

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
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10 of the Requirements for the Degree of
11 Bachelor of Science in Computer Science by

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17 May 25, 2025

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Approval Sheet

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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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32 and is the record of work carried out by us. Any significant borrowings have been
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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.

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43 moments — this work is for them.

44

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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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¹⁷⁷ Chapter 1

¹⁷⁸ Introduction

¹⁷⁹ 1.1 Overview of the Current State of Technology

¹⁸⁰ According to the National Road Length by Classification, Surface Type, and Con-
¹⁸¹ dition of the Department of Public Works and Highways (DPWH), as of October
¹⁸² 2023 approximately 98.97% of roads in the Philippines is paved which is either
¹⁸³ made of concrete or asphalt (Balita, 2024). Since the DPWH is an institution
¹⁸⁴ under the government, it is paramount to maintain such roads in order to avoid
¹⁸⁵ accidents and congested traffic situations especially in heavily urbanized areas
¹⁸⁶ where there are a lot of vehicles.

¹⁸⁷ In an interview with the Road Board of DPWH Region 6 it was stated that road
¹⁸⁸ condition assessments are mostly done manually with heavy reliance on engineer-
¹⁸⁹ ing judgment (J. Chua, Personal Interview. 16 September 2024). In addition,
¹⁹⁰ manual assessment of roads is also time consuming which leaves maintenance
¹⁹¹ operations to wait for lengthy assessments. In a study conducted by Ramos, Da-

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

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

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

²¹⁷ road condition monitoring.

²¹⁸ 1.2 Problem Statement

²¹⁹ Roads support almost every aspect of daily life, from providing a way to transport
²²⁰ goods and services to allowing people to stay connected with their communities.
²²¹ However, road defects such as cracks and potholes damage roads over time, and
²²² they can increase accident risks and affect the overall transportation. The current
²²³ way of inspecting the roads for maintenance is often slow as it is done manually,
²²⁴ which makes it harder to detect and fix defects early. The delay in addressing these
²²⁵ problems can lead to even worse road conditions (J. Chua, Personal Interview. 16
²²⁶ September 2024). There are several research studies into automated road defect
²²⁷ classification that have advanced in recent years but most of them focus on iden-
²²⁸ tifying the types of defects rather than assessing their severity or characteristics
²²⁹ like depth. Without reliable data on the depth of the defect, road maintenance
²³⁰ authorities may underestimate the severity of certain defects. To address these
²³¹ challenges, advancements are needed across various areas. An effective solution
²³² should not only detect and classify road defects but also measure their severity
²³³ to better prioritize repairs. Failing to address this problem will require more ex-
²³⁴ tensive repairs for damaged roads, which raises the cost and strains the budget.
²³⁵ Additionally, road maintenance would still be slow and cause disruptions in daily
²³⁶ activities. Using an automated system that accurately assess the severity of road
²³⁷ defects by incorporating depth is necessary to efficiently monitor road quality.

²³⁸ 1.3 Research Objectives

²³⁹ 1.3.1 General Objective

²⁴⁰ This special problem aims to develop a system that accurately estimates the depth
²⁴¹ of potholes on road surfaces by using image analysis, depth measurement tech-
²⁴² nologies, and computer vision techniques. The system will focus specifically on
²⁴³ measuring the depth of potholes to assess their severity, enabling faster and more
²⁴⁴ accurate road maintenance decisions, and there are no current practices in the
²⁴⁵ Philippines involving depth information of potholes in assessing their severity. In
²⁴⁶ accordance with the Department of Public Works and Highways Region 6's man-
²⁴⁷ ual for road maintenance, the study will classify potholes into different severity
²⁴⁸ levels such as low, medium, and high, which will be primarily based on their
²⁴⁹ depth. In order to measure the system's accuracy, linear regression in order to
²⁵⁰ represent the difference between the depth calculated from the disparity and the
²⁵¹ actual depth of the pothole from ground truth data.

²⁵² 1.3.2 Specific Objectives

²⁵³ Specifically, this special problem aims to:

- ²⁵⁴ 1. Collect high-quality stereo images of road surfaces that capture potholes
²⁵⁵ including their depth in favorable conditions,
- ²⁵⁶ 2. Measure the accuracy of the system by comparing the depth measurements
²⁵⁷ against ground truth data collected from actual road inspections and to
²⁵⁸ utilize linear regression, root mean square error, and mean absolute error as

259 a metric for evaluation, and

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

262 1.4 Scope and Limitations of the Research

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

267 Depth-sensing tools, such as stereo cameras, will be used to record the depth of
268 potholes specifically. The system will not address other road defects like cracks
269 or other surface deformations; therefore, it will detect and analyze only potholes.

270 Additionally, only accessible potholes will be measured, meaning those that are
271 filled with water or obscured by debris may not be accurately assessed.

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

278 Environmental factors such as lighting, road surface texture, and weather con-
279 ditions may impact the system's performance. The accuracy and reliability of
280 the system will depend on the quality of camera calibration and disparity map

281 finetuning. Its ability to measure the depth of pothole images needs careful vali-
282 dation.

283 1.5 Significance of the Research

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

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

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

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

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

300 **Chapter 2**

301 **Review of Related Literature**

302 **2.1 Frameworks**

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

305 **2.1.1 Depth Estimation**

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

309 **2.1.2 Image and Video Processing**

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

³¹² Usual processes are considered to treat images as 2D signals wherein different
³¹³ processing methods utilize these signals. Like image processing, RICHES Project
³¹⁴ (2014) defines video processing as being able to extract information and data from
³¹⁵ video footage through signal processing methods. However, in video processing
³¹⁶ due to the diversity of video formats, compression and decompression methods
³¹⁷ are often expected to be performed on videos before processing methods to either
³¹⁸ increase or decrease bitrate.

³¹⁹ **2.1.3 Stereo Vision**

³²⁰ MathWorks (n.d.) defines stereo vision as a process of utilizing multiple 2D per-
³²¹ spectives in order to extract information in 3D. In addition, most uses of stereo
³²² vision involve estimating an objects distance from an observer or camera. The 3D
³²³ information is stated to be extracted with stereo pairs or pair of images through es-
³²⁴ timation of relative depth of points in a scene which are then represented through
³²⁵ a stereo map that is made through the matching of the pair's corresponding points.

