

1 DEFECTRA: ROAD DEFECT SEVERITY ASSESSMENT
2 AND CLASSIFICATION

3 A Special Problem Proposal
4 Presented to
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Abstract

21 Road surveying is a crucial part of the maintenance processes of roads in the
22 Philippines that is carried out by the Department of Public Works and Highways.
23 However, the current process of road surveying is time consuming which delays
24 much needed maintenance operations. Existing studies involving automated pot-
25 hole detection lack integration of the pothole's depth in assessing its severity which
26 is essential for automating road surveying procedures. A system that incorporates
27 estimated depth information in assessing pothole severity is developed in order to
28 automate the manual process of depth measurement and severity assessment in
29 road surveying. For depth estimation, stereo vision is favorable in this context
30 as depth may be estimated through the disparity generated by a stereo pair. In
31 obtaining a stereo view of the potholes, the StereoPi V2 is utilized along with
32 some modifications that would make it eligible for outdoor use. To address cam-
33 era imperfections, a fitted inverse model was applied to improve the accuracy of
34 depth estimates. Linear regression analysis revealed a strong positive correlation
35 between estimated and actual depths, with the system measuring pothole depths
36 mostly within 2 cm of the true values.

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

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¹⁰³ **Chapter 1**

¹⁰⁴ **Introduction**

¹⁰⁵ **1.1 Overview**

¹⁰⁶ According to the National Road Length by Classification, Surface Type, and Con-
¹⁰⁷ dition of the Department of Public Works and Highways (DPWH), as of October
¹⁰⁸ 2022 approximately 98.97% of roads in the Philippines is paved which is either
¹⁰⁹ made of concrete or asphalt (DPWH, 2022). Since the DPWH is an institution
¹¹⁰ under the government, it is paramount to maintain such roads in order to avoid
¹¹¹ accidents and congested traffic situations especially in heavily urbanized areas
¹¹² where there are a lot of vehicles.

¹¹³ In an interview with the Road Board of DPWH Region 6 it was stated that
¹¹⁴ road condition assessments are mostly done manually with heavy reliance on en-
¹¹⁵ gineering judgment. In addition, manual assessment of roads is also time con-
¹¹⁶ suming which leaves maintenance operations to wait for lengthy assessments (J.
¹¹⁷ Chua, Personal Interview. 16 September 2024). In a study conducted by (Ramos,
¹¹⁸ Dacanay, & Bronuela-Ambrocio, 2023), it was found that the Philippines' current
¹¹⁹ method of manual pavement surveying is considered as a gap since it takes an
¹²⁰ average of 2-3 months to cover a 250 km road as opposed to a 1 day duration
¹²¹ in the Australian Road Research Board for the same road length. Ramos et al.
¹²² (2022) recommended that to significantly improve efficiency of surveying methods
¹²³ and data gathering processes, automated survey tools are to be employed. It was
¹²⁴ also added that use of such automated, surveying tools can also guarantee the
¹²⁵ safety of road surveyors (Ramos et al., 2023).

¹²⁶ If the process of assessment on the severity of road defects can be automated
¹²⁷ then the whole process of assessing the quality of roads can be hastened up which

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

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

144 1.2 Problem Statement

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

¹⁶⁴ 1.3 Research Objectives

¹⁶⁵ 1.3.1 General Objective

¹⁶⁶ This special problem aims to develop a system that accurately estimates the depth
¹⁶⁷ of potholes on road surfaces by using image analysis, depth measurement tech-
¹⁶⁸ nologies, and computer vision techniques. The system will focus specifically on
¹⁶⁹ measuring the depth of potholes to assess their severity, enabling faster and more
¹⁷⁰ accurate road maintenance decisions, and there are no current practices in the
¹⁷¹ Philippines involving depth information of potholes in assessing their severity. In
¹⁷² accordance with the Department of Public Works and Highways Region 6's man-
¹⁷³ ual for road maintenance, the study will classify potholes into different severity
¹⁷⁴ levels such as low, medium, and high, which will be primarily based on their
¹⁷⁵ depth. In order to measure the system's accuracy, linear regression in order to
¹⁷⁶ represent the difference between the depth calculated from the disparity and the
¹⁷⁷ actual depth of the pothole from ground truth data.

