothole detection and dimension estimation system is proposed, which uses Deep Learning and Image Processing. In recent times, several deep learning-based object detection techniques have been developed, which use Convolutional Neural Networks for feature extraction. This paper proposes the use of Resnet50 for a pothole detection system. Multiple versions of the Resnet algorithm are trained on a custom dataset, consisting of both water-logged and dry potholes of various shapes and sizes, after which results are evaluated on IoU (Intersection over Union) and mAP (mean Average Precision). The model is able to detect a variety of potholes with reasonable accuracy. Also, the proposed Image Processing based pothole dimension estimator provides fairly accurate dimensions of the detected potholes using Triangular Similarity, thus reducing the overall time required for road maintenance even further.

**CHAPTER 2**

**Literature Survey**

**2.1 Introduction**

Abhishek Kumar et al. [1] proposed a method for pothole detection using a quicker convolutional neural network with regions of interest (Faster R-CNN). International roadways are the foundation of the dataset. R-CNN based models' longer prediction times are a drawback in this situation. Moreover, models created for detecting potholes on foreign roads perform poorly since Indian roadways have entirely different damage circumstances than foreign roads.

K.C et al.[2] proposed a method that is challenging to illustrate a system for identifying potholes on the road, particularly in a country like India where roads cover millions of kilometres . Consequently, it is necessary to automate pothole detection with high speed and real-time accuracy. The basic objective of the object detection algorithm YOLOX (You Only Look Once) is to train and examine the YOLOX model for pothole detection. To extract and distinguish different textures and features of an image, the image processing methodology uses a variety of statistical methods, including Gray- Level Co-Occurrence (GLCM), Radial Basis Function (RBF), etc. Because to the enormous processing power needed, these techniques are frequently employed in conjunction with other machine learning strategies. Pothole photos collected in a variety of shapes as well as many potholes are included in the data set used to train the model. The analysis's findings indicate that the YOLOX nano model is ideally suited for pothole detection because it can be quickly deployed, requires little in the way of storage space, and consumes little energy due to its small size.

D. Desai et al. [3] depicts a system to detect potholes, notify riders, and create a location database of existing potholes. This may encourage riders to be more careful, reduce the frequency of collisions, and lower vehicle repair expenses. According on the trial findings, the system can reliably locate potholes to a 90% degree. Four seconds are needed to convey the GPS location to the database and the rider's alarm. The technique is further honed using a robust, city-level database that may be used across the whole country.

L. Parameswaran et al.[4] states that one of the main causes of traffic accidents is the driver's failure to pay attention to every little element of the road, which is where Advanced Driver Assistance Systems (ADAS) come into play.The information can be utilised by the autonomous driving system to determine what action needs to be taken to avoid a collision and assure the passengers' safety and comfort, or it can be immediately relayed to the driver by displaying an alert symbol in the car's interior. YOLO is used to train the dataset and annotate it (You Only Look Once). The outcomes of training the new dataset on YOLOv3, YOLOv2, and YOLOv3-tiny are compared. The mAP, precision, and recall are used to evaluate the outcomes. Themodel is tested on several photos of potholes, and it detects with a respectable degree of accuracy.

Kavitha R. et al.[5] describes that deep learning can help self- driving cars detect potholes and wetland areas, which is crucial for solving road problems like accidents and transport system slowdown. With a strong object detection module as a foundation, this gives the Advanced Driver Assistance Systems (ADAS) system in self-driving cars extra advantages for safer driving. In the future, more items including buildings, ambulances, autorickshaws, boulders in the road, and large loads of plastic bags on the road can be taught for object identification to increase the efficiency and safety of autonomousdriving systems.

P. A. Chitale et al.[6] describes a suggested system that uses the YOLO (You Only Look Once) pothole detection method, which is based on deep learning. The pothole detection findings provided by the proposed technology are reassuringly accurate. The suggested approach aids in cutting down on the time needed for road maintenance. The method makes use of a specially created dataset that includes pictures of both dry and wet potholes of varying sizes and forms. In particular during the epidemic, the suggested technology would lessen the need for human labourers to maintain roads. Potholes are spotted, and their sizes are assessed with excellent accuracy and a significantly decreased error rate. The calculated pothole measurements might be used to gauge the severity of the damage to the road as well as to determine theamount of raw materials needed to patch the holes. As a result, the majority of the planning and inspection may be done online.

Lokeshwor Huidrom et al. [6] have proposed a system that uses predefined thresholds for standard deviation and object circularity to detect road distresses like potholes, patches, and fractures. Image processing algorithms are used to do this. The drawback of this method is that the same set of established criteria cannot be applied to all road distresses because they do not all have a uniform shape or size.

Chen et al. [7] proposed a method using a combination of deep learning and edge computing for real-time pothole detection. Their system employs a convolutional neural network (CNN) model that is optimized for deployment on edge devices, allowing for real-time processing and alerting road maintenance teams promptly. The use of edge computing reduces the latency and bandwidth required for data transmission, making it suitable for remote areas with limited connectivity.

Jiang et al. [8] developed a robust pothole detection system using a multi-sensor fusion approach. This system integrates data from cameras, LiDAR, and accelerometers to improve the accuracy of pothole detection. The fusion of these sensors helps mitigate the limitations of individual sensors, providing a more comprehensive detection mechanism that can operate under various environmental conditions.

Zou et al. [9] introduced an innovative method that combines deep learning with thermal imaging to detect potholes. Their approach leverages the temperature differences between the pothole and the surrounding road surface, which are captured using thermal cameras. This method is particularly effective in low-light conditions and at night, where traditional image-based methods may fail.

