

¹
²
**ROAD DEFECT SEVERITY ASSESSMENT AND
CLASSIFICATION**

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

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

¹²
¹³
¹⁴
BELEBER, Benz Vrianne
CATALAN, Perserose
SENCIL, Kristian Lyle

¹⁵
¹⁶
Francis DIMZON, Ph.D.
Adviser

¹⁷
May 19, 2025

18

Approval Sheet

19

The Division of Physical Sciences and Mathematics, College of Arts and
20 Sciences, University of the Philippines Visayas

21

certifies that this is the approved version of the following special problem:

22

ROAD DEFECT SEVERITY ASSESSMENT AND 23 CLASSIFICATION

24

Approved by:

25

Name	Signature	Date
Francis D. Dimzon, Ph.D. (Adviser)	_____	_____
Ara Abigail E. Ambita (Panel Member)	_____	_____
Christi Florence C. Cala-or (Panel Member)	_____	_____
Kent Christian A. Castor (Division Chair)	_____	_____

26 Division of Physical Sciences and Mathematics
27 College of Arts and Sciences
28 University of the Philippines Visayas

29 **Declaration**

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

Name	Signature	Date
Benz Vrianne Beleber (Student)	_____	_____
Perserose Catalan (Student)	_____	_____
Kristian Lyle Sencil (Student)	_____	_____

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.

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 encouragement.

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.

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

⁸⁹ **Contents**

⁹⁰ 1 Introduction	¹
⁹¹ 1.1 Overview of the Current State of Technology	¹
⁹² 1.2 Problem Statement	²
⁹³ 1.3 Research Objectives	³
⁹⁴ 1.3.1 General Objective	³
⁹⁵ 1.3.2 Specific Objectives	³
⁹⁶ 1.4 Scope and Limitations of the Research	³
⁹⁷ 1.5 Significance of the Research	⁴
⁹⁸ 2 Review of Related Literature	⁶
⁹⁹ 2.1 Frameworks	⁶
¹⁰⁰ 2.1.1 Depth Estimation	⁶
¹⁰¹ 2.1.2 Image and Video Processing	⁶
¹⁰² 2.1.3 Stereo Vision	⁷
¹⁰³ 2.2 Related Studies	⁷
¹⁰⁴ 2.2.1 Deep Learning Studies	⁷
¹⁰⁵ 2.2.2 Machine Learning Studies	⁹
¹⁰⁶ 2.2.3 Computer Vision Studies	¹⁰

107	2.3 Chapter Summary	11
108	3 Methodology	12
109	3.1 Research Activities	12
110	3.1.1 Data Collection	12
111	3.1.2 Design, Testing, and Experimentation	13
112	3.1.3 Challenges and Limitations	19
113	4 Results and Discussion	20
114	4.1 System Calibration and Model Refinement	20
115	4.2 Testing Results	21
116	4.3 Discussion	23
117	5 Conclusion	25
118	5.1 Summary	25
119	5.2 Conclusions	26
120	5.3 Recommendations for Practice	27
121	5.4 Suggestions for Further Research	27
122	References	29
123	A Code Snippets	31
124	B Resource Persons	32
125	C Data Table and Pothole Images	34
126	D Supplementary Documents	37

¹²⁷ List of Figures

¹²⁸	3.1 Components used in the prototype development.	15
¹²⁹	3.2 Dual RPi Camera Modules attached to the custom housing.	16
¹³⁰	3.3 LCD Module connected to the StereoPi board.	16
¹³¹	3.4 The finished prototype.	16
¹³²	3.5 Calibration process with a checkerboard to correct fisheye lens distortion.	17
¹³³		
¹³⁴	3.6 Parameter tuning process to achieve cleaner and more accurate disparity maps.	17
¹³⁵		
¹³⁶	3.7 The system tested on a simulated pothole.	18
¹³⁷	3.8 Inverse Model Fit to Disparity vs. Distance.	18
¹³⁸		
	4.1 Disparity Map	22
¹³⁹	4.2 Left Stereo Image	22
¹⁴⁰	4.3 Right Stereo Image	22
¹⁴¹	4.4 Linear Regression Fit Between Actual and Estimated Depth . . .	23
¹⁴²		
	C.1 Actual Pothole Images	35
¹⁴³	C.2 Simulated Pothole Images	36
¹⁴⁴		
	D.1 Visualized pothole locations collected during the ground truth data collection within the UPV campus.	37
¹⁴⁵		

146	D.2 Letter requesting validation of data collection procedures.	38
147	D.3 Letter requesting permission for ground truth data collection within	
148	the UPV campus.	39
149	D.4 Letter requesting an interview with DPWH representatives for the	
150	process of verifying ground truth data.	40
151	D.5 Letter requesting an interview with DPWH representatives for the	
152	standard operating procedures of the agency for assessing road	
153	quality.	41
154	D.6 Validated pothole measurement procedural manual, reviewed by	
155	Engr. Ethel B. Morales, District Engineer, DPWH 1st District	
156	Engineering Office.	42
157	D.7 Second page of the pothole measurement procedural manual . . .	43
158	D.8 Third page of the pothole measurement procedural manual . . .	44
159	D.9 Fourth page of the pothole measurement procedural manual . . .	45
160	D.10 Fifth page of the pothole measurement procedural manual . . .	46

¹⁶¹ List of Tables

¹⁶²	2.1 Comparison of Related Studies on Road Anomaly Detection using Deep Learning Techniques and Stereo Vision	11
¹⁶³		
¹⁶⁴	4.1 Linear Regression Model Fit Summary	22
¹⁶⁵	4.2 Model Coefficients - Estimated Depth	22
¹⁶⁶	C.1 Actual vs. Estimated Depths with Residuals and Absolute Errors	34

¹⁶⁷ Chapter 1

¹⁶⁸ Introduction

¹⁶⁹ 1.1 Overview of the Current State of Technology

¹⁷⁰ According to the National Road Length by Classification, Surface Type, and Condition of the Department of Public Works and Highways (DPWH), as of October 2023 approximately 98.97% of roads in the Philippines is paved which is either made of concrete or asphalt (Balita, 2024). Since the DPWH is an institution under the government, it is paramount to maintain such roads in order to avoid accidents and congested traffic situations especially in heavily urbanized areas where there are a lot of vehicles.

