

1 ROAD DEFECT SEVERITY ASSESSMENT AND
2 CLASSIFICATION

3 A Special Problem
4 Presented to
5 the Faculty of the Division of Physical Sciences and Mathematics
6 College of Arts and Sciences
7 University of the Philippines Visayas
8 Miag-ao, Iloilo

9 In Partial Fulfillment
10 of the Requirements for the Degree of
11 Bachelor of Science in Computer Science by

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17 June 2, 2025

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**ROAD DEFECT SEVERITY ASSESSMENT AND
CLASSIFICATION**

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29 **Declaration**

30 We, BENZ VRIANNE BELEBER, PERSEROSE CATALAN, and KRISTIAN
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Dedication

36 This Special Problem is dedicated to the researchers' families, whose unwa-
37 vering love, patience, and support have been the foundation of their academic
38 journey.

39 To their parents, for their endless sacrifices.

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

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

44

Acknowledgment

45 The researchers would like to express their heartfelt gratitude to the individuals,
46 institutions, and organizations who made the completion of this Special
47 Problem possible:

48 To their adviser, Dr. Francis Dimzon, for his expert guidance, valuable insights,
49 for teaching Computer Vision topics, and unwavering support throughout
50 the research process.

51 To Prof. Jumar Cadondon, for lending his time and expertise during the early
52 stages of this Special Problem, especially in providing assistance with his drone.

53 To Sir Cris Beleber, for his unwavering support from the initial conceptualization
54 of this project to out consultations with the DPWH. His assistance was
55 instrumental in the successful completion of this study.

56 To the Komsai faculty and staff, for providing a nurturing and intellectually
57 stimulating environment.

58 To the university personnel who ensured the researchers' safety throughout
59 the data collection process.

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

62 To the Department of Public Works and Highways (DPWH), for providing
63 valuable data and technical insights that greatly contributed to the relevance and
64 application of the study.

65 To their families and friends, for their unconditional love, patience, and en-
66 couragement.

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

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

71

Abstract

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

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

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¹⁷⁸ **Chapter 1**

¹⁷⁹ **Introduction**

¹⁸⁰ **1.1 Overview of the Current State of Technology**

¹⁸¹ The Department of Public Works and Highways (DPWH) reported in their Na-
¹⁸² tional Road Length by Classification, Surface Type, and Condition Summary as
¹⁸³ of October 2023, that approximately 98.97% of roads in the Philippines is paved
¹⁸⁴ which is either made of concrete or asphalt (Balita, 2024). Since the DPWH is an
¹⁸⁵ institution under the government, it is paramount to maintain such roads in order
¹⁸⁶ to avoid accidents and congested traffic situations especially in heavily urbanized
¹⁸⁷ areas where there are a lot of vehicles.

¹⁸⁸ In an interview with the Road Board of DPWH Region 6 it was stated that road
¹⁸⁹ condition assessments are mostly done manually with heavy reliance on engineer-
¹⁹⁰ ing judgment (J. Chua, Personal Interview. 16 September 2024). In addition,
¹⁹¹ manual assessment of roads is also time consuming which leaves maintenance
¹⁹² operations to wait for lengthy assessments. In a study conducted by Ramos, Da-

193 canay, and Bronuela-Ambrocio (2023), it was found that the Philippines' current
194 method of manual pavement surveying is considered as a gap since it takes an
195 average of 2-3 months to cover a 250 km road as opposed to a 1 day duration
196 in the Australian Road Research Board for the same road length. Ramos et al.
197 (2023) recommended that to significantly improve efficiency of surveying methods
198 and data gathering processes, automated survey tools are to be employed. It was
199 also added that use of such automated, surveying tools can also guarantee the
200 safety of road surveyors.

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

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

²¹⁸ road condition monitoring.

²¹⁹ 1.2 Problem Statement

²²⁰ Roads support almost every aspect of daily life, from providing a way to transport
²²¹ goods and services to allowing people to stay connected with their communities.
²²² However, road defects such as cracks and potholes damage roads over time, and
²²³ they can increase accident risks and affect the overall transportation. The current
²²⁴ way of inspecting the roads for maintenance is often slow as it is done manually,
²²⁵ which makes it harder to detect and fix defects early. The delay in addressing these
²²⁶ problems can lead to even worse road conditions (J. Chua, Personal Interview. 16
²²⁷ September 2024). There are several research studies into automated road defect
²²⁸ classification that have advanced in recent years but most of them focus on iden-
²²⁹ tifying the types of defects rather than assessing their severity or characteristics
²³⁰ like depth. Without reliable data on the depth of the defect, road maintenance
²³¹ authorities may underestimate the severity of certain defects. To address these
²³² challenges, advancements are needed across various areas. An effective solution
²³³ should not only detect and classify road defects but also measure their severity
²³⁴ to better prioritize repairs. Failing to address this problem will require more ex-
²³⁵ tensive repairs for damaged roads, which raises the cost and strains the budget.
²³⁶ Additionally, road maintenance would still be slow and cause disruptions in daily
²³⁷ activities. Using an automated system that accurately assess the severity of road
²³⁸ defects by incorporating depth is necessary to efficiently monitor road quality.

²³⁹ **1.3 Research Objectives**

²⁴⁰ **1.3.1 General Objective**

²⁴¹ This special problem aims to develop a system that can estimate the depth of
²⁴² potholes on road surfaces and classify them into different severity levels such as
²⁴³ low, medium, and high by using stereo vision technology, supporting faster and
²⁴⁴ more precise road maintenance decisions.

²⁴⁵ **1.3.2 Specific Objectives**

²⁴⁶ Specifically, this special problem aims to:

²⁴⁷ 1. collect high-quality stereo images of road surfaces that capture potholes
²⁴⁸ including their depth in favorable conditions,

²⁴⁹ 2. measure the accuracy of the system by comparing the depth measurements
²⁵⁰ against ground truth data collected from actual road inspections and to
²⁵¹ utilize linear regression, root mean square error, and mean absolute error as
²⁵² metrics for evaluation, and

²⁵³ 3. develop a prototype system that can detect and measure road potholes from
²⁵⁴ image input, analyze their depth, and assess their severity.

1.4 Scope and Limitations of the Research

- 255 This system focuses solely on detecting and assessing the severity of potholes
256 through image analysis and depth measurement technologies. The scope includes
257 the collection of pothole images using cameras and depth-sensing tools under a
258 favorable weather condition.
- 260 Depth-sensing tools, such as stereo cameras, will be used to record the depth of
261 potholes specifically. The system will not address other road defects like cracks
262 or other surface deformations; therefore, it will detect and analyze only potholes.
263 Additionally, only accessible potholes will be measured, meaning those that are
264 filled with water or obscured by debris may not be accurately assessed.
- 265 The system developed focuses exclusively on detecting potholes and assessing
266 their severity through depth measurement. The accuracy of the system's depth
267 measurements is evaluated by comparing them against data collected from actual
268 field inspections. However, this comparison is limited to selected sample sites,
269 as collecting field data over a large area can be time-consuming and resource-
270 intensive.
- 271 Environmental factors such as lighting, road surface texture, and weather con-
272 ditions may impact the system's performance. The accuracy and reliability of
273 the system will depend on the quality of camera calibration and disparity map
274 finetuning. Its ability to measure the depth of pothole images needs careful vali-
275 dation.