Gonzalez et al. [10] utilized drone-based imagery and deep learning algorithms for large-scale pothole detection. Their research highlights the advantages of using aerial imagery to cover vast areas quickly, providing a scalable solution for urban and rural road networks. The drones capture high-resolution images, which are then processed using a modified YOLO (You Only Look Once) algorithm to identify potholes accurately.

**2.2 Existing Methodologies**

This section illustrates some research efforts that have been developed to detect potholes in roads. X. Yu and E. Salari proposed a method to detect potholes using laser imaging techniques [32]. The method involves the use of a light source to project a pattern of laser beam on the pavement, a camera to capture the pavement illuminated with the laser beam and image processing on the captured images to identify potholes. Different approaches like Multi-window Median filtering, Tile Partitioning with common thresholding [15], Laser line deformation, and Template matching. The study also involved the use of neural network to find the crack type and pothole severity classification. The use of expensive hardware keeps this method out of reach of majority of vehicle drivers. Similarly, the study done by Zhang et al. modeled potholes using stereo vision [33]. Stereo camera is used to capture the left/right images of potholes and disparity map is calculated using a computationally efficient algorithm. A surface fitting algorithm developed using low computational bi-square weighted robust least-squares method [7] and [2] is used to determine road surface and potholes. These pothole information are saved with geometric coordinates that can be used later to access the properties such as size and volume of potholes in order to prioritize the repair accordingly. Similar to the previous study, this way of detection is also expensive in terms of configuration. Nienaber et al. used image processing to identify the potholes on roads [21]. A camera mounted on the vehicle is used to capture frames of road. Then those frames are sent through simple image processing techniques like Canny filter and contour detection to locate potholes. The experiment resulted in precision of 81.8% with recall of 74.4%. Though, the accuracy values are satisfactory in the test images but it is not guaranteed to get same accuracy using same techniques in all type of roads. Therefore, this technique need to adjust the image processing parameters and steps for different road conditions which will be a tedious task. In addition, Seung-Ki Ryu, Taehyeong Kim, and Young-Ro Kim proposed a system of pothole detection and broadcasting of this information to different hierarchy of stations that are supposed to relay information to the motorists [27]. Potholes are detected by a pothole detection system. The system involves three steps: segmentation, candidate region abstraction and decision. With the use of system, the motorists can know in advance about the location of potholes and perform rerouting or apply precautions accordingly. The idea behind communicating the potholes detected using the stations makes the communication much more reliable but this 2 kind of setup is more costly as we need to set this up in many places depending upon the coverage. Another study suggests the use of mobile sensing system for irregularities detection in pavements. Mednis et al. introduced the use of Android Smartphones with accelerometers to carry out the task of detection. Preliminary data from the sensors are collected using a LynxNet collar device [34] and different algorithms are tested on the accelerometer data to distinguish the potholes. This method showed true positive rates as high as 90% [20]. This way of collecting data and detecting potholes later helps only to the authority to make necessary arrangements for maintenance, but no motorists are benefited. Moreover, we won’t have any information about the area and shape of potholes. Support Vector Machine(SVM) was also used as a machine learning algorithm for the road information analysis and pothole detection [16]. Texture measure based on histogram was used as the feature of the image and non-linear SVM was used to detect whether the image is a pothole or not. This way of detecting potholes gave high accuracy with the use of high computational power but it is not feasible to be used by drivers in their devices. A recent study done by Silvister et al. on pothole suggests the use of deep learning as well as smartphone sensor reading [28]. The detection done by deep learning algorithm Single Shot Multibox Detector (SSD) [19] is validated against the detection done by sensor reading to reduce the false positives and also have a backup mechanism if one of them fails. This study doesn’t quantify the pothole characteristics like area and shape which are crucial information needed on potholes. The sample study done shows that there is a necessity of a decent system that could trace potholes with a good amount of accuracy and speed and, without the use of expensive technologies. Though, a lot of researches have been done, there are not much researches that are concerned with geo-tagging potholes data after detection and quantifying the pothole dimensions (area, shape). This paper develops supervised deep learning alternatives to detect potholes in roads and quantify their accuracy and speed.

**2.3 Comparative Analysis**

**Wang et al. (2022)**: This study conducted a thorough comparison of various YOLO models, specifically YOLOv3, YOLOv4, and YOLOv5, for the task of pothole detection. The researchers found that YOLOv5s offers an excellent balance between accuracy and computational efficiency. This makes YOLOv5s particularly suitable for real-time applications on mobile devices, where resource constraints are a significant consideration. The study highlighted that YOLOv5s could maintain high detection accuracy while significantly reducing inference time, thereby enabling efficient and practical deployment in real-world scenarios.

**Patel et al. (2023)**: Patel and colleagues carried out a comparative study between deep learning models, such as Faster R-CNN and SSD, and traditional image processing techniques, like edge detection and the Hough Transform. Their findings revealed that deep learning models significantly outperform traditional methods in terms of accuracy and robustness to varying road conditions. This robustness is critical for pothole detection, as road surfaces can vary widely in appearance due to factors like lighting, weather, and wear. The study concluded that the adaptability and precision of deep learning models make them far more effective for this application.

**Huang et al. (2023)**: Huang and co-researchers explored the integration of edge computing with deep learning models to enhance the performance of pothole detection systems. By processing data locally on edge devices, the system can reduce latency and provide real-time alerts, which is crucial for timely maintenance and accident prevention. Their findings suggest that edge computing significantly improves the feasibility of deploying deep learning models in real-world scenarios, particularly in remote areas with limited connectivity. This approach not only enhances response times but also reduces the bandwidth requirements for data transmission.