³²⁶ **2.2 Related Studies**

³²⁷ This section of the chapter presents related studies conducted by other researchers
³²⁸ wherein the methodology and technologies used may serve as basis in the devel-
³²⁹ opment of this special problem.

³³⁰ **2.2.1 Deep Learning Studies**

³³¹ **Automated Detection and Classification of Road Anomalies**
³³² **in VANET Using Deep Learning**

³³³

³³⁴ In the study of Bibi et al. (2021) it was noted that identification of active road
³³⁵ defects are critical in maintaining smooth and safe flow of traffic. Detection and
³³⁶ subsequent repair of such defects in roads are crucial in keeping vehicles using
³³⁷ such roads away from mechanical failures. The study also emphasized the growth
³³⁸ in use of autonomous vehicles in research data gathering which is what the re-
³³⁹ searchers utilized in data gathering procedures. With the presence of autonomous
³⁴⁰ vehicles, this allowed the researchers to use a combination of sensors and deep
³⁴¹ neural networks in deploying artificial intelligence. The study aimed to allow au-
³⁴² tonomous vehicles to avoid critical road defects that can possibly lead to dangerous
³⁴³ situations. Researchers used Resnet-18 and VGG-11 in automatic detection and
³⁴⁴ classification of road defects. Researchers concluded that the trained model was
³⁴⁵ able to perform better than other techniques for road defect detection. The study
³⁴⁶ is able to provide the effectiveness of using deep learning models in training arti-
³⁴⁷ ficial intelligence for road defect detection and classification. However, the study
³⁴⁸ lacks findings regarding the severity of detected defects and incorporation of pot-
³⁴⁹ hole depth in their model which are both crucial in automating manual procedures
³⁵⁰ of road surveying in the Philippines.

³⁵¹ **Road Anomaly Detection through Deep Learning Approaches**

³⁵²

³⁵³ The study of Luo, Lu, and Guo (2020) aimed to utilize deep learning models in

354 classifying road anomalies. The researchers used three deep learning approaches
355 namely Convolutional Neural Network, Deep Feedforward Network, and Recurrent
356 Neural Network from data collected through the sensors in the vehicle's suspension
357 system. In comparing the performance of the three deep learning approaches, the
358 researchers fixed some hyperparameters. Results revealed that the RNN model
359 was the most stable among the three and in the case of the CNN and DFN mod-
360 els, the researchers suggested the use of wheel speed signals to ensure accuracy.
361 And lastly, the researchers concluded that the RNN model was best due to high
362 prediction performance with small set parameters. However, proper severity as-
363 sessment through depth information was not stated to be utilized in any of the
364 three approaches used in the study.

365 **Assessing Severity of Road Cracks Using Deep Learning- 366 Based Segmentation and Detection**

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

379 higher accuracy rates. Furthermore, the researchers suggest incorporating depth
380 information in the models to further enhance results.

381 **Roadway pavement anomaly classification utilizing smart-**
382 **phones and artificial intelligence**

383

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

398 **2.2.2 Machine Learning Studies**

399 **Smartphones as Sensors for Road Surface Monitoring**

400

401 In their study, Sattar, Li, and Chapman (2018) noted the rise of sensing capabil-
402 ities of smartphones which they utilized in monitoring road surface to detect and

403 identify anomalies. The researchers considered different approaches in detecting
404 road surface anomalies using smartphone sensors. One of which are threshold-
405 based approaches which was determined to be quite difficult due to several factors
406 that are affecting the process of determining the interval length of a window
407 function in spectral analysis. The researchers also utilized a machine learning
408 approach adapted from another study. It was stated that k-means was used in
409 classifying sensor data and in training the SVM algorithm. Due to the require-
410 ment of training a supervised algorithm using a labeled sample data was required
411 before classifying data from sensors, the approach was considered to be imprac-
412 tical for real-time situations. In addition, Sattar et al. (2018) also noted various
413 challenges when utilizing smartphones as sensors for data gathering such as sen-
414 sors being dependent on the device's placement and orientation, smoothness of
415 captured data, and the speed of the vehicle it is being mounted on. Lastly, it was
416 also concluded that the accuracy and performance of using smartphone sensors is
417 challenging to compare due to the limited data sets and reported algorithms.

418 **Road Surface Quality Monitoring Using Machine Learning 419 Algorithms**

420
421 The study of Singh, Bansal, Kamal, and Kumar (2021) aimed to utilize machine
422 learning algorithms in classifying road defects as well as predict their locations.
423 Another implication of the study was to provide useful information to commuters
424 and maintenance data for authorities regarding road conditions. The researchers
425 gathered data using various methods such as smartphone GPS, gyroscopes, and
426 accelerometers. (Singh et al., 2021) also argued that early existing road moni-
427 toring models are unable to predict locations of road defects and are dependent

428 on fixed roads and static vehicle speed. Neural and deep neural networks were
429 utilized in the classification of anomalies which was concluded by the researchers
430 to yield accurate results and are applicable on a larger scale of data. The study
431 of Singh et al. (2021) can be considered as an effective method in gathering data
432 about road conditions. However, it was stated in the study that relevant authori-
433 ties will be provided with maintenance operation and there is no presence of any
434 severity assessment in the study. This may cause confusion due to a lack of as-
435 sessment on what is the road condition that will require extensive maintenance or
436 repair.

437 **2.2.3 Computer Vision Studies**

438 **Stereo Vision Based Pothole Detection System for Improved** 439 **Ride Quality**

440
441 In the study of Ramaiah and Kundu (2021) it was stated that stereo vision has
442 been earning attention due to its reliable obstacle detection and recognition. Fur-
443 thermore, the study also discussed that such technology would be useful in improv-
444 ing ride quality in automated vehicles by integrating it in a predictive suspension
445 control system. The proposed study was to develop a novel stereo vision based
446 pothole detection system which also calculates the depth accurately. However,
447 the study focused on improving ride quality by using the 3D information from
448 detected potholes in controlling the damping coefficient of the suspension system.
449 Overall, the pothole detection system was able to achieve 84% accuracy and is
450 able to detect potholes that are deeper than 5 cm. The researchers concluded
451 that such system can be utilized in commercial applications. However, it is also

⁴⁵² worth noting that despite the system being able to detect potholes and measure
⁴⁵³ its depth, the overall severity of the pothole and road condition was not addressed.