¹⁷⁷ In an interview with the Road Board of DPWH Region 6 it was stated that road condition assessments are mostly done manually with heavy reliance on engineering judgment (J. Chua, Personal Interview. 16 September 2024). In addition, manual assessment of roads is also time consuming which leaves maintenance operations to wait for lengthy assessments. In a study conducted by Ramos, Dacanay, and Bronuela-Ambrocio (2023), it was found that the Philippines' current method of manual pavement surveying is considered as a gap since it takes an average of 2-3 months to cover a 250 km road as opposed to a 1 day duration in the Australian Road Research Board for the same road length. Ramos et al. (2023) recommended that to significantly improve efficiency of surveying methods and data gathering processes, automated survey tools are to be employed. It was also added that use of such automated, surveying tools can also guarantee the safety of road surveyors.

¹⁹⁰ If the process of assessment on the severity of road defects can be automated then the whole process of assessing the quality of roads can be hastened up which

192 can also enable maintenance operations to commence as soon as possible if nec-
193 essary. If not automated, the delay of assessments will continue and roads that
194 are supposedly needing maintenance may not be properly maintained which can
195 affect the general public that is utilizing public roads daily.

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

208 1.2 Problem Statement

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

²²⁸ 1.3 Research Objectives

²²⁹ 1.3.1 General Objective

²³⁰ This special problem aims to develop a system that accurately estimates the depth
²³¹ of potholes on road surfaces by using image analysis, depth measurement tech-
²³² nologies, and computer vision techniques. The system will focus specifically on
²³³ measuring the depth of potholes to assess their severity, enabling faster and more
²³⁴ accurate road maintenance decisions, and there are no current practices in the
²³⁵ Philippines involving depth information of potholes in assessing their severity. In
²³⁶ accordance with the Department of Public Works and Highways Region 6's man-
²³⁷ ual for road maintenance, the study will classify potholes into different severity
²³⁸ levels such as low, medium, and high, which will be primarily based on their
²³⁹ depth. In order to measure the system's accuracy, linear regression in order to
²⁴⁰ represent the difference between the depth calculated from the disparity and the
²⁴¹ actual depth of the pothole from ground truth data.

²⁴² 1.3.2 Specific Objectives

²⁴³ Specifically, this special problem aims:

- ²⁴⁴ 1. To collect high-quality stereo images of road surfaces that capture potholes
²⁴⁵ including their depth in favorable conditions
- ²⁴⁶ 2. To measure the accuracy of the system by comparing the depth measure-
²⁴⁷ ments against ground truth data collected from actual road inspections and
²⁴⁸ to utilize linear regression, root mean square error, and mean absolute error
²⁴⁹ as a metric for evaluation.
- ²⁵⁰ 3. To develop a prototype system that can detect and measure road potholes
²⁵¹ from image input, analyze their depth, and assess their severity.

²⁵² 1.4 Scope and Limitations of the Research

²⁵³ This system focuses solely on detecting and assessing the severity of potholes
²⁵⁴ through image analysis and depth measurement technologies. The scope includes

255 the collection of pothole images using cameras and depth-sensing tools under a
256 favorable weather condition.

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

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

268 Environmental factors such as lighting, road surface texture, and weather con-
269 ditions may impact the system's performance. The accuracy and reliability of
270 the system will depend on the quality of camera calibration and disparity map
271 finetuning. Its ability to measure the depth of pothole images needs careful vali-
272 dation.

273 1.5 Significance of the Research

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

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

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

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

²⁸⁸ *Future Researchers.* The special problem may serve as a baseline and guide of
²⁸⁹ researchers with the aim to pursue special problems similar or related to this.

²⁹⁰ **Chapter 2**

²⁹¹ **Review of Related Literature**

²⁹² **2.1 Frameworks**

²⁹³ This section of the chapter presents related frameworks that is considered essential
²⁹⁴ for the development of this special problem.

²⁹⁵ **2.1.1 Depth Estimation**

²⁹⁶ Depth estimation as defined by Sanz, Mezcua, and Pena (2012) is a set of processes
²⁹⁷ that aims to extract a representation of a certain scene's spatial composition.
²⁹⁸ Stereo vision is stated to be among the depth estimation strategies.

²⁹⁹ **2.1.2 Image and Video Processing**

³⁰⁰ Kumar (2024) defines image processing as a process of turning an image into its
³⁰¹ digital form and extracting data from it through certain functions and operations.
³⁰² Usual processes are considered to treat images as 2D signals wherein different
³⁰³ processing methods utilize these signals. Like image processing, RICHES Project
³⁰⁴ (2014) defines video processing as being able to extract information and data from
³⁰⁵ video footage through signal processing methods. However, in video processing
³⁰⁶ due to the diversity of video formats, compression and decompression methods
³⁰⁷ are often expected to be performed on videos before processing methods to either
³⁰⁸ increase or decrease bitrate.

309 2.1.3 Stereo Vision

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

316 2.2 Related Studies

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

320 2.2.1 Deep Learning Studies

321 Automated Detection and Classification of Road Anomalies 322 in VANET Using Deep Learning

323
324 In the study of Bibi et al. (2021) it was noted that identification of active road
325 defects are critical in maintaining smooth and safe flow of traffic. Detection and
326 subsequent repair of such defects in roads are crucial in keeping vehicles using
327 such roads away from mechanical failures. The study also emphasized the growth
328 in use of autonomous vehicles in research data gathering which is what the re-
329 searchers utilized in data gathering procedures. With the presence of autonomous
330 vehicles, this allowed the researchers to use a combination of sensors and deep
331 neural networks in deploying artificial intelligence. The study aimed to allow au-
332 tonomous vehicles to avoid critical road defects that can possibly lead to dangerous
333 situations. Researchers used Resnet-18 and VGG-11 in automatic detection and
334 classification of road defects. Researchers concluded that the trained model was
335 able to perform better than other techniques for road defect detection. The study
336 is able to provide the effectiveness of using deep learning models in training arti-
337 ficial intelligence for road defect detection and classification. However, the study
338 lacks findings regarding the severity of detected defects and incorporation of pot-
339 hole depth in their model which are both crucial in automating manual procedures
340 of road surveying in the Philippines.

341 Road Anomaly Detection through Deep Learning Approaches

342

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

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

357

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

**371 Roadway pavement anomaly classification utilizing smart-
372 phones and artificial intelligence**

373

374 The study of Kyriakou, Christodoulou, and Dimitriou (2016) presented what is
375 considered as a low-cost technology which was the use of Artificial Neural Net-
376 works in training a model for road anomaly detection from data gathered by
377 smartphone sensors. The researchers were able to collect case study data us-
378 ing two-dimensional indicators of the smartphone's roll and pitch values. In the
379 study's discussion, the data collected displayed some complexity due to accelera-
380 tion and vehicle speed which lead to detected anomalies being not as conclusive as

381 planned. The researchers also added that the plots are unable to show parameters
382 that could verify the data's correctness and accuracy. Despite the setbacks, the
383 researchers still fed the data into the Artificial Neural Network that was expected
384 to produce two outputs which were “no defect” and “defect.” The method still
385 yielded above 90% accuracy but due to the limited number of possible outcomes
386 in the data processing the researchers still needed to test the methodology with
387 larger data sets and roads with higher volumes of anomalies.