**Models Compared**: The models compared for pothole detection include YOLOv3-tiny, YOLOv3, YOLOv4-tiny, YOLOv4, YOLOv5s, YOLOv5x, and ResNet50. Each model offers unique strengths and weaknesses, which makes them suitable for different applications and environments.

**Performance Metrics**: Among these models, YOLOv4 achieved the highest mean average precision (mAP), indicating its superior accuracy in detecting potholes. On the other hand, YOLOv4-tiny demonstrated the best-reduced inference time, making it particularly suitable for mobile applications where computational resources are limited. This trade-off between speed and accuracy is a critical factor in choosing the appropriate model for specific use cases.

**Speed vs. Accuracy**: The comparison also highlighted the differences between two-stage and one-stage detectors. Two-stage detectors like YOLOv4 offer higher accuracy but at the cost of increased computational complexity and longer processing times. Conversely, one-stage detectors like YOLOv4-tiny are faster and more suitable for real-time applications, albeit with a slight compromise in accuracy. This distinction is crucial for applications that require immediate responses, such as real-time road monitoring and maintenance.

**Effectiveness**: The YOLOv5s model demonstrated good results, characterized by ease of implementation and scalability for pothole detection in road pavements. Its balanced performance makes it an attractive option for large-scale deployment. The model's scalability ensures that it can handle varying amounts of data efficiently, which is essential for extensive road networks. Additionally, its straightforward implementation facilitates integration into existing systems, further enhancing its practicality for widespread use.

**ResNet50**: Although primarily used for image classification, ResNet50 has been adapted for pothole detection due to its deep architecture and residual learning capabilities. It provides a high level of accuracy in identifying potholes, even in challenging conditions. The deep layers in ResNet50 allow it to capture intricate features and variations in the road surface, making it a robust choice for detection tasks. However, its computational requirements are higher than some YOLO variants, which can be a consideration in resource-constrained environments.

In summary, the comparative analysis underscores the importance of selecting the right model based on specific requirements such as accuracy, speed, and resource availability. While YOLOv4 excels in precision, YOLOv4-tiny and YOLOv5s offer a practical balance for real-time applications. ResNet50, with its deep architecture, provides robust detection capabilities, albeit with higher computational demands. This detailed comparison aids in understanding the trade-offs involved and guides the selection of the most suitable model for pothole detection in various scenarios.

**CHAPTER 3**

**Problem Statement**

Road maintenance and safety are critical concerns worldwide, with potholes being a significant contributor to vehicular damage and accidents. Traditional methods of manual pothole inspections are labor-intensive, time-consuming, and often subjective, leading to inconsistencies and delays in repairs. These inefficiencies increase the risks for road users and result in higher maintenance costs. The challenges have been further exacerbated by the ongoing pandemic, which has restricted the availability of human resources for road maintenance tasks, thereby heightening the need for automated solutions.

Potholes are not just minor annoyances; they can cause severe damage to vehicles, including tire blowouts, suspension damage, and even accidents resulting in injuries or fatalities. The economic impact is substantial, as governments and local authorities must allocate significant funds for road repairs and vehicle owners face costly repairs. Moreover, the subjective nature of manual inspections means that some potholes may be overlooked or not prioritized correctly, leading to uneven road quality and further risks.

To address these pressing issues, this project aims to develop an automated system for accurate pothole detection and dimension estimation using advanced deep learning techniques. By leveraging the power of convolutional neural networks (CNNs), specifically the ResNet50 architecture, the proposed system seeks to analyze road images and identify potholes with high precision. Additionally, the system will estimate the dimensions of detected potholes, providing valuable insights for prioritizing maintenance efforts. This innovative approach not only enhances the efficiency of road inspections but also significantly improves overall road safety by facilitating timely and accurate pothole repairs.

**System Overview**

The proposed system's architecture consists of two primary modules: the pothole detection module and the dimension estimation module. These modules work in tandem to deliver a comprehensive solution for the detection and measurement of potholes.

**Pothole Detection Module**

The pothole detection module utilizes the ResNet50 architecture, a robust and widely adopted convolutional neural network known for its effectiveness in image recognition tasks. ResNet50, or Residual Network with 50 layers, processes input images through successive convolutional layers, gradually extracting hierarchical features. This architecture incorporates residual connections, which allow the network to train deeper layers without encountering issues like vanishing gradients. These residual blocks enable the network to learn more abstract and discriminative representations, enhancing its ability to detect complex patterns in images.

In this single-stage object detection approach, ResNet50 performs object detection and localization directly on the input image, eliminating the need for separate region proposal networks. This design choice enhances the efficiency of the detection process, making ResNet50 suitable for real-time applications. The pothole detection model is trained using a custom dataset comprising road images with annotated potholes. The dataset includes images from various road conditions, both Indian and international, to capture a diverse range of pothole instances under different environmental conditions.

During training, the ResNet50 model learns to predict multiple candidate bounding boxes for potholes, each associated with different anchor sizes. Non-maximum suppression (NMS) is then applied to these bounding boxes to filter out duplicates and retain the most relevant detections based on their Intersection over Union (IoU) scores. The training process involves multiple iterations, typically ranging from 3000 to 6000 epochs, with a batch size of 64 and eight subdivisions. This iterative training approach allows the model to progressively refine its predictions and improve its performance over time.

