Road Defect Severity Assessment and Classification

A Special Problem

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Road Defect Severity Assessment and Classification

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Declaration

We, BENZ VRIANNE BELEBER, PERSEROSE CATALAN, and KRISTIAN LYLE SENCIL, hereby certify that this Special Problem has been written by us and is the record of work carried out by us. Any significant borrowings have been properly acknowledged and referred.

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Dedication

This Special Problem is dedicated to the researchers' families, whose unwavering love, patience, and support have been the foundation of their academic journey.

To their parents, for their endless sacrifices.

To their mentors and teachers, for believing in them and guiding them with wisdom.

And to all those who inspired them to keep going even in the most challenging moments — this work is for them.

Acknowledgment

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To the Department of Science and Technology (DOST), for their support and promotion of scientific research and innovation.

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To their families and friends, for their unconditional love, patience, and encouragement.

Lastly, to the University of the Philippines Visayas, for providing the resources and environment necessary for the researchers to explore and grow.

This work stands as a testament to the collaboration, support, and trust the researchers have received. They are deeply grateful.

Abstract

Road surveying is a crucial part of the maintenance processes of roads in the Philippines that is carried out by the Department of Public Works and Highways. However, the current process of road surveying is time consuming which delays much needed maintenance operations. Existing studies involving automated pothole detection lack integration of the pothole's depth in assessing its severity which is essential for automating road surveying procedures. A system that incorporates estimated depth information in assessing pothole severity is developed in order to automate the manual process of depth measurement and severity assessment in road surveying. For depth estimation, stereo vision is favorable in this context as depth may be estimated through the disparity generated by a stereo pair. In obtaining a stereo view of the potholes, the StereoPi V2 is utilized along with some modifications that would make it eligible for outdoor use. To address camera imperfections, a fitted inverse model was applied to improve the accuracy of depth estimates. Linear regression analysis revealed a strong positive correlation ($R = 0.978$) between estimated and actual depths, with the system measuring pothole depths mostly within 3 cm of the true values.

Keywords: pothole, depth estimation, stereo vision, StereoPi V2

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Chapter 1

Introduction

1.1 Overview of the Current State of Technology

The Department of Public Works and Highways (DPWH) reported in their National Road Length by Classification, Surface Type, and Condition Summary as of October 2023, that approximately 98.97% of roads in the Philippines is paved which is either made of concrete or asphalt (Balita, 2024). Since the DPWH is an institution under the government, it is paramount to maintain such roads in order to avoid accidents and congested traffic situations especially in heavily urbanized areas where there are a lot of vehicles.

In an interview with the Road Board of DPWH Region 6 it was stated that road condition assessments are mostly done manually with heavy reliance on engineering judgment (J. Chua, Personal Interview. 16 September 2024). In addition, manual assessment of roads is also time consuming which leaves maintenance operations to wait for lengthy assessments. In a study conducted by Ramos, Dacanay, and Bronuela-Ambrocio (2023), it was found that the Philippines' current method of manual pavement surveying is considered as a gap since it takes an average of 2-3 months to cover a 250 km road as opposed to a 1 day duration in the Australian Road Research Board for the same road length. Ramos et al. (2023) recommended that to significantly improve efficiency of surveying methods and data gathering processes, automated survey tools are to be employed. It was also added that use of such automated, surveying tools can also guarantee the safety of road surveyors.

If the process of assessment on the severity of road defects can be automated then the whole process of assessing the quality of roads can be hastened up which can also enable maintenance operations to commence as soon as possible if necessary. If not automated, the delay of assessments will continue and roads that are supposedly needing maintenance may not be properly maintained which can affect the general public that is utilizing public roads daily.

Existing studies involving road defects such as potholes mainly focus on the detection of potholes using deep learning models and almost not considering the severity of detected potholes or did not incorporate any depth information from potholes (Ha, Kim, & Kim, 2022; Kumar, 2024; Bibi et al., 2021). In addition, for studies that include severity assessment on potholes, the main goal of the study is not directed towards road maintenance automation but other factors such as improvement of ride quality for the vehicle. Another issue found in existing solutions is the lack of incorporation to the context of Philippine roads. With these issues in mind, the study aims to utilize stereo vision from StereoPi V2 in order to obtain multi-perspective views of detected potholes to be used in severity asssessment by focusing on estimating the depth of individual potholes for automated road condition monitoring.

1.2 Problem Statement

Roads support almost every aspect of daily life, from providing a way to transport goods and services to allowing people to stay connected with their communities. However, road defects such as cracks and potholes damage roads over time, and they can increase accident risks and affect the overall transportation. The current way of inspecting the roads for maintenance is often slow as it is done manually, which makes it harder to detect and fix defects early. The delay in addressing these problems can lead to even worse road conditions (J. Chua, Personal Interview. 16 September 2024). There are several research studies into automated road defect classification that have advanced in recent years but most of them focus on identifying the types of defects rather than assessing their severity or characteristics like depth. Without reliable data on the depth of the defect, road maintenance authorities may underestimate the severity of certain defects. To address these challenges, advancements are needed across various areas. An effective solution should not only detect and classify road defects but also measure their severity to better prioritize repairs. Failing to address this problem will require more extensive repairs for damaged roads, which raises the cost and strains the budget. Additionally, road maintenance would still be slow and cause disruptions in daily activities. Using an automated system that accurately assess the severity of road defects by incorporating depth is necessary to efficiently monitor road quality.

1.3 Research Objectives

1.3.1 General Objective

This special problem aims to develop a system that can estimate the depth of potholes on road surfaces and classify them into different severity levels such as low, medium, and high by using stereo vision technology, supporting faster and more precise road maintenance decisions.

1.3.2 Specific Objectives

Specifically, this special problem aims to:

1. collect high-quality stereo images of road surfaces that capture potholes including their depth in favorable conditions,

2. measure the accuracy of the system by comparing the depth measurements against ground truth data collected from actual road inspections and to utilize linear regression, root mean square error, and mean absolute error as metrics for evaluation, and

3. develop a prototype system that can detect and measure road potholes from image input, analyze their depth, and assess their severity.

1.4 Scope and Limitations of the Research

This system focuses solely on detecting and assessing the severity of potholes through image analysis and depth measurement technologies. The scope includes the collection of pothole images using cameras and depth-sensing tools under a favorable weather condition.

Depth-sensing tools, such as stereo cameras, will be used to record the depth of potholes specifically. The system will not address other road defects like cracks or other surface deformations; therefore, it will detect and analyze only potholes. Additionally, only accessible potholes will be measured, meaning those that are filled with water or obscured by debris may not be accurately assessed.

The system developed focuses exclusively on detecting potholes and assessing their severity through depth measurement. The accuracy of the system's depth measurements is evaluated by comparing them against data collected from actual field inspections. However, this comparison is limited to selected sample sites, as collecting field data over a large area can be time-consuming and resource-intensive.

Environmental factors such as lighting, road surface texture, and weather conditions may impact the system's performance. The accuracy and reliability of the system will depend on the quality of camera calibration and disparity map finetuning. Its ability to measure the depth of pothole images needs careful validation.

1.5 Significance of the Research

This special problem aims to be significant to the following:

Computer Science Community. This system can contribute to advancements in computer vision and machine learning by using both visual and depth data to assess the severity of road defects. It introduces a more comprehensive approach compared to the usual image-only or manual inspection methods. This combination can be applied to other fields that need both visual and depth analysis like medical imaging.

Concerned Government Agencies. This system offers a valuable tool for road safety and maintenance. Not only can this detect and classify anomalies, it can also assess the defect's severity which allows them to prioritize repairs, optimal project expenditures, and better overall road safety and quality.

Field Engineers. In the scorching heat, field engineers are no longer required to be on foot unless it requires their engineering judgement when surveying a road segment. It can hasten the overall assessment process.

Future Researchers. The special problem may serve as a baseline and guide of researchers with the aim to pursue special problems similar or related to this.

Chapter 2

Review of Related Literature

2.1 Frameworks

This section of the chapter presents related frameworks that is considered essential for the development of this special problem.

2.1.1 Depth Estimation

Depth estimation as defined by Sanz, Mezcua, and Pena (2012) is a set of processes that aims to extract a representation of a certain scene's spatial composition. Stereo vision is stated to be among the depth estimation strategies.

2.1.2 Image and Video Processing

Kumar (2024) defines image processing as a process of turning an image into its digital form and extracting data from it through certain functions and operations.

Usual processes are considered to treat images as 2D signals wherein different processing methods utilize these signals. Like image processing, RICHES Project (2014) defines video processing as being able to extract information and data from video footage through signal processing methods. However, in video processing due to the diversity of video formats, compression and decompression methods are often expected to be performed on videos before processing methods to either increase or decrease bitrate.

2.1.3 Stereo Vision

MathWorks (n.d.) defines stereo vision as a process of utilizing multiple 2D perspectives in order to extract information in 3D. In addition, most uses of stereo vision involve estimating an objects distance from an observer or camera. The 3D information is stated to be extracted with stereo pairs or pair of images through estimation of relative depth of points in a scene which are then represented through a stereo map that is made through the matching of the pair's corresponding points.

2.2 Related Studies

This section of the chapter presents related studies conducted by other researchers wherein the methodology and technologies used may serve as basis in the development of this special problem.

