SIDDAGANGA INSTITUTE OF TECHNOLOGY, TUMAKURU-572103

(An Autonomous Institute under Visvesvaraya Technological University, Belagavi)

Project Report on

"Computer Vision-based Speed Bump and Pothole Detection System for Vehicles"

submitted in partial fulfillment of the requirement for the completion of VI semester of

BACHELOR OF ENGINEERING

in

ELECTRONICS & COMMUNICATION ENGINEERING

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DEPARTMENT OF ELECTRONICS & COMMUNICATION ENGINEERING

2023-24

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DEPARTMENT OF ELECTRONICS & COMMUNICATION ENGINEERING

CERTIFICATE

Certified that the mini project work entitled "COMPUTER VISION-BASED SPEED BUMP AND POTHOLE DETECTION SYSTEM FOR VEHICLES" is a bonafide work carried out by Ansh Singhal (1SI21EC007), Suraj Aribenchi (1SI21EC008), Aryan Kumar (1SI21EC010) and Jaya Chandak (1SI21EC045) in partial fulfillment for the completion of VI Semester of Bachelor of Engineering in Electronics & Communication Engineering from Siddaganga Institute of Technology, an autonomous institute under Visvesvaraya Technological University, Belagavi during the academic year 2023-24. It is certified that all corrections/suggestions indicated for internal assessment have been incorporated in the report deposited in the department library. The Mini project report has been approved as it satisfies the academic requirements in respect of project work prescribed for the Bachelor of Engineering degree.

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Course Outcomes

CO1: To identify a problem through literature survey and knowledge of contemporary engineering technology.
CO2: To consolidate the literature search to identify issues/gaps and formulate the engineering problem
CO3: To prepare project schedule for the identified design methodology and engage in budget analysis, and share responsibility for every member in the team
CO4: To provide sustainable engineering solution considering health, safety, legal, cultural issues and also demonstrate concern for environment
CO5: To identify and apply the mathematical concepts, science concepts, engineering and management concepts necessary to implement the identified engineering problem
CO6: To select the engineering tools/components required to implement the proposed solution for the identified engineering problem
CO7: To analyze, design, and implement optimal design solution, interpret results of experiments and draw valid conclusion
CO8: To demonstrate effective written communication through the project report, the one-page poster presentation, and preparation of the video about the project and the four page IEEE/Springer/ paper format of the work
CO9: To engage in effective oral communication through power point presentation and demonstration of the project work
CO10:To demonstrate compliance to the prescribed standards/ safety norms and abide by the norms of professional ethics
CO11: To perform in the team, contribute to the team and mentor/lead the team

Attainment level: - 1: Slight (low) 2: Moderate (medium) 3: Substantial (high)
POs: PO1: Engineering Knowledge, PO2: Problem analysis, PO3: Design/Development of solutions, PO4: Conduct investigations of complex problems, PO5: Modern tool usage, PO6: Engineer and society, PO7: Environment and sustainability, PO8: Ethics, PO9: Individual and team work, PO10: Communication, PO11: Project management and finance, PO12: Lifelong learning

CO-PO Mapping

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2
CO-1												3		3
CO-2		3											3	
CO-3											3			3
CO-4						3	3							3
CO-5	3	3											3	
CO-6					3									3
CO-7			3	3									3	
CO-8										3				3
CO-9										3				3
CO-10								3						3
CO-11									3					3

Abstract

Road surface irregularities, such as bumps and potholes, are significant concerns for transportation infrastructure. A bump in the road is characterized by a raised area on the pavement surface while potholes are localized disruptions that form cavity within the roadway. The traditional sensor-based methods typically employed devices such as accelerometers and gyroscopes. However, these methods often suffer from limitations such as early detection, accuracy, limited sensing range, and susceptibility to environmental interference. In contrast, computer vision-based methods use high-resolution cameras and machine learning algorithms to automatically detect and classify road anomalies with greater accuracy and efficiency. This approach enables early detection, real-time monitoring and timely maintenance thus improving road safety.

The system for detecting speed bumps and potholes uses a high-resolution web camera for detailed road data and Roboflow for data management and segmentation. The Raspberry Pi handles real-time processing, running YOLO V8 for accurate detection in video streams. OpenCV enhances image preprocessing, and a buzzer provides audible alerts for timely driver response. This setup ensures compact, efficient road anomaly detection and notification.

For implementing the project, Raspberry Pi 4B, webcam for capturing road data, and a buzzer for alerting driver are used. The software includes RoboFlow for dataset management, Google Collaboratory for cloud-based model training, Thonny for Python programming on the Raspberry Pi, and VNC for remote desktop access.

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Chapter 1

Introduction

In modern urban and rural road infrastructure, the detection and monitoring of road anomalies such as speed bumps and potholes play a crucial role in ensuring road safety and infrastructure maintenance. Speed bumps are raised pavement structures designed to slow down vehicles at specific locations, while potholes are depressions or holes in the road surface that can pose hazards to vehicles and pedestrians alike. Detecting these anomalies accurately and efficiently is essential to mitigate associated risks and ensure timely maintenance.

Potholes as shown in Fig 1.1 are localized disruptions or depressions in the road surface, typically caused by weathering, traffic wear, or poor maintenance. They can vary in size and depth, posing risks to vehicles by potentially causing tire damage, vehicle instability, and accidents.

Figure 1.1: Potholes of various sizes [11]

Speed bumps, also known as speed humps are referred in Fig 1.2 or traffic calming devices, are raised structures placed across roadways to reduce vehicle speed. They are designed to improve safety in areas where speeding poses risks to pedestrians or where traffic needs to be slowed down.

Figure 1.2: Speed Bump [12]

Detecting and addressing road irregularities like potholes and speed bumps are crucial due to the following reasons:

- Safety Risks: Both potholes and speed bumps can pose safety risks to vehicles, cyclists, and pedestrians if not detected and managed promptly.
- Infrastructure Damage: Potholes can cause significant damage to vehicles, including tire punctures, wheel damage, and suspension issues, leading to increased maintenance costs.
- Traffic Disruption: Speed bumps can disrupt smooth traffic flow, potentially causing congestion and delays, particularly in high-traffic areas or emergency situations.