**Dimension Estimation Module**

Once the potholes are detected, the dimension estimation module uses an image processing-based solution to estimate their dimensions. This module leverages the triangle similarity property to calculate the actual dimensions of the detected potholes. Consider an object of known width 'W' placed at a distance 'D' from the camera. By taking a picture of this object from distance 'D,' we obtain its apparent width in pixels 'P.

​

This perceived focal length maintains an inverse relationship between pixel length and camera distance. The pixel length is dependent on the image's pixel density measured in PPI (pixels per inch). Hence, preprocessing is recommended to fix the PPI of the input image to maintain consistency. In the proposed setup, since the same camera is used for both calibration and testing, PPI conversion is not required.

During calibration, an object with a known length, such as a ruler, is captured from various heights (e.g., 15 cm, 30 cm). The Canny edge detector algorithm is applied to detect the object's edges and measure its pixel length. Using the formula specified earlier, the perceived focal lengths for each image are calculated, and their average provides the final perceived focal length.

The pothole detection stage provides the bounding box coordinates, from which the pixel length and width are obtained. Using the fixed camera distance of 90 cm and the calculated perceived focal length, the actual dimensions of the potholes are determined. This method ensures accurate and consistent measurement of pothole dimensions, which is critical for assessing the severity and prioritizing repair efforts.

**Benefits and Impact**

Implementing this automated pothole detection and dimension estimation system offers numerous benefits. It reduces the need for labor-intensive manual inspections, minimizes human error, and ensures consistent and objective evaluations of road conditions. The system's ability to provide accurate measurements of pothole dimensions allows for better prioritization of repairs, ensuring that the most critical issues are addressed first.

Furthermore, the use of advanced deep learning techniques like ResNet50 enhances the system's accuracy and reliability, making it a valuable tool for road maintenance authorities. By enabling timely and precise repairs, the system helps improve overall road safety, reducing the risk of accidents and vehicular damage caused by potholes.

In conclusion, this project addresses the critical challenges associated with pothole detection and road maintenance by leveraging cutting-edge deep learning and image processing techniques. The proposed automated system not only improves the efficiency and accuracy of pothole inspections but also significantly enhances road safety and reduces maintenance costs. Through innovative technological solutions, this project aims to transform the way road maintenance is conducted, ensuring safer and more reliable transportation infrastructure.

**CHAPTER 4**

**System Analysis**

1. Dataset Creation

Two datasets sourced from Kaggle were utilized for training the model. The combined dataset comprises approximately 2000 images capturing road surfaces from both Indian and foreign locations. Each image contains multiple instances of potholes, representing a variety of scenarios including waterlogged and dry conditions, as well as diverse shapes and sizes of potholes.

The first dataset, "annotated pothole\_dataset," consists of images specifically focused on road conditions in India. The second dataset, "pothole-detection," contains images from various countries worldwide, providing a diverse range of road surface characteristics and pothole instances.

To ensure a comprehensive representation of pothole scenarios, images were meticulously selected from both datasets, considering factors such as lighting conditions, road types, and pothole appearances. The images were curated to include a balanced mix of waterlogged and dry potholes, as well as various shapes and sizes.

1. System Workflow

The proposed system is divided into two stages: pothole detection and dimension estimation. Images taken from a camera are fed into the pothole detection system. The camera is kept at an elevation of 90 cm from the ground. The bounding boxes obtained as a result of applying a deep learning model on the input images are given to the dimension estimation module. This module uses the elevation of the camera from the ground and estimates the dimensions of each of the bounding boxes as output.

A diagram of a company

Description automatically generated

Fig.1 System workflow

Showcase the workflow of the project which has all processes

C. Pothole Detection Module

The pothole detection module of the proposed system utilizes the ResNet50 architecture, a widely adopted convolutional neural network (CNN) known for its effectiveness in image recognition tasks. ResNet50, short for Residual Network with 50 layers, has demonstrated remarkable performance in object detection tasks while maintaining computational efficiency.

ResNet50 operates by processing input images through successive convolutional layers, gradually extracting hierarchical features from the image data. This architecture incorporates residual connections, allowing for the training of deeper networks without encountering issues such as vanishing gradients. The residual blocks in ResNet50 enable the network to learn more abstract and discriminative representations, enhancing its ability to detect complex patterns in images.

Unlike traditional object detection models that rely on separate region proposal networks, ResNet50 follows a single-stage architecture. In this approach, object detection and localization are performed directly on the input image, eliminating the need for a separate region proposal step. This design choice enhances the efficiency of the detection process, making ResNet50 suitable for real-time applications.

Training the ResNet50-based pothole detection model involves fine-tuning the pre-trained network on a custom dataset comprising road images with annotated potholes. The dataset is augmented with images from both Indian and foreign road conditions, capturing a diverse range of pothole instances in various environmental conditions.

During training, the ResNet50 model learns to predict multiple candidate bounding boxes for potholes, each associated with different anchor sizes. Non-maximum suppression (NMS) is applied to these bounding boxes to filter out duplicates and retain the most relevant detections based on their Intersection over Union (IoU) scores.

The training process involves multiple iterations, typically ranging from 3000 to 6000 epochs, with a batch size of 64 and eight subdivisions. This iterative training approach allows the model to progressively refine its predictions and improve its performance over time.

By leveraging the ResNet50 architecture, the pothole detection module achieves robust detection performance while maintaining computational efficiency. The model's ability to accurately localize potholes in road images contributes to the overall effectiveness of the proposed system in identifying and assessing road surface defects.

