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**ROAD DEFECT SEVERITY ASSESSMENT AND
CLASSIFICATION**

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A Special Problem Proposal
Presented to
the Faculty of the Division of Physical Sciences and Mathematics
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Miag-ao, Iloilo

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

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ROAD DEFECT SEVERITY ASSESSMENT AND 23 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
33 properly acknowledged and referred.

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Dedication

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

39 To their parents, for their endless sacrifices.

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

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

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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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¹⁷⁴ **Chapter 1**

¹⁷⁵ **Introduction**

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

¹⁷⁷ 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.

¹⁸⁴ 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.

¹⁹⁷ 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

¹⁹⁹ can also enable maintenance operations to commence as soon as possible if nec-
²⁰⁰ essary. If not automated, the delay of assessments will continue and roads that
²⁰¹ are supposedly needing maintenance may not be properly maintained which can
²⁰² affect the general public that is utilizing public roads daily.

²⁰³ Existing studies involving road defects such as potholes mainly focus on the
²⁰⁴ detection of potholes using deep learning models and almost not considering the
²⁰⁵ severity of detected potholes or did not incorporate any depth information from
²⁰⁶ potholes (Ha, Kim, & Kim, 2022; Kumar, 2024; Bibi et al., 2021). In addition,
²⁰⁷ for studies that include severity assessment on potholes, the main goal of the
²⁰⁸ study is not directed towards road maintenance automation but other factors such
²⁰⁹ as improvement of ride quality for the vehicle. Another issue found in existing
²¹⁰ solutions is the lack of incorporation to the context of Philippine roads. With
²¹¹ these issues in mind, the study aims to utilize stereo vision from StereoPi V2
²¹² in order to obtain multi-perspective views of detected potholes to be used in
²¹³ severity assessment by focusing on estimating the depth of individual potholes
²¹⁴ for automated road condition monitoring.

²¹⁵ 1.2 Problem Statement

²¹⁶ Roads support almost every aspect of daily life, from providing a way to transport
²¹⁷ goods and services to allowing people to stay connected with their communities.
²¹⁸ However, road defects such as cracks and potholes damage roads over time, and
²¹⁹ they can increase accident risks and affect the overall transportation. The current
²²⁰ way of inspecting the roads for maintenance is often slow as it is done manually,
²²¹ which makes it harder to detect and fix defects early. The delay in addressing these
²²² problems can lead to even worse road conditions (J. Chua, Personal Interview. 16
²²³ September 2024). There are several research studies into automated road defect
²²⁴ classification that have advanced in recent years but most of them focus on iden-
²²⁵ tifying the types of defects rather than assessing their severity or characteristics
²²⁶ like depth. Without reliable data on the depth of the defect, road maintenance
²²⁷ authorities may underestimate the severity of certain defects. To address these
²²⁸ challenges, advancements are needed across various areas. An effective solution
²²⁹ should not only detect and classify road defects but also measure their severity
²³⁰ to better prioritize repairs. Failing to address this problem will require more ex-
²³¹ tensive repairs for damaged roads, which raises the cost and strains the budget.
²³² Additionally, road maintenance would still be slow and cause disruptions in daily
²³³ activities. Using an automated system that accurately assess the severity of road
²³⁴ defects by incorporating depth is necessary to efficiently monitor road quality.

²³⁵ 1.3 Research Objectives

²³⁶ 1.3.1 General Objective

²³⁷ This special problem aims to develop a system that accurately estimates the depth
²³⁸ of potholes on road surfaces by using image analysis, depth measurement tech-
²³⁹ nologies, and computer vision techniques. The system will focus specifically on
²⁴⁰ measuring the depth of potholes to assess their severity, enabling faster and more
²⁴¹ accurate road maintenance decisions, and there are no current practices in the
²⁴² Philippines involving depth information of potholes in assessing their severity. In
²⁴³ accordance with the Department of Public Works and Highways Region 6's man-
²⁴⁴ ual for road maintenance, the study will classify potholes into different severity
²⁴⁵ levels such as low, medium, and high, which will be primarily based on their
²⁴⁶ depth. In order to measure the system's accuracy, linear regression in order to
²⁴⁷ represent the difference between the depth calculated from the disparity and the
²⁴⁸ actual depth of the pothole from ground truth data.

²⁴⁹ 1.3.2 Specific Objectives

²⁵⁰ Specifically, this special problem aims:

- ²⁵¹ 1. To collect high-quality stereo images of road surfaces that capture potholes
²⁵² including their depth in favorable conditions
- ²⁵³ 2. To measure the accuracy of the system by comparing the depth measure-
²⁵⁴ ments against ground truth data collected from actual road inspections and
²⁵⁵ to utilize linear regression, root mean square error, and mean absolute error
²⁵⁶ as a metric for evaluation.
- ²⁵⁷ 3. To develop a prototype system that can detect and measure road potholes
²⁵⁸ from image input, analyze their depth, and assess their severity.

²⁵⁹ 1.4 Scope and Limitations of the Research

²⁶⁰ This system focuses solely on detecting and assessing the severity of potholes
²⁶¹ through image analysis and depth measurement technologies. The scope includes

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

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

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

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

280 1.5 Significance of the Research

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

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

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

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

²⁹⁵ *Future Researchers.* The special problem may serve as a baseline and guide of
²⁹⁶ researchers with the aim to pursue special problems similar or related to this.

²⁹⁷ **Chapter 2**

²⁹⁸ **Review of Related Literature**

²⁹⁹ **2.1 Frameworks**

³⁰⁰ This section of the chapter presents related frameworks that is considered essential
³⁰¹ for the development of this special problem.