Historically, the detection of potholes and speed bumps relied on manual inspection and reporting, which are time-consuming and prone to human error. The traditional methods were sensor based like use of accelerometers, gyroscopes,etc . However, these methods often suffer from limitations such as accuracy, limited sensing range, and susceptibility to environmental interference.

Hence the computer vision and image processing based techniques acquired fame due to the accessibility of cameras which are inexpensive and feasible, and have been proved to be the replacement of old fashioned manual inspection methods for pothole detection. The primary objective of this project is to develop a robust and efficient system for detecting road irregularities using computer vision. By harnessing the power of image processing and analysis, the system aims to overcome the limitations associated with traditional sensor-based methods.

1.1 Motivation

The primary motivation of this project is to enhance road safety by detecting speed bumps and potholes in real-time, reducing accidents and vehicle damage. It aims to improve driver and passenger comfort by allowing vehicles to adjust speed and suspension. The system also supports proactive infrastructure maintenance by providing valuable road condition data to authorities, promoting efficient driving practices and environmental conservation. Integration into smart city initiatives can optimize traffic flow and urban planning. Its adaptability ensures global applicability, benefiting both developed and developing regions.

1.2 Objective of the project

The primary objectives of the project are:

1.To develop a system for early detection of potholes and speed bumps, using deep learning technique.

2.To implement potholes and bump detection system using Raspberry pi to provide prior alert to the driver.

1.3 Organisation of the report

The report is divided into 7 chapters. Chapter 2 shows the literature survey of the papers taken as reference. Chapter 3 consists of the system overview. In Chapter 4, In Chapter 5, hardware and software descriptions are mentions respectively. Results are described in Chapter 6. Chapter 7 draws conclusions on the result followed by the future work possible in this direction.

Chapter 2

Literature Survey

"Detection of Speed Humps and Bumps Using Deep Learning" presents a novel approach to identifying both marked and unmarked speed humps and bumps on roads by leveraging deep learning techniques. The study addresses the limitations of previous methods, which relied on accelerometer data or basic image processing techniques that struggled with unmarked bumps. The researchers collected a dataset of around 3000 images in various conditions and used the SSD Mobilenet v1 model for object detection due to its balance of speed and accuracy. The model was trained and tested using the TensorFlow framework, and real-time testing was conducted with an Android smartphone to validate its effectiveness. The proposed method shows significant improvements in detection accuracy and real-time applicability, potentially enhancing road safety by providing timely alerts to drivers about upcoming speed humps and bumps [1].

The study on enhancing the safety of autonomous vehicles through the detection of road damage using a combination of OpenCV image processing and Convolutional Neural Networks (CNN) [2]. The research highlights the importance of identifying static obstacles like poor road conditions, which pose significant risks. By training a CNN model with 350 images (280 for training and 70 for testing), the implementation involves data augmentation techniques such as random flips and histogram equalization to enhance image quality and training effectiveness. The results demonstrate that integrating such technologies can substantially improve the detection and management of road damage, thereby enhancing the overall safety of autonomous vehicle operations.

The system in [3] addresses the challenges of detecting unmarked speed bumps, particularly on roads without clear markings. The process starts with converting RGB images to grayscale and applying a Gaussian filter to reduce noise. Canny edge detection is used to identify edges, aiding in locating speed bumps despite their color blending with the road. The primary goal is to develop a detection system using Gaussian filtering and

Hough Transform methods. Hardware approaches like sensors and GPS face difficulties with low-height bumps and require extensive data collection. Video analysis involves fragmenting footage into frames, resizing images to reduce computational load, and applying edge detection techniques. Canny edge detection is favored for its precision, and the Hough Transform helps detect lines and shapes, addressing noisy edge points. Classifying speed bumps based on thickness further improves detection accuracy. Despite the challenges, these combined techniques provide a robust solution for identifying unmarked speed bumps.

The research article “Automated Detection and Classification of Pavement Distresses using 3D Pavement Surface Images and Deep Learning” by Rohit Ghosh and Omar Smadi [4] explores the application of deep learning techniques to enhance the detection and classification of pavement distresses from high-resolution 3D images. Utilizing two advanced models, Faster R-CNN and YOLO v3, the study analyzes images of asphalt and concrete pavements to achieve high accuracy and precision in identifying road defects. The dataset includes 625 annotated distress images and 798 no-distress images, with data augmentation to ensure balanced class representation. The results show that both models achieved significant accuracy, with YOLO slightly outperforming Faster R-CNN. The research highlights the potential of these methods to replace traditional manual QA/QC processes, improving the efficiency of infrastructure maintenance. This study marks a significant step forward in using deep learning for automated pavement distress detection, suggesting substantial benefits for future infrastructure management practices.

The proposed system in [5] has vision-based methods offer cost-effective, real-time pothole and speed hump detection using image and video analysis. They bypass limitations of vibration-based and 3D reconstruction approaches, providing efficient detection without expensive equipment. Combining low-cost hardware like ODROID-XU4 and LIDAR Lite v1 with robust image processing enhances road safety and enables proactive maintenance. However, these methods may struggle with weather and lighting, affecting accuracy. Integration complexities require specialized expertise, increasing maintenance overheads. Reliance on single-camera depth perception and LIDAR can lead to occasional errors, necessitating continuous refinement for reliable performance. Despite these challenges, they significantly advance autonomous vehicle technology.

The method in [6] provides advanced detection technologies for speed breakers enhance road safety and traffic flow. Real-time methods like 3D reconstruction, vibration-based detection, and computer vision provide timely warnings, reducing accidents, especially in low visibility. LiDAR systems offer high-resolution data for accurate road feature detection, while smartphone-based vibration detection is cost-effective. Decision trees and genetic algorithms offer effective detection, and Neural Networks (NNs), especially Convolutional Neural Networks (CNNs), achieve high accuracy. Vision-based methods using cameras provide real-time alerts. However, these technologies can be costly, complex, and computationally intensive, but they significantly improve road safety and traffic management.