⁴⁵⁴ 2.3 Chapter Summary

⁴⁵⁵ The reviewed literature involved various techniques and approaches in road anomaly
⁴⁵⁶ detection and classification. These approaches are discussed and summarized be-
⁴⁵⁷ low 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 | 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

⁴⁵⁸ Chapter 3

⁴⁵⁹ Research Methodology

⁴⁶⁰ This chapter outlines the systematic approach that were taken to address the
⁴⁶¹ problem of pothole depth estimation using StereoPi V2. The methodology is
⁴⁶² divided into key phases: data collection, algorithm selection, design, testing and
⁴⁶³ experimentation, and challenges and limitations. Each phase will play a crucial
⁴⁶⁴ role in accurately classifying and assessing road defects. Each phase is essential
⁴⁶⁵ for accurately estimating the depth of potholes using StereoPi V2.

⁴⁶⁶ 3.1 Research Activities

⁴⁶⁷ 3.1.1 Data Collection

⁴⁶⁸ The researchers conducted initial inquiries to understand the problem domain and
⁴⁶⁹ existing road maintenance practices. This phase included consulting the engineers
⁴⁷⁰ under the Road Maintenance Department of the government agency Department

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

494 3.1.1.1 Data Collection (Ground Truth Data)

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



505

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

506

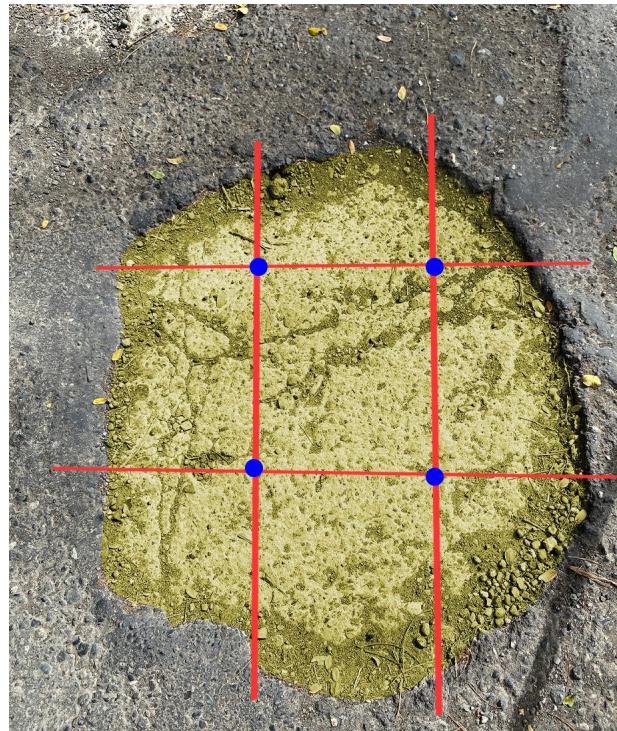


Figure 3.2: Four measure points of the pothole.

507

3.1.2 Design, Testing, and Experimentation

508

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

510

3.1.2.1 Depth Measurement

511

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,

516 the system estimates the relative depth of the pothole. This approach improves
517 accuracy by normalizing disparity measurements against the nearby road surface,
518 effectively isolating the pothole's depth from overall scene variation.

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

522 **3.1.2.2 Severity Assessment**

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

530 **3.1.2.3 Materials and Equipment**

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

- 533 • StereoPi V2 Board
- 534 • Raspberry Pi Compute Module 4 (CM4)
- 535 • Dual RaspberryPi Camera Modules with Fisheye Lens