²⁷⁶ 1.5 Significance of the Research

²⁷⁷ This special problem aims to be significant to the following:

²⁷⁸ *Computer Science Community.* This system can contribute to advancements in
²⁷⁹ computer vision and machine learning by using both visual and depth data to
²⁸⁰ assess the severity of road defects. It introduces a more comprehensive approach
²⁸¹ compared to the usual image-only or manual inspection methods. This combina-
²⁸² tion can be applied to other fields that need both visual and depth analysis like
²⁸³ medical imaging.

²⁸⁴ *Concerned Government Agencies.* This system offers a valuable tool for road
²⁸⁵ safety and maintenance. Not only can this detect and classify anomalies, it can
²⁸⁶ also assess the defect's severity which allows them to prioritize repairs, optimal
²⁸⁷ project expenditures, and better overall road safety and quality.

²⁸⁸ *Field Engineers.* In the scorching heat, field engineers are no longer required to
²⁸⁹ be on foot unless it requires their engineering judgement when surveying a road
²⁹⁰ segment. It can hasten the overall assessment process.

²⁹¹ *Future Researchers.* The special problem may serve as a baseline and guide of
²⁹² researchers with the aim to pursue special problems similar or related to this.

²⁹³ **Chapter 2**

²⁹⁴ **Review of Related Literature**

²⁹⁵ **2.1 Frameworks**

²⁹⁶ This section of the chapter presents related frameworks that is considered essential
²⁹⁷ for the development of this special problem.

²⁹⁸ **2.1.1 Depth Estimation**

²⁹⁹ Depth estimation as defined by Sanz, Mezcua, and Pena (2012) is a set of processes
³⁰⁰ that aims to extract a representation of a certain scene's spatial composition.
³⁰¹ Stereo vision is stated to be among the depth estimation strategies.

³⁰² **2.1.2 Image and Video Processing**

³⁰³ Kumar (2024) defines image processing as a process of turning an image into its
³⁰⁴ digital form and extracting data from it through certain functions and operations.

305 Usual processes are considered to treat images as 2D signals wherein different
306 processing methods utilize these signals. Like image processing, RICHES Project
307 (2014) defines video processing as being able to extract information and data from
308 video footage through signal processing methods. However, in video processing
309 due to the diversity of video formats, compression and decompression methods
310 are often expected to be performed on videos before processing methods to either
311 increase or decrease bitrate.

312 **2.1.3 Stereo Vision**

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

319 **2.2 Related Studies**

320 This section of the chapter presents related studies conducted by other researchers
321 wherein the methodology and technologies used may serve as basis in the devel-
322 opment of this special problem.

³²³ **2.2.1 Deep Learning Studies**

³²⁴ **Automated Detection and Classification of Road Anomalies**
³²⁵ **in VANET Using Deep Learning**

³²⁶

³²⁷ In the study of Bibi et al. (2021) it was noted that identification of active road
³²⁸ defects are critical in maintaining smooth and safe flow of traffic. Detection and
³²⁹ subsequent repair of such defects in roads are crucial in keeping vehicles using
³³⁰ such roads away from mechanical failures. The study also emphasized the growth
³³¹ in use of autonomous vehicles in research data gathering which is what the re-
³³² searchers utilized in data gathering procedures. With the presence of autonomous
³³³ vehicles, this allowed the researchers to use a combination of sensors and deep
³³⁴ neural networks in deploying artificial intelligence. The study aimed to allow au-
³³⁵ tonomous vehicles to avoid critical road defects that can possibly lead to dangerous
³³⁶ situations. Researchers used Resnet-18 and VGG-11 in automatic detection and
³³⁷ classification of road defects. Researchers concluded that the trained model was
³³⁸ able to perform better than other techniques for road defect detection. The study
³³⁹ is able to provide the effectiveness in automating road defect detection and clas-
³⁴⁰ sification. However, the study lacks findings regarding the severity of detected
³⁴¹ defects and incorporation of pothole depth in their model which are both crucial
³⁴² in automating manual procedures of road surveying in the Philippines.

³⁴³ **Single Image Depth Estimation: An Overview**

³⁴⁴

³⁴⁵ In the study by Mertan, Duff, and Unal (2022), the authors argued that machine
³⁴⁶ learning methods, specifically convolutional neural networks (CNNs), are among

347 the most effective approaches for solving the depth estimation problem. They
348 noted that most existing depth estimation studies address this task by utilizing
349 relative depth information derived from labeled datasets. Additionally, visual cues
350 such as ground plane contact, vanishing points, and object edges were identified
351 as key features for estimating depth from a single image. The researchers also
352 pointed out that relying on labeled data may introduce biases, which can affect
353 the accuracy of these learned cues. While the limitations of single-image depth
354 estimation were acknowledged, the study did not thoroughly explore alternative
355 methods such as stereo imaging, which can produce more precise depth maps and
356 potentially address some of these limitations.

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

359
360 In the study of Ha et al. (2022), it was argued that the detection, classification,
361 and severity assessment of road cracks should be automated due to the bottleneck
362 it causes during the entire process of surveying. For the study, the researchers
363 utilized SqueezeNet, U-Net, and MobileNet-SSD models for crack classification and
364 severity assessment. Furthermore, the researchers also employed separate U-nets
365 for linear and area cracking cases. For crack detection, the researchers followed
366 the process of pre-processing, detection, classification. During preprocessing im-
367 ages were smoothed out using image processing techniques. The researchers also
368 utilized YOLOv5 object detection models for classification of pavement cracking
369 wherein the YOLOv51 model recorded the highest accuracy. The researchers how-
370 ever stated images used for the study are only 2D images which may have allowed
371 higher accuracy rates. Furthermore, the researchers suggest incorporating depth

372 information in the models to further enhance results. Despite the accuracy of the
373 deep learning models in identification and classification of road cracks, the lack
374 of depth estimation and severity assessment suggests that the study is still not
375 geared towards road surveying processes wherein depth estimation with severity
376 assessment of individually detected road cracks may be required.

377 2.2.2 Machine Learning Studies

378 Smartphones as Sensors for Road Surface Monitoring

379

380 In their study, Sattar, Li, and Chapman (2018) noted the rise of sensing ca-
381 pabilities of smartphones which they utilized in monitoring road surface to de-
382 tect and identify anomalies. The researchers considered different approaches in
383 detecting road surface anomalies using smartphone sensors. One of which are
384 threshold-based approaches which was determined to be quite difficult due to sev-
385 eral factors that are affecting the process of determining the interval length of
386 a window function in spectral analysis. The researchers also utilized a machine
387 learning approach adapted from another study. It was stated that k-means was
388 used in classifying sensor data and in training the SVM algorithm. Due to the
389 requirement of training a supervised algorithm using a labeled sample data was
390 required before classifying data from sensors, the approach was considered to be
391 impractical for real-time situations. In addition, Sattar et al. (2018) also noted
392 various challenges when utilizing smartphones as sensors for data gathering such
393 as sensors being dependent on the device's placement and orientation, smooth-
394 ness of captured data, and the speed of the vehicle it is being mounted on. Lastly,
395 it was also concluded that the accuracy and performance of using smartphone

396 sensors is challenging to compare due to the limited data sets and reported algo-
397 rithms. With the smartphone's observed limitations in surveying road conditions,
398 this indicates that much more sophisticated imaging technologies may be utilized
399 in realtime surveying procedures. In addition, the smartphone's over reliance on
400 several factors also makes it quite incapable in accurate depth estimation.