2.2.1 Deep Learning Studies

Automated Detection and Classification of Road Anomalies in VANET Using Deep Learning

In the study of Bibi et al. (2021) it was noted that identification of active road defects are critical in maintaining smooth and safe flow of traffic. Detection and subsequent repair of such defects in roads are crucial in keeping vehicles using such roads away from mechanical failures. The study also emphasized the growth in use of autonomous vehicles in research data gathering which is what the researchers utilized in data gathering procedures. With the presence of autonomous vehicles, this allowed the researchers to use a combination of sensors and deep neural networks in deploying artificial intelligence. The study aimed to allow autonomous vehicles to avoid critical road defects that can possibly lead to dangerous situations. Researchers used Resnet-18 and VGG-11 in automatic detection and classification of road defects. Researchers concluded that the trained model was able to perform better than other techniques for road defect detection. The study is able to provide the effectiveness of using deep learning models in training artificial intelligence for road defect detection and classification. However, the study lacks findings regarding the severity of detected defects and incorporation of pothole depth in their model which are both crucial in automating manual procedures of road surveying in the Philippines.

Road Anomaly Detection through Deep Learning Approaches

The study of Luo, Lu, and Guo (2020) aimed to utilize deep learning models in classifying road anomalies. The researchers used three deep learning approaches namely Convolutional Neural Network, Deep Feedforward Network, and Recurrent Neural Network from data collected through the sensors in the vehicle's suspension system. In comparing the performance of the three deep learning approaches, the researchers fixed some hyperparameters. Results revealed that the RNN model was the most stable among the three and in the case of the CNN and DFN models, the researchers suggested the use of wheel speed signals to ensure accuracy. And lastly, the researchers concluded that the RNN model was best due to high prediction performance with small set parameters. However, proper severity assessment through depth information was not stated to be utilized in any of the three approaches used in the study.

Assessing Severity of Road Cracks Using Deep Learning-Based Segmentation and Detection

In the study of Ha et al. (2022), it was argued that the detection, classification, and severity assessment of road cracks should be automated due to the bottleneck it causes during the entire process of surveying. For the study, the researchers utilized SqueezNet, U-Net, and MobileNet-SSD models for crack classification and severity assessment. Furthermore, the researchers also employed separate U-nets for linear and area cracking cases. For crack detection, the researchers followed the process of pre-processing, detection, classification. During preprocessing images were smoothed out using image processing techniques. The researchers also utilized YOLOv5 object detection models for classification of pavement cracking wherein the YOLOv51 model recorded the highest accuracy. The researchers however stated images used for the study are only 2D images which may have allowed higher accuracy rates. Furthermore, the researchers suggest incorporating depth information in the models to further enhance results.

Roadway pavement anomaly classification utilizing smartphones and artificial intelligence

The study of Kyriakou, Christodoulou, and Dimitriou (2016) presented what is considered as a low-cost technology which was the use of Artificial Neural Networks in training a model for road anomaly detection from data gathered by smartphone sensors. The researchers were able to collect case study data using two-dimensional indicators of the smartphone's roll and pitch values. In the study's discussion, the data collected displayed some complexity due to acceleration and vehicle speed which lead to detected anomalies being not as conclusive as planned. The researchers also added that the plots are unable to show parameters that could verify the data's correctness and accuracy. Despite the setbacks, the researchers still fed the data into the Artificial Neural Network that was expected to produce two outputs which were "no defect" and "defect." The method still yielded above 90% accuracy but due to the limited number of possible outcomes in the data processing the researchers still needed to test the methodology with larger data sets and roads with higher volumes of anomalies.

2.2.2 Machine Learning Studies

Smartphones as Sensors for Road Surface Monitoring

In their study, Sattar, Li, and Chapman (2018) noted the rise of sensing capabilities of smartphones which they utilized in monitoring road surface to detect and identify anomalies. The researchers considered different approaches in detecting road surface anomalies using smartphone sensors. One of which are threshold-based approaches which was determined to be quite difficult due to several factors that are affecting the process of determining the interval length of a window function in spectral analysis. The researchers also utilized a machine learning approach adapted from another study. It was stated that k-means was used in classifying sensor data and in training the SVM algorithm. Due to the requirement of training a supervised algorithm using a labeled sample data was required before classifying data from sensors, the approach was considered to be impractical for real-time situations. In addition, Sattar et al. (2018) also noted various challenges when utilizing smartphones as sensors for data gathering such as sensors being dependent on the device's placement and orientation, smoothness of captured data, and the speed of the vehicle it is being mounted on. Lastly, it was also concluded that the accuracy and performance of using smartphone sensors is challenging to compare due to the limited data sets and reported algorithms.

Road Surface Quality Monitoring Using Machine Learning Algorithms

The study of Singh, Bansal, Kamal, and Kumar (2021) aimed to utilize machine learning algorithms in classifying road defects as well as predict their locations. Another implication of the study was to provide useful information to commuters and maintenance data for authorities regarding road conditions. The researchers gathered data using various methods such as smartphone GPS, gyroscopes, and accelerometers. (Singh et al., 2021) also argued that early existing road monitoring models are unable to predict locations of road defects and are dependent on fixed roads and static vehicle speed. Neural and deep neural networks were utilized in the classification of anomalies which was concluded by the researchers to yield accurate results and are applicable on a larger scale of data. The study of Singh et al. (2021) can be considered as an effective method in gathering data about road conditions. However, it was stated in the study that relevant authorities will be provided with maintenance operation and there is no presence of any severity assessment in the study. This may cause confusion due to a lack of assessment on what is the road condition that will require extensive maintenance or repair.

2.2.3 Computer Vision Studies

Stereo Vision Based Pothole Detection System for Improved Ride Quality

In the study of Ramaiah and Kundu (2021) it was stated that stereo vision has been earning attention due to its reliable obstacle detection and recognition. Furthermore, the study also discussed that such technology would be useful in improving ride quality in automated vehicles by integrating it in a predictive suspension control system. The proposed study was to develop a novel stereo vision based pothole detection system which also calculates the depth accurately. However, the study focused on improving ride quality by using the 3D information from detected potholes in controlling the damping coefficient of the suspension system. Overall, the pothole detection system was able to achieve 84% accuracy and is able to detect potholes that are deeper than 5 cm. The researchers concluded that such system can be utilized in commercial applications. However, it is also worth noting that despite the system being able to detect potholes and measure its depth, the overall severity of the pothole and road condition was not addressed.

2.3 Chapter Summary

The reviewed literature involved various techniques and approaches in road anomaly detection and classification. These approaches are discussed and summarized below along with their limitations and research gaps.

Study	**Technology/ Techniques Used**	**Key Findings**	**Limitations**
Automated Detection and Classification of Road Anomalies in VANET Using Deep Learning	Resnet-18 and VGG-11	Trained model is able to provide the effectiveness of using deep learning models in training artificial intelligence for road defect detection and classification.	Lacks findings regarding the severity of detected defects.
Smartphones as sensors for Road surface monitoring	Machine Learning, Smartphones	Approach was considered impractical for real-life applications.	Sensors are dependent on device's placement and orientation, smoothness of data, and speed of vehicle it is mounted on. Accuracy of results is difficult to compare.
Road Anomaly Detection through Deep Learning Approaches	Convolutional Neural Network, Deep Feedforward Network, and Recurrent Neural Network	Identified that RNN was the best deep learning approach due to high prediction performance.	Data collection is considered too difficult and complicated to execute due to sensors being mounted on an integral part of the vehicle.
Assessing Severity of Road Cracks Using Deep Learning-Based Segmentation and Detection	SqueezNet, U-Net, YOLOv5, and MobileNet-SSD models	YOLOv51 model recorded the highest accuracy.	Only 2D images are used for the study which may have allowed higher accuracy rates, and the study also lacked depth information.
Stereo Vision Based Pothole Detection System for Improved Ride Quality	Pair of stereo images captured by a stereo camera	System was able to achieve 84% accuracy and is able to detect potholes that are deeper than 5 cm.	Overall severity of the pothole and road condition was not addressed.

Table 2.1: Comparison of Related Studies on Road Anomaly Detection using Deep Learning Techniques and Stereo Vision

Chapter 3

Research Methodology

This chapter outlines the systematic approach that were taken to address the problem of pothole depth estimation using StereoPi V2. The methodology is divided into key phases: data collection, algorithm selection, design, testing and experimentation, and challenges and limitations. Each phase will play a crucial role in accurately classifying and assessing road defects. Each phase is essential for accurately estimating the depth of potholes using StereoPi V2.