The pothole detection method was developed using wavelet energy and morphological processing, achieving 88.6% accuracy through segmentation with a Markov random field model. Arbawa et al. [7] employed a GLCM feature extractor and SVM classifier, analyzing contrast, correlation, and dissimilarity, resulting in 92% accuracy. Convolutional neural networks was employed particularly on optimized prepooling CNN trained on 96,000 images which achieved 98.95% precision, addressing issues like camera angle and lighting. The YOLO algorithm, divides images into NXN grid cells, excels in multi-object detection, classification, and localization in one step. YOLOv5, developed by Ultralytics in PyTorch, is noted for its lightweight and speedy performance. YOLO's training utilizes fast, open-source neural network frameworks like PyTorch and TensorFlow with wide range of tools and libraries. Considering all the factors YOLO models are best employed for training purposes.

The system comprises computer vision technologies like YOLO and Mask-R-CNN enable cost-effective, real-time pothole detection, enhancing road safety by providing timely maintenance insights and reducing accidents. AI-driven CNN algorithms improve decision-making with swift, accurate analyses across sectors. Video recognition and deep learning cover large areas quickly, identifying potholes through visual cues. However, detection accuracy can be hindered by light conditions and image quality. YOLO, while fast, may be less accurate than Mask-R-CNN. These methods require significant computational power and are sensitive to environmental factors. Preprocessing can remove critical details, and continual parameter refinement is necessary. [8]

"Detection of Potholes and Speed Breaker for Autonomous Vehicles" [9] presents a method for identifying road anomalies using the YOLOv5 deep learning model, enhancing the safety and performance of autonomous vehicles. The study focuses on challenges posed by poor road conditions, such as potholes from heavy rainfall and improperly marked speed breakers, which can cause vehicle damage and accidents. Researchers collected and annotated real-time data from various Indian roads to create a comprehensive dataset. This dataset trained the YOLOv5 model, chosen for its high accuracy and efficiency in object detection. The model demonstrated impressive accuracy in detecting potholes and speed breakers. Integrating this detection system in autonomous vehicles can significantly enhance safety by providing timely alerts for immediate responses to road hazards. The paper also suggests incorporating additional sensors in climate-vulnerable regions to improve vehicle suspension systems and other components.

The system in [10] compares the performance of SSD-TensorFlow, YOLOv3, and YOLOv4 for pothole detection, noting that while SSD-TensorFlow had lower precision and recall, YOLOv3 and YOLOv4 achieved high precision, recall, and mean average precision (mAP), with YOLOv4 being particularly efficient for real-time applications. The study plans to expand its dataset to over 2000 images, including various road conditions and severities, and aims to integrate manhole detection into the system for improved accuracy. Future work involves deploying the system in multiple vehicles for real-time road condition analysis with GPS integration for maintenance coordination.

2.1 Summary of Literature Survey

The summary of the literature survey has been mentioned below:

- YOLOv8 is utilized for high-accuracy detection of road anomalies and suggests the integration of additional sensors to enhance detection capabilities in climate-vulnerable regions.
- Computer vision technologies like YOLO and CNN offer cost-effective, real-time pothole detection, enhancing road safety through AI-driven algorithms.

Chapter 3

System Overview

This chapter explores the development of a system using computer vision techniques to detect speed bumps and potholes in vehicle-captured videos. The system employs a YOLO V8 model trained for this purpose, with Roboflow used for data annotation and segmentation, and OpenCV for image preprocessing. Road imaging is the initial step, typically using web cameras for visual data acquisition. OpenCV helps optimize image size and performance, aiding accurate detection. Roboflow manages and optimizes datasets, offering annotation tools and compatibility with machine learning frameworks like YOLO. YOLO V8 excels in speed and accuracy, making it suitable for real-time detection in video streams. The system is deployed on a Raspberry Pi, enabling real-time hazard detection and immediate driver feedback via a buzzer, enhancing driving safety. The system overiew has been displayed in Fig 3.1 and explanation of each block is given.

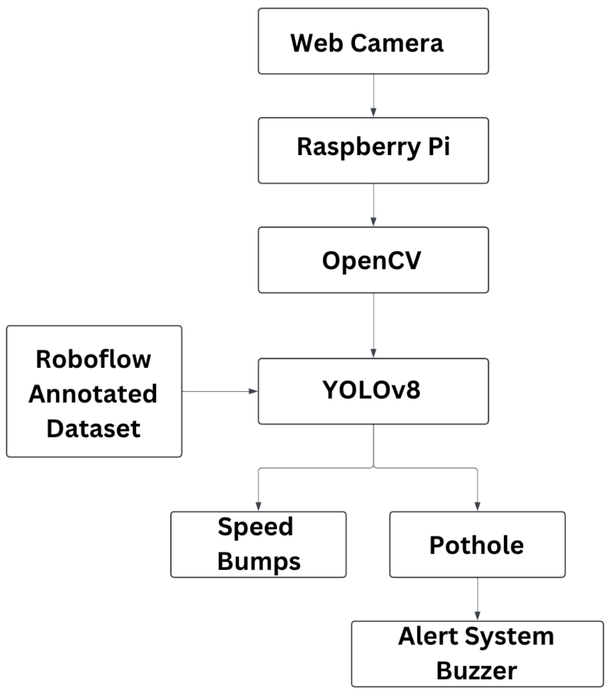


Figure 3.1: Block Diagram of Speed Bumps and Potholes Detection System

- **Web Camera:** The web camera captures real-time video footage of the road ahead, serving as the primary input source for the detection system. It continuously streams visual data, which is essential for identifying speed bumps and potholes. The quality and frame rate of the video captured by the web camera significantly influence the system's detection accuracy and responsiveness. High-resolution, fast frame rate video ensures more detailed and frequent data for analysis, improving the reliability of hazard detection.