³⁰² **2.1.1 Depth Estimation**

³⁰³ Depth estimation as defined by Sanz, Mezcua, and Pena (2012) is a set of processes
³⁰⁴ that aims to extract a representation of a certain scene's spatial composition.
³⁰⁵ Stereo vision is stated to be among the depth estimation strategies.

³⁰⁶ **2.1.2 Image and Video Processing**

³⁰⁷ Kumar (2024) defines image processing as a process of turning an image into its
³⁰⁸ digital form and extracting data from it through certain functions and operations.
³⁰⁹ Usual processes are considered to treat images as 2D signals wherein different
³¹⁰ processing methods utilize these signals. Like image processing, RICHES Project
³¹¹ (2014) defines video processing as being able to extract information and data from
³¹² video footage through signal processing methods. However, in video processing
³¹³ due to the diversity of video formats, compression and decompression methods
³¹⁴ are often expected to be performed on videos before processing methods to either
³¹⁵ increase or decrease bitrate.

316 2.1.3 Stereo Vision

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

323 2.2 Related Studies

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

327 2.2.1 Deep Learning Studies

328 Automated Detection and Classification of Road Anomalies 329 in VANET Using Deep Learning

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

348 Road Anomaly Detection through Deep Learning Approaches

349

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

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

364

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

**378 Roadway pavement anomaly classification utilizing smart-
379 phones and artificial intelligence**

380

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

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

395 **2.2.2 Machine Learning Studies**

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

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

415 **Road Surface Quality Monitoring Using Machine Learning 416 Algorithms**

417
418 The study of Singh, Bansal, Kamal, and Kumar (2021) aimed to utilize machine
419 learning algorithms in classifying road defects as well as predict their locations.
420 Another implication of the study was to provide useful information to commuters
421 and maintenance data for authorities regarding road conditions. The researchers
422 gathered data using various methods such as smartphone GPS, gyroscopes, and
423 accelerometers. (Singh et al., 2021) also argued that early existing road monitoring
424 models are unable to predict locations of road defects and are dependent
425 on fixed roads and static vehicle speed. Neural and deep neural networks were

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

434 **2.2.3 Computer Vision Studies**

435 **Stereo Vision Based Pothole Detection System for Improved**
436 **Ride Quality**

437

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

⁴⁵¹ 2.3 Chapter Summary

- ⁴⁵² 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

⁴⁵⁵ **Chapter 3**

⁴⁵⁶ **Methodology**

⁴⁵⁷ This chapter outlines the systematic approach that were taken to address the
⁴⁵⁸ problem of pothole depth estimation using StereoPi V2. The methodology is
⁴⁵⁹ divided into key phases: data collection, algorithm selection, design, testing and
⁴⁶⁰ experimentation, and challenges and limitations. Each phase will play a crucial
⁴⁶¹ role in accurately classifying and assessing road defects. Each phase is essential
⁴⁶² for accurately estimating the depth of potholes using StereoPi V2.

⁴⁶³ **3.1 Research Activities**

⁴⁶⁴ **3.1.1 Data Collection**

⁴⁶⁵ The researchers conducted initial inquiries to understand the problem domain and
⁴⁶⁶ existing road maintenance practices. This phase included consulting the engineers
⁴⁶⁷ under the Road Maintenance Department of the government agency Department
⁴⁶⁸ of Public Works and Highways (DPWH). An interview with Engr. Jane Chua pro-
⁴⁶⁹ vided a comprehensive overview of the DPWH's road maintenance manual, which
⁴⁷⁰ was crucial in aligning this project with existing standards. This collaboration
⁴⁷¹ with DPWH provided insights into road pothole classification standards, ensuring
⁴⁷² that the collected data will align with industry standards. The DPWH manual
⁴⁷³ primarily focuses on the volume of detected potholes within a road segment as a
⁴⁷⁴ measure of severity. However, since depth is not explicitly measured in their cur-
⁴⁷⁵ rent procedures, the study will supplement this by referencing international stan-
⁴⁷⁶ dards such as the Long-Term Pavement Performance (LTPP) classification used
⁴⁷⁷ in the United States (Miller & Bellinger, 2014). The LTPP categorizes potholes

478 based on depth thresholds, which will be integrated with DPWH's volume-based
479 assessment to provide a more comprehensive severity classification framework.
480 The data collection involved capturing around 130 images of potholes from vari-
481 ous locations within the UP Visayas Campus. Ground truth data of pothole depth
482 were collected by the researchers by measuring the depth of different points in an
483 individual pothole and then solving for its average depth. The researchers devel-
484 oped a manual specifically designed for depth measurement, which underwent a
485 review by Engr. Benjamin Javellana, Assistant Director of the Maintenance Divi-
486 sion at the Department of Public Works and Highways (DPWH) Regional Office
487 VI. The finalized version of the manual was subsequently validated by the DPWH
488 First District Engineering Office. In order to individually locate or determine each
489 pothole where the ground truth data is collected, images taken were labeled with
490 their corresponding coordinates, street names, and nearby landmarks.

491 **3.1.1.1 Data Collection (Ground Truth Data)**

492 Data collection took place between January and March 2025, during which the re-
493 searchers collected depth information from 130 potholes around the University of
494 the Philippines Visayas Miagao Campus. During data collection, the researchers
495 are equipped with safety vests and an early warning device to give caution to in-
496 coming vehicles. Following the validated manual for pothole depth measurement,
497 the researchers recorded four measure points within the pothole and the resulting
498 average is recorded as the pothole's depth.