3.1 Research Activities

3.1.1 Data Collection

The researchers conducted initial inquiries to understand the problem domain and existing road maintenance practices. This phase included consulting the engineers under the Road Maintenance Department of the government agency Department of Public Works and Highways (DPWH). An interview with Engr. Jane Chua provided a comprehensive overview of the DPWH's road maintenance manual, which was crucial in aligning this project with existing standards. This collaboration with DPWH provided insights into road pothole classification standards, ensuring that the collected data will align with industry standards. The interview with Engr. Chua revealed that the current way to measure potholes is by their area. Additionally, the DPWH manual primarily focuses on the volume of detected potholes within a road segment as a measure of severity. However, since depth is not explicitly measured in their current procedures, the study will supplement this by referencing international standards such as the Long-Term Pavement Performance (LTPP) classification used in the United States (Miller & Bellinger, 2014). The LTPP categorizes potholes baed on depth thresholds, which will be integrated with DPWH's volume-based assessment to provide a more comprehensive severity classification framework. The data collection involved capturing around 130 images of potholes from various locations within the UP Visayas Campus. Ground truth data of pothole depth were collected by the researchers by measuring the depth of different points in an individual pothole and then solving for its average depth. The researchers developed a manual specifically designed for depth measurement, which underwent a review by Engr. Benjamin Javellana, Assistant Director of the Maintenance Division at the Department of Public Works and Highways (DPWH) Regional Office VI. The finalized version of the manual was subsequently validated by the DPWH First District Engineering Office. In order to individually locate or determine each pothole where the ground truth data is collected, images taken were labeled with their corresponding coordinates, street names, and nearby landmarks.

3.1.1.1 Data Collection (Ground Truth Data)

Data collection took place between January and March 2025, during which the researchers collected depth information from 130 potholes around the University of the Philippines Visayas Miagao Campus. During data collection, the researchers are equipped with safety vests and an early warning device to give caution to incoming vehicles. Following the validated manual for pothole depth measurement, a ruler and a measuring tape were used in both vertical and horizontal positions as shown in Figure 3.1. This setup helped determine the distance from the road surface to the bottom of the pothole. The researchers then recorded four measurement points within each pothole, as illustrated in Figure 3.2. The average of these values was taken as the pothole's depth. Figure 3.3 shows the mapped locations of the potholes measured within the UPV campus.

Figure 3.1: Manual depth measurement of pothole using a ruler and measuring tape.

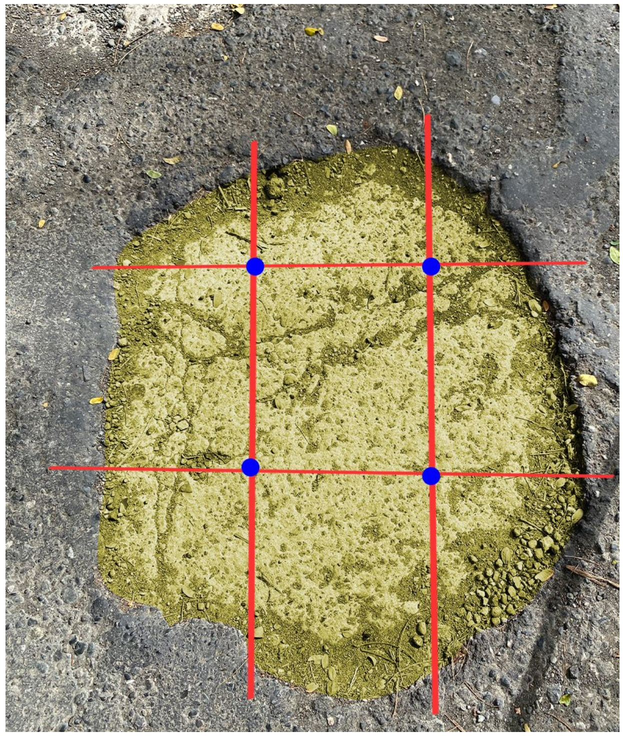

Figure 3.2: Four measurement points of the pothole.

Figure 3.3: Visualized pothole locations during the ground truth data collection within the UPV campus.

3.1.2 Design, Testing, and Experimentation

This section outlines both the design and testing of the system, as well as the experimentation process to validate the selected methodologies.

3.1.2.1 Depth Measurement

Depth estimation is performed by generating disparity maps from the calibrated stereo image pairs captured by the StereoPi V2. In this process, two key measurement points are selected for each pothole: one targeting the pothole area itself, and another targeting the adjacent road surface considered as the reference plane. By calculating the difference in disparity values between these two points, the system estimates the relative depth of the pothole. This approach improves accuracy by normalizing disparity measurements against the nearby road surface, effectively isolating the pothole's depth from overall scene variation.

The disparity-to-depth conversion utilizes an inverse model derived from calibration data, ensuring that the depth estimates reflect real-world distances accurately within the effective operational range of the stereo camera setup.

3.1.2.2 Severity Assessment

The estimated pothole depths were classified using the Long-Term Pavement Performance (LTPP) depth thresholds, an internationally recognized framework for pavement distress evaluation. This classification provides standardized criteria to assess pothole severity objectively based on measured depth values. Specifically, potholes with depths less than 2.5 cm are categorized as low severity, those between 2.5 cm and 5 cm as medium severity, and potholes exceeding 5 cm are classified as high severity (Miller & Bellinger, 2014).

3.1.2.3 Materials and Equipment

The prototype system was constructed using several hardware components, which include the items listed below and shown in Figure 3.3:

- StereoPi V2 Board
- Raspberry Pi Compute Module 4 (CM4)
- Dual RaspberryPi Camera Modules with Fisheye Lens
- 3D Printed Custom Housing
- 2-inch LCD Module
- Micro SD Card
- Antenna
- Momentary Push Button

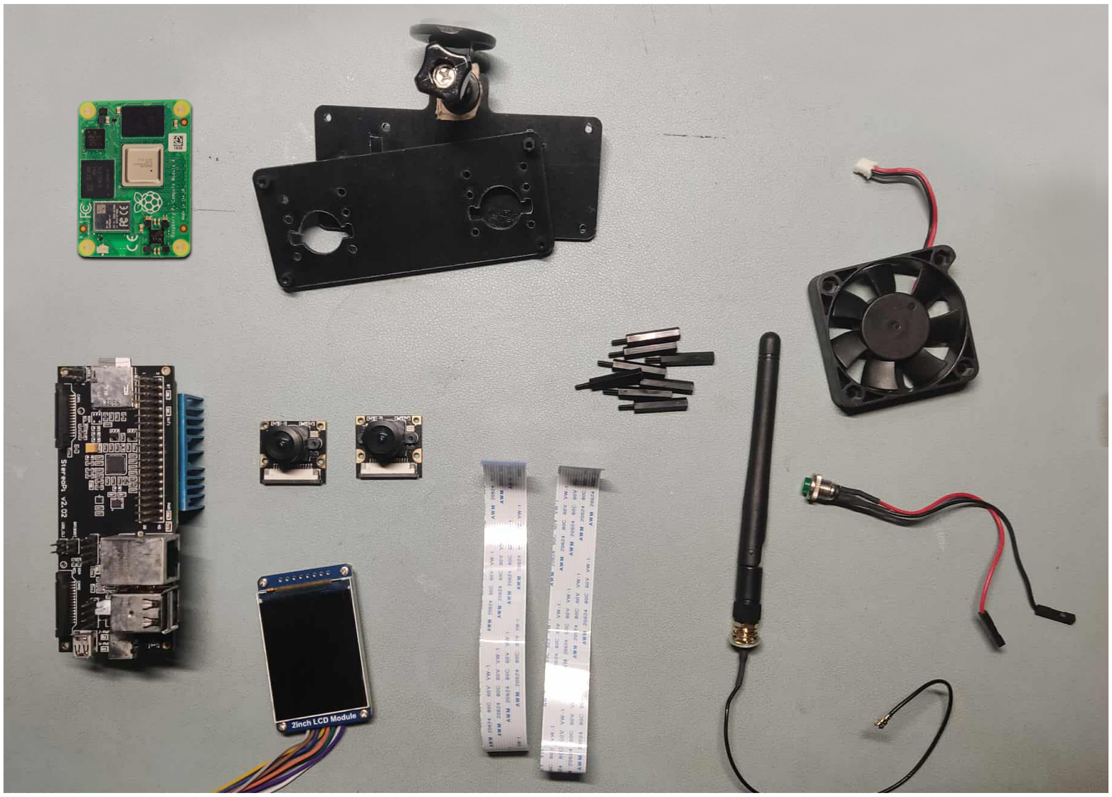

Figure 3.4: Components used in the prototype development. From the top left: Raspberry Pi Computer Module 4, 3D Printed Custom Housing, cooling fan, StereoPi V2 Board, two camera modules, antenna, momentary push button, and 2-inch LCD module.

3.1.2.4 Prototype Building

The prototype involved the StereoPi V2 Kit which was acquired through an official international distributer. After assembling the camera, it was further modified to address the it's heating by incorporating a heat sink and a small computer fan to make it suitable for outdoor use.As shown in Figure 3.4, the dual Raspberry Pi camera modules were securely mounted onto the custom housing. To facilitate user interaction and real-time monitoring, an LCD module was connected to the StereoPi board, as illustrated in Figure 3.5. The final assembled and fully functional prototype is presented in Figure 3.6.

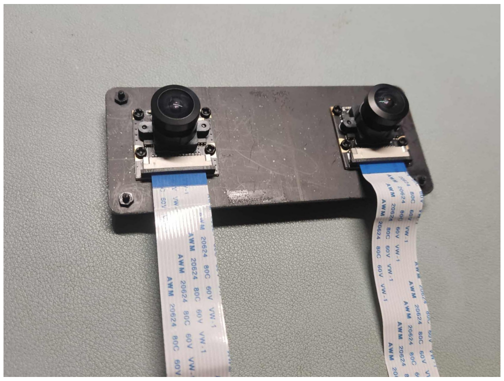

Figure 3.5: Dual RPi Camera Modules attached to the custom housing.