- **Raspberry Pi:** The Raspberry Pi is a small, cost-effective computing platform used to process the video feed from the web camera. It runs the necessary software and machine learning models, specifically YOLO V8, to detect speed bumps and potholes in real-time. Its compact size allows for easy integration into a vehicle, and its processing capabilities are sufficient to handle the computational demands of running object detection algorithms, making it ideal for this application.

- **OpenCV:** OpenCV is employed for two main purposes: adjusting the resolution of video frames and drawing bounding boxes around detected objects. Resolution adjustment involves resizing images to a balance between processing speed and detection accuracy, optimizing computational efficiency. After the YOLO V8 model detects objects, OpenCV draws bounding boxes around identified speed bumps and potholes, providing a visual representation of detection results. This step enhances interpretability and helps validate the model's performance.

- **Roboflow Annotated Dataset:** Roboflow is utilized for annotating and managing the dataset used to train the YOLO V8 model. This dataset includes labeled images of speed bumps and potholes, which are crucial for teaching the model to recognize these features accurately. Roboflow offers tools for efficient data labeling, augmentation, and exporting datasets in formats compatible with various machine learning frameworks. Accurate annotations are vital for the model's training process, directly impacting detection accuracy.

- **YOLOv8:** YOLO (You Only Look Once) V8 is an advanced object detection model known for its speed and accuracy. It processes preprocessed video frames to identify speed bumps and potholes. The model operates in real-time, making it suitable for applications where immediate hazard detection is necessary. YOLO V8 detects objects in a single pass through the network, which allows for quick and efficient processing of video streams, ensuring timely detection of road hazards.

- **Alert System Buzzer:** The alert system buzzer is triggered when the system detects speed potholes, providing immediate auditory feedback to the driver. This real-time alert helps the driver take necessary actions to navigate safely, enhancing road safety by preventing accidents and vehicle damage. The buzzer ensures the driver is constantly aware of upcoming hazards, allowing for proactive driving adjustments and improving overall driving safety.

The speed bump and pothole detection system begins with a web camera capturing real-time video of the road ahead. This video feed serves as the primary input, providing continuous visual data essential for detecting road hazards. The web camera's quality and frame rate directly impact the system's detection accuracy and responsiveness, with higher resolutions and faster frame rates offering more detailed and frequent data for analysis.

The captured video feed is sent to a Raspberry Pi, a compact and cost-effective computing platform capable of processing the video in real-time. The Raspberry Pi utilizes OpenCV for two main purposes: adjusting the resolution of video frames to balance processing speed and detection accuracy, and drawing bounding boxes around detected objects. OpenCV's preprocessing capabilities help optimize image size and performance, enhancing the detection process. The video frames are then analyzed by the YOLO V8 model, a state-of-the-art object detection algorithm known for its speed and accuracy. The model, trained on a Roboflow-annotated dataset of speed bumps and potholes, processes each frame and identifies these hazards, outputting the coordinates of the bounding boxes.

After the YOLO V8 model identifies speed bumps and potholes, OpenCV uses the coordinates to draw bounding boxes around these objects in video frames. This visual annotation validates the model's performance and provides clear feedback. The system differentiates between speed bumps and potholes, triggering appropriate responses. A buzzer alert system provides immediate auditory feedback to the driver upon detection, ensuring timely awareness and enhancing road safety by preventing accidents and vehicle damage.

Chapter 4

System Hardware

This chapter offers a detailed insight into the hardware components, their functionalities, and their collaborative role in detecting potholes and speed bumps using Open CV.

4.1 Raspberry Pi 4B

The Raspberry Pi 4B as referred in Fig 4.1 is a minicomputer the size of a credit card that is interoperable with any input and output hardware device like a monitor, a television, a mouse, or a keyboard – effectively converting the set-up into a full-fledged PC at a low cost. It is used in pothole and hump detection systems by capturing and processing real-time road surface images with computer vision libraries like OpenCV . Mounted on vehicles or drones, it performs edge computing to enable immediate detection and alerts. Upon detecting road anomalies, it triggers alerts via buzzers, LEDs, or notifications to drivers and central servers. Additionally, it runs and updates pre-trained machine learning models for precise classification and detection of road anomalies, making it a versatile and cost-effective solution for road safety.

Specifications:

- Processor: Broadcom BCM2711, quad-core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz
- Memory: 1GB, 2GB or 4GB LPDDR4 (depending on model)
- Connectivity: 2.4 GHz and 5.0 GHz IEEE 802.11b/g/n/ac wireless LAN, Bluetooth 5.0, BLE Gigabit Ethernet 2 × USB 3.0 ports 2 × USB 2.0 ports.
- GPIO: Standard 40-pin GPIO header (fully backwards-compatible with previous boards)
- Video & sound: 2 × micro HDMI ports (up to 4Kp60 supported) 2-lane MIPI DSI display port 2-lane MIPI CSI camera port 4-pole stereo audio and video port