388 **2.2.2 Machine Learning Studies**

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

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

408 **Road Surface Quality Monitoring Using Machine Learning 409 Algorithms**

410 The study of Singh, Bansal, Kamal, and Kumar (2021) aimed to utilize machine
411 learning algorithms in classifying road defects as well as predict their locations.
412 Another implication of the study was to provide useful information to commuters
413 and maintenance data for authorities regarding road conditions. The researchers
414 gathered data using various methods such as smartphone GPS, gyroscopes, and
415 accelerometers. (Singh et al., 2021) also argued that early existing road moni-
416 toring models are unable to predict locations of road defects and are dependent
417 on fixed roads and static vehicle speed. Neural and deep neural networks were

419 utilized in the classification of anomalies which was concluded by the researchers
420 to yield accurate results and are applicable on a larger scale of data. The study
421 of Singh et al. (2021) can be considered as an effective method in gathering data
422 about road conditions. However, it was stated in the study that relevant authori-
423 ties will be provided with maintenance operation and there is no presence of any
424 severity assessment in the study. This may cause confusion due to a lack of as-
425 sessment on what is the road condition that will require extensive maintenance or
426 repair.

427 **2.2.3 Computer Vision Studies**

428 **Stereo Vision Based Pothole Detection System for Improved**
429 **Ride Quality**

430
431 In the study of Ramaiah and Kundu (2021) it was stated that stereo vision has
432 been earning attention due to its reliable obstacle detection and recognition. Fur-
433 thermore, the study also discussed that such technology would be useful in improv-
434 ing ride quality in automated vehicles by integrating it in a predictive suspension
435 control system. The proposed study was to develop a novel stereo vision based
436 pothole detection system which also calculates the depth accurately. However,
437 the study focused on improving ride quality by using the 3D information from
438 detected potholes in controlling the damping coefficient of the suspension system.
439 Overall, the pothole detection system was able to achieve 84% accuracy and is
440 able to detect potholes that are deeper than 5 cm. The researchers concluded
441 that such system can be utilized in commercial applications. However, it is also
442 worth noting that despite the system being able to detect potholes and measure
443 its depth, the overall severity of the pothole and road condition was not addressed.

444 2.3 Chapter Summary

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

Study	Technology/ Techniques Used	Key Findings	Limitations
Automated Detection and Classification of Road Anomalies in VANET Using Deep Learning	Resnet-18 and VGG-11	Trained model is able to provide the effectiveness of using deep learning models in training artificial intelligence for road defect detection and classification.	Lacks findings regarding the severity of detected defects.
Smartphones as sensors for Road surface monitoring	Machine Learning, Smartphones	Approach was considered impractical for real-life applications.	Sensors are dependent on device's placement and orientation, smoothness of data, and speed of vehicle it is mounted on. Accuracy of results is difficult to compare.
Road Anomaly Detection through Deep Learning Approaches	Convolutional Neural Network, Deep Feedforward Network, and Recurrent Neural Network	Identified that RNN was the best deep learning approach due to high prediction performance.	Data collection is considered too difficult and complicated to execute due to sensors being mounted on an integral part of the vehicle.
Assessing Severity of Road Cracks Using Deep Learning-Based Segmentation and Detection	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

448 **Chapter 3**

449 **Methodology**

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

456 **3.1 Research Activities**

457 **3.1.1 Data Collection**

458 The researchers conducted initial inquiries to understand the problem domain and
459 existing road maintenance practices. This phase included consulting the engineers
460 under the Road Maintenance Department of the government agency Department
461 of Public Works and Highways (DPWH). An interview with Engr. Jane Chua pro-
462 vided a comprehensive overview of the DPWH's road maintenance manual, which
463 was crucial in aligning this project with existing standards. This collaboration
464 with DPWH provided insights into road pothole classification standards, ensuring
465 that the collected data will align with industry standards. The DPWH manual
466 primarily focuses on the volume of detected potholes within a road segment as a
467 measure of severity. However, since depth is not explicitly measured in their cur-
468 rent procedures, the study will supplement this by referencing international stan-
469 dards such as the Long-Term Pavement Performance (LTPP) classification used
470 in the United States (Miller & Bellinger, 2014). The LTPP categorizes potholes

471 based on depth thresholds, which will be integrated with DPWH's volume-based
472 assessment to provide a more comprehensive severity classification framework.
473 The data collection involved capturing around 130 images of potholes from var-
474 ious locations within the UP Visayas Campus. Ground truth data of pothole
475 depth were collected by the researchers by measuring the depth of different points
476 in an individual pothole and then solving for its average depth. The aforemen-
477 tioned process was validated by Engr. Benjamin Javellana, Assistant Director
478 of the DPWH Regional Office 6 Maintenance Division. In order to individually
479 locate or determine each pothole where the ground truth data is collected, images
480 taken were labeled with their corresponding coordinates, street names, and nearby
481 landmarks.

482 **3.1.1.1 Data Collection (Ground Truth Data)**

483 Data collection took place between January and March 2025, during which the
484 researchers collected depth information from 130 potholes around the University of
485 the Philippines Visayas Miagao Campus. During data collection, the researchers
486 are equipped with safety vests and an early warning device to give caution to
487 incoming vehicles. To measure the depth of each pothole, the researchers recorded
488 four depth points within the pothole and calculated their average.

489 **3.1.2 Design, Testing, and Experimentation**

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

492 **3.1.2.1 Depth Measurement**

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

501 The disparity-to-depth conversion utilizes an inverse model derived from cali-

502 bration data, ensuring that the depth estimates reflect real-world distances accu-
503 rately within the effective operational range of the stereo camera setup.