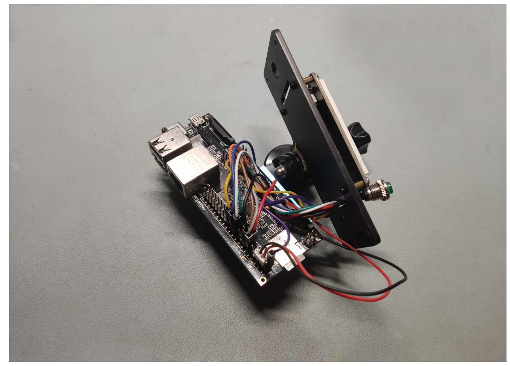

Figure 3.6: LCD Module connected to the StereoPi board.

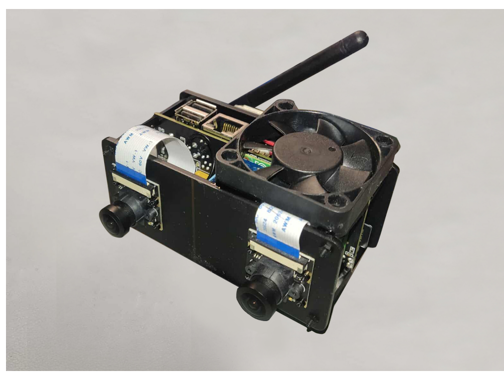

Figure 3.7: The finished prototype.

3.1.2.5 Camera Calibration (Fisheye Distortion)

The StereoPi V2 was first calibrated using a 9×6 checkerboard, with a checker size of 55mm, from different angles using calibration scripts that came with the package. The calibration process, shown in Figure 3.7, involved capturing multiple images of the checkerboard pattern to correct fisheye lens distortion. This process ensured that the camera is working properly in capturing stereo imagery. This removed distortion from captured imaged allowing depth estimation with more accuracy.

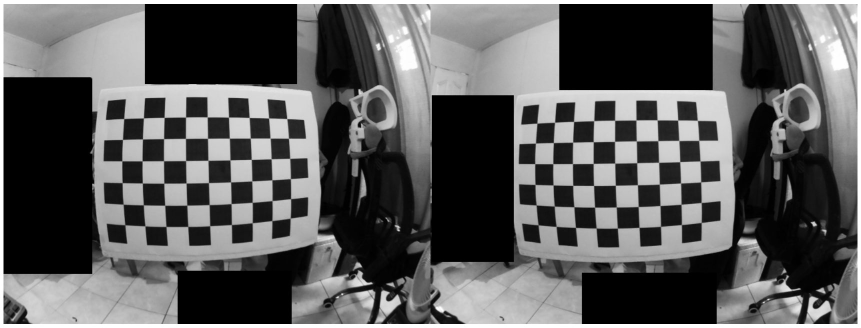

Figure 3.8: Calibration process with a checkerboard to correct fisheye lens distortion.

3.1.2.6 Camera Calibration (Disparity Map Fine-tuning)

The stereo image pairs captured by the system were first rectified to ensure proper alignment of corresponding features. Block matching parameters were then fine-tuned to produce clearer and more accurate disparity maps. This tuning process is illustrated in Figure 3.8. It was observed that the effective operational range of the stereo camera system extends from approximately 30 to 80 cm. At distances closer than 30 cm, the disparity maps exhibited significant noise, while at distances beyond 80 cm, disparity information became sparse or blank.

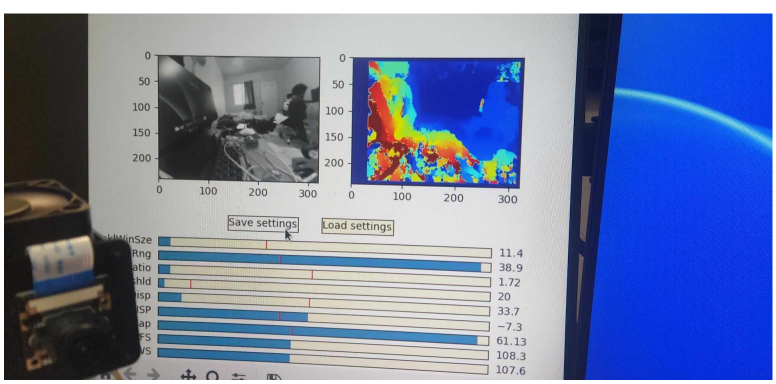

Figure 3.9: Parameter tuning process to achieve cleaner and more accurate disparity maps.

3.1.2.7 Initial Testing

Initial testing was conducted to verify the functionality and basic accuracy of the stereoscopic camera system in a controlled environment. Artificial potholes with known depths were created to simulate varying real-world scenarios. The system captured disparity maps, and estimated depths were computed using the standard stereo camera depth formula. The LCD module displayed the disparity map and estimated depth readings in real-time during these tests, as shown in Figure 3.9.

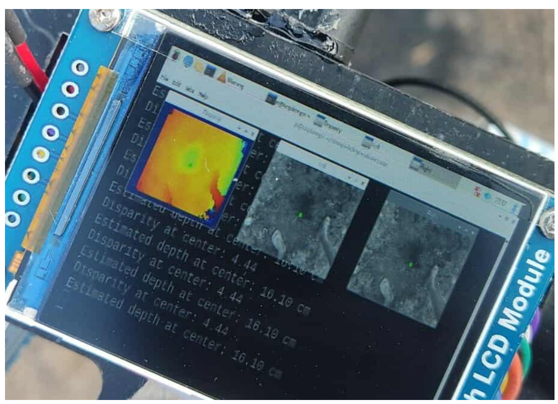

Figure 3.10: The system tested on a simulated pothole.

However, the results revealed a non-linear relationship between the computed disparity values and the actual distances. This discrepancy indicated that the traditional depth estimation method was insufficient for the current setup. To address this, the researchers collected multiple data points and correlating known distances to their respective disparity readings and fitted an inverse model to better represent the system's behavior (see Figure 3.10). This updated disparity-to-depth model was subsequently used in the final testing phase.

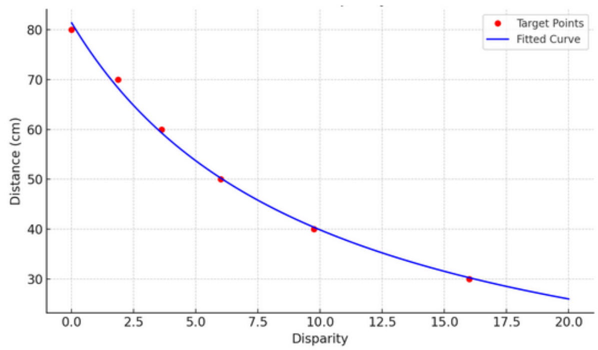

Figure 3.11: Inverse Model Fit to Disparity vs. Distance.

3.1.2.8 Performance Metrics

The accuracy of the pothole depth estimated by StereoPi V2 was analyzed using Linear Regression in order to model the difference between the disparity and distance. The lower the disparity indicates that the pothole is deeper.

3.1.2.9 Final Testing and Validation

The testing process began with a detailed testing plan that includes both simulated and real-world testing scenarios. Initially, the system is tested in controlled environments to verify its capability to estimate pothole depth effectively. Following this, real-world testing was conducted using the StereoPi kit on previously located potholes, specifically at the University of the Philippines Visayas Miagao Campus. As illustrated in Figures 3.11 to 3.14, the procedure for estimating pothole depth closely followed the validated depth measurement manual, where the system captured depth measurements at four designated points within each pothole, corresponding to the measurement points used in the manual measurement data. These four estimated depths were then averaged to determine the final depth estimate for each pothole. The system's performance was validated by comparing its predictions with ground-truth data collected from manual inspections.

Figure 3.12: First measure point

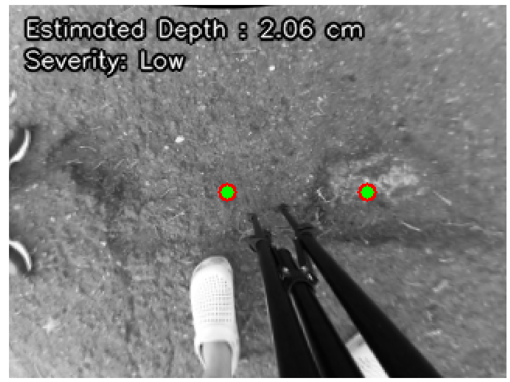

Figure 3.13: Second measure point

Figure 3.14: Third measure point

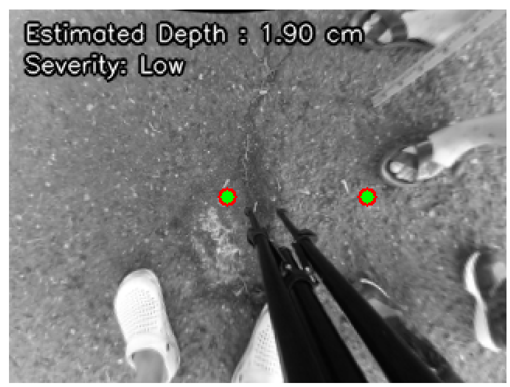

Figure 3.15: Fourth measure point

3.1.2.10 Documentation

Throughout the research activities, thorough documentation was maintained. This documentation captured all methods, results, challenges, and adjustments made during the experimentation phases. It ensured the reproducibility of the work and provided transparency for future research endeavors.