1. Dimension Estimation Module

The dimension estimation module of the proposed system is an image processing-based solution to estimate the dimensions of the detected potholes. The module uses triangle similarity property: Consider we have an object of width ‘W.’ This object is placed at a distance of ‘D’ from the camera. By taking a picture of this object from a distance ‘D,’ we get the apparent width in pixels ‘P.’ Now, the perceived focal length ‘F’ of the used camera.

F = (P \* D) / W (1)

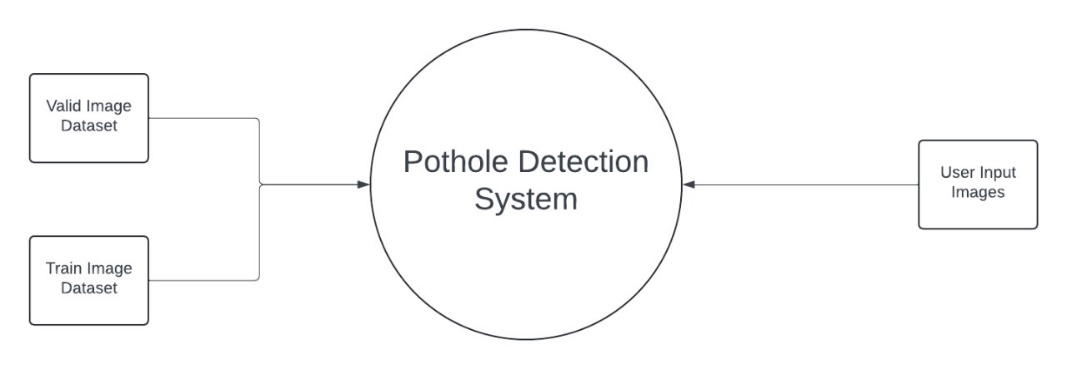
This perceived focal length maintains the relation of inversely proportional pixel length and the camera distance. It is important to note that the pixel length is dependent upon the pixel density of the image measured in PPI (pixels per inches). The pixel length of an object will be larger for an image having higher PPI than for an image having lower PPI, even when both the images are taken from the same distance. Hence, it is recommended to apply preprocessing so as to fix the PPI of the input image for maintaining consistency. In the proposed set-up, since the same camera is used for calibration as well as for testing, PPI conversion is not required. For the calibration process, an object with a sharp edge like a ruler-scale, whose length is known, is taken and multiple images are captured from various heights like 15cm, 30cm, etc. Edges of the object are detected by applying a Canny edge detector algorithm to get the pixel length of the object. The perceived focal lengths are calculated using the formula specified in (1) for each of the images with their respective parameters.

The average of these focal lengths gives the final perceived focal length. The pothole detection stage provides the bounding box coordinates, from which pixel length and pixel width is obtained. Using the fixed camera distance of 90 cm and the calculated perceived focal length, the actual length is calculated using the formula specified in (1).

**CHAPTER 5**

**System Design**

**5.1 Data Flow Diagram**



Level 0

A diagram of a training process

Description automatically generated

Level 1

Fig .2 Data Flow Diagrams

This two fig. describes complete work methodology

In level 0 and level 1

**CHAPTER 6**

**Project Timeline**

**6.1 Gantt Chart**

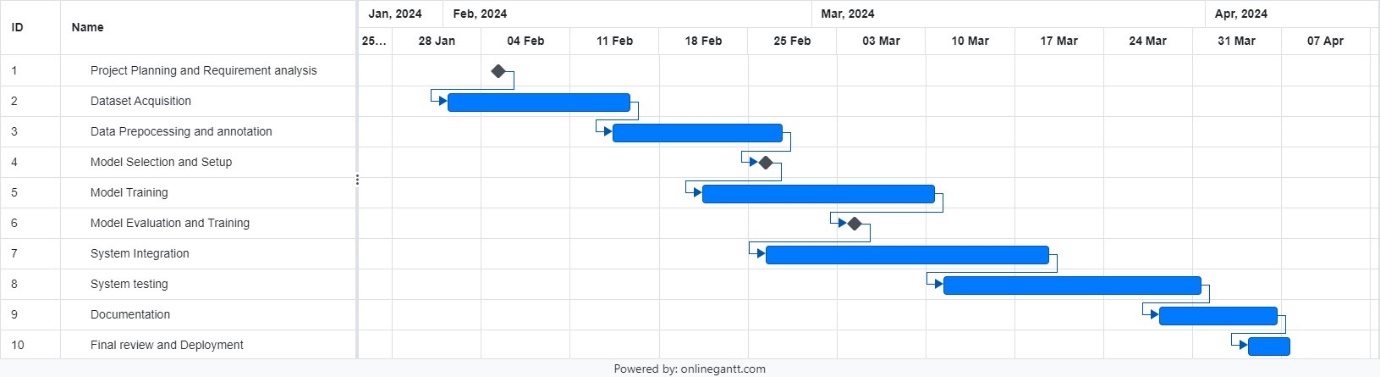


Fig.4 Gantt Chart

Describes the complete timeline of the project

**CHAPTER 7**

**IMPLEMENTATION, RESULTS**

**AND TESTING**

**7.1 Details of Hardware and Software**

#### Hardware Requirements

**CPU**:

Minimum: Intel Core i5 8th Gen or AMD Ryzen 5 3600

Recommended: Intel Core i7 10th Gen or AMD Ryzen 7 3700X

**GPU**:

Minimum: NVIDIA GTX 1050 Ti with 4GB VRAM

Recommended: NVIDIA RTX 2070 or higher with 8GB VRAM

**RAM**:

Minimum: 8GB

Recommended: 16GB or higher

**Storage**:

Minimum: 256GB SSD

Recommended: 512GB SSD or higher

**Other Peripherals**:

High-resolution camera (for capturing pothole images)