¹⁷⁸ 1.3.2 Specific Objectives

¹⁷⁹ Specifically, this special problem aims:

- ¹⁸⁰ 1. To collect high-quality stereo images of road surfaces that capture potholes
¹⁸¹ including their depth in favorable conditions
- ¹⁸² 2. To measure the accuracy of the system by comparing the depth measure-
¹⁸³ ments against ground truth data collected from actual road inspections and
¹⁸⁴ to utilize linear regression, root mean square error, and mean absolute error
¹⁸⁵ as a metric for evaluation.
- ¹⁸⁶ 3. To develop a prototype system that can detect and measure road potholes
¹⁸⁷ from image input, analyze their depth, and assess their severity.

¹⁸⁸ 1.4 Scope and Limitations of the Research

¹⁸⁹ This system focuses solely on detecting and assessing the severity of potholes
¹⁹⁰ through image analysis and depth measurement technologies. The scope includes

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

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

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

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

209 1.5 Significance of the Research

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

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

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

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

²²⁴ *Future Researchers.* The special problem may serve as a baseline and guide of
²²⁵ researchers with the aim to pursue special problems similar or related to this.

²²⁶ **Chapter 2**

²²⁷ **Review of Related Literature**

²²⁸ **2.1 Frameworks**

²²⁹ This section of the chapter presents related literature that is considered essential
²³⁰ for the development of this special problem.

²³¹ **2.1.1 Depth Estimation**

²³² Depth estimation as defined by Sanz, Mezcua, and Pena (2012) as a set of processes
²³³ that aims to extract a representation of a certain scene's spatial composition.
²³⁴ Stereo vision is stated to be among the depth estimation strategies (Sanz et al.,
²³⁵ 2012).

²³⁶ **2.1.2 Image and Video Processing**

²³⁷ Kumar (2024) defines image processing as a process of turning an image into its
²³⁸ digital form and extracting data from it through certain functions and operations.
²³⁹ Usual processes are considered to treat images as 2D signals wherein different
²⁴⁰ processing methods utilize these signals. Like image processing, Resources (2020)
²⁴¹ defines video processing as being able to extract information and data from video
²⁴² footage through signal processing methods. However, in video processing due to
²⁴³ the diversity of video formats, compression and decompression methods are often
²⁴⁴ expected to be performed on videos before processing methods to either increase
²⁴⁵ or decrease bitrate.

²⁴⁶ 2.1.3 Stereo Vision

²⁴⁷ MathWorks (n.d.) defines stereo vision as a process of utilizing multiple 2D per-
²⁴⁸ spectives in order to extract information in 3D. In addition, most uses of stereo
²⁴⁹ vision involve estimating an objects distance from an observer or camera. The 3D
²⁵⁰ information is stated to be extracted with stereo pairs or pair of images through es-
²⁵¹ timation of relative depth of points in a scene which are then represented through
²⁵² a stereo map that is made through the matching of the pair's corresponding points.

²⁵³ 2.2 Related Studies

²⁵⁴ This section of the chapter presents related studies conducted by other researchers
²⁵⁵ wherein the methodology and technologies used may serve as basis in the devel-
²⁵⁶ opment of this special problem.