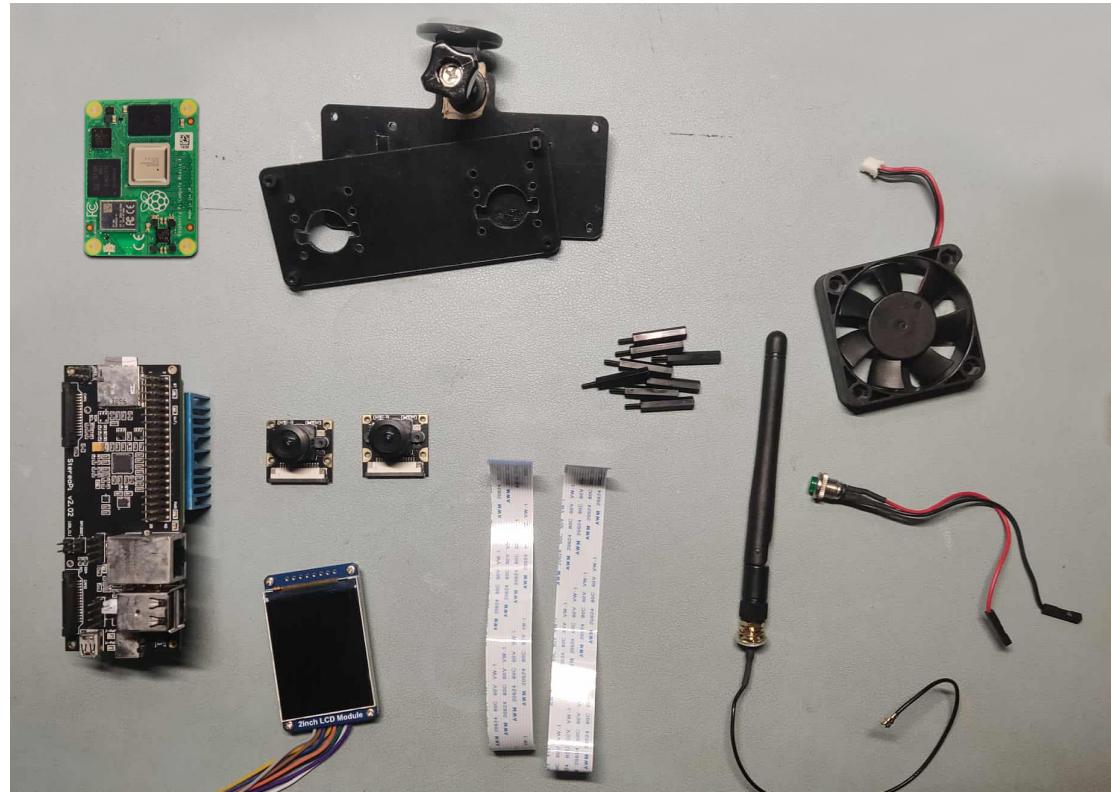
504 **3.1.2.2 Severity Assessment**

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

512 **3.1.2.3 Materials and Equipment**

513 The prototype system was constructed using several hardware components, which
514 include the items listed below and shown in Figure 3.1:

- 515 • StereoPi V2 Board
- 516 • Raspberry Pi Compute Module 4 (CM4)
- 517 • Dual RaspberryPi Camera Modules with Fisheye Lens
- 518 • 3D Printed Custom Housing
- 519 • 2-inch LCD Module
- 520 • Micro SD Card
- 521 • Antenna
- 522 • Momentary Push Button



523

Figure 3.1: Components used in the prototype development.

524 3.1.2.4 Prototype Building

525 The prototype involved the StereoPi V2 Kit which was acquired through an official
526 international distributor. After assembling the camera, it was further modified to
527 address the it's heating by incorporating a heat sink and a small computer fan to
528 make it suitable for outdoor use.

529

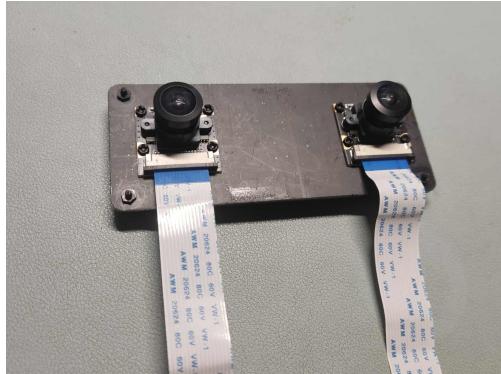


Figure 3.2: Dual RPi Camera Modules attached to the custom housing.

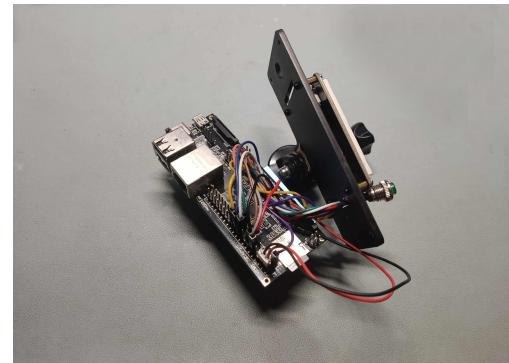


Figure 3.3: LCD Module connected to the StereoPi board.

530



Figure 3.4: The finished prototype.

531 3.1.2.5 Camera Calibration (Fisheye Distortion)

532 The StereoPi V2 is first calibrated using a 9 by 6 checkerboard, with a checker
533 size of 55mm, from different angles through calibration scripts that came with the
534 package. This process ensured that the camera is working properly in capturing
535 stereo imagery. This removed distortion from captured images allowing depth
536 estimation with more accuracy.

537

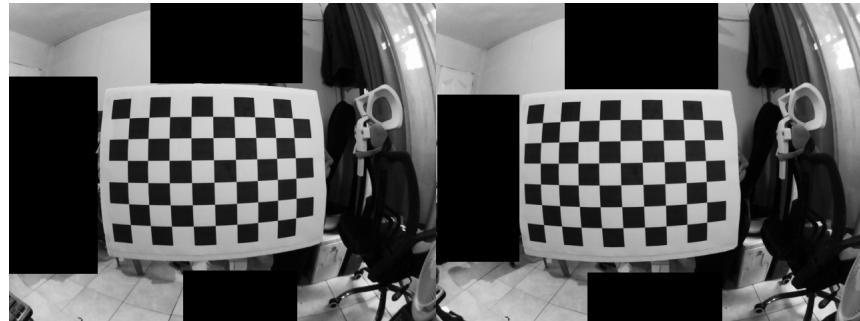


Figure 3.5: Calibration process with a checkerboard to correct fisheye lens distortion.