499

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

500

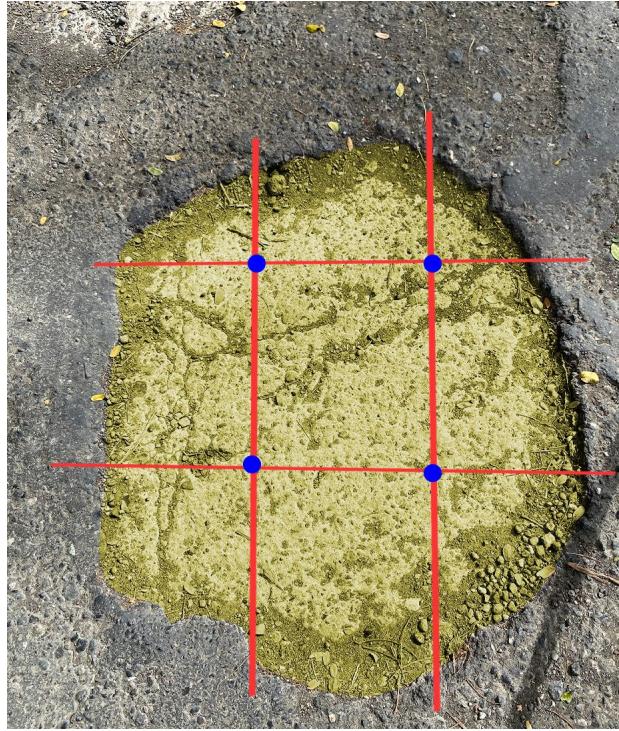


Figure 3.2: Four measure points of the pothole.

501

3.1.2 Design, Testing, and Experimentation

502

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

504

3.1.2.1 Depth Measurement

505

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

513

The disparity-to-depth conversion utilizes an inverse model derived from cali-
514 bration data, ensuring that the depth estimates reflect real-world distances accu-

515 rarely within the effective operational range of the stereo camera setup.

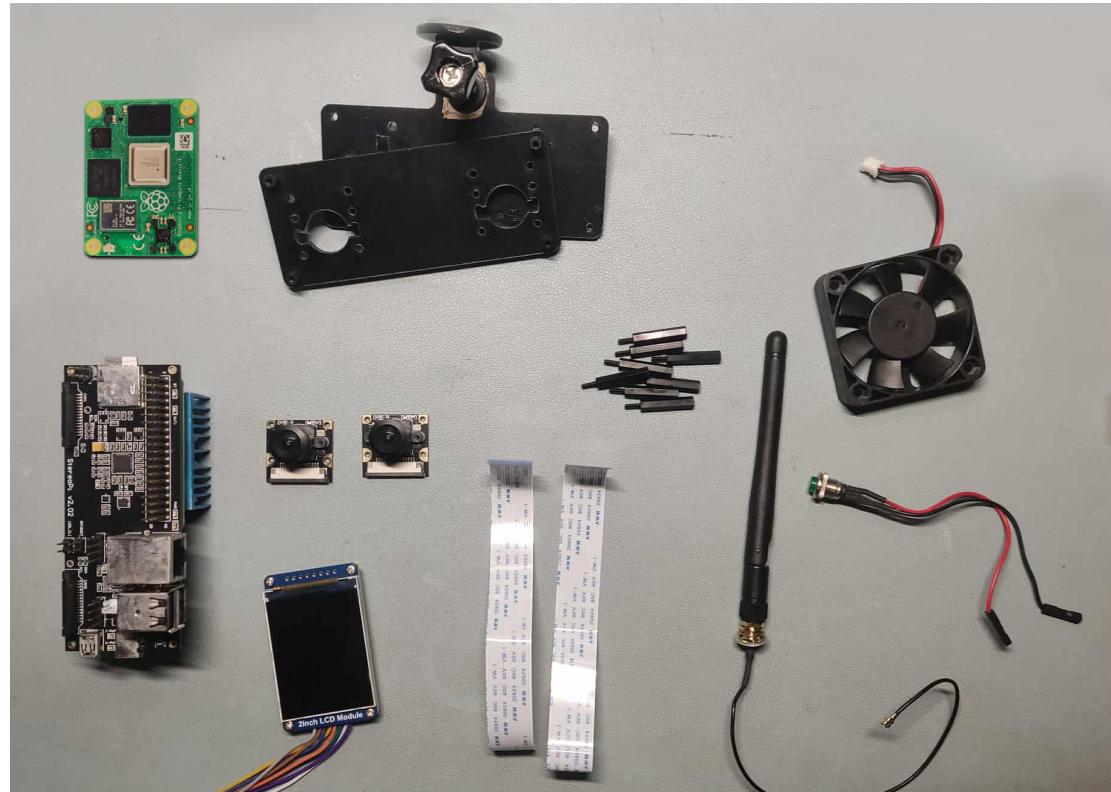
516 **3.1.2.2 Severity Assessment**

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

524 **3.1.2.3 Materials and Equipment**

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

- 527 ● StereoPi V2 Board
- 528 ● Raspberry Pi Compute Module 4 (CM4)
- 529 ● Dual RaspberryPi Camera Modules with Fisheye Lens
- 530 ● 3D Printed Custom Housing
- 531 ● 2-inch LCD Module
- 532 ● Micro SD Card
- 533 ● Antenna
- 534 ● Momentary Push Button



535

Figure 3.3: Components used in the prototype development.

536 3.1.2.4 Prototype Building

537 The prototype involved the StereoPi V2 Kit which was acquired through an official
538 international distributor. After assembling the camera, it was further modified to
539 address the its heating by incorporating a heat sink and a small computer fan to
540 make it suitable for outdoor use.