²⁵⁷ 2.2.1 Deep Learning Studies

²⁵⁸ 2.2.1.1 Automated Detection and Classification of Road Anomalies in ²⁵⁹ VANET Using Deep Learning

²⁶⁰ In the study of Bibi et al. (2021) it was noted that identification of active road
²⁶¹ defects are critical in maintaining smooth and safe flow of traffic. Detection and
²⁶² subsequent repair of such defects in roads are crucial in keeping vehicles using
²⁶³ such roads away from mechanical failures. The study also emphasized the growth
²⁶⁴ in use of autonomous vehicles in research data gathering which is what the re-
²⁶⁵ searchers utilized in data gathering procedures. With the presence of autonomous
²⁶⁶ vehicles, this allowed the researchers to use a combination of sensors and deep
²⁶⁷ neural networks in deploying artificial intelligence. The study aimed to allow au-
²⁶⁸ tonomous vehicles to avoid critical road defects that can possibly lead to dangerous
²⁶⁹ situations. Researchers used Resnet-18 and VGG-11 in automatic detection and
²⁷⁰ classification of road defects. Researchers concluded that the trained model was
²⁷¹ able to perform better than other techniques for road defect detection (Bibi et
²⁷² al., 2021). The study is able to provide the effectiveness of using deep learning
²⁷³ models in training artificial intelligence for road defect detection and classification.
²⁷⁴ However, the study lacks findings regarding the severity of detected defects and in-
²⁷⁵ corporation of pothole depth in their model which are both crucial in automating
²⁷⁶ manual procedures of road surveying in the Philippines.

277 2.2.1.2 Road Anomaly Detection through Deep Learning Approaches

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

**290 2.2.1.3 Assessing Severity of Road Cracks Using Deep Learning-Based
291 Segmentation and Detection**

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

**305 2.2.1.4 Roadway pavement anomaly classification utilizing smartphones
306 and artificial intelligence**

307 The study of Kyriakou, Christodoulou, and Dimitriou (2016) presented what is
308 considered as a low-cost technology which was the use of Artificial Neural Net-
309 works in training a model for road anomaly detection from data gathered by
310 smartphone sensors. The researchers were able to collect case study data us-

³¹¹ ing two-dimensional indicators of the smartphone's roll and pitch values. In the
³¹² study's discussion, the data collected displayed some complexity due to acceleration
³¹³ and vehicle speed which lead to detected anomalies being not as conclusive as
³¹⁴ planned. The researchers also added that the plots are unable to show parameters
³¹⁵ that could verify the data's correctness and accuracy. Despite the setbacks, the
³¹⁶ researchers still fed the data into the Artificial Neural Network that was expected
³¹⁷ to produce two outputs which were "no defect" and "defect." The method still
³¹⁸ yielded above 90% accuracy but due to the limited number of possible outcomes
³¹⁹ in the data processing the researchers still needed to test the methodology with
³²⁰ larger data sets and roads with higher volumes of anomalies.

³²¹ **2.2.2 Machine Learning Studies**

³²² **2.2.2.1 Smartphones as Sensors for Road Surface Monitoring**

³²³ In their study, Sattar, Li, and Chapman (2018) noted the rise of sensing capabilities of smartphones which they utilized in monitoring road surface to detect and
³²⁴ identify anomalies. The researchers considered different approaches in detecting
³²⁵ road surface anomalies using smartphone sensors. One of which are threshold-based
³²⁶ approaches which was determined to be quite difficult due to several factors
³²⁷ that are affecting the process of determining the interval length of a window
³²⁸ function in spectral analysis (Sattar et al., 2018). The researchers also utilized
³²⁹ a machine learning approach adapted from another study. It was stated that k-means
³³⁰ was used in classifying sensor data and in training the SVM algorithm. Due
³³¹ to the requirement of training a supervised algorithm using a labeled sample data
³³² was required before classifying data from sensors, the approach was considered to
³³³ be impractical for real-time situations (Sattar et al., 2018). In addition, Sattar
³³⁴ et al. (2018) also noted various challenges when utilizing smartphones as sensors
³³⁵ for data gathering such as sensors being dependent on the device's placement and
³³⁶ orientation, smoothness of captured data, and the speed of the vehicle it is being
³³⁷ mounted on. Lastly, it was also concluded that the accuracy and performance of
³³⁸ using smartphone sensors is challenging to compare due to the limited data sets
³³⁹ and reported algorithms.