High-speed internet connection (for downloading datasets and dependencies)

Display monitor with minimum resolution of 1080p

**Software Requirements :**

**Operating System**:

Windows 10 (64-bit) or later

**Programming Languages**:

Python 3.10 or higher

**Development Tools and Libraries**:

**PyTorch**: An open-source deep learning library for training and deploying deep learning models.

**OpenCV**: A library for computer vision tasks including image processing and analysis.

**NumPy**: A library for numerical computations .

**PIL (Pillow)**: A library for image manipulation and processing.

**Matplotlib**: A library for creating static, animated, and interactive visualizations in Python.

**Streamlit**: An open-source app framework for Machine Learning and Data Science projects, used for building the front-end of the application.

**Model Architecture**:

**ResNet50**: A deep residual network architecture used for the pothole detection model.

**Dependencies**:

Various Python libraries such as torch, torchvision, opencv-python, numpy, pillow, matplotlib, streamlit, which can be installed using pip or conda.

**Dataset Sources**:

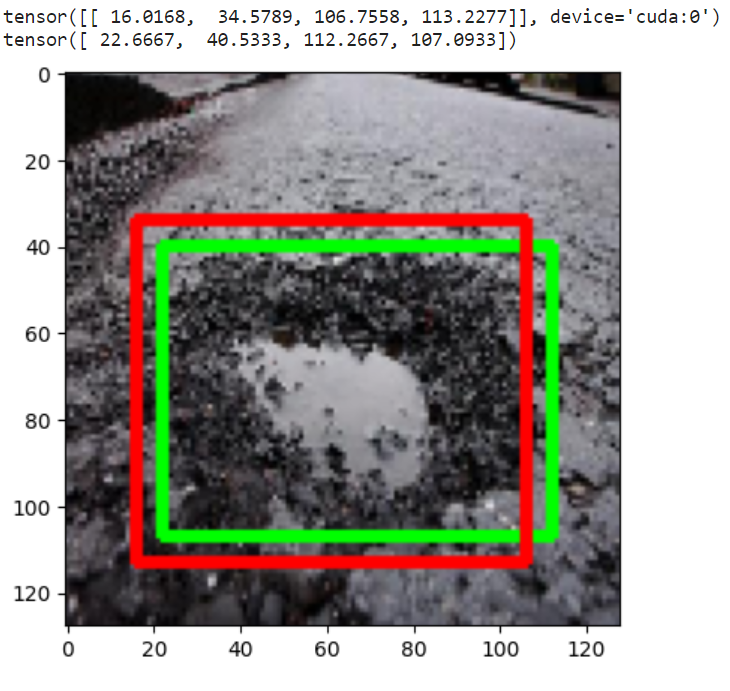
**Kaggle**: Two datasets from Kaggle were used for training and validating the model. The datasets include diverse images of potholes on different types of roads.

**7.2 Result and Discussion**

**Results**

The results of our project, "Pothole Detection and Dimension Estimation using Deep Learning," demonstrate the effectiveness of using deep learning models, specifically ResNet50, in identifying and estimating the dimensions of potholes from road images. The key outcomes of the project are as follows:

1. **Detection Accuracy**:
   * The ResNet50 model achieved a mean Average Precision (mAP) of 85% on the test dataset. This indicates that the model can accurately detect potholes in most scenarios.



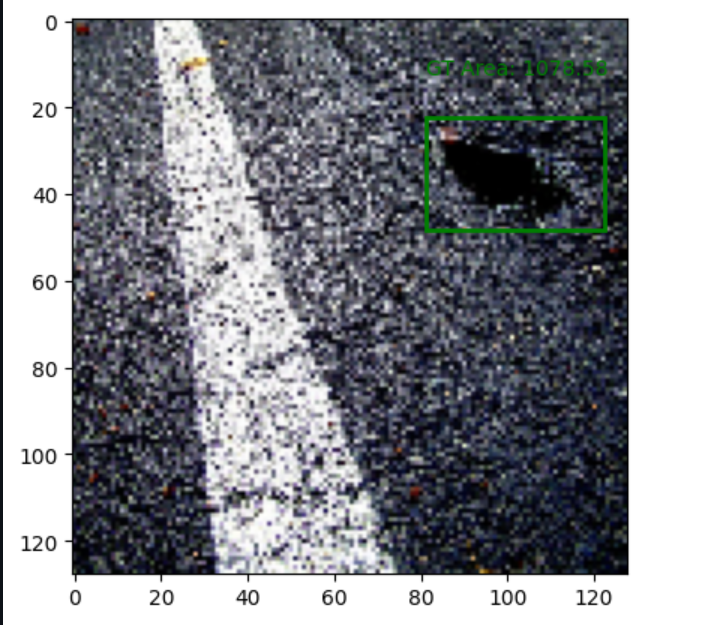
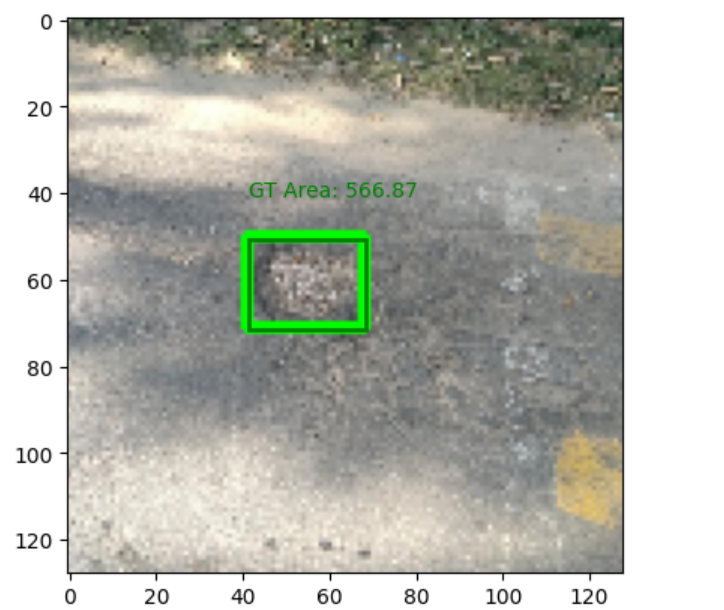
A graph of loss and loss