401 **2.2.3 Computer Vision Studies**

402 **Stereo Vision Based Pothole Detection System for Improved
403 Ride Quality**

404

405 In the study of Ramaiah and Kundu (2021) it was stated that stereo vision has
406 been earning attention due to its reliable obstacle detection and recognition. Fur-
407 thermore, the study also discussed that such technology would be useful in improv-
408 ing ride quality in automated vehicles by integrating it in a predictive suspension
409 control system. The proposed study was to develop a novel stereo vision based
410 pothole detection system which also calculates the depth accurately. However,
411 the study focused on improving ride quality by using the 3D information from
412 detected potholes in controlling the damping coefficient of the suspension system.
413 Overall, the pothole detection system was able to achieve 84% accuracy and is
414 able to detect potholes that are deeper than 5 cm. The researchers concluded
415 that such system can be utilized in commercial applications. However, it is also
416 worth noting that despite the system being able to detect potholes and measure
417 its depth, the overall severity of the pothole and road condition was not addressed
418 which makes it quite inapplicable for automated road surveying purposes.

420 **Depth and Image Fusion for Road Obstacle Detection Us-**
421 **ing Stereo Camera**

422

423 In the study of Perezyabov, Gavrilenkova, and Afanasyev (2022), the researchers
424 utilized stereo imaging in detecting obstacles in the road as well as their distance
425 from the camera through the use of depth information gathered from the stereo
426 cameras. It was stated that obstacle detection was a challenge due to certain fac-
427 tors such as artificial illumination and various road textures. In order to address
428 these limitations, the researchers developed an RGB-based and obstacle detection
429 stereo-based approach where SLIC superpixel segmentation was integrated for
430 object segmentation. The findings were reported to give encouraging results due
431 to the researchers being able to prove that RGB-based methods were capable of
432 searching small contrasts objects making road obstacle detection possible. How-
433 ever, it was noted that significant background noise was visible in their captures
434 which may affect a detected obstacle's accuracy. In addition, due to this limi-
435 tation, RGB-based methods for stereo image depth estimation may not produce
436 accurate results. Furthermore, the researchers were only able to test such model
437 in a parking lot wherein vehicle movement is slow and obstacles are almost easily
438 recognizable, lack of testing in actual roads may indicate the model's unreadiness
439 in an actual road applications.

440 2.3 Synthesis

*441 In majority of the studies discussed, road defect detection and classification is a
442 common point of discussion. However, despite deep learning approaches being
443 successful in solving the problem of road defect detection, most of the studies still
444 lack depth incorporation in their models which is considered as a factor in assess-
445 ing pothole depth as based on the Long Term Pavement Performance (Miller &
446 Bellinger, 2014). Furthermore, for stereo vision studies, the detection aspect is
447 also addressed however the studies are not geared towards road surveying pro-
448 cesses due to the emphasis on driver and ride quality improvement. With the
449 observed limitations in related studies, the researchers of this study focused on
450 incorporating severity assessment with depth estimation through a stereo vision
451 based approach to be able to build a foundation on depth based severity assess-
452 ment that could be integrated in future deep learning models.*

⁴⁵³ 2.4 Chapter Summary

- ⁴⁵⁴ 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.
Depth and Image Fusion for Road Obstacle Detection Using Stereo Camera	Stereo Imaging, RGB-based method	Model was able to take advantage of small contrast objects and detect obstacles.	Approach was conducted in a controlled setting with inadequate practical application.
Single Image Depth Estimation: An Overview	Deep Learning Models	Identified various issues with single image depth estimation and effective deep learning model approaches in solving the problem.	Other alternatives to depth estimation with respect to the limitations of single image depth estimation was not mentioned or thoroughly discussed.
Assessing Severity of Road Cracks Using Deep Learning-Based Segmentation and Detection	SqueezeNet, U-Net, YOLOv5, and MobileNet-SSD models	YOLOv5 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

⁴⁵⁷ Chapter 3

⁴⁵⁸ Research Methodology

⁴⁵⁹ This chapter outlines the systematic approach that were taken to address the
⁴⁶⁰ problem of pothole depth estimation using StereoPi V2. The methodology is
⁴⁶¹ divided into key phases: data collection, algorithm selection, design, testing and
⁴⁶² experimentation, and challenges and limitations. Each phase will play a crucial
⁴⁶³ role in accurately classifying and assessing road defects. Each phase is essential
⁴⁶⁴ for accurately estimating the depth of potholes using StereoPi V2.

⁴⁶⁵ 3.1 Research Activities

⁴⁶⁶ 3.1.1 Data Collection

⁴⁶⁷ The researchers conducted initial inquiries to understand the problem domain and
⁴⁶⁸ existing road maintenance practices. This phase included consulting the engineers
⁴⁶⁹ under the Road Maintenance Department of the government agency Department

470 of Public Works and Highways (DPWH). An interview with Engr. Jane Chua pro-
471 vided a comprehensive overview of the DPWH's road maintenance manual, which
472 was crucial in aligning this project with existing standards. This collaboration
473 with DPWH provided insights into road pothole classification standards, ensuring
474 that the collected data will align with industry standards. The interview with
475 Engr. Chua revealed that the current way to measure potholes is by their area.
476 Additionally, the DPWH manual primarily focuses on the volume of detected pot-
477 holes within a road segment as a measure of severity. However, since depth is not
478 explicitly measured in their current procedures, the study will supplement this by
479 referencing international standards such as the Long-Term Pavement Performance
480 (LTPP) classification used in the United States (Miller & Bellinger, 2014). The
481 LTPP categorizes potholes based on depth thresholds, which will be integrated
482 with DPWH's volume-based assessment to provide a more comprehensive sever-
483 ity classification framework. The data collection involved capturing around 130
484 images of potholes from various locations within the UP Visayas Campus. Ground
485 truth data of pothole depth were collected by the researchers by measuring the
486 depth of different points in an individual pothole and then solving for its aver-
487 age depth. The researchers developed a manual specifically designed for depth
488 measurement, which underwent a review by Engr. Benjamin Javellana, Assistant
489 Director of the Maintenance Division at the Department of Public Works and
490 Highways (DPWH) Regional Office VI. The finalized version of the manual was
491 subsequently validated by the DPWH First District Engineering Office. In order
492 to individually locate or determine each pothole where the ground truth data is
493 collected, images taken were labeled with their corresponding coordinates, street
494 names, and nearby landmarks.

495 3.1.1.1 Data Collection (Ground Truth Data)

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



507

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

508

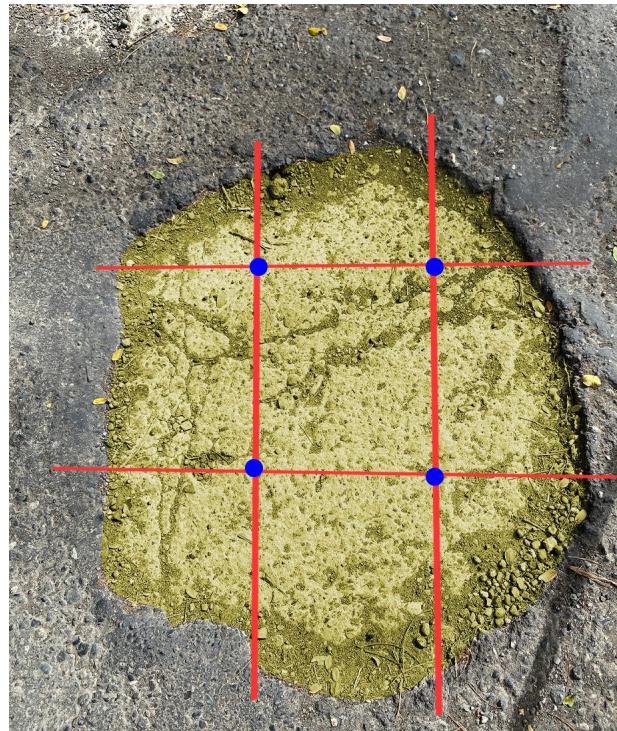


Figure 3.2: Four measurement points of the pothole.