³⁴¹ **2.2.2.2 Road Surface Quality Monitoring Using Machine Learning Al-** ³⁴² **gorithms**

³⁴³ The study of Singh, Bansal, Kamal, and Kumar (2021) aimed to utilize machine
³⁴⁴ learning algorithms in classifying road defects as well as predict their locations.

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

359 **2.2.3 Computer Vision Studies**

360 **2.2.3.1 Stereo Vision Based Pothole Detection System for Improved 361 Ride Quality**

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

³⁷⁵ 2.3 Chapter Summary

³⁷⁶ 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

³⁷⁹ **Chapter 3**

³⁸⁰ **Methodology**

³⁸¹ This chapter outlines the systematic approach that were taken to address the
³⁸² problem of pothole depth estimation using StereoPi V2. The methodology is
³⁸³ divided into key phases: data collection, algorithm selection, design, testing and
³⁸⁴ experimentation, and challenges and limitations. Each phase will play a crucial
³⁸⁵ role in accurately classifying and assessing road defects. Each phase is essential
³⁸⁶ for accurately estimating the depth of potholes using StereoPi V2.

³⁸⁷ **3.1 Research Activities**

³⁸⁸ **3.1.1 Data Collection**

³⁸⁹ The researchers conducted initial inquiries to understand the problem domain and
³⁹⁰ existing road maintenance practices. This phase included consulting the engineers
³⁹¹ under the Road Maintenance Department of the government agency Department
³⁹² of Public Works and Highways (DPWH). An interview with Engr. Jane Chua pro-
³⁹³ vided a comprehensive overview of the DPWH's road maintenance manual, which
³⁹⁴ was crucial in aligning this project with existing standards. This collaboration
³⁹⁵ with DPWH provided insights into road pothole classification standards, ensuring
³⁹⁶ that the collected data will align with industry standards. The DPWH manual
³⁹⁷ primarily focuses on the volume of detected potholes within a road segment as
³⁹⁸ a measure of severity. However, since depth is not explicitly measured in their
³⁹⁹ current procedures, the study will supplement this by referencing international
⁴⁰⁰ standards such as the Long-Term Pavement Performance (LTPP) classification
⁴⁰¹ used in the United States. The LTPP categorizes potholes based on depth thresh-

402 olds, which will be integrated with DPWH's volume-based assessment to provide
403 a more comprehensive severity classification framework. The data collection in-
404 volved capturing around 130 images of potholes from various locations within the
405 UP Visayas Campus. Ground truth data of pothole depth were collected by the
406 researchers by measuring the depth of different points in an individual pothole
407 and then solving for its average depth. The aforementioned process was validated
408 by Engr. Benjamin Javellana, Assistant Director of the DPWH Regional Office 6
409 Maintenance Division. In order to individually locate or determine each pothole
410 where the ground truth data is collected, images taken were labeled with their
411 corresponding coordinates, street names, and nearby landmarks.

412 **3.1.1.1 Data Collection (Ground Truth Data)**

413 The researchers collected depth information from 130 potholes around the Uni-
414 versity of the Philippines Visayas Miagao Campus. During data collection, the
415 researchers are equipped with safety vests and an early warning device to give cau-
416 tion to incoming vehicles. To measure the depth of each pothole, the researchers
417 recorded four depth points within the pothole and calculated their average.

418 **3.1.2 Algorithm Selection**

419 Potential solutions, algorithms, and system architectures were discussed by the
420 researchers and the special problem adviser in this phase. These sessions, con-
421 ducted in class and virtually via Zoom, helped narrow down the overview of the
422 system, leading to the selection of the main architecture Epipolar Spatio-Temporal
423 Networks (ESTN) for depth estimation.