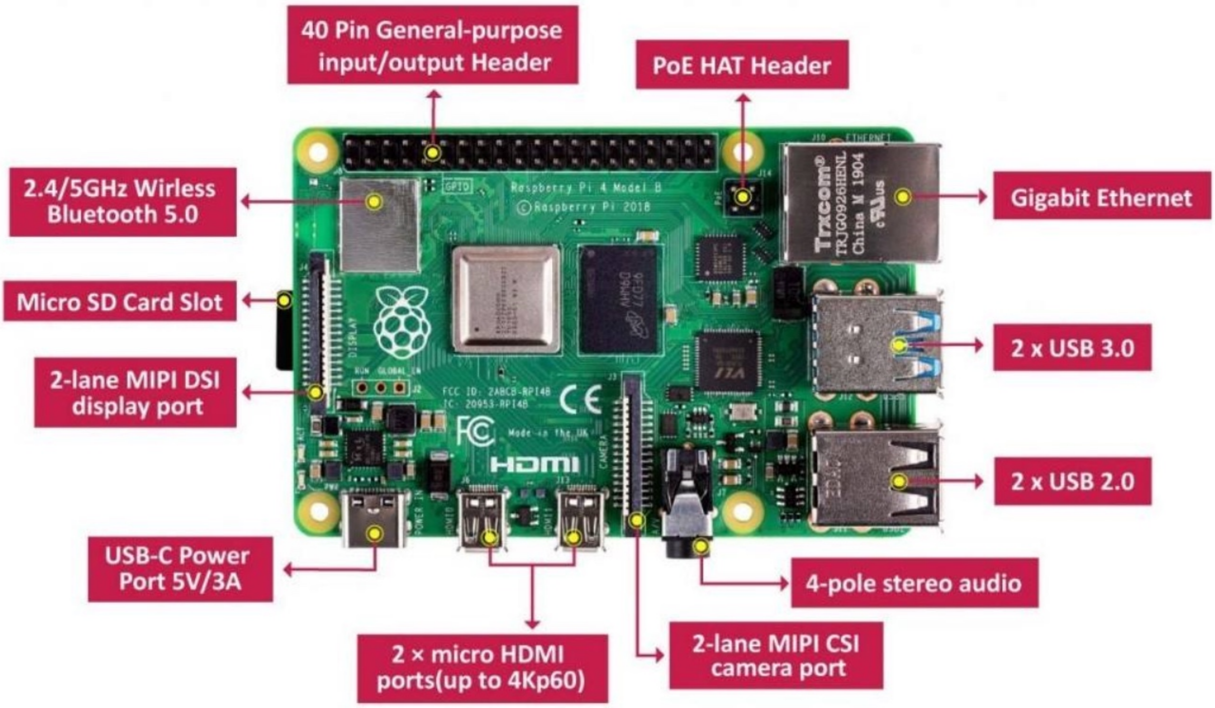


Figure 4.1: Pin Details of Raspberry Pi 4B [13]

- Multimedia: H.265 (4Kp60 decode); H.264 (1080p60 decode, 1080p30 encode); OpenGL ES, 3.0 graphics
- SD card support: Micro SD card slot for loading operating system and data storage
- Input power: 5V DC via USB-C connector (minimum 3A1) 5V DC via GPIO header (minimum 3A1) Power over Ethernet (PoE)–enabled (requires separate PoE HAT)
- Environment: Operating temperature 0–50ºC

4.2 Webcam

Webcams as shown in Fig 4.2 can be an effective and low-cost tool for detecting potholes and speed bumps on roads. By leveraging computer vision and image processing techniques, webcams can continuously monitor road conditions and identify irregularities in real-time.

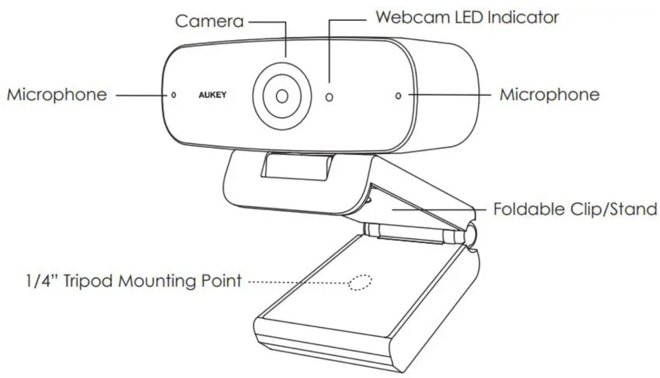


Figure 4.2: Pin Details of Webcam [14]

4.3 Buzzer

In the context of pothole and hump detection using computer vision, a buzzer as referred in Fig 4.3 serves as an audible alert mechanism integrated into a larger detection system. This system typically includes cameras, sensors, and advanced image processing algorithms. The camera captures real-time images or video of the road surface, while computer vision techniques analyze the data to identify anomalies such as potholes and speed humps. Once detected, the system triggers the buzzer to alert the driver or operator, ensuring timely awareness and response.

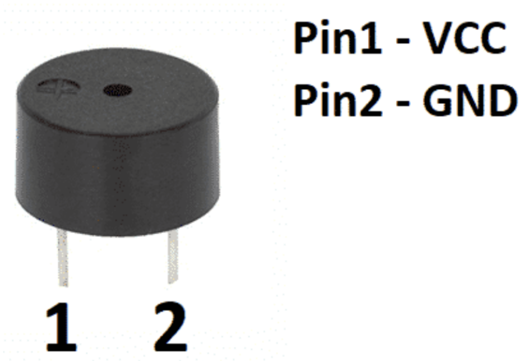


Figure 4.3: Pin Details of Buzzer [15]

Chapter 5

System Software

5.1 Roboflow

Roboflow is a Computer Vision developer framework for better data collection to preprocessing, and model training techniques. Roboflow has public datasets readily available to users and has access for users to upload their own custom data also. Roboflow accepts various annotation formats. In data pre-processing, there are steps involved such as image orientations, resizing, contrasting, and data augmentations.

The entire workflow can be co-ordinated with teams within the framework. For model training, there's a bunch of model libraries already present such as EfficientNet, MobileNet, Yolo, TensorFlow, PyTorch, etc.

5.2 Thonny

Thonny is a free Python Integrated Development Environment(IDE) for writing and testing Python code. Smoother code completion is possible with Thonny for both internal and external packages Thonny is well-suited for developing software components like data processing, image analysis, and machine learning, all of which are useful for implementing traffic management algorithms.

5.3 Google Colaboratory

Google Colaboratory is a free, cloud-based Jupyter notebook environment that enables users to write and execute Python code in a web-based, collaborative interface. It is especially popular for machine learning and data science tasks due to its seamless integration with popular Python libraries and access to powerful computing resources, including GPUs and TPUs. The labeled datasets using Roboflow is uploaded either thorugh drive and the model has been trained using Yolov8.

5.4 Real VNC viewer

Virtual Network Computing (VNC) is a graphical desktop-sharing system that uses the Remote Frame Buffer protocol (RFB) to remotely control another computer. It transmits the keyboard and mouse input from one computer to another, relaying the graphical-screen updates, over a network.

RealVNC Connect gives modern organizations of all sizes the remote access and support solution they need. Secure, reliable, and easy-to-use, you can deliver fast, effective IT support and servicing at scale.