538

3.1.2.6 Camera Calibration (Disparity Map Fine-tuning)

539

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

546

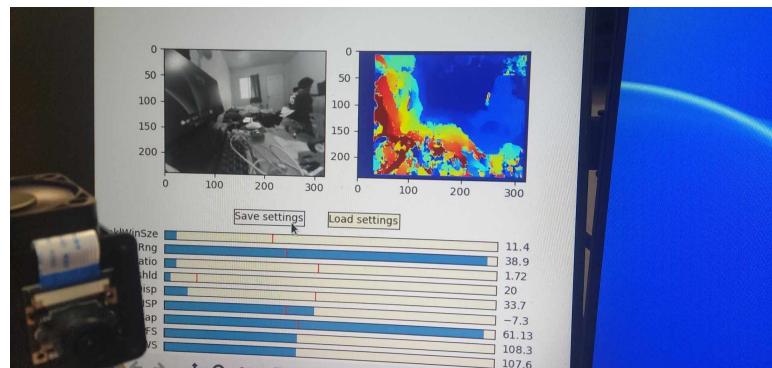


Figure 3.6: Parameter tuning process to achieve cleaner and more accurate disparity maps.

547

3.1.2.7 Initial Testing

548

Initial testing was conducted to verify the functionality and basic accuracy of the stereoscopic camera system in a controlled environment. Artificial potholes with

550 known depths were created to simulate varying real-world scenarios. The system
551 captured disparity maps, and estimated depths were computed using the standard
552 stereo camera depth formula.

553

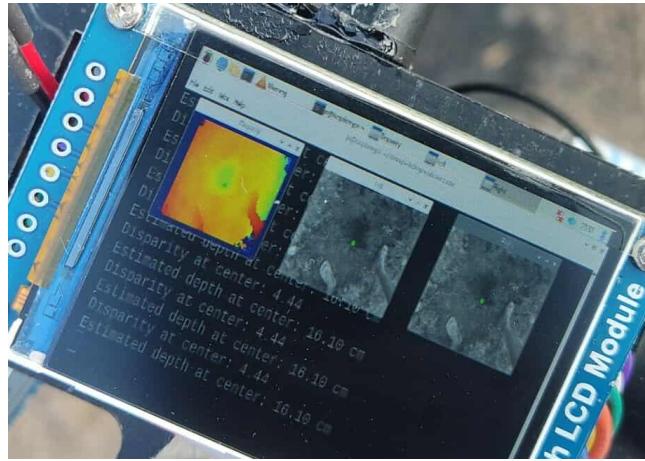


Figure 3.7: The system tested on a simulated pothole.

554 However, the results revealed a non-linear relationship between the computed
555 disparity values and the actual distances. This discrepancy indicated that the
556 traditional depth estimation method was insufficient for the current setup. To
557 address this, the researchers collected multiple data points and correlating known
558 distances to their respective disparity readings and fitted an inverse model to
559 better represent the system's behavior (see Figure 4.4). This updated disparity-
560 to-depth model was subsequently used in the final testing phase.

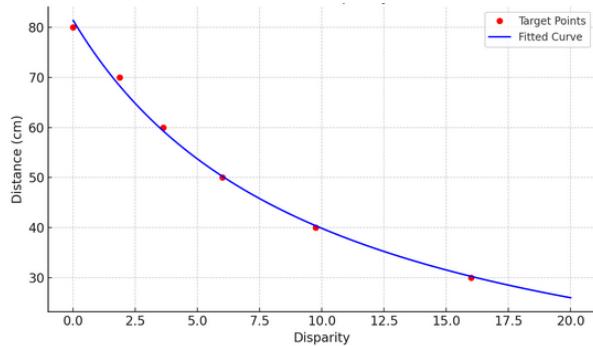


Figure 3.8: Inverse Model Fit to Disparity vs. Distance.

561 **3.1.2.8 Performance Metrics**

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

565 **3.1.2.9 Final Testing and Validation**

566 The testing process began with a detailed testing plan that includes both simu-
567 lated and real-world testing scenarios. Initially, the system is tested in controlled
568 environments to ensure it can estimate pothole depth effectively. Following this,
569 real-world testing was conducted using the StereoPi kit on previously located
570 potholes, specifically at the University of the Philippines Visayas Miagao Cam-
571 pus. The system's performance was validated by comparing its predictions with
572 ground-truth data collected from manual inspections.

573 **3.1.2.10 Documentation**

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

578 **3.1.3 Challenges and Limitations**

579 **3.1.3.1 Camera Limitations**

580 During the data collection process, the researchers were faced with various issues
581 involving the StereoPi V2 kit. Issues like inaccuracies in the rectified image pair
582 and generated disparity map were very apparent in the early stages of data collec-
583 tion due to limited related studies and literature involving the camera. In addition,
584 the camera also yielded some inaccurate depth estimation and over reliance on
585 controlled environments which prompted the researchers to further improve its
586 tuning and calibration.

587 **Chapter 4**

588 **Results and Discussion**

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

596 **4.1 System Calibration and Model Refinement**

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

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

601 where:

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

605 However, preliminary observations revealed that the relationship between mea-
606 sured disparity and depth was shifted from the ideal. Their relationship is in-
607 herently nonlinear, specifically an inverse relationship (of the form $y=1/x$). As
608 disparity decreases, depth increases rapidly and nonlinearly. However, due to
609 real-world factors such as lens distortion, imperfect calibration, stereo matching
610 errors, and pixel quantization, the actual relationship between measured disparity
611 and true depth often deviates from the theoretical ideal (Scharstein & Szeliski,
612 2002).

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

616 An inverse function of the form:

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

617 where:

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

621 4.2 Testing Results

622 Following calibration, actual potholes located around the University of the Philip-
623 pines Visayas (UPV) campus were tested. The ground truth depths of the potholes
624 were measured manually and compared with the depths estimated by the Stereo-
625 Pi camera. Based on the results, the StereoPi camera was able to estimate the
626 depths fairly close to the actual measurements.

627 The smallest error occurred in one pothole, where the estimated depth was
628 only 0.02 cm off from the ground truth. The largest observed error was 3.45 cm.
629 Most of the time, the camera's estimated depths were within approximately 1 to
630 3 centimeters of the actual depths. This demonstrates reasonable accuracy given
631 the hardware setup and environmental conditions.

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

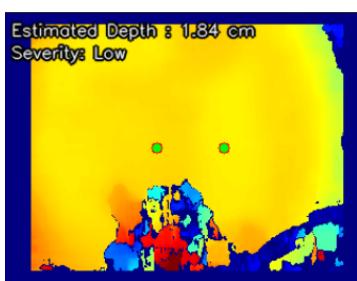


Figure 4.1: Disparity Map



Figure 4.2: Left Stereo Image



Figure 4.3: Right Stereo Image

634 The results show that the StereoPi system provides highly accurate estimates
 635 of pothole depth. The strong correlation ($R=0.978$) and high coefficient of de-
 636 termination ($R^2=0.956$) indicate that the actual depth significantly predicts the
 637 estimated values. The regression coefficient for actual depth was statistically sig-
 638 nificant ($p < 0.001$), suggesting that the relationship is not due to chance. While
 639 the RMSE of 0.844 cm and MAE of 0.945 cm suggest generally small errors, the
 640 presence of a maximum error of 3.45 cm indicates that there may be occasional
 641 outliers or limitations in specific scenarios. Nonetheless, the overall model per-
 642 formance demonstrates that the StereoPi system is suitable for practical pothole
 643 depth estimation.