541

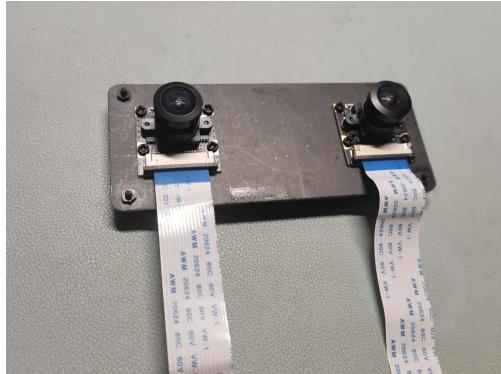


Figure 3.4: Dual RPi Camera Modules attached to the custom housing.

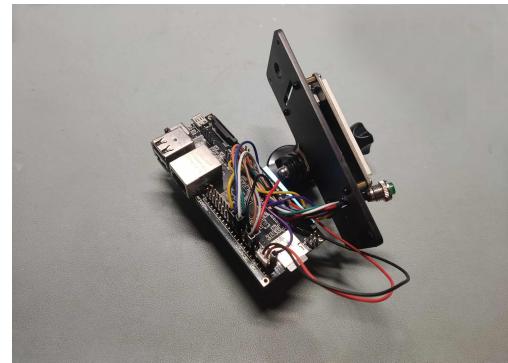


Figure 3.5: LCD Module connected to the StereoPi board.

542



Figure 3.6: The finished prototype.

543 3.1.2.5 Camera Calibration (Fisheye Distortion)

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

549

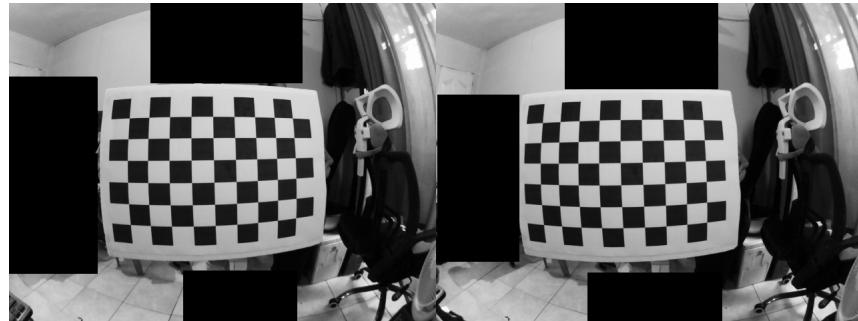


Figure 3.7: Calibration process with a checkerboard to correct fisheye lens distortion.

550

3.1.2.6 Camera Calibration (Disparity Map Fine-tuning)

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

558

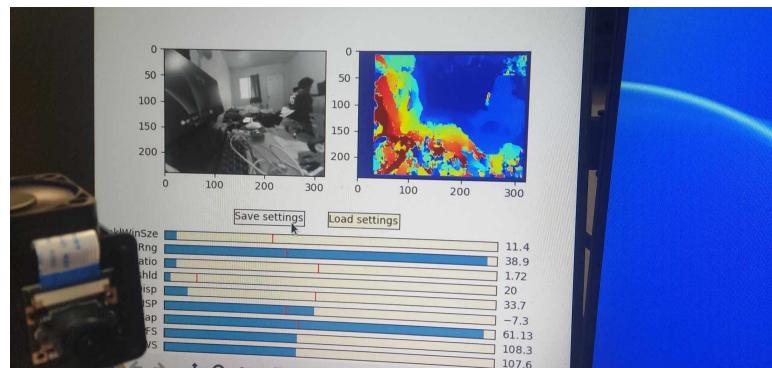


Figure 3.8: Parameter tuning process to achieve cleaner and more accurate disparity maps.

559

3.1.2.7 Initial Testing

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

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

565

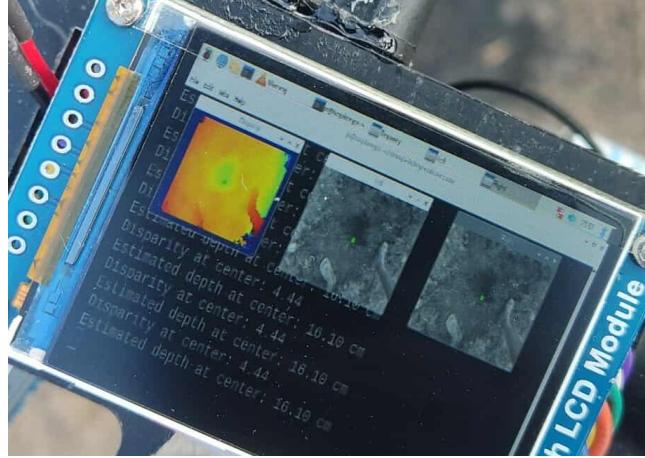


Figure 3.9: The system tested on a simulated pothole.

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

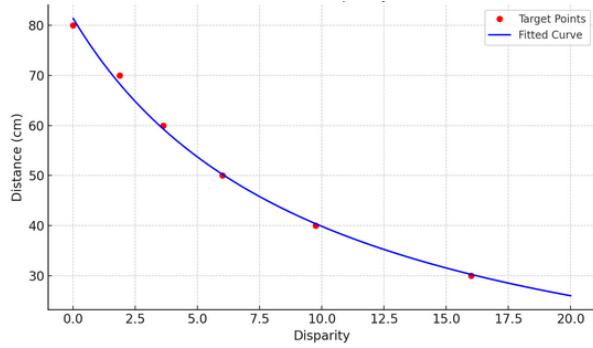


Figure 3.10: Inverse Model Fit to Disparity vs. Distance.