3.1.3 Challenges and Limitations

3.1.3.1 Camera Limitations

During the data collection process, the researchers were faced with various issues involving the StereoPi V2 kit. Issues like inaccuracies in the rectified image pair and generated disparity map were very apparent in the early stages of data collection due to limited related studies and literature involving the camera. In addition, the camera also yielded some inaccurate depth estimation and over reliance on controlled environments which prompted the researchers to further improve its tuning and calibration. It was also observed that the effective working range of the camera for accurate depth estimation was limited to a distance of approximately 30cm to 80cm from the subject. Measurements taken outside of this range tended to result in noisy disparity maps or failed to distinguish objects properly in the disparity output, leading to unreliable depth values.

Chapter 4

Results and Discussion

This chapter presents the results on estimating the depth of potholes using the StereoPi system. It details the prototype construction, calibration of the system, and the application of regression analysis to improve depth estimation. It also contains the measurements taken during the testing phases, comparing the ground truth depths with the value estimated by the camera. Findings are presented systematically, supported by tables showing the collected data, images of the outputs, and discussion on the analysis of results.

4.1 System Calibration and Model Refinement

After the initial testing, the system was calibrated using a controlled setup, where artificial potholes with known depths were created. The stereo camera system captured disparity maps, from which depth was calculated using the standard stereo vision formula:

$$\text{Depth} = \frac{f \times B}{d}$$

where:

- f is the focal length in pixels,
- B is the baseline distance between the two cameras,
- d is the disparity.

However, preliminary observations revealed that the relationship between measured disparity and depth was shifted from the ideal. Their relationship is inherently nonlinear, specifically an inverse relationship (of the form y=1/x). As disparity decreases, depth increases rapidly and nonlinearly. However, due to real-world factors such as lens distortion, imperfect calibration, stereo matching errors, and pixel quantization, the actual relationship between measured disparity and true depth often deviates from the theoretical ideal (Scharstein & Szeliski, 2002).

To address the shifting behavior, a curve fitting approach was introduced. Specifically, an inverse model was fitted to the collected data points, relating disparity and ground-truth distance measurements.

An inverse function of the form:

$$y = a + \frac{b}{x}$$

where:

- y is the estimated distance (in cm),
- x is the measured disparity,
- a and b are coefficients obtained through regression analysis.

4.2 Testing Results

Following calibration, actual potholes located around the University of the Philippines Visayas (UPV) campus were tested. The ground truth depths of the potholes were measured manually and compared with the depths estimated by the StereoPi camera. The input data used for this estimation process, including the disparity map and corresponding stereo image pairs, are shown in Figures 4.1 to 4.3. Based on the results, the StereoPi camera was able to estimate the depths fairly close to the actual measurements.

The smallest error occurred in one pothole, where the estimated depth was only 0.02 cm off from the ground truth. The largest observed error was 3.45 cm. Most of the time, the camera's estimated depths were within approximately 1 to 3 centimeters of the actual depths.

A complete comparison of ground truth and estimated depth values can be found in Appendix C.

The results show that the StereoPi system provides highly accurate estimates of pothole depth. As shown in Table 4.1, the strong correlation (R=0.978) and

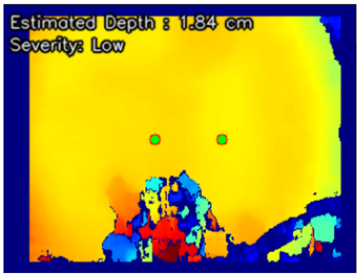

Figure 4.1: Disparity Map

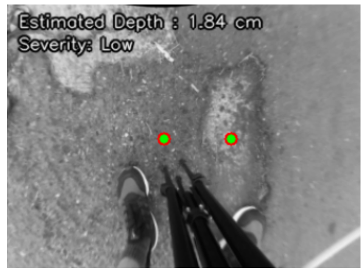

Figure 4.2: Left Stereo Image

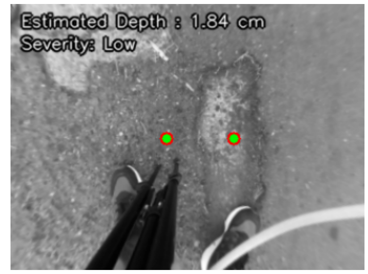

Figure 4.3: Right Stereo Image

high coefficient of determination (R^2=0.956) indicate that the actual depth significantly predicts the estimated values. Additionally, Table 4.2 presents the model coefficients, showing that the regression coefficient for actual depth was statistically significant ($p < 0.001$), suggesting that the relationship is not due to chance. While the RMSE of 0.844 cm and MAE of 0.945 cm suggest generally small errors, the presence of a maximum error of 3.45 cm indicates that there may be occasional outliers or limitations in specific scenarios. Nonetheless, the overall model performance demonstrates that the StereoPi system is suitable for practical pothole depth estimation, showing reasonable accuracy given the hardware setup and environmental conditions.

R	**R^2**	**Root Mean Square Error (cm)**	**Mean Absolute Error (cm)**
0.978	0.956	0.844	0.945

Table 4.1: Linear Regression Model Fit Summary

Predictor	**Estimate**	**SE**	**t**	**p**
Intercept	0.159	0.2544	0.625	0.536
Actual Depth	0.848	0.0317	26.752	<0.001

Table 4.2: Model Coefficients - Estimated Depth

In figure 4.4, a linear relationship between actual and estimated depth is observed with points closely clustered around the regression line. Indicating the accurate depth estimation. The close alignment of most data points with the fitted line and narrow confidence interval suggest high predictive accuracy and minimal deviation, especially at lower depth values.

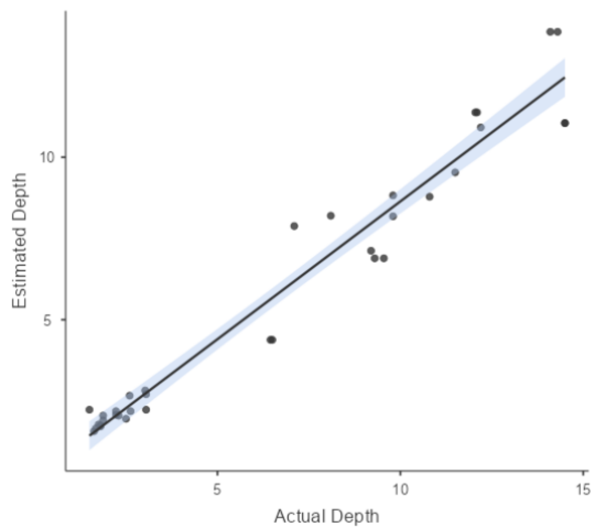

Figure 4.4: Linear Regression Fit Between Actual and Estimated Depth

4.3 Discussion

The study found that stereo vision works effectively in helping estimate the depth of road potholes. The system built using the StereoPi V2 camera was able to measure pothole depths with results mostly within ±3 cm of the actual ground truth values, with an overall root mean square error (RMSE) of 0.844 cm and mean absolute error (MAE) of 0.945 cm. This matches the general observation in earlier studies such as those by Ramaiah and Kundu (2021), which showed that stereo vision can provide useful 3D information for road obstacle detection.

However, this study advances previous work by focusing not just on detection, but on depth-based severity classification, which was largely missing in earlier research.

A strong positive correlation ($R = 0.978$) and coefficient of determination ($R^2 = 0.956$) indicate that the actual pothole depths strongly predict the estimated values. The regression model's significant predictor ($p < 0.001$) further supports the robustness of the depth estimation approach. This level of accuracy and model performance highlights the suitability of the StereoPi system for practical field applications in pothole monitoring and maintenance prioritization. This finding is significant because earlier machine learning-based road detection studies such as those by Bibi et al. (2021) focused mostly on classifying the existence of defects, not measuring their severity.

The outputs of the system were generally positive, showing that with proper calibration and tuning, consistent and reliable depth estimates can be produced. Calibration using checkerboards and tuning block matching parameters were crucial steps in achieving these results. Similar to the findings of Sanz et al. (2012), proper stereo camera calibration was found to be critical to achieving acceptable disparity maps. This reinforces the importance of calibration techniques, especially in real-world outdoor conditions where environmental factors introduce noise.

However, the study also highlighted limitations affecting system performance, including sensitivity to camera calibration quality, lighting conditions, road surface texture, and the camera's vertical positioning during image capture. Outdoor testing revealed that low lighting and shallow potholes made it difficult to generate clean disparity maps, sometimes causing minor estimation errors. These observations are consistent with Sattar et al. (2018), who reported that mobile road sensing systems often struggle in low-light or highly variable surface conditions. Understanding these challenges is important because it points to practical improvements, such as using better cameras, adding lighting support, or applying more robust image enhancement methods in future versions of the system.

Chapter 5

Conclusion

This chapter provides conclusions based on the research findings from data collected on the development of a pothole depth estimation system using stereo vision technology.It then presents recommendations for practice and suggestions for further research.