5.5 Algorithm

YOLOv8 is the latest iteration in the YOLO series of real-time object detectors, offering cutting-edge performance in terms of accuracy and speed. Building upon the advancements of previous YOLO versions, YOLOv8 introduces new features and optimizations that make it an ideal choice for various object detection tasks in a wide range of applications. The architecture of it is shown in Fig 5.1.

5.5.1 Features of YOLOv8

- Advanced Backbone and Neck Architectures: YOLOv8 employs state-of-the-art backbone and neck architectures, resulting in improved feature extraction and object detection performance.

- Anchor-free Split Ultralytics Head: YOLOv8 adopts an anchor-free split Ultralytics head, which contributes to better accuracy and a more efficient detection process compared to anchor-based approaches.

5.5.2 YOLOv8 Architecture

- **Backbone**: YOLOv8 employs a feature-rich backbone network as its foundation. The network serves to extract hierarchical features from the input image, providing a comprehensive representation of the visual information.

- **Neck Architecture**: The architecture includes a novel neck structure, which is responsible for feature fusion. This is crucial for combining multi-scale information and improving the model's ability to detect objects of varying sizes.

- **YOLO Head** : YOLOv8 retains the characteristic feature of the YOLO series – the YOLO head. This component generates predictions based on the features extracted by the backbone network and the neck architecture.

  The YOLO head predicts bounding box coordinates, objectness scores, and class probabilities for each anchor box associated with a grid cell. The architecture uses anchor boxes to efficiently predict objects of different shapes and sizes.

- **Training Techniques**: YOLOv8 leverages advancements in training strategies to improve convergence speed and model performance. MixUp, a data augmentation technique, is employed to create linear interpolations of images, enhancing the model's generalization capabilities.

- **Model Variants**: YOLOv8 is available in different variants, each designed for specific use cases. YOLOv8-CSP, for instance, focuses on striking a balance between accuracy and speed. YOLOv8x-Mish, another variant, employs the Mish activation function for improved non-linearity, leading to better generalization and performance.

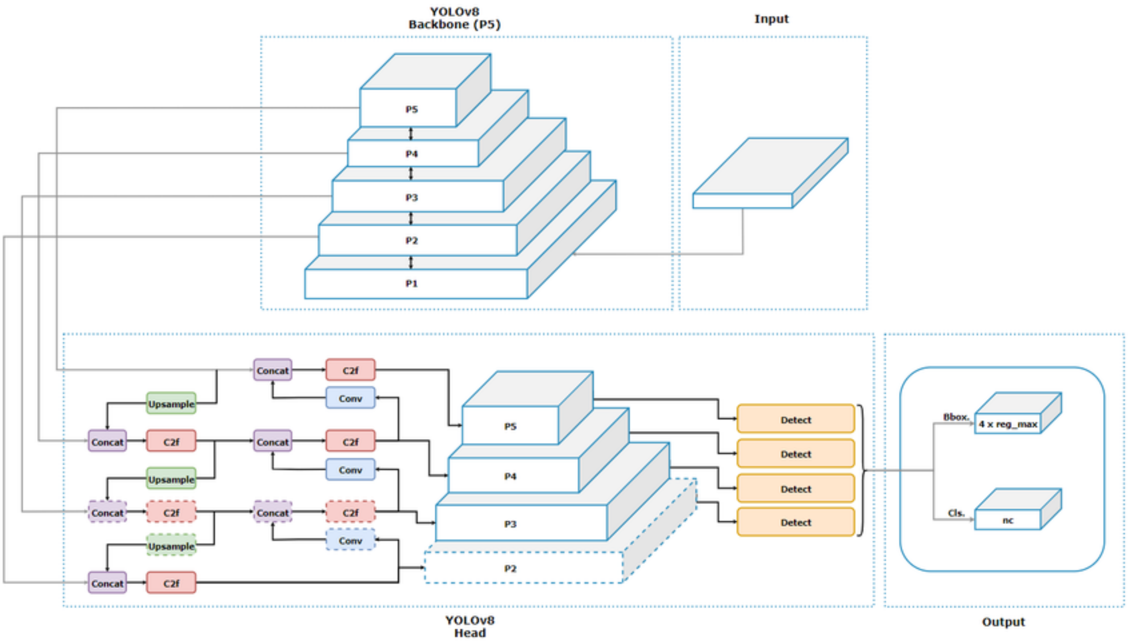


Figure 5.1: YOLOv8 Architecture [16]

5.6 Flow Diagram

The flow chart of the system has been shown in Fig 5.2. This flowchart outlines the process of creating a YOLOv8 model for object detection. The process starts with Scene Acquisition, capturing the necessary data. This is followed by Frame Extraction to break down the video into individual frames. Next, image preprocessing is performed to enhance the quality and suitability of the images for analysis. Using Roboflow, images are annotated and the dataset is split into training and validation sets. Finally, the YOLOv8 model is trained and generated using the prepared dataset.