- 536 • 3D Printed Custom Housing

- 537 • 2-inch LCD Module

- 538 • Micro SD Card

- 539 • Antenna

- 540 • Momentary Push Button

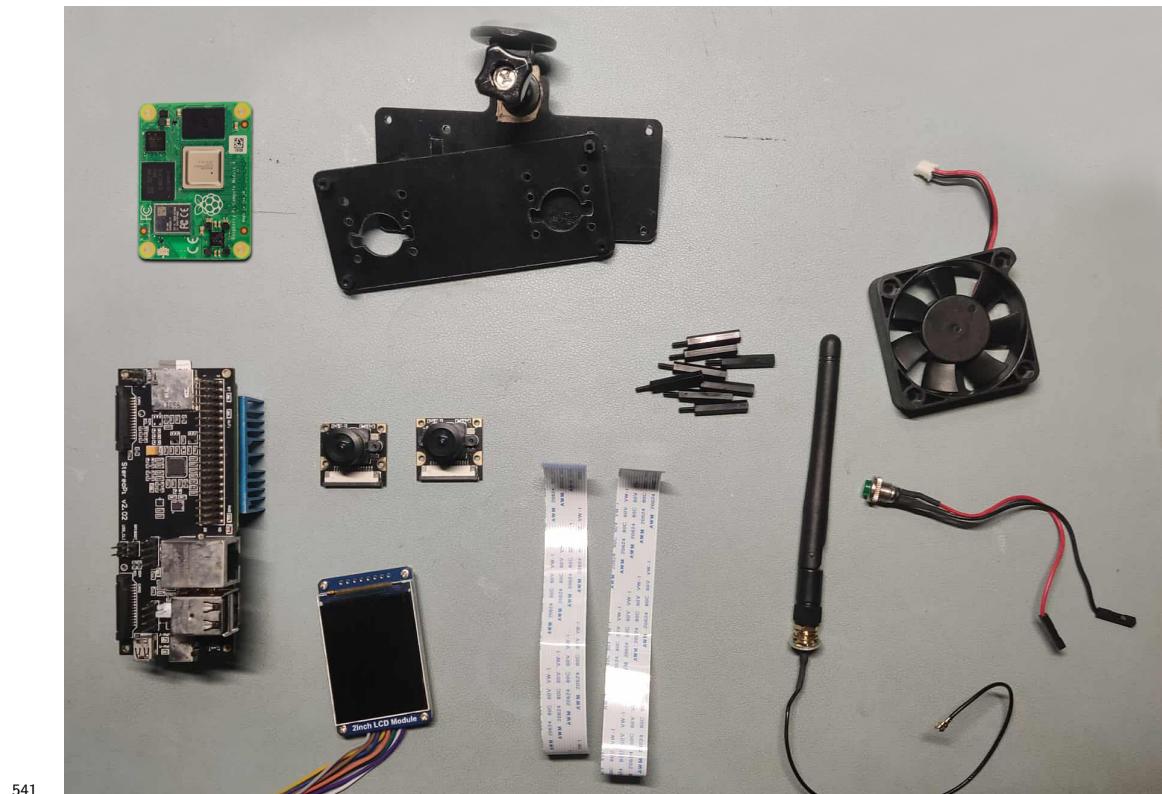


Figure 3.3: Components used in the prototype development. From the top left: Raspberry Pi Computer Module 4, 3D Printed Custom Housing, cooling fan, StereoPi V2 Board, two camera modules, antenna,momentary push button, and 2-inch LCD module.

542 3.1.2.4 Prototype Building

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

551

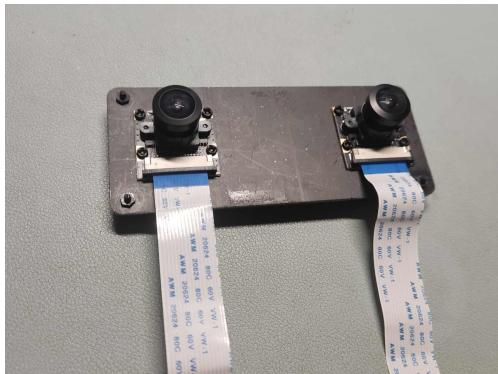


Figure 3.4: Dual RPi Camera Modules attached to the custom housing.

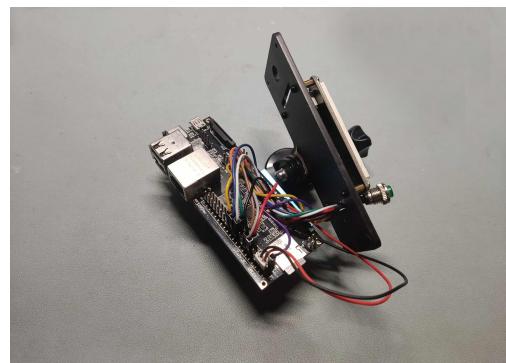


Figure 3.5: LCD Module connected to the StereoPi board.

552



Figure 3.6: The finished prototype.

553 **3.1.2.5 Camera Calibration (Fisheye Distortion)**

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



561 Figure 3.7: Calibration process with a checkerboard to correct fisheye lens distortion.

562 **3.1.2.6 Camera Calibration (Disparity Map Fine-tuning)**

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

569 beyond 80 cm, disparity information became sparse or blank.

570

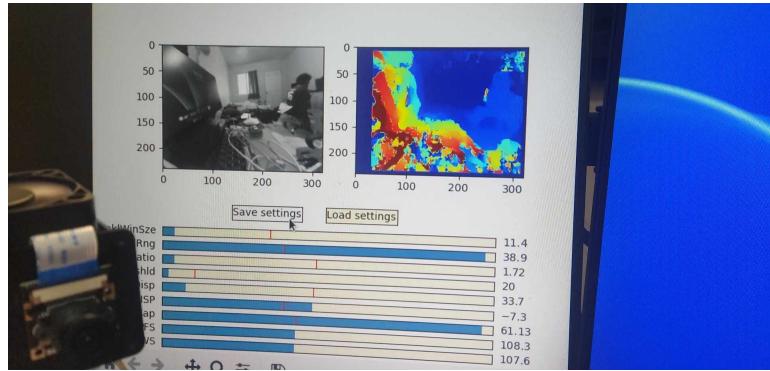


Figure 3.8: Parameter tuning process to achieve cleaner and more accurate disparity maps.

571

3.1.2.7 Initial Testing

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

578

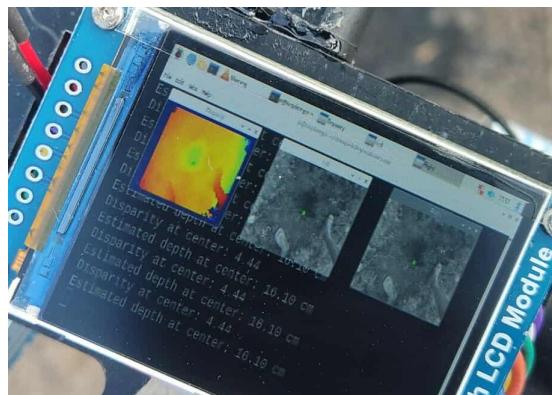


Figure 3.9: The system tested on a simulated pothole.

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

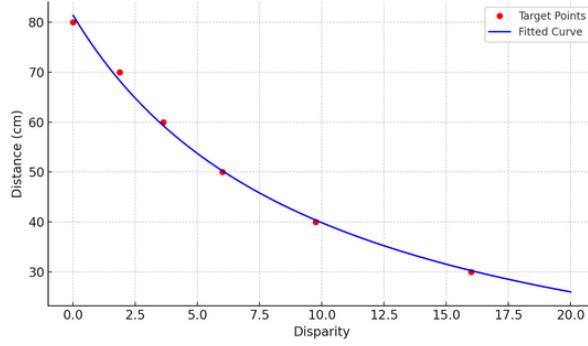


Figure 3.10: Inverse Model Fit to Disparity vs. Distance.