573 **3.1.2.8 Performance Metrics**

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

577 **3.1.2.9 Final Testing and Validation**

578 The testing process began with a detailed testing plan that includes both simu-
579 lated and real-world testing scenarios. Initially, the system is tested in controlled
580 environments to verify its capability to estimate pothole depth effectively. Fol-
581 lowing this, real-world testing was conducted using the StereoPi kit on previously
582 located potholes, specifically at the University of the Philippines Visayas Mia-
583 gao Campus. The procedure for estimating pothole depth closely followed the
584 validated depth measurement manual where the system captured depth measure-
585 ments at four designated points within each pothole, corresponding to the measure
586 points used in the manual measurement data. These four estimated depths were
587 then averaged to determine the final depth estimate for each pothole. The sys-
588 tem's performance was validated by comparing its predictions with ground-truth
589 data collected from manual inspections.

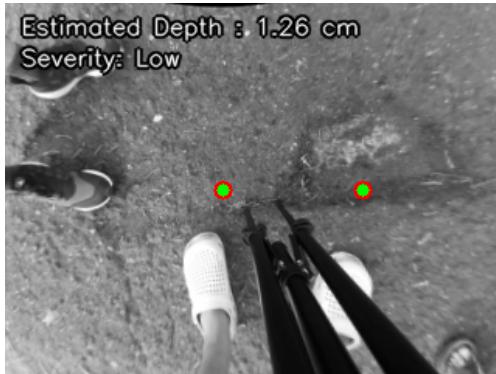


Figure 3.11: First measure point



Figure 3.12: Second measure point



Figure 3.13: Third measure point



Figure 3.14: Fourth measure point

590 3.1.2.10 Documentation

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

595 3.1.3 Challenges and Limitations

596 3.1.3.1 Camera Limitations

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

608 **Chapter 4**

609 **Results and Discussion**

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

617 **4.1 System Calibration and Model Refinement**

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

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

622 where:

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

626 However, preliminary observations revealed that the relationship between mea-
627 sured disparity and depth was shifted from the ideal. Their relationship is in-
628 herently nonlinear, specifically an inverse relationship (of the form $y=1/x$). As
629 disparity decreases, depth increases rapidly and nonlinearly. However, due to
630 real-world factors such as lens distortion, imperfect calibration, stereo matching
631 errors, and pixel quantization, the actual relationship between measured disparity
632 and true depth often deviates from the theoretical ideal (Scharstein & Szeliski,
633 2002).

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

637 An inverse function of the form:

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

638 where:

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

642 4.2 Testing Results

643 Following calibration, actual potholes located around the University of the Philip-
644 pines Visayas (UPV) campus were tested. The ground truth depths of the potholes
645 were measured manually and compared with the depths estimated by the Stereo-
646 oPi camera. Based on the results, the StereoPi camera was able to estimate the
647 depths fairly close to the actual measurements.

648 The smallest error occurred in one pothole, where the estimated depth was
649 only 0.02 cm off from the ground truth. The largest observed error was 3.45 cm.
650 Most of the time, the camera's estimated depths were within approximately 1 to
651 3 centimeters of the actual depths. This demonstrates reasonable accuracy given
652 the hardware setup and environmental conditions.

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

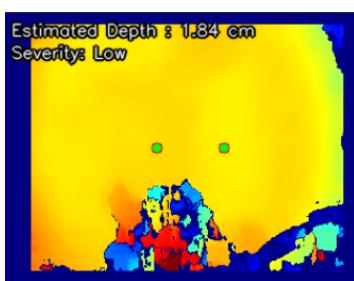


Figure 4.1: Disparity Map



Figure 4.2: Left Stereo Image

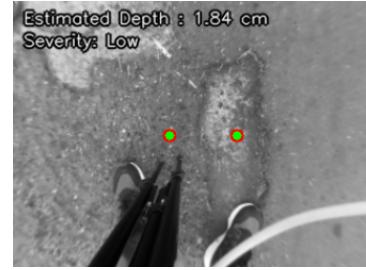


Figure 4.3: Right Stereo Image

655 The results show that the StereoPi system provides highly accurate estimates
 656 of pothole depth. The strong correlation ($R=0.978$) and high coefficient of de-
 657 termination ($R^2=0.956$) indicate that the actual depth significantly predicts the
 658 estimated values. The regression coefficient for actual depth was statistically sig-
 659 nificant ($p < 0.001$), suggesting that the relationship is not due to chance. While
 660 the RMSE of 0.844 cm and MAE of 0.945 cm suggest generally small errors, the
 661 presence of a maximum error of 3.45 cm indicates that there may be occasional
 662 outliers or limitations in specific scenarios. Nonetheless, the overall model per-
 663 formance demonstrates that the StereoPi system is suitable for practical pothole
 664 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

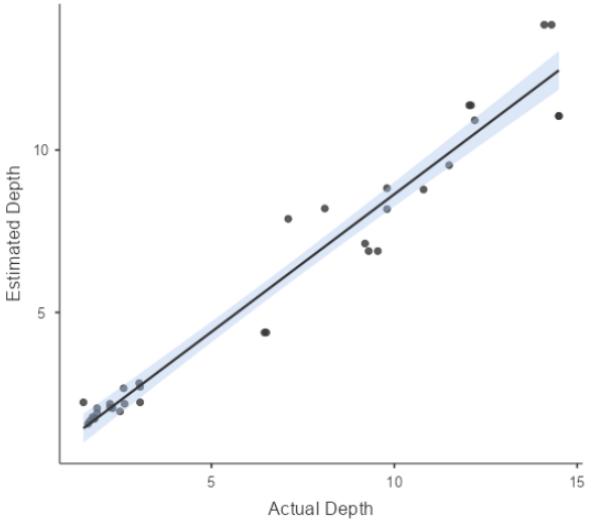


Figure 4.4: Linear Regression Fit Between Actual and Estimated Depth

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

670 4.3 Discussion

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

681 A strong positive correlation ($R = 0.978$) and coefficient of determination (R^2
 682 = 0.956) indicate that the actual pothole depths strongly predict the estimated
 683 values. The regression model's significant predictor ($p < 0.001$) further supports