509

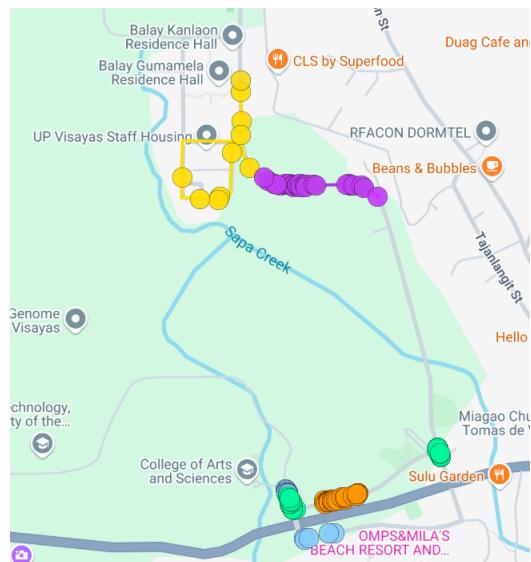


Figure 3.3: Visualized pothole locations during the ground truth data collection within the UPV campus.

510 3.1.2 Design, Testing, and Experimentation

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

513 3.1.2.1 Depth Measurement

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

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

525 3.1.2.2 Severity Assessment

526 The estimated pothole depths were classified using the Long-Term Pavement Per-
527 formance (LTPP) depth thresholds, an internationally recognized framework for
528 pavement distress evaluation. This classification provides standardized criteria
529 to assess pothole severity objectively based on measured depth values. Specifi-

530 cally, potholes with depths less than 2.5 cm are categorized as low severity, those
531 between 2.5 cm and 5 cm as medium severity, and potholes exceeding 5 cm are
532 classified as high severity (Miller & Bellinger, 2014).

533 **3.1.2.3 Materials and Equipment**

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

536 • StereoPi V2 Board

537 • Raspberry Pi Compute Module 4 (CM4)

538 • Dual RaspberryPi Camera Modules with Fisheye Lens

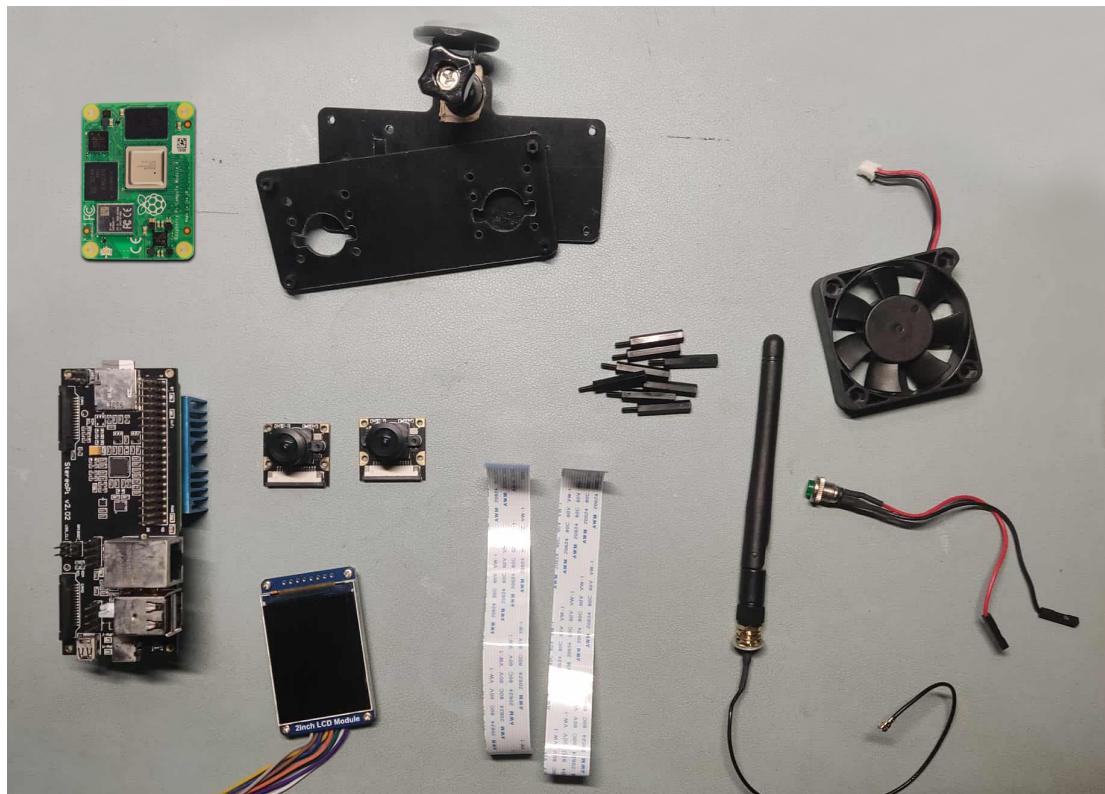
539 • 3D Printed Custom Housing

540 • 2-inch LCD Module

541 • Micro SD Card

542 • Antenna

543 • Momentary Push Button



544

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.

545

3.1.2.4 Prototype Building

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

553 functional prototype is presented in Figure 3.6.

554

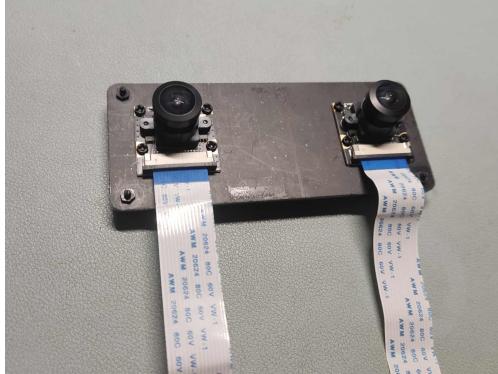


Figure 3.5: Dual RPi Camera Modules attached to the custom housing.

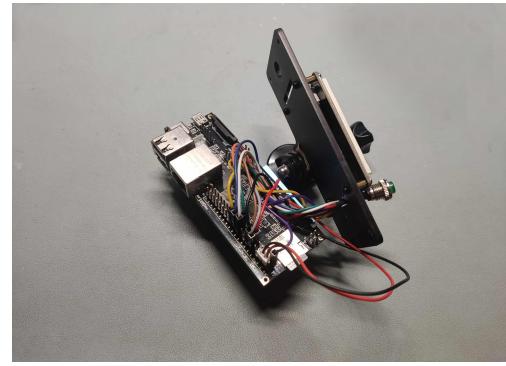


Figure 3.6: LCD Module connected to the StereoPi board.

555



Figure 3.7: The finished prototype.

556 3.1.2.5 Camera Calibration (Fisheye Distortion)

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

563 accuracy.

564

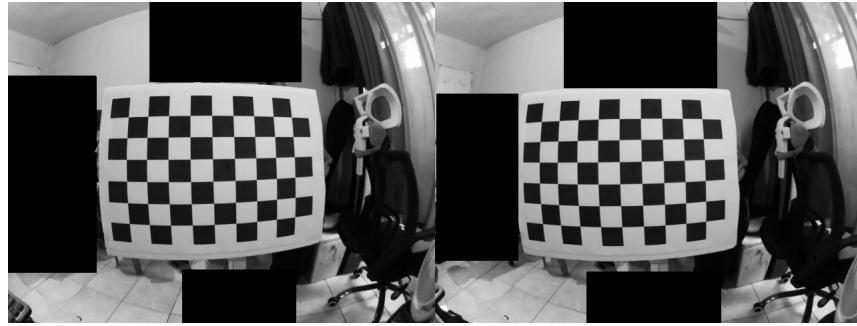


Figure 3.8: Calibration process with a checkerboard to correct fisheye lens distortion.