586 3.1.2.8 Performance Metrics

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

590 3.1.2.9 Final Testing and Validation

591 The testing process began with a detailed testing plan that includes both simu-
 592 lated and real-world testing scenarios. Initially, the system is tested in controlled
 593 environments to verify its capability to estimate pothole depth effectively. Fol-

594 lowing this, real-world testing was conducted using the StereoPi kit on previously
595 located potholes, specifically at the University of the Philippines Visayas Miagao
596 Campus. As illustrated in Figures 3.11 to 3.14, the procedure for estimating pot-
597 hole depth closely followed the validated depth measurement manual, where the
598 system captured depth measurements at four designated points within each pot-
599 hole, corresponding to the measurement points used in the manual measurement
600 data. These four estimated depths were then averaged to determine the final depth
601 estimate for each pothole. The system's performance was validated by comparing
602 its predictions with ground-truth data collected from manual inspections.



Figure 3.11: First measure point



Figure 3.12: Second measure point



Figure 3.13: Third measure point



Figure 3.14: Fourth measure point

603 3.1.2.10 Documentation

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

608 3.1.3 Challenges and Limitations**609 3.1.3.1 Camera Limitations**

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

621 Chapter 4

622 Results and Discussion

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

630 4.1 System Calibration and Model Refinement

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

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

635 where:

636 • f is the focal length in pixels,

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

638 • d is the disparity.

639 However, preliminary observations revealed that the relationship between mea-
640 sured disparity and depth was shifted from the ideal. Their relationship is in-
641herently nonlinear, specifically an inverse relationship (of the form $y=1/x$). As
642disparity decreases, depth increases rapidly and nonlinearly. However, due to
643real-world factors such as lens distortion, imperfect calibration, stereo matching
644errors, and pixel quantization, the actual relationship between measured disparity
645and true depth often deviates from the theoretical ideal (Scharstein & Szeliski,
6462002).

647 To address the shifting behavior, a curve fitting approach was introduced. Specif-
648ically, an inverse model was fitted to the collected data points, relating disparity
649and ground-truth distance measurements.

650 An inverse function of the form:

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

651 where:

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

655 4.2 Testing Results

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

663 The smallest error occurred in one pothole, where the estimated depth was only
664 0.02 cm off from the ground truth. The largest observed error was 3.45 cm. Most
665 of the time, the camera's estimated depths were within approximately 1 to 3
666 centimeters of the actual depths.

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

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

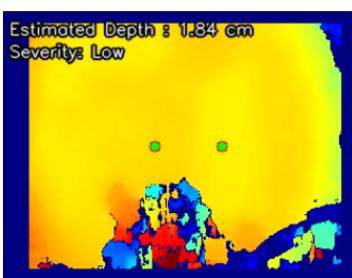


Figure 4.1: Disparity Map

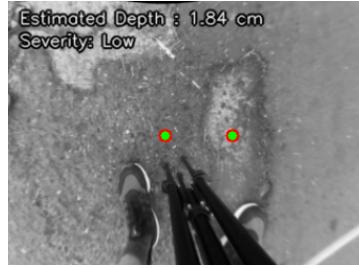


Figure 4.2: Left Stereo Image



Figure 4.3: Right Stereo Image

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

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

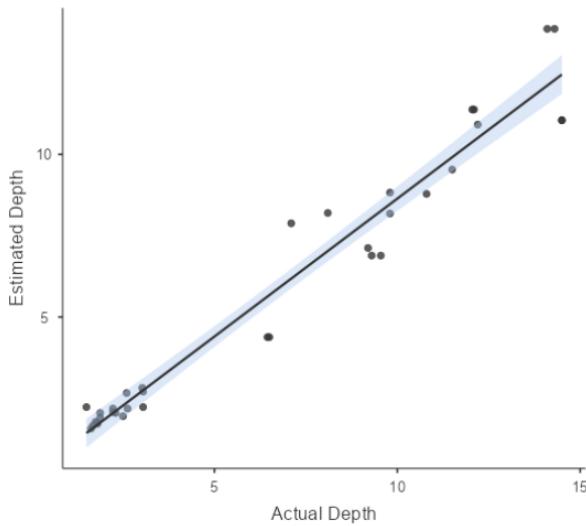


Figure 4.4: Linear Regression Fit Between Actual and Estimated Depth

686 4.3 Discussion

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

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

697 A strong positive correlation ($R = 0.978$) and coefficient of determination (R^2
698 = 0.956) indicate that the actual pothole depths strongly predict the estimated
699 values. The regression model's significant predictor ($p < 0.001$) further supports
700 the robustness of the depth estimation approach. This level of accuracy and model
701 performance highlights the suitability of the StereoPi system for practical field
702 applications in pothole monitoring and maintenance prioritization. This finding
703 is significant because earlier machine learning-based road detection studies such as
704 those by Bibi et al. (2021) focused mostly on classifying the existence of defects,
705 not measuring their severity.

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

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

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

⁷²⁴ Chapter 5

⁷²⁵ Conclusion

⁷²⁶ This chapter provides conclusions based on the research findings from data collected
⁷²⁷ on the development of a pothole depth estimation system using stereo
⁷²⁸ vision technology. It then presents recommendations for practice and suggestions
⁷²⁹ for further research.

⁷³⁰ 5.1 Summary

⁷³¹ This special project addressed the critical issue of road maintenance by developing
⁷³² a system capable of estimating the depth of potholes to help prioritize repairs.
⁷³³ The purpose of the project was to create an automated method that not only
⁷³⁴ detects potholes but also assesses their severity based on depth, responding to
⁷³⁵ the current manual and slow road inspection practices. The researchers aimed to
⁷³⁶ collect high-quality images of potholes under varying conditions, to validate the
⁷³⁷ system's depth estimation accuracy using ground truth measurements and linear

⁷³⁸ regression analysis, and to build a working prototype using stereo vision that can
⁷³⁹ detect, measure, and assess potholes.