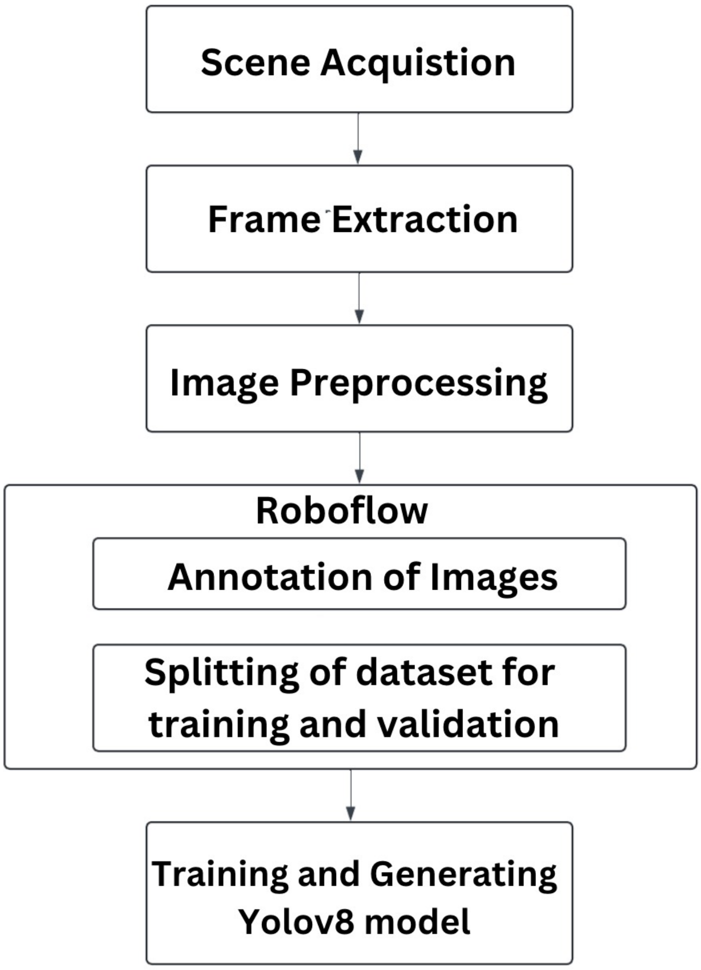


Figure 5.2: Flow Diagram on training and generating the YOLOv8 model

Chapter 6

Results

6.1 Dataset

The data has been collected from the Roboflow tool. There are a total of 461 images taken for training, out of which 220 images are of speed bumps and 241 images are of potholes. Further, the images have been preprocessed using OpenCV and compressed to size 640 x 640. Few data of speed bump and pothole taken as sample can be seen in Fig 6.1 and Fig 6.2 respectively.

(a) Sample for speed bump 1

(b) Sample for speed bump 2

Figure 6.1: Data for speed bump

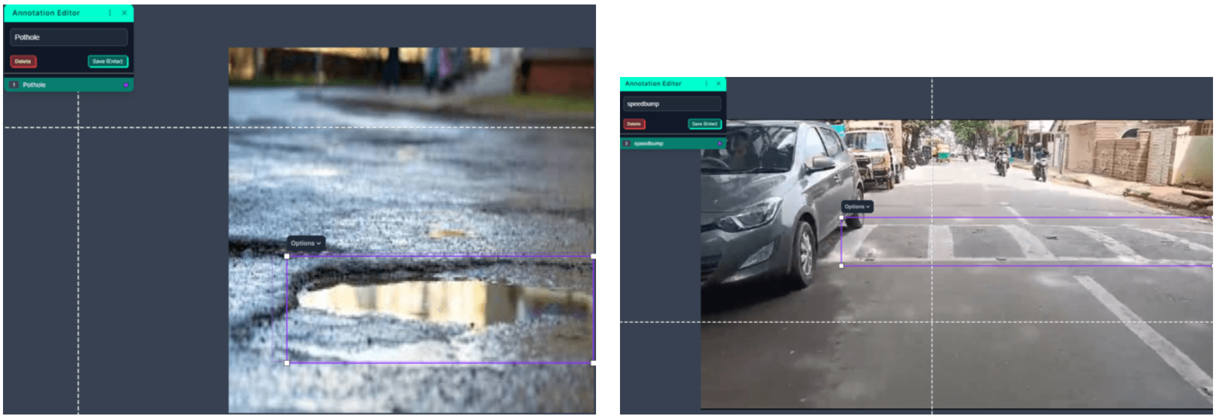
(a) Sample for pothole 1

(b) Sample for pothole 2

Figure 6.2: Data for pothole

6.2 Annotation

In order to train the model data that have been collected are labeled as speed bumps and potholes as seen in Fig 6.3.



(a) Annotation for pothole (b) Annotation for speed bump

Figure 6.3: Annotation of both pothole and speed bump

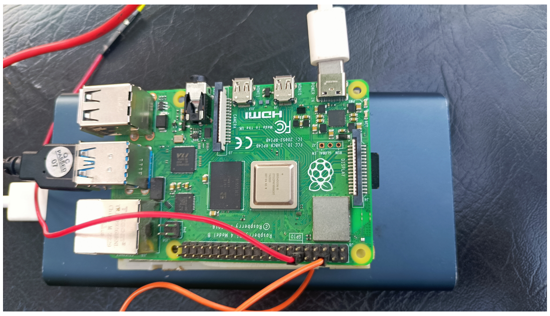
6.3 Prototype of the system

Figure 6.4: Complete Set-up

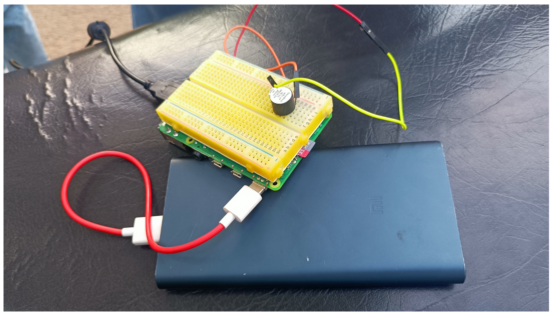
In the hardware setup for detecting speed bumps and potholes, a webcam is mounted between the number plate and the headlight. The webcam is connected to the Raspberry Pi, a series of small single-board computers (SBCs), using USB. A buzzer, which alerts the driver about potholes, is connected to the Raspberry Pi. The hardware setup has been displayed in Fig 6.4 and each component is dispalyed in Fig 6.5.