684 the robustness of the depth estimation approach. This level of accuracy and model
685 performance highlights the suitability of the StereoPi system for practical field
686 applications in pothole monitoring and maintenance prioritization. This finding
687 is significant because earlier machine learning-based road detection studies such as
688 those by Bibi et al. (2021) focused mostly on classifying the existence of defects,
689 not measuring their severity.

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

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

708 **Chapter 5**

709 **Conclusion**

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

714 **5.1 Summary**

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

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

⁷³² linear behavior present in stereo vision depth measurements. It was observed that
⁷³³ using the standard stereo depth formula led to inaccuracies, particularly at greater
⁷³⁴ distances.

⁷³⁵ The calibrated system and fitted regression model were validated by comparing
⁷³⁶ the estimated depths with the manually measured depths. The findings showed
⁷³⁷ that the system was able to estimate pothole depths within approximately ± 3
⁷³⁸ cm of actual measurements, achieving a Mean Absolute Error (MAE) of 0.945 cm
⁷³⁹ and a Root Mean Square Error (RMSE) of 0.844 cm. A strong positive linear
⁷⁴⁰ relationship was observed between the estimated and actual depths ($R = 0.978$,
⁷⁴¹ $R^2 = 0.956$).

⁷⁴² 5.2 Conclusions

⁷⁴³ The researchers conclude the following based on the findings:

- ⁷⁴⁴ • The system effectively captures and analyzes depth information from stereo
⁷⁴⁵ images, providing a viable method for automated pothole severity assess-
⁷⁴⁶ ment.
- ⁷⁴⁷ • Incorporating depth measurements significantly improves pothole repair pri-
⁷⁴⁸ oritization compared to traditional visual-only inspections, allowing main-
⁷⁴⁹ tenance decisions to be based on objective, measurable data.
- ⁷⁵⁰ • The system achieved an acceptable regression model fit, with a strong posi-
⁷⁵¹ tive correlation ($R = 0.978$) and a coefficient of determination ($R^2 = 0.956$),
⁷⁵² confirming that the depth estimates closely align with the ground truth
⁷⁵³ measurements. The system obtained satisfactory error metrics, with a Mean
⁷⁵⁴ Absolute Error (MAE) of 0.945 cm and a Root Mean Square Error (RMSE)
⁷⁵⁵ of 0.844 cm, indicating reliable performance for both pothole detection and
⁷⁵⁶ depth estimation tasks.
- ⁷⁵⁷ • The proposed approach fills a critical gap in current road maintenance prac-
⁷⁵⁸ tices, especially within the Philippine context where depth-based severity
⁷⁵⁹ classification is not yet systematically implemented.

⁷⁶⁰ This special project has successfully developed a system that addresses the
⁷⁶¹ problem of pothole severity assessment using depth measurement. The research
⁷⁶² shows that stereo vision, even using accessible and affordable technology, holds
⁷⁶³ strong potential for future development in road maintenance automation. By

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

766 5.3 Recommendations for Practice

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

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

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

778 5.4 Suggestions for Further Research

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

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

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

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

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

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

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853 **Appendix A**

854 **Code Snippets**

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

```
855
856     def stereo_depth_map(rectified_pair,
857         ↪ save_path_prefix=None):
858         global disp_max, disp_min
859         dmLeft, dmRight = rectified_pair
860
861         disparity_raw = sbm.compute(dmLeft, dmRight).astype(
862             ↪ np.float32)
863         disparity_raw /= 16.0 # normalize disparity
864
865         local_max, local_min = disparity_raw.max(),
866             ↪ disparity_raw.min()
867
868         if dm_colors_autotune:
869             disp_max = max(local_max, disp_max)
870             disp_min = min(local_min, disp_min)
871             local_max, local_min = disp_max, disp_min
872
873             # Normalize for visualization
874             disparity_vis = (disparity_raw - local_min) * (255.0
875                 ↪ / (local_max - local_min))
876             disparity_vis = np.uint8(np.clip(disparity_vis, 0,
877                 ↪ 255))
878             disparity_color = cv2.applyColorMap(disparity_vis,
879                 ↪ cv2.COLORMAP_JET)
880
881             # Calculate depth
882             depth_map = calculate_depth(disparity_raw)
```

```

823
824     # Define two points
825     center_y, center_x = depth_map.shape[0] // 2,
826         ↪ depth_map.shape[1] // 2 - 20
827     second_y = center_y
828     second_x = center_x + offset_x
829
830
831     # Read depth and disparity values
832     center_depth_cm = (depth_map[center_y, center_x])
833     second_depth_cm = (depth_map[second_y, second_x])
834     estimated_depth_cm = abs(center_depth_cm -
835         ↪ second_depth_cm)
836
837
838     # Define severity based on estimated depth
839     if estimated_depth_cm < 2.5:
840         severity = "Low"
841     elif estimated_depth_cm >= 2.5 and
842         ↪ estimated_depth_cm < 5.0:
843         severity = "Medium"
844     elif estimated_depth_cm > 5.0:
845         severity = "High"
846     else:
847         severity = "Unknown"