424 **3.1.3 Design, Testing, and Experimentation**

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

427 **3.1.3.1 Materials and Equipment**

428

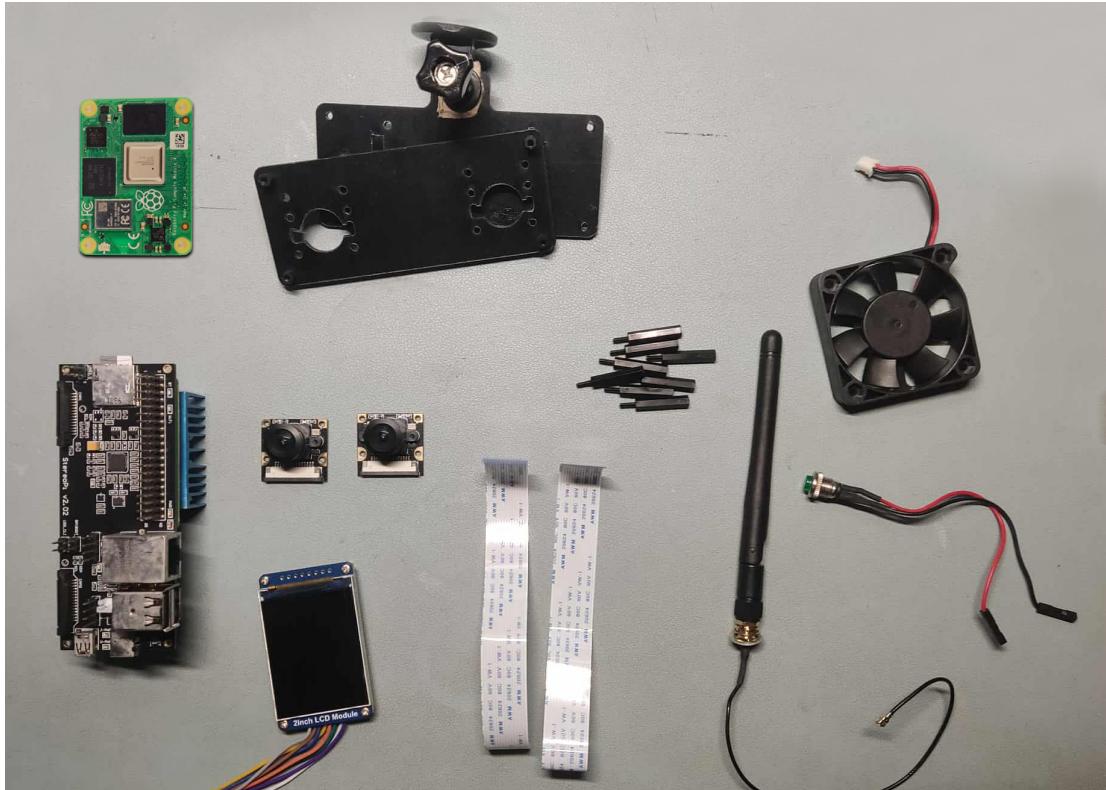


Figure 3.1: Components used in the prototype development.

429 The prototype system was constructed using the following materials and com-
430 ponents:

- 431 • StereoPi V2 Board
432 • Raspberry Pi Compute Module 4 (CM4)
433 • Dual RaspberryPi Camera Modules with Fisheye Lens
434 • 3D Printed Custom Housing
435 • 2-inch LCD Module
436 • Micro SD Card
437 • Antenna
438 • Momentary Push Button

439 **3.1.3.2 Prototype Building**

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

444

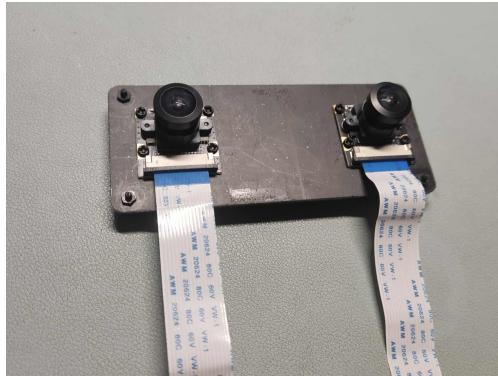


Figure 3.2: Dual RPi Camera Modules attached to the custom housing.