⁷⁴⁰ To achieve these objectives, a hardware prototype was built using the StereoPi
⁷⁴¹ V2 board and Raspberry Pi Compute Module 4, equipped with dual fisheye-lens
⁷⁴² cameras. Camera calibration was performed using a 9x6 checkerboard pattern
⁷⁴³ with known square sizes to correct for fisheye lens distortion and ensure proper
⁷⁴⁴ alignment of the stereo pair. After calibration, disparity map generation was
⁷⁴⁵ fine-tuned by adjusting block matching parameters to produce clearer and more
⁷⁴⁶ reliable disparity maps. Initial testing was conducted using simulated potholes
⁷⁴⁷ with known depths to verify the functionality of the system and identify the non-
⁷⁴⁸ linear behavior present in stereo vision depth measurements. It was observed that
⁷⁴⁹ using the standard stereo depth formula led to inaccuracies, particularly at greater
⁷⁵⁰ distances.

⁷⁵¹ The calibrated system and fitted regression model were validated by comparing
⁷⁵² the estimated depths with the manually measured depths. The findings showed
⁷⁵³ that the system was able to estimate pothole depths within approximately ± 3
⁷⁵⁴ cm of actual measurements, achieving a Mean Absolute Error (MAE) of 0.945 cm
⁷⁵⁵ and a Root Mean Square Error (RMSE) of 0.844 cm. A strong positive linear
⁷⁵⁶ relationship was observed between the estimated and actual depths ($R = 0.978$,
⁷⁵⁷ $R^2 = 0.956$).

⁷⁵⁸ 5.2 Conclusions

⁷⁵⁹ The researchers conclude the following based on the findings:

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

782 5.3 Recommendations for Practice

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

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

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

794 5.4 Suggestions for Further Research

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

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

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

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

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

⁸¹⁷ **Chapter 6**

⁸¹⁸ **References**

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864 Singh, P., Bansal, A., Kamal, A. E., & Kumar, S. (2021). Road Surface Quality
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867

868 **Appendix A**

869 **Code Snippets**

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

```
870     def stereo_depth_map(rectified_pair ,  
871                           save_path_prefix=None):  
872         global disp_max , disp_min  
873         dmLeft , dmRight = rectified_pair  
874  
875         disparity_raw = sbm.compute(dmLeft , dmRight) .  
876             astype(np.float32)  
877         disparity_raw /= 16.0    # normalize disparity  
878  
879         local_max , local_min = disparity_raw.max() ,  
880             disparity_raw.min()  
881  
882         if dm_colors_autotune:
```

```

883     disp_max = max(local_max , disp_max)
884     disp_min = min(local_min , disp_min)
885     local_max , local_min = disp_max , disp_min
886
887     # Normalize for visualization
888     disparity_vis = (disparity_raw - local_min) *
889         (255.0 / (local_max - local_min))
890     disparity_vis = np.uint8(np.clip(disparity_vis , 0 ,
891         255))
892     disparity_color = cv2.applyColorMap(disparity_vis ,
893         cv2.COLORMAP_JET)
894
895     # Calculate depth
896     depth_map = calculate_depth(disparity_raw)
897
898     # Define two points
899     center_y , center_x = depth_map.shape[0] // 2 ,
900         depth_map.shape[1] // 2 - 20
901     second_y = center_y
902     second_x = center_x + offset_x
903
904     # Read depth and disparity values
905     center_depth_cm = (depth_map[center_y , center_x])
906     second_depth_cm = (depth_map[second_y , second_x])
907     estimated_depth_cm = abs(center_depth_cm -

```

```

908     second_depth_cm)

909

910     # Define severity based on estimated depth
911
912     if estimated_depth_cm < 2.5:
913
914         severity = "Low"
915
916     elif estimated_depth_cm >= 2.5 and
917
918         estimated_depth_cm < 5.0:
919
920         severity = "Medium"
921
922     elif estimated_depth_cm > 5.0:
923
924         severity = "High"
925
926     else:
927
928         severity = "Unknown"

```

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

```

920     for frame in camera.capture_continuous(capture ,
921
922         format="bgra", use_video_port=True, resize=(
923             img_width, img_height)):
924
925         pair_img = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
926
927         imgLeft = pair_img[:, :img_width // 2]
928         imgRight = pair_img[:, img_width // 2:]
929
930         imgL = cv2.remap(imgLeft, leftMapX, leftMapY,
931
932             interpolation=cv2.INTER_LINEAR, borderMode=cv2.
933             BORDER_CONSTANT)

```

```

931     imgR = cv2.remap(imgRight, rightMapX, rightMapY,
932                        interpolation=cv2.INTER_LINEAR, borderMode=cv2.
933                        BORDER_CONSTANT)
934
935    if useStripe:
936        imgL = imgL[80:160,:]
937        imgR = imgR[80:160,:]
938
939    stereo_depth_map((imgL, imgR), save_path_prefix=
940                      None)
941
942    button_held_time = 0
943    HOLD_THRESHOLD = 1.0 # seconds
944
945    if GPIO.input(BUTTON_PIN) == GPIO.LOW:
946        press_start = time.time()
947        while GPIO.input(BUTTON_PIN) == GPIO.LOW:
948            time.sleep(0.01)
949            button_held_time = time.time() - press_start
950
951        if button_held_time < HOLD_THRESHOLD:
952            timestamp = datetime.now().strftime("%Y%m%d_%H%M%S"
953                                         )
954            prefix = f"./captures/capture_{timestamp}"
955            print(f"\n[!] - Capturing - snapshot - at - {timestamp} ...")