(a) Camera mounted on vehicle

(b) Display of Road



(c) Raspberry Pi 4B setup

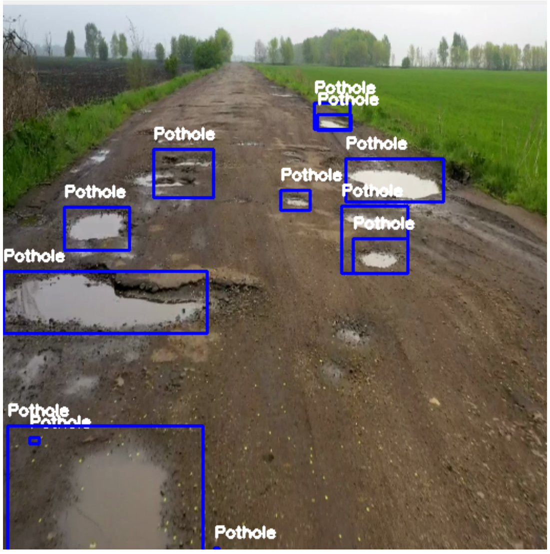


(d) Buzzer setup

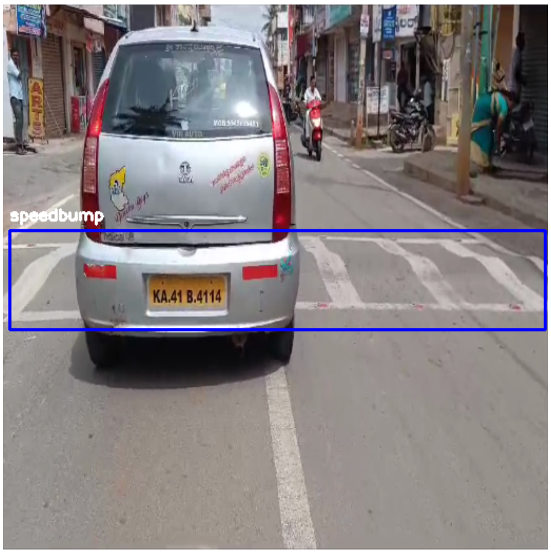
Figure 6.5: Various components of the hardware setup

6.4 Detection Output

The model after being trained for multiple data has been tested in realtime. It is observed that both potholes and speed bumps are being detected .The determined outputs have been shown in Fig 6.6.



(a) Pothole Detected



(b) Speed Bump Detected

Figure 6.6: Determined Output at (a) Pothole and (b) Speed bump

6.5 Accuracy

The model achieved an overall accuracy of approximately 88.6% performing significantly better in detecting speed bumps compared to potholes. For speed bumps, the model showed high precision of 91.9%, recall of 96.2%. The potholes showed these metrics a bit lower with precision of 42.7% and recall of 66.7%.

Chapter 7

Conclusion

"Computer Vision-based Speed Bump and Pothole Detection System for Vehicles" has been implemented and tested on various conditions. The dataset taken from roboflow has different variations of speed bumps and pothole. The hardware such as webcam and raspberry pi have been integrated with software like google collaboratory, thonny and VNC viewer for better detection and accuracy. YOLO V8 algorithm was found to be better for model training due to high precision, processing speed and better accuracy. The model performs better on detecting speedbumps compared to potholes, with higher precision, recall, and mean average precision (mAP) metrics for speedbumps. The overall accuracy of the model is approximately 88.6%.

7.1 Scope for future work

The future of speed bump and pothole detection, with precise measurements of height, width, and location data sent to the cloud, promises transformative advancements. This technology empowers proactive maintenance strategies and efficient resource allocation by municipalities, enhancing road safety and durability. Integration with smart city infrastructure ensures timely public access to road condition updates, optimizing route planning and urban mobility.

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Appendices

Appendix A

Data Sheet of component 1

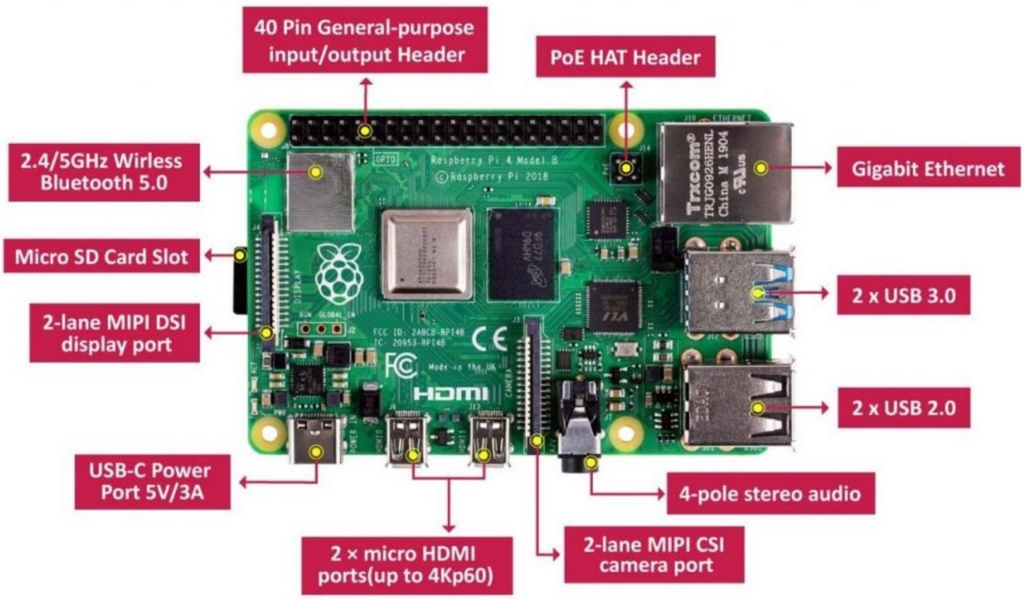

Figure A.1: Raspberry Pi 4B

- CPU : Quad-core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz
- RAM : 4GB
- Ethernet : Gigabit Ethernet
- Wi-Fi : 2.4 GHz and 5.0 GHz IEEE 802.11ac wireless
- Bluetooth : Bluetooth 5.0, BLE
- USB : 2 × USB 3.0 ports, 2 × USB 2.0 ports
- Video Output : 2 × micro-HDMI ports (up to 4K resolution)
- Audio Output : 3.5mm stereo audio/composite video jack

- Power Input : USB-C (5V 3A)
- GPIO : 40-pin GPIO header, supporting various interfaces like UART, I2C
- SPIOS : Supports a variety of operating systems, including Raspberry Pi OS,