565

3.1.2.6 Camera Calibration (Disparity Map Fine-tuning)

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

573

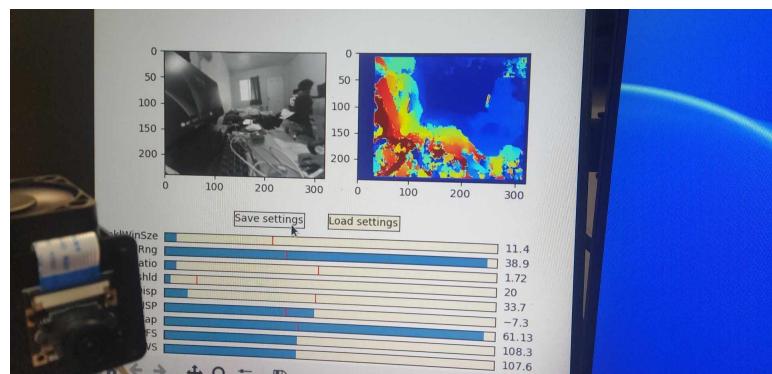


Figure 3.9: Parameter tuning process to achieve cleaner and more accurate disparity maps.

574 **3.1.2.7 Initial Testing**

575 Initial testing was conducted to verify the functionality and basic accuracy of the
576 stereoscopic camera system in a controlled environment. Simulated potholes with
577 known depths were created to cover a wider range of pothole depth and shape,
578 and also to consider the extremes. The system captured disparity maps, and
579 estimated depths were computed using the standard stereo camera depth formula.
580 The LCD module displayed the disparity map and estimated depth readings in
581 real-time during these tests, as shown in Figure 3.9.

582

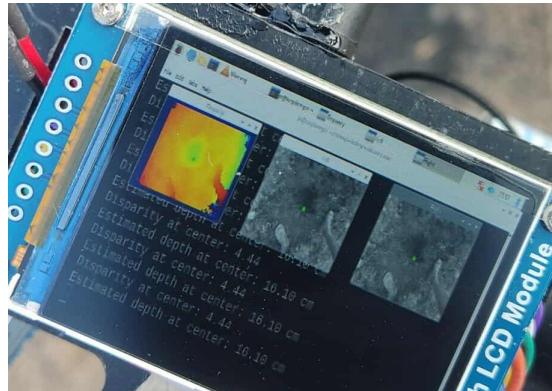


Figure 3.10: The system tested on a simulated pothole.

583 However, the results revealed a non-linear relationship between the computed
584 disparity values and the actual distances. This discrepancy indicated that the
585 traditional depth estimation method was insufficient for the current setup. To
586 address this, the researchers collected multiple data points and correlating known
587 distances to their respective disparity readings and fitted an inverse model to

588 better represent the system's behavior (see Figure 3.10). This updated disparity-
589 to-depth model was subsequently used in the final testing phase.

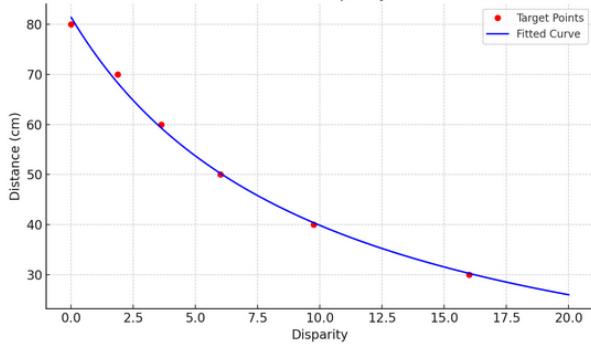


Figure 3.11: Inverse Model Fit to Disparity vs. Distance.

590 3.1.2.8 Performance Metrics

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

594 3.1.2.9 Final Testing and Validation

595 The testing process began with a detailed testing plan that includes both simu-
596 lated and real-world testing scenarios. Initially, the system is tested in controlled
597 environments to verify its capability to estimate pothole depth effectively. Fol-
598 lowing this, real-world testing was conducted using the StereoPi kit on previously
599 located potholes, specifically at the University of the Philippines Visayas Miagao
600 Campus. Although 130 potholes were originally identified, only 35 potholes that
601 were in the most favorable conditions and practical to measure within the avail-
602 able time were considered for final testing. This was due to factors like debris

and water being present in the pothole, making it difficult to obtain measurements. 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.

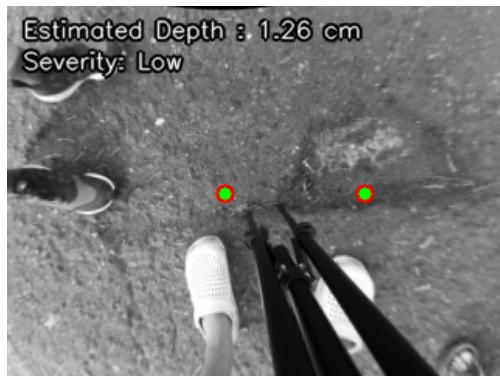


Figure 3.12: First measure point



Figure 3.13: Second measure point



Figure 3.14: Third measure point



Figure 3.15: Fourth measure point

611 3.1.2.10 Documentation

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

616 3.1.3 Challenges and Limitations**617 3.1.3.1 Camera Limitations**

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

629 Chapter 4

630 Results and Discussion

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

638 4.1 System Calibration and Model Refinement

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

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

643 where:

644 • f is the focal length in pixels,

645 • B is the baseline distance between the two cameras,

646 • d is the disparity.

647 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).

655 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.

658 An inverse function of the form:

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

659 where:

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

663 4.2 Testing Results

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

671 The smallest error occurred in one pothole, where the estimated depth was only
672 0.02 cm off from the ground truth. The largest observed error was 3.45 cm. Most
673 of the time, the camera's estimated depths were within approximately 1 to 3
674 centimeters of the actual depths.

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

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

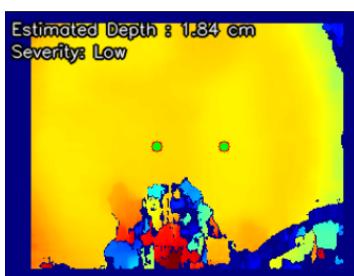


Figure 4.1: Disparity Map

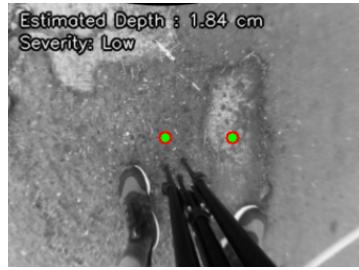


Figure 4.2: Left Stereo Image

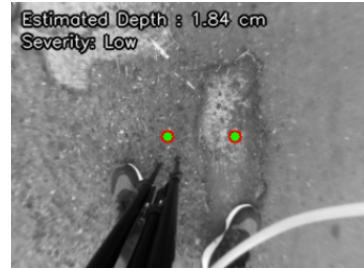


Figure 4.3: Right Stereo Image

679 high coefficient of determination ($R^2=0.956$) indicate that the actual depth signif-
 680 icantly predicts the estimated values. Additionally, Table 4.2 presents the model
 681 coefficients, showing that the regression coefficient for actual depth was statisti-
 682 cally significant ($p < 0.001$), suggesting that the relationship is not due to chance.
 683 While the RMSE of 0.844 cm and MAE of 0.945 cm suggest generally small errors,
 684 the presence of a maximum error of 3.45 cm indicates that there may be occa-
 685 sional outliers or limitations in specific scenarios. Nonetheless, the overall model
 686 performance demonstrates that the StereoPi system is suitable for practical pot-
 687 hole depth estimation, showing reasonable accuracy given the hardware setup and
 688 environmental conditions.