```

```
956         ” )  
957         stereo_depth_map( (imgL, imgR) , save_path_prefix=  
958             prefix)  
959         time.sleep(0.5)  
960     else:  
961         cycle_offset()  
962         time.sleep(0.5)
```


⁹⁶³ **Appendix B**

⁹⁶⁴ **Resource Persons**

⁹⁶⁵ **Prof. Jumar Cadondon**

⁹⁶⁶ Assistant Professor

⁹⁶⁷ Division of Physical Sciences and Mathematics

⁹⁶⁸ University of the Philippines Visayas

⁹⁶⁹ jgcadondon@up.edu.ph

⁹⁷⁰

⁹⁷¹ **Engr. Jane Chua**

⁹⁷² Engineer

⁹⁷³ Planning and Design

⁹⁷⁴ DPWH Region 6

⁹⁷⁵ chua.jane@dpwh.gov.ph

⁹⁷⁶

⁹⁷⁷

978 **Engr. Marilou Zamora**

979 Chief

980 Planning and Design

981 DPWH Region 6

982 zamora.marilou@dpwh.gov.ph

983

984 **Engr. Benjamin Javellana**

985 Assistant Director

986 Maintenance

987 DPWH Region 6

988 javellana.benjamin@dpwh.gov.ph

989

990 **Mr. Cris Beleber**

991 Engineering Assistant

992 Planning and Design

993 DPWH Region 6

994 beleber.cris@dpwh.gov.ph

995

⁹⁹⁶ Appendix C

⁹⁹⁷ Data Table and Pothole Images

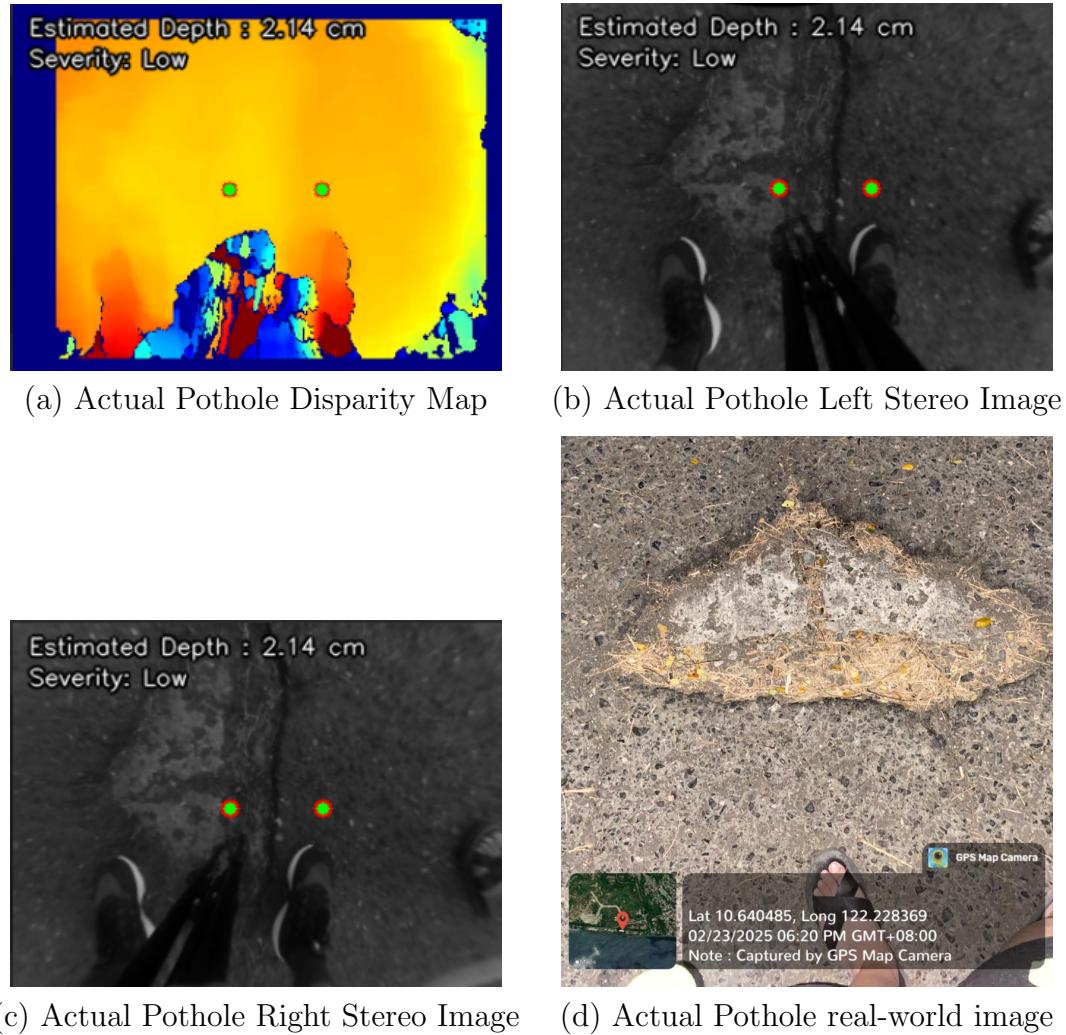
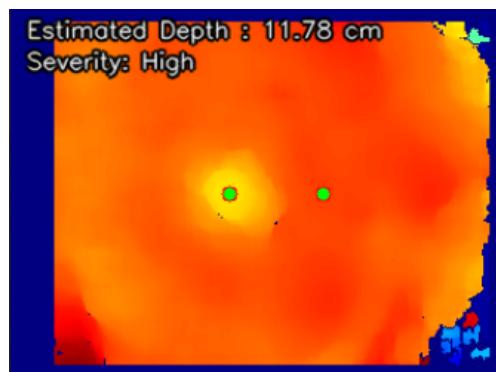