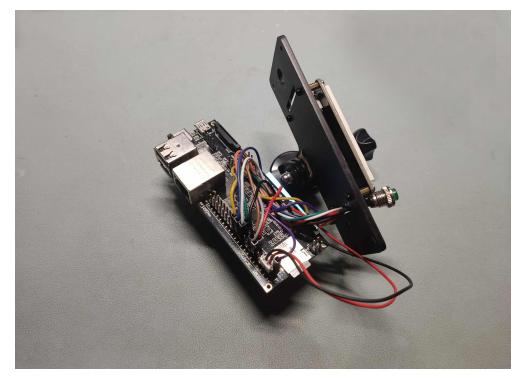


Figure 3.3: LCD Module connected to the StereoPi board.

445

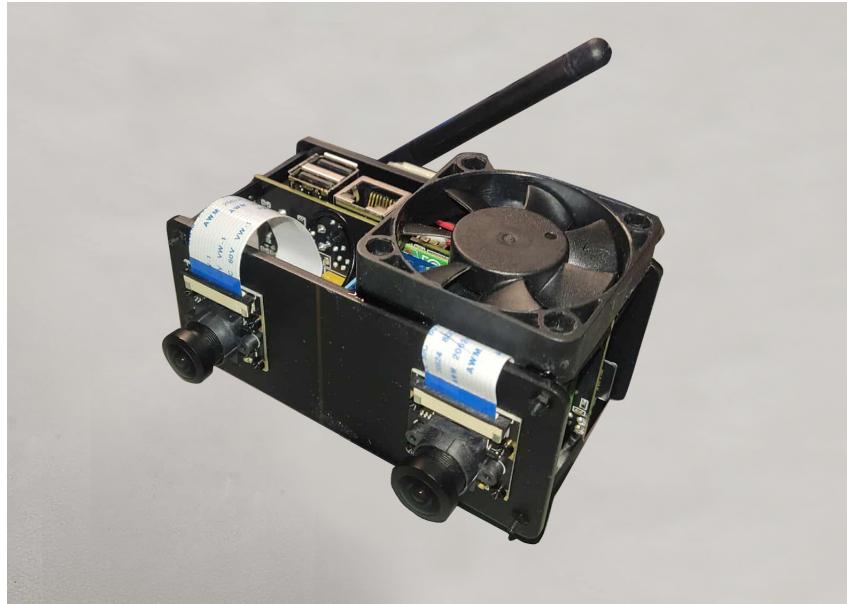


Figure 3.4: The finished prototype.

446 **3.1.3.3 Camera Calibration (Fisheye Distortion)**

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

452

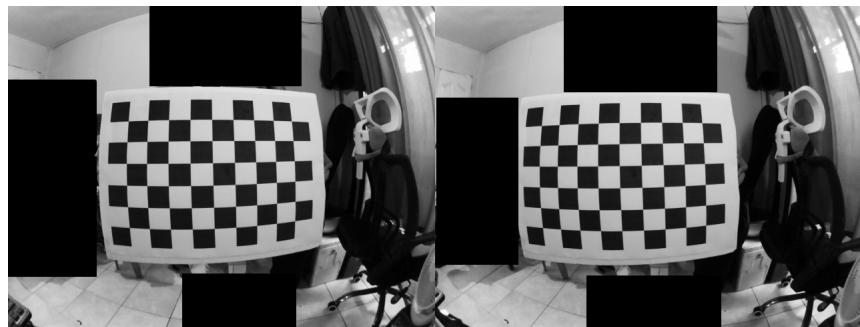


Figure 3.5: Calibration process with a checkerboard to correct fisheye lens distortion.