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

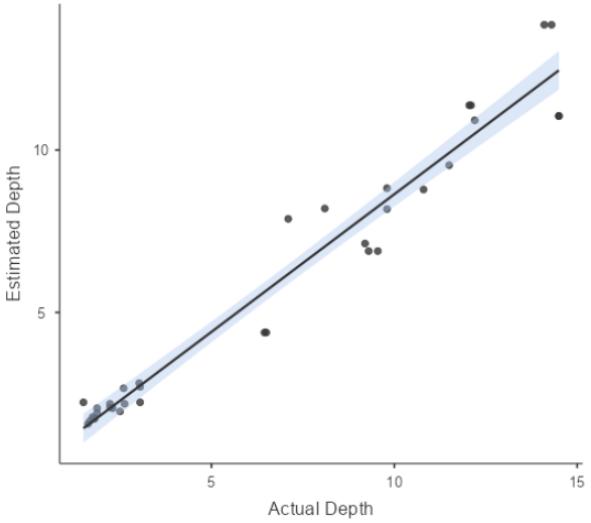


Figure 4.4: Linear Regression Fit Between Actual and Estimated Depth

644 4.3 Discussion

645 The study found that stereo vision works effectively in helping estimate the depth
 646 of road potholes. The system built using the StereoPi V2 camera was able to
 647 measure pothole depths with results mostly within ± 3 cm of the actual ground
 648 truth values, with an overall root mean square error (RMSE) of 0.844 cm and
 649 mean absolute error (MAE) of 0.945 cm. This matches the general observation
 650 in earlier studies such as those by Ramaiah and Kundu (2021), which showed
 651 that stereo vision can provide useful 3D information for road obstacle detection.
 652 However, this study advances previous work by focusing not just on detection,
 653 but on depth-based severity classification, which was largely missing in earlier
 654 research.

655 A strong positive correlation ($R = 0.978$) and coefficient of determination (R^2
 656 = 0.956) indicate that the actual pothole depths strongly predict the estimated
 657 values. The regression model's significant predictor ($p < 0.001$) further supports
 658 the robustness of the depth estimation approach. This level of accuracy and model
 659 performance highlights the suitability of the StereoPi system for practical field
 660 applications in pothole monitoring and maintenance prioritization. This finding
 661 is significant because earlier machine learning-based road detection studies such as
 662 those by Bibi et al. (2021) focused mostly on classifying the existence of defects,
 663 not measuring their severity.

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

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

682 **Chapter 5**

683 **Conclusion**

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

688 **5.1 Summary**

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

698 To achieve these objectives, a hardware prototype was built using the StereoPi
699 V2 board and Raspberry Pi Compute Module 4, equipped with dual fisheye-lens
700 cameras. Camera calibration was performed using a 9x6 checkerboard pattern
701 with known square sizes to correct for fisheye lens distortion and ensure proper
702 alignment of the stereo pair. After calibration, disparity map generation was
703 fine-tuned by adjusting block matching parameters to produce clearer and more
704 reliable disparity maps. Initial testing was conducted using simulated potholes
705 with known depths to verify the functionality of the system and identify the non-

⁷⁰⁶ linear behavior present in stereo vision depth measurements. It was observed that
⁷⁰⁷ using the standard stereo depth formula led to inaccuracies, particularly at greater
⁷⁰⁸ distances.

⁷⁰⁹ The calibrated system and fitted regression model were validated by comparing
⁷¹⁰ the estimated depths with the manually measured depths. The findings showed
⁷¹¹ that the system was able to estimate pothole depths within approximately ± 3
⁷¹² cm of actual measurements, achieving a Mean Absolute Error (MAE) of 0.945 cm
⁷¹³ and a Root Mean Square Error (RMSE) of 0.844 cm. A strong positive linear
⁷¹⁴ relationship was observed between the estimated and actual depths ($R = 0.978$,
⁷¹⁵ $R^2 = 0.956$).

⁷¹⁶ 5.2 Conclusions

⁷¹⁷ The researchers conclude the following based on the findings:

- ⁷¹⁸ • The system effectively captures and analyzes depth information from stereo
⁷¹⁹ images, providing a viable method for automated pothole severity assess-
⁷²⁰ ment.
- ⁷²¹ • Incorporating depth measurements significantly improves pothole repair pri-
⁷²² oritization compared to traditional visual-only inspections, allowing main-
⁷²³ tenance decisions to be based on objective, measurable data.
- ⁷²⁴ • The system achieved an acceptable regression model fit, with a strong posi-
⁷²⁵ tive correlation ($R = 0.978$) and a coefficient of determination ($R^2 = 0.956$),
⁷²⁶ confirming that the depth estimates closely align with the ground truth
⁷²⁷ measurements. The system obtained satisfactory error metrics, with a Mean
⁷²⁸ Absolute Error (MAE) of 0.945 cm and a Root Mean Square Error (RMSE)
⁷²⁹ of 0.844 cm, indicating reliable performance for both pothole detection and
⁷³⁰ depth estimation tasks.
- ⁷³¹ • The proposed approach fills a critical gap in current road maintenance prac-
⁷³² tices, especially within the Philippine context where depth-based severity
⁷³³ classification is not yet systematically implemented.

⁷³⁴ This special project has successfully developed a system that addresses the
⁷³⁵ problem of pothole severity assessment using depth measurement. The research
⁷³⁶ shows that stereo vision, even using accessible and affordable technology, holds
⁷³⁷ strong potential for future development in road maintenance automation. By

738 building upon the foundation laid by this project, future systems can become
739 even more accurate, efficient, and practical for real-world deployment

740 5.3 Recommendations for Practice

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

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

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

752 5.4 Suggestions for Further Research

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

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

761 *Improve camera calibration and tuning.* While the StereoPi system produced
762 good depth estimates, the results still varied depending on the precision of the
763 camera calibration. Future researchers can explore better calibration techniques
764 and finer parameter adjustments to minimize errors, especially in challenging en-
765 vironments.

766 *Use of multi-camera arrays.* Instead of relying solely on a two-camera stereo
767 setup, future research could explore the use of multi-point or multi-angle camera

768 arrays. These systems can offer improved depth perception and coverage, partic-
769 ularly for complex or uneven road surfaces, by capturing more comprehensive 3D
770 data.