R	R²	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

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

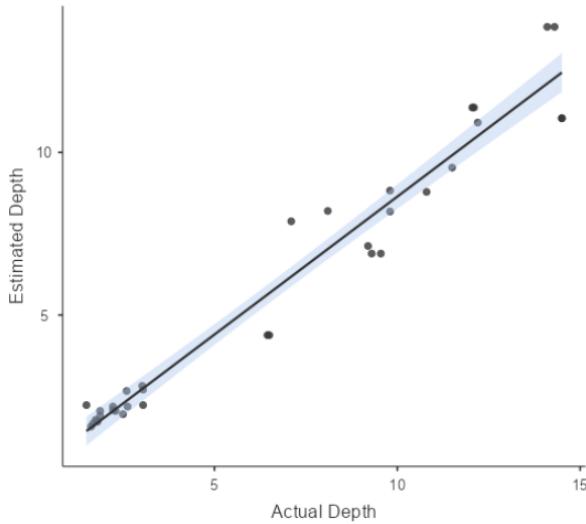


Figure 4.4: Linear Regression Fit Between Actual and Estimated Depth

694 4.3 Discussion

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

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

705 A strong positive correlation ($R = 0.978$) and coefficient of determination (R^2
706 = 0.956) indicate that the actual pothole depths strongly predict the estimated
707 values. The regression model's significant predictor ($p < 0.001$) further supports
708 the robustness of the depth estimation approach. This level of accuracy and model
709 performance highlights the suitability of the StereoPi system for practical field
710 applications in pothole monitoring and maintenance prioritization. This finding
711 is significant because earlier machine learning-based road detection studies such as
712 those by Bibi et al. (2021) focused mostly on classifying the existence of defects,
713 not measuring their severity.

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

722 However, the study also highlighted limitations affecting system performance, in-
723 cluding sensitivity to camera calibration quality, lighting conditions, road surface
724 texture, and the camera's vertical positioning during image capture. Outdoor
725 testing revealed that low lighting and shallow potholes made it difficult to gen-

726 erate clean disparity maps, sometimes causing minor estimation errors. These
727 observations are consistent with Sattar et al. (2018), who reported that mobile
728 road sensing systems often struggle in low-light or highly variable surface condi-
729 tions. Understanding these challenges is important because it points to practical
730 improvements, such as using better cameras, adding lighting support, or applying
731 more robust image enhancement methods in future versions of the system.

⁷³² Chapter 5

⁷³³ Conclusion

⁷³⁴ 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.

⁷³⁸ 5.1 Summary

⁷³⁹ 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

⁷⁴⁶ regression analysis, and to build a working prototype using stereo vision that can
⁷⁴⁷ detect, measure, and assess potholes.

⁷⁴⁸ To achieve these objectives, a hardware prototype was built using the StereoPi
⁷⁴⁹ V2 board and Raspberry Pi Compute Module 4, equipped with dual fisheye-lens
⁷⁵⁰ cameras. Camera calibration was performed using a 9x6 checkerboard pattern
⁷⁵¹ with known square sizes to correct for fisheye lens distortion and ensure proper
⁷⁵² alignment of the stereo pair. After calibration, disparity map generation was
⁷⁵³ fine-tuned by adjusting block matching parameters to produce clearer and more
⁷⁵⁴ reliable disparity maps. Initial testing was conducted using simulated potholes
⁷⁵⁵ with known depths to verify the functionality of the system and identify the non-
⁷⁵⁶ linear behavior present in stereo vision depth measurements. It was observed that
⁷⁵⁷ using the standard stereo depth formula led to inaccuracies, particularly at greater
⁷⁵⁸ distances.

⁷⁵⁹ The calibrated system and fitted regression model were validated by comparing
⁷⁶⁰ the estimated depths with the manually measured depths. The findings showed
⁷⁶¹ that the system was able to estimate pothole depths within approximately ± 3
⁷⁶² cm of actual measurements, achieving a Mean Absolute Error (MAE) of 0.945 cm
⁷⁶³ and a Root Mean Square Error (RMSE) of 0.844 cm. A strong positive linear
⁷⁶⁴ relationship was observed between the estimated and actual depths ($R = 0.978$,
⁷⁶⁵ $R^2 = 0.956$).

⁷⁶⁶ 5.2 Conclusions

⁷⁶⁷ The researchers conclude the following based on the findings:

- 768 ● The system effectively captures and analyzes depth information from stereo
769 images, providing a viable method for automated pothole severity assess-
770 ment.
- 771 ● Incorporating depth measurements significantly improves pothole repair pri-
772 oritization compared to traditional visual-only inspections, allowing main-
773 tenance decisions to be based on objective, measurable data.
- 774 ● The system achieved an acceptable regression model fit, with a strong posi-
775 tive correlation ($R = 0.978$) and a coefficient of determination ($R^2 = 0.956$),
776 confirming that the depth estimates closely align with the ground truth
777 measurements. The system obtained satisfactory error metrics, with a Mean
778 Absolute Error (MAE) of 0.945 cm and a Root Mean Square Error (RMSE)
779 of 0.844 cm, indicating reliable performance for both pothole detection and
780 depth estimation tasks.
- 781 ● The proposed approach fills a critical gap in current road maintenance prac-
782 tices, especially within the Philippine context where depth-based severity
783 classification is not yet systematically implemented.
- 784 This special project has successfully developed a system that addresses the prob-
785 lem of pothole severity assessment using depth measurement. The research shows
786 that stereo vision, even using accessible and affordable technology, holds strong
787 potential for future development in road maintenance automation. By building
788 upon the foundation laid by this project, future systems can become even more
789 accurate, efficient, and practical for real-world deployment

790 5.3 Recommendations for Practice

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

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

799 *Incorporate depth-based severity classification in maintenance procedures.* Au-
800 thorities should update road inspection protocols to include depth measurements,
801 making pothole severity assessment more objective and standardized.

802 5.4 Suggestions for Further Research

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

806 *Better camera.* While the StereoPi V2 camera was effective for basic depth es-
807 timation, its performance is limited by its resolution, sensitivity to lighting, and
808 depth range. Future researchers could consider using higher-quality stereo cam-
809 eras or depth sensors with better image resolution and low-light capabilities to
810 achieve more accurate and consistent disparity maps.