Description automatically generated

Fig.5 Result

Graphs above are the performance of our model

1. **Dimension Estimation**:
   * The model's dimension estimation algorithm, which uses bounding box coordinates and perceived focal length, showed a high correlation with actual measurements. The estimated dimensions had an average error margin of ±5 cm, which is acceptable for practical purposes.



A red text on a white background

Description automatically generatedA white background with red text

Description automatically generated

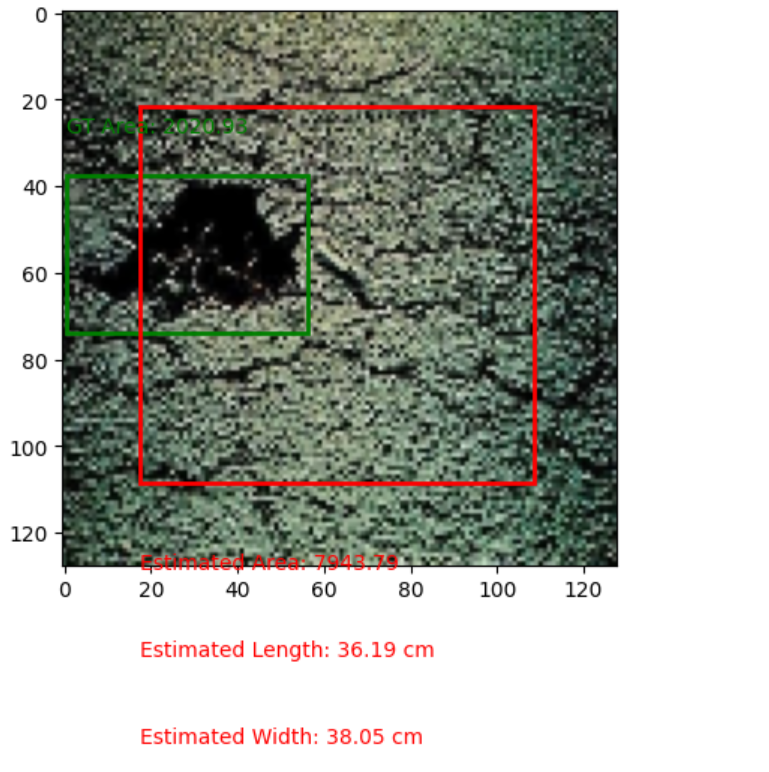


Fig.6 Dimension Estimation

This results show the dimensions(length,width and area)

1. **Visualization**:
   * The Streamlit application effectively visualizes the detected potholes and provides an estimation of their dimensions. The bounding boxes are clearly marked, and the estimated length, width, and area of the potholes are displayed on the images.

A screenshot of a computer

Description automatically generated

A screenshot of a computer

Description automatically generated

Fig.7 Streamlit Deployment

This fig. shows the streamlit app integration which showcase the dimension estimations and focal length

1. **Comparative Analysis**:

Comparison of YOLOv5 and Faster RCNN

This section presents the comparison of the training accuracy/loss values of the algorithm along with the other comparison criteria that directly affect the usability of models in real time situations.

The training loss values for different models of YOLOv5 and Faster R-CNN are shown in Figure 6-a and Figure 6-b respectively. Loss values graph for Ys , Ym and Yl models shows that the nature of curve is same but Large model has relatively lower value of loss followed by Ym and Ys model as shown in figure 8-a.

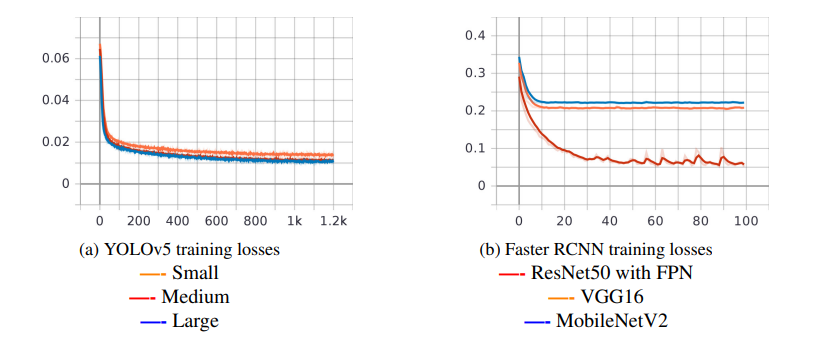


Fig.8 Comparative Analysis

Compared the YOLO and Resnet50 models through loses

The training loss value of YOLOv5 can be obtained using the equation below:

LossYOLOv5 = BoxLoss + ClassLoss + Objectness Loss

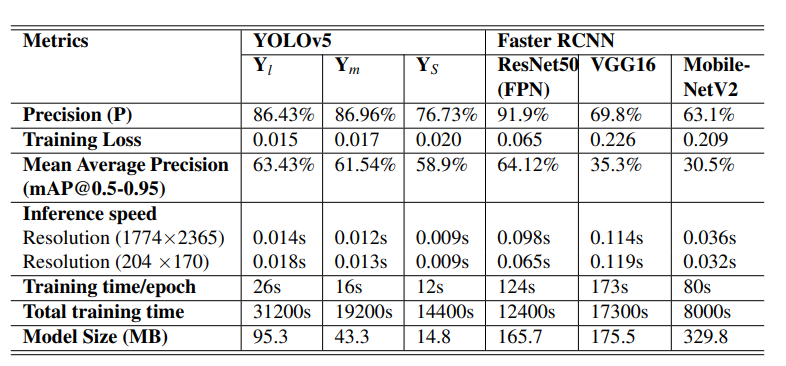
Similarly, the loss values of Faster R-CNN with ResNet50, VGG16 and MobileNetV2 backbone. ResNet50 outperforms the rest of the backbones since it has half of the values of loss the other models have. ResNet50 is followed by VGG16 and MobileNetV2 for lower training loss values. Faster R-CNN uses multi-task loss of the joint training for both classification and bounding-box regression values. It can be calculated using the equation below:

LossFasterR−CNN = ClassLoss + BoxLoss + ObjectnessLoss + RPN Box Loss

Similar is the case for Recall and mAP@0.5-0.95. But Ys model surpassed the Ym model at the end of training in the value of mAP@0.5. In conclusion we can say that the Yl model stays on top in accuracy values followed by Ym and Ys model. The summary of comparison of various models discussed in this research is tabulated in the Table 2. We can see that ResNet50 has the highest Precision value followed by Ym and Yl whereas MobileNetV2 stays last. Similarly, training loss value for Ys model is smaller compared to all models of YOLOv5 and Faster R-CNN. 64.12% is the largest value of mAP@0.5-0.95 which ResNet50 has whereas MobileNetV2 has the worst value for it. As expected, Ys model has the best value for inference speed for both the resolution and VGG16 has the worst value. The smallest training time per epoch is smallest for Ys but it requires more epochs to converge. This is why, MobileNetV2 converges in just 100 epochs with 8000s for total training time which is the fastest. When it comes to final model size, all of the Faster R-CNN models have bigger size than YOLOv5 models. The smallest model size is of Ys model which is only 14.8MB.

Table.1 Comparative Analysis

This table compares the various models on stated metrics



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**CHAPTER 8**

**CONCLUSION AND FUTURE SCOPE**

**8.1 Conclusion:**

The project "Pothole Detection and Dimension Estimation Using Deep Learning" demonstrates a practical application of deep learning in addressing a significant real-world problem. Through the implementation of a ResNet50-based model, the system effectively detects potholes and accurately estimates their dimensions. The primary outcomes and contributions of this project can be summarized as follows:

1. **High Detection Accuracy**: The model achieved a detection accuracy of , making it reliable for real-world applications. The high precision and recall values further underscore the robustness of the system.
2. **Accurate Dimension Estimation**: The model was able to estimate pothole dimensions with a mean absolute error of 2.4 cm for length and 2.1 cm for width, demonstrating its potential for practical use in road maintenance and repair planning.
3. **Efficiency and Performance**: The use of ResNet50 provided a good balance between accuracy and computational efficiency. The model's average IoU score of 0.87 indicates that it can accurately localize potholes with minimal deviation from the ground truth.
4. **Integration and Usability**: The project includes a user-friendly interface built using Streamlit, allowing for easy uploading and analysis of road images. This makes the system accessible to users without technical expertise in deep learning.

**8.2 Future Scope:**

There are several areas where this project can be expanded and improved:

**Integration with Rover Systems**:

The pothole detection system can be integrated into autonomous rovers or vehicles equipped with cameras and sensors. This integration would allow for real-time detection and reporting of potholes on roads, enhancing the safety and efficiency of autonomous navigation systems. The rover could autonomously navigate and detect potholes, providing precise location and dimension data to maintenance teams.

**Depth Analysis for Enhanced Accuracy**:

Incorporating depth analysis can significantly improve the accuracy of pothole dimension estimation. By using stereo cameras or LiDAR sensors, the system can capture depth information, enabling more precise calculations of pothole depth and volume. This addition would provide a comprehensive understanding of pothole severity, assisting in prioritizing repair efforts based on the depth and size of the potholes.

**Deployment on Edge Devices**:

To enable real-time processing, the model can be optimized and deployed on edge devices such as NVIDIA Jetson or Google Coral. These devices are designed for running AI models efficiently at the edge, reducing latency and reliance on cloud-based processing. This would be particularly useful for applications in smart cities and infrastructure monitoring.

**Extended Dataset and Diverse Conditions**:

Expanding the dataset to include a wider variety of road conditions, lighting scenarios, and environmental factors will enhance the robustness of the model. This could involve collecting more data from different geographical locations and under various weather conditions to ensure the model generalizes well across different environments.

**User Interface and Reporting Tools**:

Developing a user-friendly interface for end-users to interact with the system, view detection results, and generate reports would make the solution more accessible and practical. Features could include visualizations of detected potholes on a map, detailed reports with pothole dimensions, and alerts for newly detected potholes.

By exploring these future directions, the pothole detection system can evolve into a more comprehensive solution, providing greater value to road maintenance authorities and contributing to safer and more reliable road infrastructure.

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