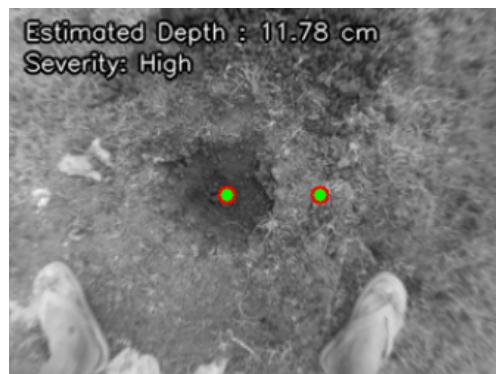
Figure C.1: Actual Pothole Images



(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

⁹⁹⁸ **Appendix D**

⁹⁹⁹ **Supplementary Documents**

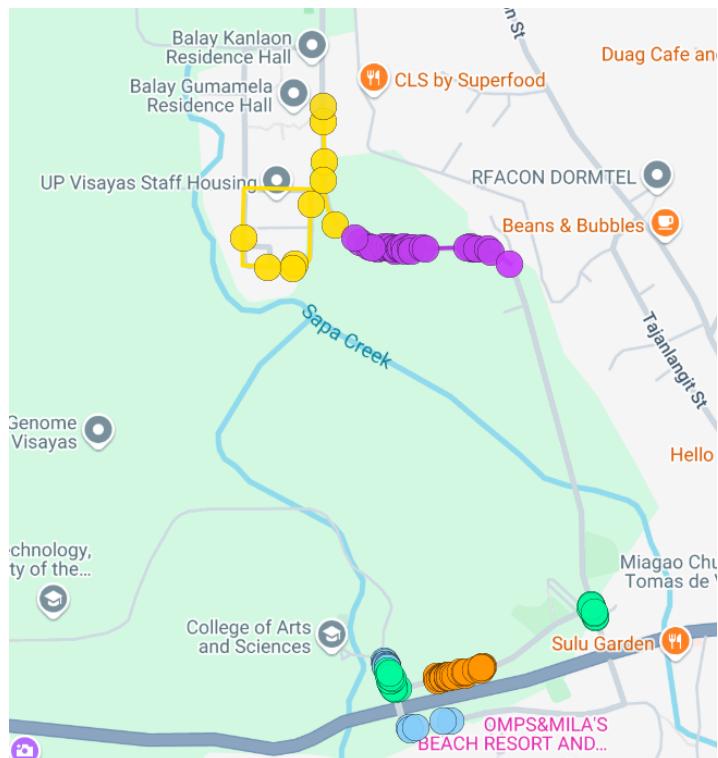


Figure D.1: Visualized pothole locations during the ground truth data collection within the UPV campus.

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.2: 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

Kristian Lyle Sencil
Kristian Lyle Sencil
Team Member

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

31 JAN 2025
REF NO. PRF 2025-023

09614415782

Figure D.3: 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.4: Letter requesting an interview with DPWH representatives for the process of verifying ground truth data.

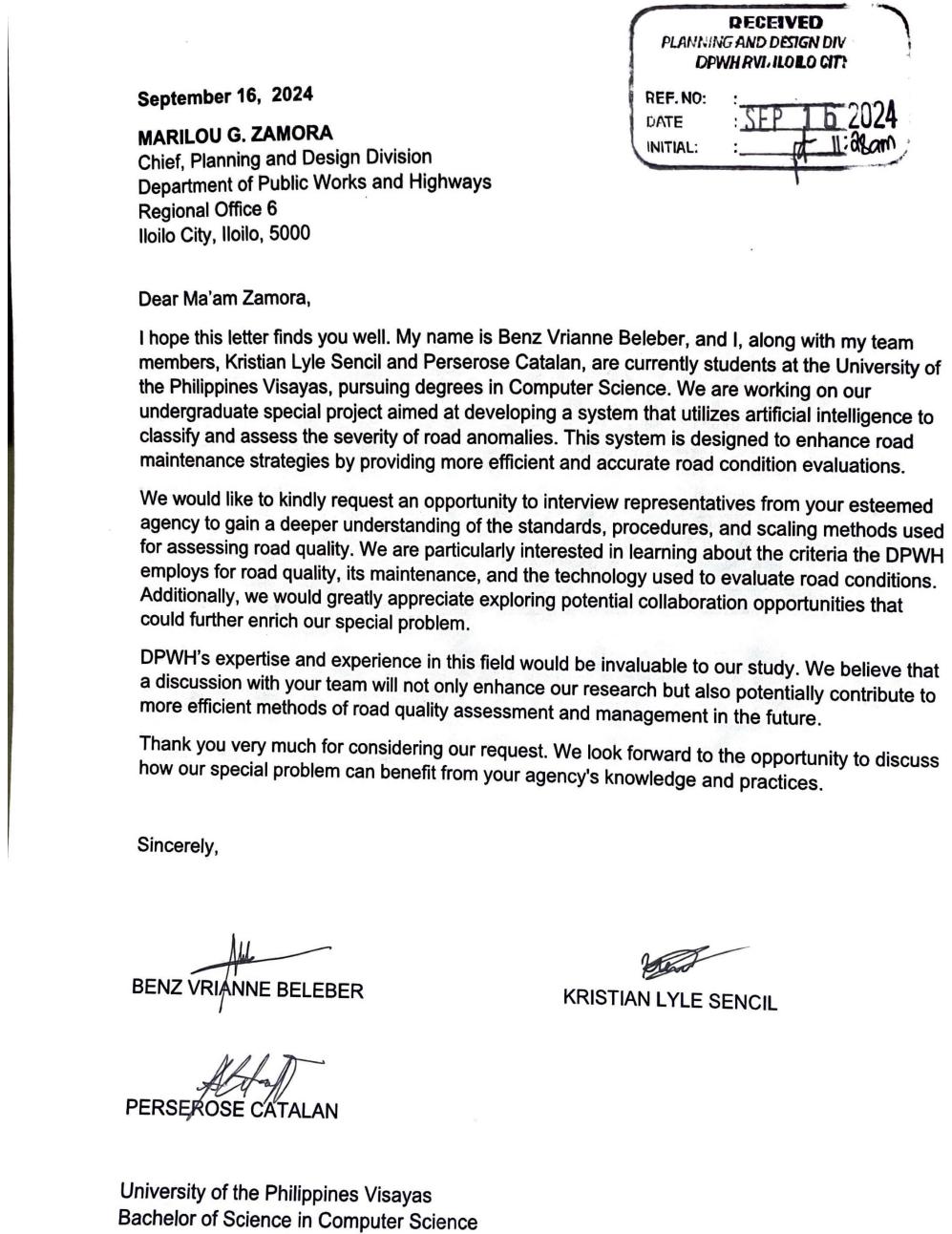


Figure D.5: Letter requesting an interview with DPWH representatives for the standard operating procedures of the agency for assessing road quality.



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.6: 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.7: 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.8: Third page of the pothole measurement procedural manual



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DIVISION OF PHYSICAL SCIENCES AND MATHEMATICS**

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.9: Fourth page of the pothole measurement procedural manual



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COLLEGE OF ARTS AND SCIENCES
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.10: Fifth page of the pothole measurement procedural manual