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

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

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

⁸²⁵ **Chapter 6**

⁸²⁶ **References**

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872

873 **Appendix A**

874 **Code Snippets**

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

```
875     def stereo_depth_map(rectified_pair ,  
876                           save_path_prefix=None):  
877         global disp_max , disp_min  
878         dmLeft , dmRight = rectified_pair  
879  
880         disparity_raw = sbm.compute(dmLeft , dmRight) .  
881             astype(np.float32)  
882         disparity_raw /= 16.0    # normalize disparity  
883  
884         local_max , local_min = disparity_raw.max() ,  
885             disparity_raw.min()  
886  
887         if dm_colors_autotune:
```

```

888     disp_max = max(local_max , disp_max)
889     disp_min = min(local_min , disp_min)
890     local_max , local_min = disp_max , disp_min
891
892     # Normalize for visualization
893     disparity_vis = (disparity_raw - local_min) *
894         (255.0 / (local_max - local_min))
895     disparity_vis = np.uint8(np.clip(disparity_vis , 0 ,
896         255))
897     disparity_color = cv2.applyColorMap(disparity_vis ,
898         cv2.COLORMAP_JET)
899
900     # Calculate depth
901     depth_map = calculate_depth(disparity_raw)
902
903     # Define two points
904     center_y , center_x = depth_map.shape[0] // 2 ,
905         depth_map.shape[1] // 2 - 20
906     second_y = center_y
907     second_x = center_x + offset_x
908
909     # Read depth and disparity values
910     center_depth_cm = (depth_map[center_y , center_x])
911     second_depth_cm = (depth_map[second_y , second_x])
912     estimated_depth_cm = abs(center_depth_cm -

```

```

913     second_depth_cm)

914

915     # Define severity based on estimated depth
916
917     if estimated_depth_cm < 2.5:
918
919         severity = "Low"
920
921     elif estimated_depth_cm >= 2.5 and
922
923         estimated_depth_cm < 5.0:
924
925         severity = "Medium"
926
927     elif estimated_depth_cm > 5.0:
928
929         severity = "High"
930
931     else:
932
933         severity = "Unknown"

```

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

```

925     for frame in camera.capture_continuous(capture ,
926
927         format="bgra", use_video_port=True, resize=(
928             img_width, img_height)):
929
930         pair_img = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
931
932
933         imgLeft = pair_img[:, :img_width // 2]
934
935         imgRight = pair_img[:, img_width // 2:]
936
937
938         imgL = cv2.remap(imgLeft, leftMapX, leftMapY,
939
940             interpolation=cv2.INTER_LINEAR, borderMode=cv2.
941
942             BORDER_CONSTANT)

```

```

936     imgR = cv2.remap(imgRight, rightMapX, rightMapY,
937                        interpolation=cv2.INTER_LINEAR, borderMode=cv2.
938                        BORDER_CONSTANT)
939
940    if useStripe:
941        imgL = imgL[80:160,:]
942        imgR = imgR[80:160,:]
943
944    stereo_depth_map((imgL, imgR), save_path_prefix=
945                      None)
946
947    button_held_time = 0
948    HOLD_THRESHOLD = 1.0 # seconds
949
950    if GPIO.input(BUTTON_PIN) == GPIO.LOW:
951        press_start = time.time()
952    while GPIO.input(BUTTON_PIN) == GPIO.LOW:
953        time.sleep(0.01)
954        button_held_time = time.time() - press_start
955
956    if button_held_time < HOLD_THRESHOLD:
957        timestamp = datetime.now().strftime("%Y%m%d_%H%M%S"
958                                         )
959        prefix = f"./captures/capture_{timestamp}"
960        print(f"\n[!] - Capturing - snapshot - at - {timestamp} ..."

```

```
961         ” )  
962         stereo_depth_map( (imgL, imgR) , save_path_prefix=  
963             prefix )  
964         time.sleep(0.5)  
965     else:  
966         cycle_offset()  
967         time.sleep(0.5)
```


⁹⁶⁸ **Appendix B**

⁹⁶⁹ **Resource Persons**

⁹⁷⁰ **Jumar Cadondon, Ph.D.**

⁹⁷¹ Assistant Professor

⁹⁷² Division of Physical Sciences and Mathematics

⁹⁷³ University of the Philippines Visayas

⁹⁷⁴ jgcadondon@up.edu.ph

⁹⁷⁵

⁹⁷⁶ **Engr. Jane Chua**

⁹⁷⁷ Engineer

⁹⁷⁸ Planning and Design

⁹⁷⁹ DPWH Region 6

⁹⁸⁰ chua.jane@dpwh.gov.ph

⁹⁸¹

⁹⁸²

⁹⁸³ **Engr. Marilou Zamora**

⁹⁸⁴ Chief

⁹⁸⁵ Planning and Design

⁹⁸⁶ DPWH Region 6

⁹⁸⁷ zamora.marilou@dpwh.gov.ph

⁹⁸⁸

⁹⁸⁹ **Engr. Benjamin Javellana**

⁹⁹⁰ Assistant Director

⁹⁹¹ Maintenance

⁹⁹² DPWH Region 6

⁹⁹³ javellana.benjamin@dpwh.gov.ph

⁹⁹⁴

⁹⁹⁵ **Mr. Cris Beleber**

⁹⁹⁶ Engineering Assistant

⁹⁹⁷ Planning and Design

⁹⁹⁸ DPWH Region 6

⁹⁹⁹ beleber.cris@dpwh.gov.ph

1000

₁₀₀₁ **Appendix C**

₁₀₀₂ **Data Table and Pothole Images**

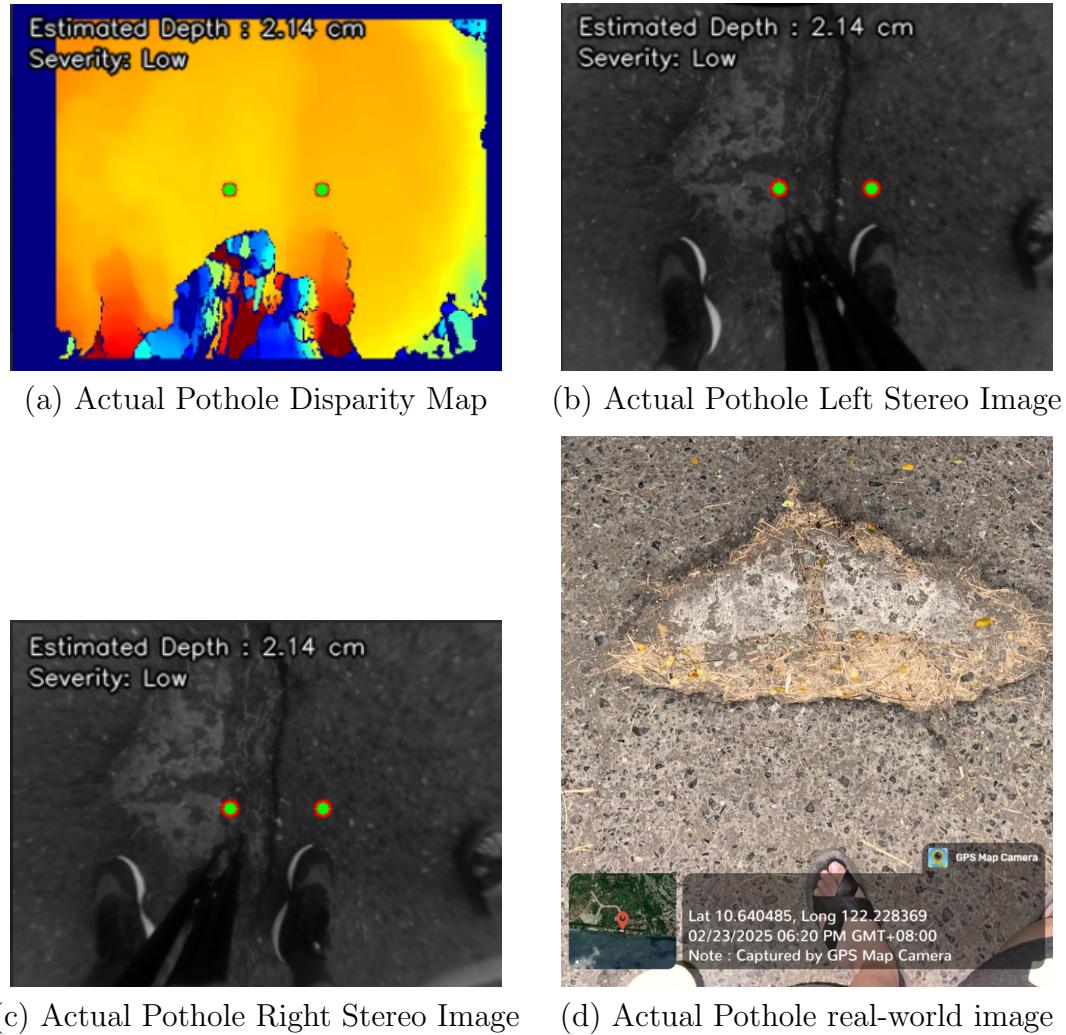
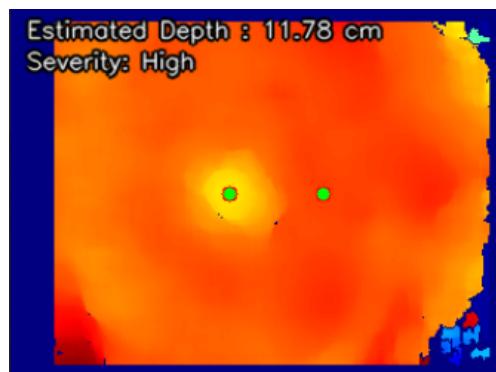