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

777 References

- 778 Balita, C. (2024, June 14). *Road length Philippines 2023, by classification*. Retrieved from <https://www.statista.com/statistics/1276356/philippines-road-length-by-classification/>
- 781 Bibi, R., Saeed, Y., Zeb, A., Ghazal, T. M., Rahman, T., Said, R. A., ... Khan, M. A. (2021). Edge AI-Based Automated Detection and Classification of Road Anomalies in VANET Using Deep Learning. *Computational Intelligence and Neuroscience*, 2021(1). doi: 10.1155/2021/6262194
- 785 Ha, J., Kim, D., & Kim, M. (2022). Assessing Severity of Road Cracks Using Deep Learning-Based Segmentation and Detection. *The Journal of Supercomputing*, 78(16), 17721–17735. doi: 10.1007/s11227-022-04560-x
- 788 Kumar, A. (2024, October). What is Image Processing: Overview, Applications, Benefits, and More. *AI and Machine Learning*. Retrieved from <https://www.simplilearn.com/image-processing-article> (Accessed: January 1, 2025)
- 792 Kyriakou, C., Christodoulou, S. E., & Dimitriou, L. (2016, April). Roadway Pavement Anomaly Classification Utilizing Smartphones and Artificial Intelligence. In *Proceedings of the IEEE Conference*. Retrieved from <https://ieeexplore.ieee.org/abstract/document/7495459>
- 796 Luo, D., Lu, J., & Guo, G. (2020, June). Road Anomaly Detection Through Deep Learning Approaches. *IEEE Journals and Magazine*. (<https://ieeexplore.ieee.org/document/9123753/>)
- 799 Miller, J. S., & Bellinger, W. Y. (2014). *Distress Identification Manual for the Long-Term Pavement Performance Program*. U.S. Department of Transportation, Federal Highway Administration. Retrieved from <https://rosap.ntl.bts.gov/view/dot/28612>
- 803 Ramaiah, N. K. B., & Kundu, S. (2021). Stereo Vision Based Pothole Detection System for Improved Ride Quality. *SAE International Journal of Advances and Current Practices in Mobility*, 3(5), 2603–2610. doi: 10.4271/2021-01-0085
- 807 Ramos, J. A., Dacanay, J. P., & Bronuela-Ambrocio, L. (2023). *A Review of the Current Practices in the Pavement Surface Monitoring in*

- 809 *the Philippines* (Doctoral dissertation, University of the Philippines Dil-
810 iman). Retrieved from https://ncts.upd.edu.ph/tssp/wp-content/uploads/2023/01/TSSP2022_09.pdf
- 812 RICHES Project. (2014). *Video Processing*. Retrieved from <https://resources.riches-project.eu/glossary/video-processing/>
- 814 Sanz, P., Mezcua, B., & Pena, J. (2012). Depth Estimation: An Introduction.
815 *Current Advancements in Stereo Vision*. Retrieved from <http://dx.doi.org/10.5772/45904> doi: 10.5772/45904
- 817 Sattar, S., Li, S., & Chapman, M. (2018). Road Surface Monitoring Us-
818 ing Smartphone Sensors: A Review. *Sensors*, 18(11), 3845–3845. doi:
819 10.3390/s18113845
- 820 Scharstein, D., & Szeliski, R. (2002). A Taxonomy and Evaluation of Dense Two-
821 Frame Stereo Correspondence Algorithms. *International Journal of Com-
822 puter Vision*, 47(1), 7–42. Retrieved from <https://link.springer.com/article/10.1023/A:1014573219977> doi: 10.1023/A:1014573219977
- 824 Singh, P., Bansal, A., Kamal, A. E., & Kumar, S. (2021). Road Surface Quality
825 Monitoring Using Machine Learning Algorithm. In *Smart Innovation, Sys-
826 tems and Technologies* (pp. 423–432). doi: 10.1007/978-981-16-6482-3_42

⁸²⁷ **Appendix A**

⁸²⁸ **Code Snippets**

⁸²⁹ **Appendix B**

⁸³⁰ **Resource Persons**

⁸³¹ **Prof. Jumar Cadondon**

⁸³² Assistant Professor

⁸³³ Division of Physical Sciences and Mathematics

⁸³⁴ University of the Philippines Visayas

⁸³⁵ jgcadondon@up.edu.ph

⁸³⁶ **Engr. Jane Chua**

⁸³⁷ Engineer

⁸³⁸ DPWH Region 6

⁸³⁹ chua.jane@dpwh.gov.ph

⁸⁴⁰

⁸⁴¹ **Engr. Marilou Zamora**

⁸⁴² Chief

⁸⁴³ Planning and Design

⁸⁴⁴ DPWHRegion6

⁸⁴⁵ zamora.marilou@dpwh.gov.ph

⁸⁴⁶ **Engr. Benjamin Javellana**

⁸⁴⁷ Assistant Director

⁸⁴⁸ Maintenance

⁸⁴⁹ DPWHRegion6

⁸⁵⁰ javellana.benjamin@dpwh.gov.ph

⁸⁵¹ **Mr. Cris Beleber**

⁸⁵² Engineering Assistant

⁸⁵³ Planning and Design

⁸⁵⁴ DPWHRegion6

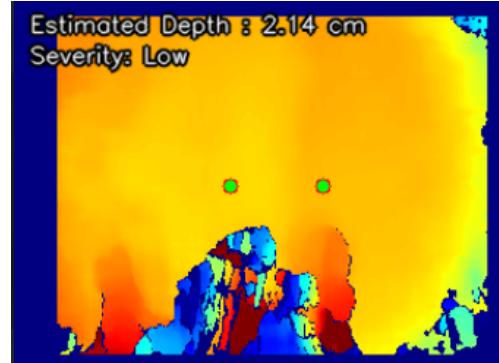
⁸⁵⁵ beleber.cris@dpwh.gov.ph

⁸⁵⁶ **Appendix C**

⁸⁵⁷ **Data Table and 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

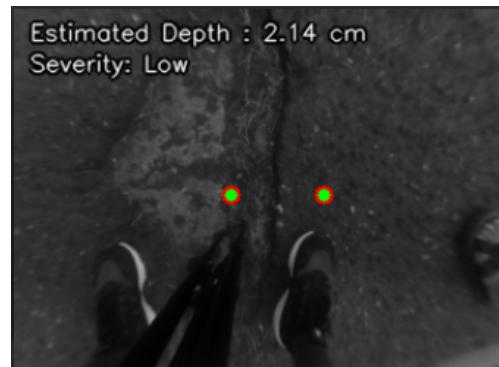
Table C.1: Actual vs. Estimated Depths with Residuals and Absolute Errors