5.1 Summary

This special project addressed the critical issue of road maintenance by developing a system capable of estimating the depth of potholes to help prioritize repairs. The purpose of the project was to create an automated method that not only detects potholes but also assesses their severity based on depth, responding to the current manual and slow road inspection practices. The researchers aimed to collect high-quality images of potholes under varying conditions, to validate the system's depth estimation accuracy using ground truth measurements and linear regression analysis, and to build a working prototype using stereo vision that can detect, measure, and assess potholes.

To achieve these objectives, a hardware prototype was built using the StereoPi V2 board and Raspberry Pi Compute Module 4, equipped with dual fisheye-lens cameras. Camera calibration was performed using a 9x6 checkerboard pattern with known square sizes to correct for fisheye lens distortion and ensure proper alignment of the stereo pair. After calibration, disparity map generation was fine-tuned by adjusting block matching parameters to produce clearer and more reliable disparity maps. Initial testing was conducted using simulated potholes with known depths to verify the functionality of the system and identify the non-linear behavior present in stereo vision depth measurements. It was observed that using the standard stereo depth formula led to inaccuracies, particularly at greater distances.

The calibrated system and fitted regression model were validated by comparing the estimated depths with the manually measured depths. The findings showed that the system was able to estimate pothole depths within approximately ± 3 cm of actual measurements, achieving a Mean Absolute Error (MAE) of 0.945 cm and a Root Mean Square Error (RMSE) of 0.844 cm. A strong positive linear relationship was observed between the estimated and actual depths (R = 0.978, $R^2 = 0.956$).

5.2 Conclusions

The researchers conclude the following based on the findings:

- The system effectively captures and analyzes depth information from stereo images, providing a viable method for automated pothole severity assessment.

- Incorporating depth measurements significantly improves pothole repair prioritization compared to traditional visual-only inspections, allowing maintenance decisions to be based on objective, measurable data.

- The system achieved an acceptable regression model fit, with a strong positive correlation ($R = 0.978$) and a coefficient of determination ($R^2 = 0.956$), confirming that the depth estimates closely align with the ground truth measurements.The system obtained satisfactory error metrics, with a Mean Absolute Error (MAE) of 0.945 cm and a Root Mean Square Error (RMSE) of 0.844 cm, indicating reliable performance for both pothole detection and depth estimation tasks.

- The proposed approach fills a critical gap in current road maintenance practices, especially within the Philippine context where depth-based severity classification is not yet systematically implemented.

This special project has successfully developed a system that addresses the problem of pothole severity assessment using depth measurement.The research shows that stereo vision, even using accessible and affordable technology, holds strong potential for future development in road maintenance automation. By building upon the foundation laid by this project, future systems can become even more accurate, efficient, and practical for real-world deployment

5.3 Recommendations for Practice

Based on the findings of this special project, the following recommendations are proposed for future researchers, engineers, and road maintenance agencies:

Use stereo vision systems for road surveys. In contexts where LiDAR-based technologies may be cost-prohibitive, maintenance agencies should consider adopting calibrated stereo vision systems for estimating pothole depth. This approach offers a more cost-effective alternative while still enabling depth-based severity classification, thereby allowing for more objective and data-driven prioritization of road repairs compared to traditional visual inspections.

Incorporate depth-based severity classification in maintenance procedures. Authorities should update road inspection protocols to include depth measurements, making pothole severity assessment more objective and standardized.

5.4 Suggestions for Further Research

Based on the limitations encountered and the results obtained,the researchers have observed that there are lapses and possible improvements to further better this system.

Better camera. While the StereoPi V2 camera was effective for basic depth estimation, its performance is limited by its resolution, sensitivity to lighting, and depth range. Future researchers could consider using higher-quality stereo cameras or depth sensors with better image resolution and low-light capabilities to achieve more accurate and consistent disparity maps.

Improve camera calibration and tuning. While the StereoPi system produced good depth estimates, the results still varied depending on the precision of the camera calibration. Future researchers can explore better calibration techniques and finer parameter adjustments to minimize errors, especially in challenging environments.

Use of multi-camera arrays. Instead of relying solely on a two-camera stereo setup, future research could explore the use of multi-point or multi-angle camera arrays. These systems can offer improved depth perception and coverage, particularly for complex or uneven road surfaces, by capturing more comprehensive 3D data.

Integration of stereo vision with motion-based analysis. Incorporating frame differencing techniques, similar to motion detection algorithms, could be beneficial for dynamic environments or mobile applications. This approach may simulate the effect of a moving vehicle and allow the system to detect and estimate potholes more robustly in real time, enhancing its applicability for onboard vehicle-mounted systems.

Chapter 6

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Appendix A

Code Snippets

Listing A.1: Function for generating stereo depth map and classifying pothole severity based on depth difference between two points

```
def stereo_depth_map(rectified_pair,
    save_path_prefix=None):
global disp_max, disp_min
dmLeft, dmRight = rectified_pair

disparity_raw = sbm.compute(dmLeft, dmRight).
    astype(np.float32)
disparity_raw /= 16.0  # normalize disparity

local_max, local_min = disparity_raw.max(),
    disparity_raw.min()

if dm_colors_autotune:
```

```
        disp_max = max(local_max, disp_max)
        disp_min = min(local_min, disp_min)
        local_max, local_min = disp_max, disp_min

        # Normalize for visualization
        disparity_vis = (disparity_raw - local_min) *
            (255.0 / (local_max - local_min))
        disparity_vis = np.uint8(np.clip(disparity_vis, 0,
             255))
        disparity_color = cv2.applyColorMap(disparity_vis,
             cv2.COLORMAP_JET)

        # Calculate depth
        depth_map = calculate_depth(disparity_raw)

        # Define two points
        center_y, center_x = depth_map.shape[0] // 2,
            depth_map.shape[1] // 2 - 20
        second_y = center_y
        second_x = center_x + offset_x

        # Read depth and disparity values
        center_depth_cm = (depth_map[center_y, center_x])
        second_depth_cm = (depth_map[second_y, second_x])
        estimated_depth_cm = abs(center_depth_cm -
```

```
            second_depth_cm)

        # Define severity based on estimated depth
        if estimated_depth_cm < 2.5:
        severity = "Low"
        elif estimated_depth_cm >= 2.5 and
            estimated_depth_cm < 5.0:
        severity = "Medium"
        elif estimated_depth_cm > 5.0:
        severity = "High"
        else:
        severity = "Unknown"
```

Listing A.2: Main loop for capturing stereo image pairs, remapping them for rectification,and estimating depth

```
        for frame in camera.capture_continuous(capture,
            format="bgra", use_video_port=True, resize=(
            img_width,img_height)):
        pair_img = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)

        imgLeft = pair_img[:, :img_width//2]
        imgRight = pair_img[:, img_width//2:]

        imgL = cv2.remap(imgLeft, leftMapX, leftMapY,
            interpolation=cv2.INTER_LINEAR, borderMode=cv2.
            BORDER_CONSTANT)
```

```
imgR = cv2.remap(imgRight, rightMapX, rightMapY,
    interpolation=cv2.INTER_LINEAR, borderMode=cv2.
    BORDER_CONSTANT)

if useStripe:
imgL = imgL[80:160,:]
imgR = imgR[80:160,:]

stereo_depth_map((imgL, imgR), save_path_prefix=
    None)

button_held_time = 0
HOLD_THRESHOLD = 1.0  # seconds

if GPIO.input(BUTTON_PIN) == GPIO.LOW:
press_start = time.time()
while GPIO.input(BUTTON_PIN) == GPIO.LOW:
time.sleep(0.01)
button_held_time = time.time() - press_start

if button_held_time < HOLD_THRESHOLD:
timestamp = datetime.now().strftime("%Y%m%d_%H%M%S
    ")
prefix = f"./captures/capture_{timestamp}"
print(f"\n[!] Capturing snapshot at {timestamp}...
```

```
    ")
stereo_depth_map((imgL, imgR), save_path_prefix=
    prefix)
time.sleep(0.5)
else:
cycle_offset()
time.sleep(0.5)
```

Appendix B

Resource Persons

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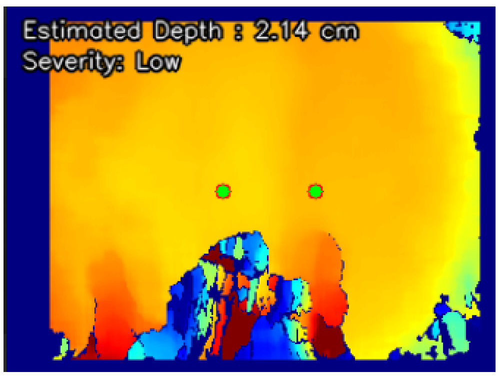
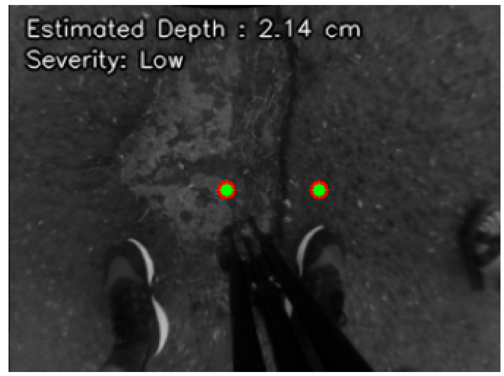
Appendix C