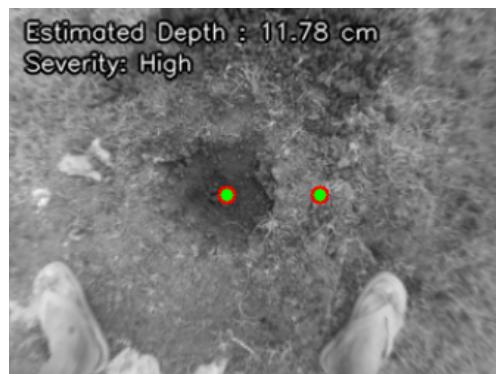
Figure C.1: Actual Pothole Images



(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

¹⁰⁰³ Appendix D

¹⁰⁰⁴ Supplementary Documents

January 31, 2025

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


PERSEROE 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

RECEIVED

January 31, 2025

Dr. Farisal U. Bagsit
Vice Chancellor for Administration

UP VISAYAS
(through channels) OFFICE OF THE CHANCELLOR

NOA 25-0226
REF. NO. FEB 01 2025

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.
APPROVED / DISAPPROVED
Thank you very much.

Sincerely yours,

CLEMENT O. CAMPASANO
CLEMENT O. CAMPASANO
CHANCELLOR

Benz Vrianne Beleber
Benz Vrianne Beleber
Team Member

Perserose Catalan
Perserose Catalan
Team Leader

Kent Christian A. Castor
Kent Christian A. Castor
Chairperson, DPM

RECOMMENDING APPROVAL/DISAPPROVAL:
FARISAL U. BAGSIT, Ph.D.
Vice Chancellor for Administration

It would be nice if the research team can present some their data to UPV admin

RECOMMEND APPROVAL:
PEPITO R. FERNANDEZ JR.,
DEAN, COLLEGE OF ARTS & SCIENCES
IP VISAYAS

31 JAN 2025
REF NO. PRF 2025-023

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

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


 PERSE ROSE P. CATALAN

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

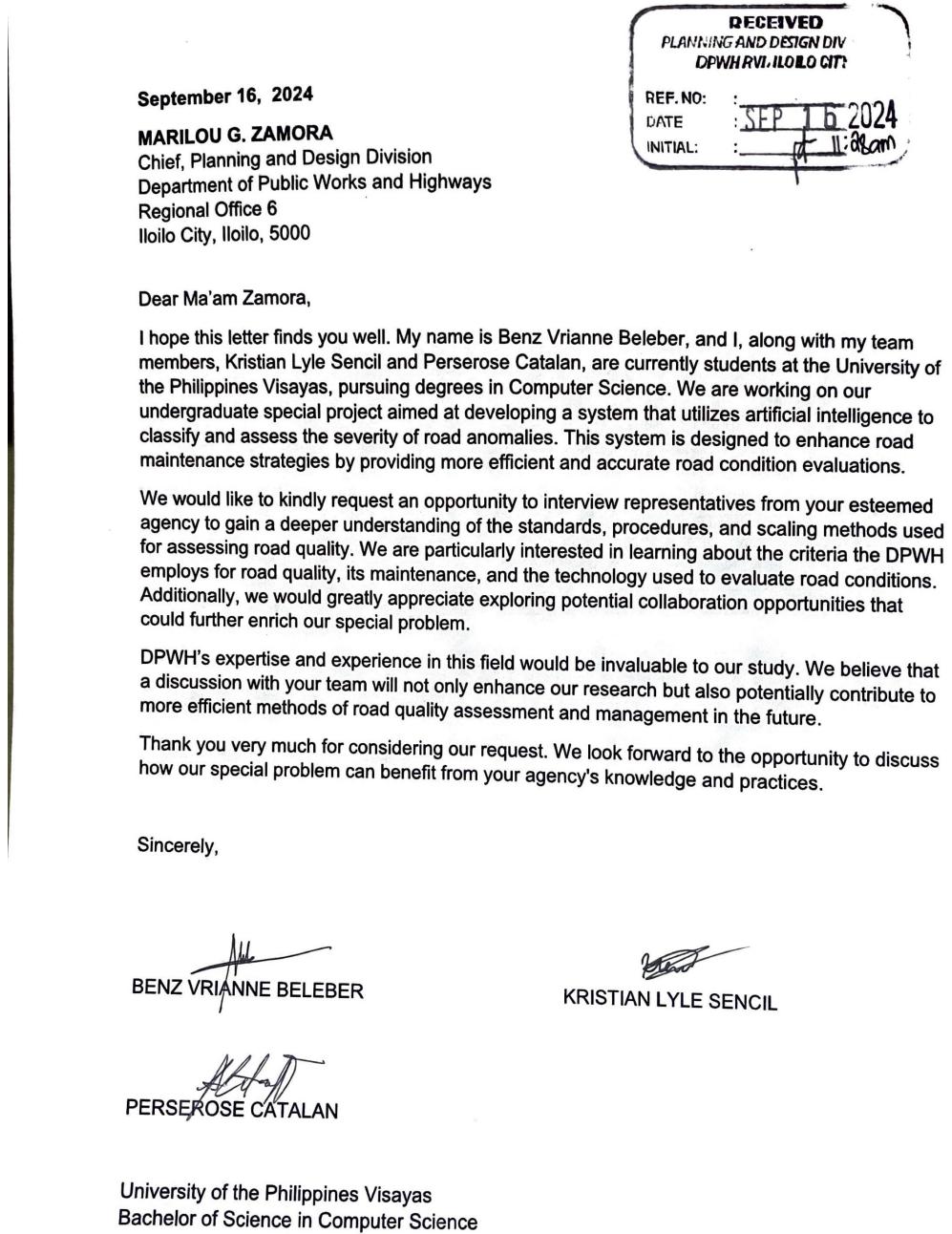


Figure D.4: Letter requesting an interview with DPWH representatives for the standard operating procedures of the agency for assessing road quality.



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.



**UNIVERSITY OF THE PHILIPPINES VISAYAS
COLLEGE OF ARTS AND SCIENCES
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.

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



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COLLEGE OF ARTS AND SCIENCES
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.

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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DIVISION OF PHYSICAL SCIENCES AND MATHEMATICS**

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.

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