```

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

```

907
908     for frame in camera.capture_continuous(capture,
909         ↪ format="bgra", use_video_port=True, resize=(
910             ↪ img_width, img_height)):
911         pair_img = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
912
913         imgLeft = pair_img[:, :img_width//2]
914         imgRight = pair_img[:, img_width//2:]
915
916         imgL = cv2.remap(imgLeft, leftMapX, leftMapY,
917             ↪ interpolation=cv2.INTER_LINEAR, borderMode=cv2
918             ↪ .BORDER_CONSTANT)
919         imgR = cv2.remap(imgRight, rightMapX, rightMapY,
920             ↪ interpolation=cv2.INTER_LINEAR, borderMode=cv2
921             ↪ .BORDER_CONSTANT)
922
923         if useStripe:
924             imgL = imgL[80:160,:]
925             imgR = imgR[80:160,:]

```

```

928
929     stereo_depth_map((imgL, imgR), save_path_prefix=None
930     ↪ )
931
932     button_held_time = 0
933     HOLD_THRESHOLD = 1.0 # seconds
934
935     if GPIO.input(BUTTON_PIN) == GPIO.LOW:
936         press_start = time.time()
937         while GPIO.input(BUTTON_PIN) == GPIO.LOW:
938             time.sleep(0.01)
939             button_held_time = time.time() - press_start
940
941             if button_held_time < HOLD_THRESHOLD:
942                 timestamp = datetime.now().strftime("%Y%m%d_%H%M%S")
943                 prefix = f"./captures/capture_{timestamp}"
944                 print(f"\n[!] Capturing snapshot at {timestamp}...")
945                 stereo_depth_map((imgL, imgR), save_path_prefix=
946                               ↪ prefix)
947                 time.sleep(0.5)
948             else:
949                 cycle_offset()
950                 time.sleep(0.5)

```

⁹⁵⁰ **Appendix B**

⁹⁵¹ **Resource Persons**

⁹⁵² **Prof. Jumar Cadondon**

⁹⁵³ Assistant Professor

⁹⁵⁴ Division of Physical Sciences and Mathematics

⁹⁵⁵ University of the Philippines Visayas

⁹⁵⁶ jgcadondon@up.edu.ph

⁹⁵⁷

⁹⁵⁸ **Engr. Jane Chua**

⁹⁵⁹ Engineer

⁹⁶⁰ Planning and Design

⁹⁶¹ DPWH Region 6

⁹⁶² chua.jane@dpwh.gov.ph

⁹⁶³

⁹⁶⁴ **Engr. Marilou Zamora**

⁹⁶⁵ Chief

⁹⁶⁶ Planning and Design

⁹⁶⁷ DPWH Region 6

⁹⁶⁸ zamora.marilou@dpwh.gov.ph

⁹⁶⁹

⁹⁷⁰ **Engr. Benjamin Javellana**

⁹⁷¹ Assistant Director

⁹⁷² Maintenance

⁹⁷³ DPWH Region 6

⁹⁷⁴ javellana.benjamin@dpwh.gov.ph

975

976 **Mr. Cris Beleber**
977 Engineering Assistant
978 Planning and Design
979 DPWH Region 6
980 beleber.cris@dpwh.gov.ph

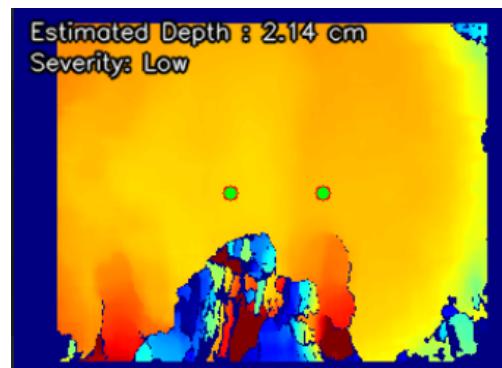
981

⁹⁸² **Appendix C**

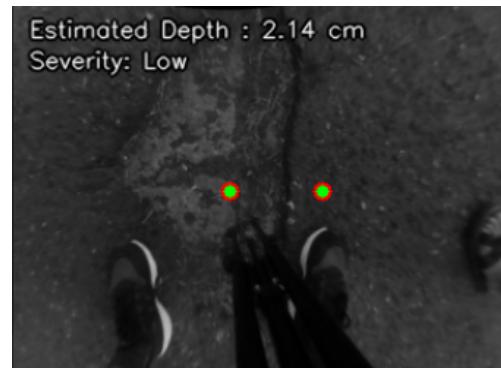
⁹⁸³ **Data Table and Pothole Images**

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

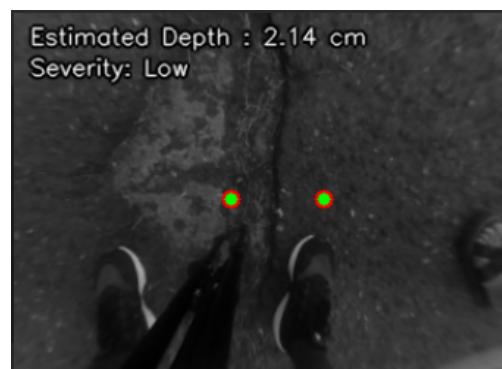
Table C.1: Actual vs. Estimated Depths with Residuals and Absolute Errors