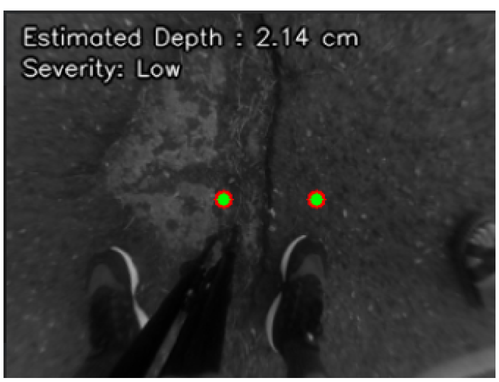
Data Table and Pothole Images



(a) Actual Pothole Disparity Map



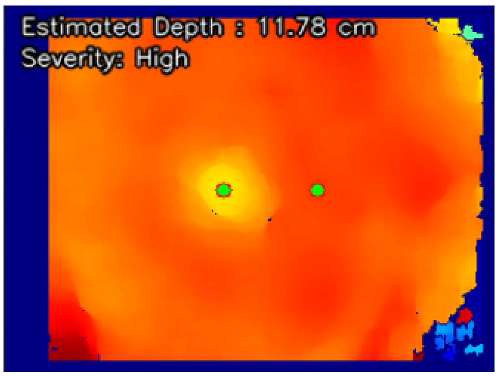
(b) Actual Pothole Left Stereo Image



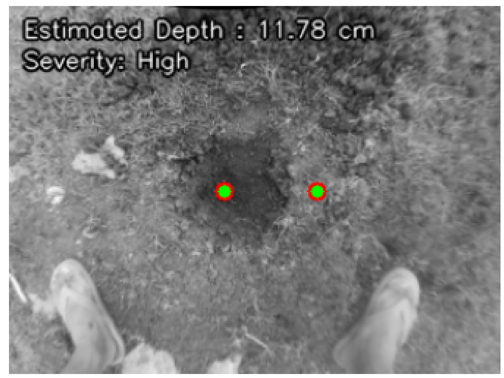
(c) Actual Pothole Right Stereo Image

(d) Actual Pothole real-world image

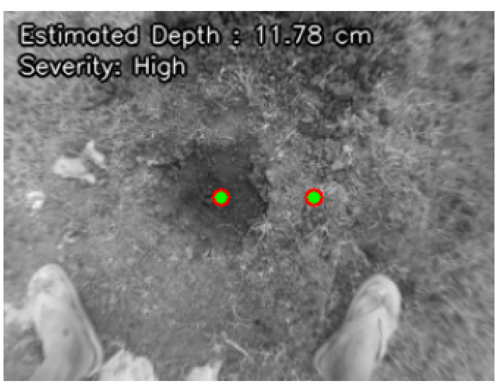
Figure C.1: Actual Pothole Images



(a) Simulated Pothole Disparity Map



(b) Simulated Pothole Left Stereo Image



(c)Simulated Pothole Right Stereo Image

(d) Simulated Pothole StereoPi capture

Figure C.2: Simulated Pothole Images

Sample	Actual Depth (cm)	Estimated Depth (cm)	Residual	Absolute Error (cm)
1	14.500	11.050	-3.450	3.450
2	12.050	11.380	-0.670	0.670
3	6.450	4.380	-2.070	2.070
4	9.550	6.890	-2.660	2.660
5	14.300	13.860	-0.240	0.240
6	1.875	2.050	0.175	0.175
7	2.600	2.663	0.063	0.063
8	1.500	2.230	0.730	0.730
9	1.750	1.775	0.025	0.025
10	1.625	1.567	-0.058	0.058
11	1.800	1.745	-0.055	0.055
12	1.675	1.653	-0.022	0.022
13	2.225	2.078	-0.147	0.147
14	1.875	1.903	0.028	0.028
15	3.050	2.230	-0.820	0.820
16	2.625	2.185	-0.440	0.440
17	3.050	2.708	-0.342	0.342
18	2.225	2.185	-0.040	0.040
19	3.025	2.822	-0.203	0.203
20	1.800	1.718	-0.083	0.083
21	2.300	2.047	-0.252	0.252
22	2.500	1.950	-0.550	0.550
23	10.800	8.785	-2.015	2.015
24	14.500	11.050	-3.450	3.450
25	9.200	7.122	-2.077	2.077
26	9.800	8.825	-0.975	0.975
27	14.300	13.860	-0.440	0.440
28	7.100	7.883	0.783	0.783
29	9.800	8.182	-1.618	1.618
30	8.100	8.200	0.100	0.100
31	11.500	9.533	-1.967	1.967
32	12.100	11.380	-0.720	0.720
33	6.500	4.380	-2.120	2.120
34	9.300	6.890	-2.410	2.410
35	12.200	10.918	-1.282	1.282

Table C.1: Actual vs. Estimated Depths with Residuals and Absolute Errors

Appendix D

Supplementary Documents

January 31, 2025

RECEIVED
Records Unit
NO.:
DATE: JAN 31 2025
TIME: 11:35 am

ENGR. ETHEL B. MORALES
OIC – District Engineer
Department of Public Works and Highways (DPWH)
1st District Engineering Office
Rizal St., Guimbal, Iloilo

Dear Engr. Morales:

Greetings of Honor and Excellence!

We are 4th year Bachelor of Science in Computer Science students from the University of the Philippines Visayas, currently working on a special problem for our CMSC 198.2 course. Our project focuses on developing a system for the depth estimation of potholes.

In line with this, we recently had an opportunity to interview representatives from your esteemed agency at the regional office in Fort San Pedro, Iloilo City. It was under their advice to approach the 1st district office of DPWH since it is where our data gathering process will take place.

We would greatly appreciate your review and validation of these procedures so that this special problem will be accurate and compliant with engineering standards.

Your support will not only guide our research but also ensure our system could one day be a valuable tool in improving road maintenance practices. We understand the importance of these standards, and we assure you that any information provided will be strictly used for academic purposes.

We sincerely hope that you accept our humble request, as it will play a crucial role in our project.

Thank you very much for your time and consideration. We look forward to your positive response.

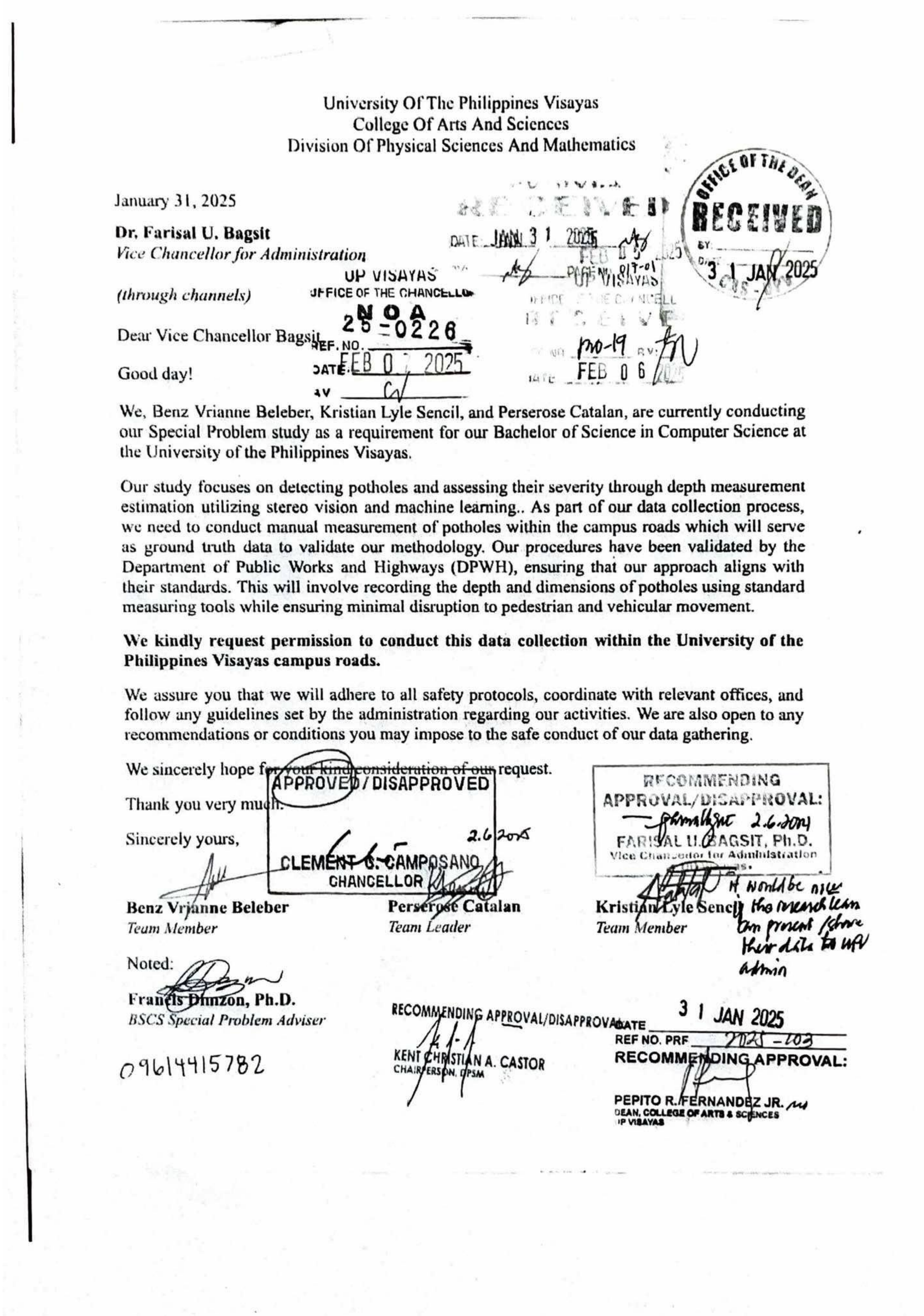
Sincerely,

BENZ VRIANNE BELEBER
Team Leader

KRISTIAN LYLE SENCIL
Team Member

PERSEROSE CATALAN
Team Member

Figure D.1: Letter requesting validation of data collection procedures.