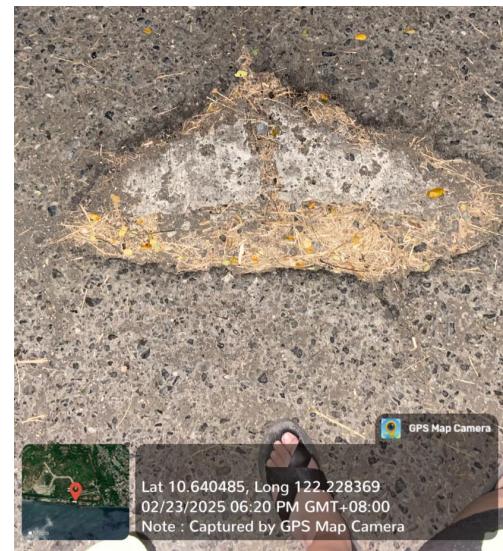
(a) Actual Pothole Disparity Map



(b) Actual Pothole Left Stereo Image

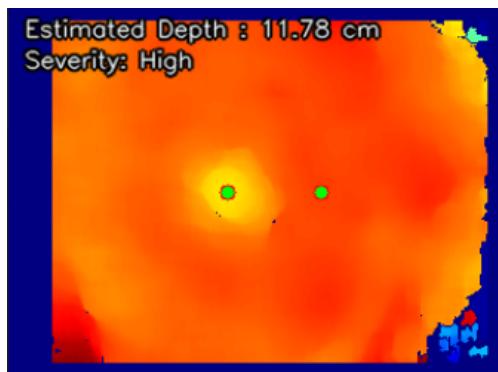


(c) Actual Pothole Right Stereo Image



(d) Actual Pothole real-world image

Figure C.1: Actual Pothole Images



(a) Simulated Pothole Disparity Map



(b) Simulated Pothole Left Stereo Image



(c) Simulated Pothole Right Stereo Image



(d) Simulated Pothole StereoPi capture

Figure C.2: Simulated Pothole Images

⁸⁵⁸ **Appendix D**

⁸⁵⁹ **Supplementary Documents**

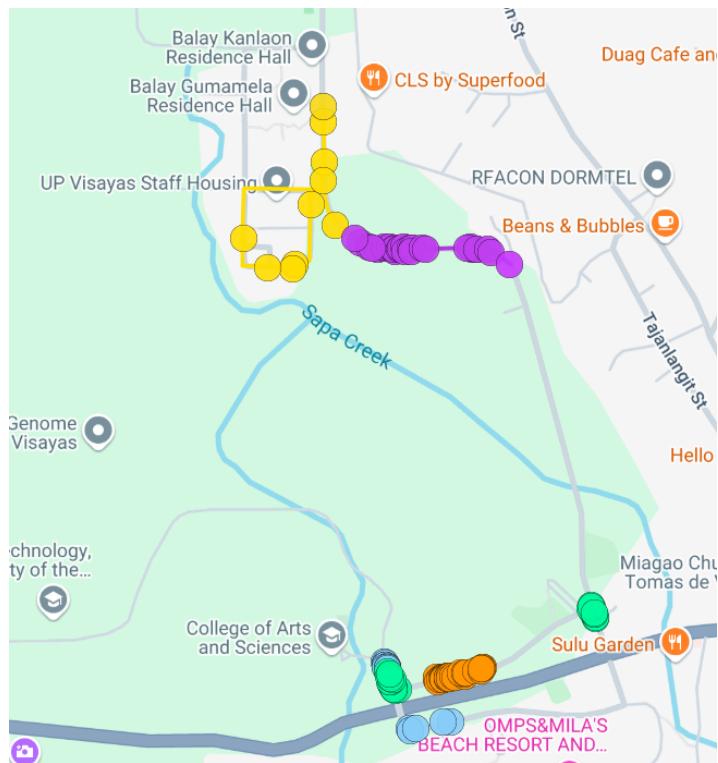


Figure D.1: Visualized pothole locations collected during the ground truth data collection within the UPV campus.

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


PERSEROÉ 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

January 31, 2025

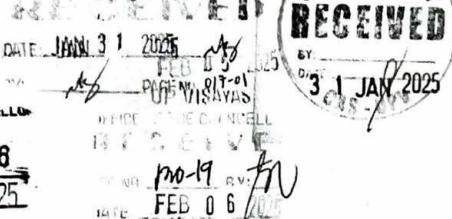
Dr. Farisal U. Bagsit
Vice Chancellor for Administration

(through channels) **UP VISAYAS**
OFFICE OF THE CHANCELLOR

25-0226
 Dear Vice Chancellor Bagsit

REF. NO. **FEB 07 2025**

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,

Benz Vrianne Beleber
 Team Member

CLEMENT G. CAMPOSANO
CHANCELLOR
 26.2025

Perserose Catalan
 Team Leader

Noted:

Francis Dimzon, Ph.D.
 BSCS Special Problem Adviser

09614415782

RECOMMENDING APPROVAL/DISAPPROVAL:
Farisal U. Bagsit 2.6.2024
 FARISAL U. BAGSIT, Ph.D.
 Vice Chancellor for Administration

Kristian Lyle Sencil
 Team Member
It would be nice if we can present some of our data to UPV admin

RECOMMEND APPROVAL/DISAPPROVAL:
 DATE **31 JAN 2025**
 REF NO. PRF **2025-103**
RECOMMEND APPROVAL:
Kent Christian A. Castor
 CHAIRPERSON, DPSM
 PEPITO R. FERNANDEZ JR.
 DEAN, COLLEGE OF ARTS & SCIENCES
 UP VISAYAS

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

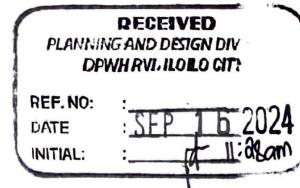
KRISTIAN LYLE SENCIL

PERSEROSE P. CATALAN

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

September 16, 2024

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



Dear Ma'am Zamora,

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

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

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

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

Sincerely,


BENZ VRIANNE BELEBER


KRISTIAN LYLE SENCIL


PERSEROSE CATALAN

University of the Philippines Visayas
Bachelor of Science in Computer Science

Figure D.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



**UNIVERSITY OF THE PHILIPPINES VISAYAS
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



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



UNIVERSITY OF THE PHILIPPINES VISAYAS
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