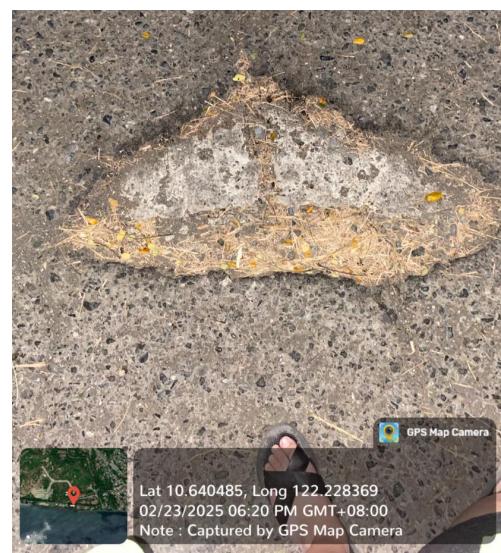
(a) Actual Pothole Disparity Map



(b) Actual Pothole Left Stereo Image

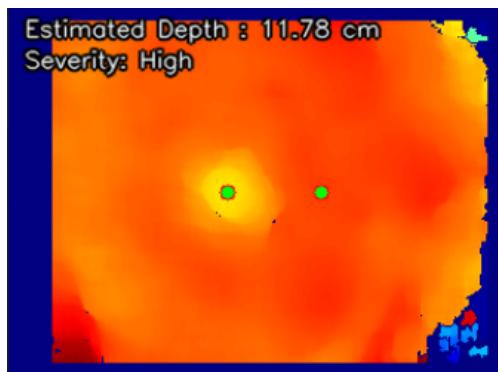


(c) Actual Pothole Right Stereo Image



(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

⁹⁸⁴ **Appendix D**

⁹⁸⁵ **Supplementary Documents**

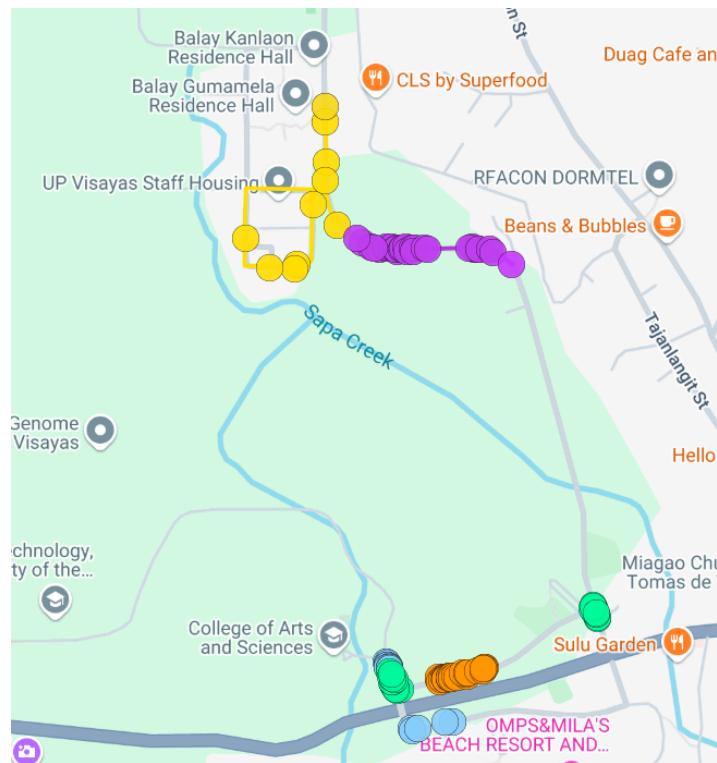


Figure D.1: Visualized pothole locations during the ground truth data collection within the UPV campus.

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


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

UP VISAYAS
OFFICE OF THE CHANCELLOR

N O A 25-0226

REF. NO. _____
DATE: FEB 07 2025
Good day!

We, Benz-Vianna, Belcher, Kristian, Lyle Sencil

We, Benz & Fritze Belebter, Kristian Lyle Schell,
one Special Problem study as a requirement for

our Special Problem study as a requirement for the University of the Philippines Visayas.

Our study focuses on detecting potholes and assessing their severity through depth measurement

estimation utilizing stereo vision and machine learning.. As part of our data collection process,

we need to conduct manual measurement of potholes within the campus roads which will serve

as ground truth data to validate our methodology. Our procedures have been validated by the Department of Public Works and Highways (DPWH), ensuring that our approach aligns with their standards. This will involve recording the depth and dimensions of potholes using standard measuring tools while ensuring minimal disruption to pedestrian and vehicular movement.

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

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

We sincerely hope for your kind consideration of our request.

Thank you very much.

Sincerely yours,

Sincerely yours,

Benz Vrijanne Beleber

Noted:

[Signature]
Frances Dimzon, Ph.D.
BSCS Special Problem Adviser

09614415782

on your kind consideration of our request
APPROVED / DISAPPROVED
H.
CLEMENT G. CAMPASANO
CHANCELLOR

~~Personality~~
Perserose Catalan

RECOMMENDING
APPROVAL/DISAPPROVAL:
formalized 2-6-2014
FARIBAL U. MAGSIT, Ph.D.
Vice Chancellor for Administration

Kristian Lyle Sencik the merchantman
Team Member am present / have
their data to my
admin

RECOMMENDING APPROVAL/DISAPPROVAL		DATE <u>31 JAN 2025</u>
 KENT CHRISTIAN A. CASTOR CHAIRPERSON, DPMU		
REF NO. PRF <u>2024-103</u>		
RECOMMENDING APPROVAL:		
 PEPITO R. FERNANDEZ JR. DEAN, COLLEGE OF ARTS & SCIENCES		

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

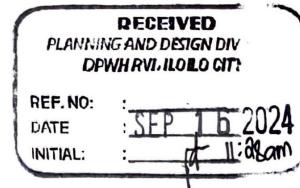
KRISTIAN LYLE SENCIL

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



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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



**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