University Of The Philippines Visayas
College Of Arts And Sciences
Division Of Physical Sciences And Mathematics

January 31, 2025

Dr. Farisal U. Bagsit
Vice Chancellor for Administration

(through channels)

Dear Vice Chancellor Bagsit,

Good day!

We, Benz Vrianne Beleber, Kristian Lyle Sencil, and Perserose Catalan, are currently conducting our Special Problem study as a requirement for our Bachelor of Science in Computer Science at the University of the Philippines Visayas.

Our study focuses on detecting potholes and assessing their severity through depth measurement estimation utilizing stereo vision and machine learning.. As part of our data collection process, we need to conduct manual measurement of potholes within the campus roads which will serve as ground truth data to validate our methodology. Our procedures have been validated by the Department of Public Works and Highways (DPWH), ensuring that our approach aligns with their standards. This will involve recording the depth and dimensions of potholes using standard measuring tools while ensuring minimal disruption to pedestrian and vehicular movement.

We kindly request permission to conduct this data collection within the University of the Philippines Visayas campus roads.

We assure you that we will adhere to all safety protocols, coordinate with relevant offices, and follow any guidelines set by the administration regarding our activities. We are also open to any recommendations or conditions you may impose to the safe conduct of our data gathering.

We sincerely hope for your kind consideration of our request.

Thank you very much.

Sincerely yours,

Benz Vrianne Beleber
Team Member

Perserose Catalan
Team Leader

Kristian Lyle Sencil
Team Member

Noted:

Francis Dimzon, Ph.D.
BSCS Special Problem Adviser

09614415782

Figure D.2: Letter requesting permission for ground truth data collection within the UPV campus.

January 17, 2025

ENGR. SANNY BOY O. OROPEL, CES E
Regional Director
Department of Public Works and Highways (DPWH)
Regional Office VI
Fort San Pedro, Iloilo City

REC'D
RECORDS SECTION
NO.
DATE: JAN 1 7 2025
TIME: 10:40am
INITIAL:

Dear Engr. Oropel:

Greetings of Honor and Excellence!

We are Computer Science students from the University of the Philippines Visayas, currently working on a special problem for our CMSC 198.2 course. Our project focuses on developing a system for the depth estimation of potholes.

In line with this, we kindly request an opportunity to interview representatives from your esteemed agency to gain insights into the process of verifying our research data, including ground truth data. This will greatly assist us in ensuring that our system adheres to the standards and requirements upheld by your agency.

We would also greatly appreciate your advice on the specific procedures, documentation, and requirements necessary for submitting our data for review. Your expertise and assistance would be invaluable to the success of our project, and we are eager to learn from your knowledge and experience.

Your support will not only guide our research but also ensure our system could one day be a valuable tool in improving road maintenance practices. We understand the importance of these standards, and we assure you that any information provided will be strictly used for academic purposes.

We sincerely hope that you accept our humble request, as it will play a crucial role in our project.

Thank you very much for your time and consideration. We look forward to your positive response.

Sincerely,

BENZ VRIANNE BELEBER

KRISTIAN LYLE SENCIL

PERSEROSE P. CATALAN

Figure D.3: Letter requesting an interview with DPWH representatives for the process of verifying ground truth data.

RECEIVED
PLANNING AND DESIGN DIV
DPWH RVI, ILOILO CITY
REF. NO: :
DATE : SEP 16 2024
INITIAL: : 11:28am

September 16, 2024

MARILOU G. ZAMORA
Chief, Planning and Design Division
Department of Public Works and Highways
Regional Office 6
Iloilo City, Iloilo, 5000

Dear Ma'am Zamora,

I hope this letter finds you well. My name is Benz Vrianne Beleber, and I, along with my team members, Kristian Lyle Sencil and Perserose Catalan, are currently students at the University of the Philippines Visayas, pursuing degrees in Computer Science. We are working on our undergraduate special project aimed at developing a system that utilizes artificial intelligence to classify and assess the severity of road anomalies. This system is designed to enhance road maintenance strategies by providing more efficient and accurate road condition evaluations.

We would like to kindly request an opportunity to interview representatives from your esteemed agency to gain a deeper understanding of the standards, procedures, and scaling methods used for assessing road quality. We are particularly interested in learning about the criteria the DPWH employs for road quality, its maintenance, and the technology used to evaluate road conditions. Additionally, we would greatly appreciate exploring potential collaboration opportunities that could further enrich our special problem.

DPWH's expertise and experience in this field would be invaluable to our study. We believe that a discussion with your team will not only enhance our research but also potentially contribute to more efficient methods of road quality assessment and management in the future.

Thank you very much for considering our request. We look forward to the opportunity to discuss how our special problem can benefit from your agency's knowledge and practices.

Sincerely,

BENZ VRIANNE BELEBER

KRISTIAN LYLE SENCIL

PERSEROSE CATALAN

University of the Philippines Visayas
Bachelor of Science in Computer Science

Figure D.4: Letter requesting an interview with DPWH representatives for the standard operating procedures of the agency for assessing road quality.

UNIVERSITY OF THE PHILIPPINES VISAYAS
COLLEGE OF ARTS AND SCIENCES
DIVISION OF PHYSICAL SCIENCES AND MATHEMATICS

POTHOLE MEASUREMENT PROCEDURAL MANUAL

Prepared by:

Benz Vrianne BELEBER
Perserose CATALAN
Kristian Lyle SENCIL

Figure D.5: Validated pothole measurement procedural manual, reviewed by Engr. Ethel B. Morales, District Engineer, DPWH 1st District Engineering Office.

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DIVISION OF PHYSICAL SCIENCES AND MATHEMATICS

I. PURPOSE

This manual is developed as part of the special project *Defectra: Road Defect Severity Assessment and Classification* at the University of the Philippines Visayas. The study focuses on evaluating road defects, particularly potholes, by assessing their severity based on the depth measurements. This manual establishes a standardized procedure for measuring pothole depth, ensuring consistency, accuracy, and compliance with engineering best practices.

II. SCOPE

This procedure applies to research personnel, faculty members, and students involved in pothole assessment and measurement activities within the University of the Philippines Visayas and designated research sites.

III. PROCEDURE

a. Preparation and Safety Measures

- Ensure the availability and functionality of required equipment, including a GPS-enabled camera for location tagging, rulers, and measuring tape.
- Wear appropriate personal protective equipment (PPE), such as reflective vests and hard hats, to ensure visibility and safety.
- Set up early warning device if working on active roads to alert motorists and pedestrians
- Ensure all equipment is in optimal working condition before use.

1

Figure D.6: Second page of the pothole measurement procedural manual

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DIVISION OF PHYSICAL SCIENCES AND MATHEMATICS

b. Pothole Depth Measurement

- Place straight edge across the pothole's edge to measure depth.
- Use a measuring tape or depth gauge to record depth.
- Repeat the process at multiple points to account for uneven depths and allow for an average value that represents the overall depth of the pothole.

2

Figure D.7: Third page of the pothole measurement procedural manual

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c. Data Documentation

- Capture photographs of the pothole from multiple angles, ensuring that measurement tools are visible in the images for scale reference.
- Record depth measurements alongside GPS coordinates for accurate geotagging.
- Save the data in organized format and proper identification using unique identifiers for easy tracking and analysis.

IV. SAFETY CONSIDERATIONS

Compliance with university guidelines on safety is mandatory throughout the measurement process. Ensuring safety during pothole measurement is essential to protect personnel and road users. All team members must wear the required personal protective equipment (PPE), including reflective vests and hard hats, to enhance visibility and minimize risk. Researchers must remain aware of their surroundings and avoid working in high-traffic areas without proper traffic control measures.

Figure D.8: Fourth page of the pothole measurement procedural manual

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V. QUALITY CONTROL

To ensure the accuracy and reliability of data collected, all measurements and documentation must be subject to review by qualified engineers from the Department of Public Works and Highways (DPWH). Multiple measurements should be taken at different points within the pothole to ensure consistency and eliminate human error. All recorded data must undergo verification through cross-checking by designated personnel. Any discrepancies observed during validation should be addressed, and corrective measures implemented. The final reports and findings must be reviewed and approved by DPWH engineers to validate compliance with national road assessment standards.

VI. RECORDS AND DOCUMENTATION

All measurements, including depth readings and GPS coordinates, must be logged in a standardized format with clear labels. Photographic documentation should be taken from various angles to provide visual evidence of pothole conditions. Data should be stored electronically with appropriate file naming conventions for easy retrieval.

4

Figure D.9: Fifth page of the pothole measurement procedural manual