453 **3.1.3.4 Camera Calibration (Disparity Map Fine-tuning)**

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

461

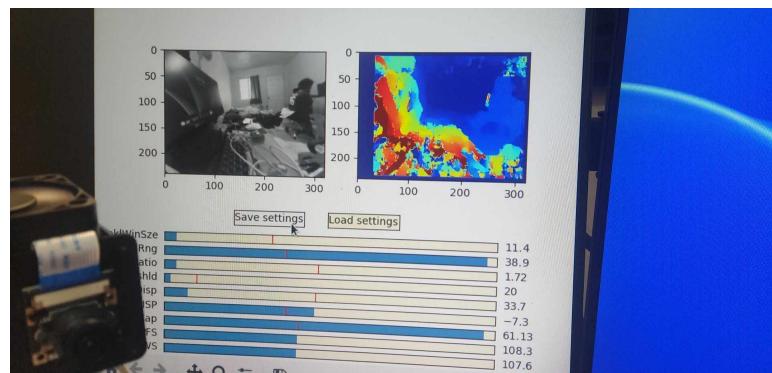


Figure 3.6: Parameter tuning process to achieve cleaner and more accurate disparity maps.

462 **3.1.3.5 Initial Testing**

463 Initial testing was conducted to verify the functionality and basic accuracy of the
464 stereoscopic camera system in a controlled environment. Artificial potholes with
465 known depths were created to simulate varying real-world scenarios. The system
466 captured disparity maps, and estimated depths were computed using the standard
467 stereo camera depth formula.

468

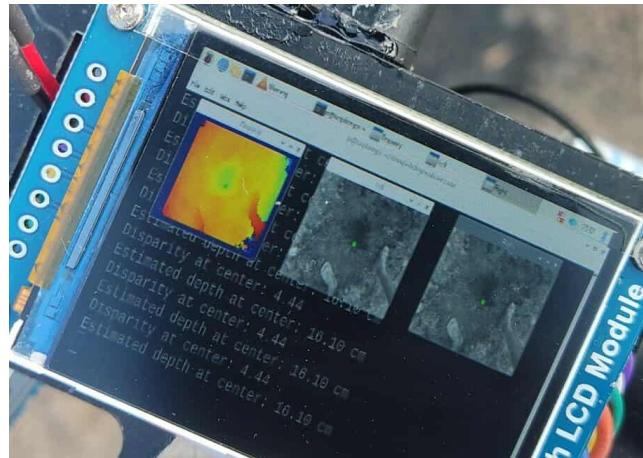


Figure 3.7: The system tested on a simulated pothole.

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

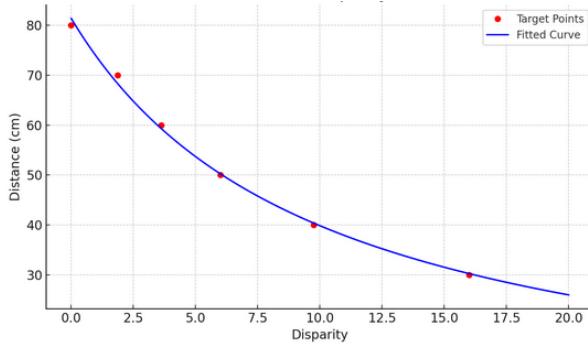


Figure 3.8: Inverse Model Fit to Disparity vs. Distance.

⁴⁷⁶ 3.1.3.6 Performance Metrics

⁴⁷⁷ The accuracy of the pothole depth estimated by StereoPi V2 was analyzed using
⁴⁷⁸ Linear Regression in order to model the difference between the disparity and
⁴⁷⁹ distance. The lower the disparity indicates that the pothole is deeper.

⁴⁸⁰ 3.1.3.7 Final Testing and Validation

⁴⁸¹ The testing process began with a detailed testing plan that includes both simu-
⁴⁸² lated and real-world testing scenarios. Initially, the system is tested in controlled
⁴⁸³ environments to ensure it can estimate pothole depth effectively. Following this,
⁴⁸⁴ real-world testing was conducted using the StereoPi kit on previously located
⁴⁸⁵ potholes, specifically at the University of the Philippines Visayas Miagao Cam-
⁴⁸⁶ pus. The system's performance was validated by comparing its predictions with
⁴⁸⁷ ground-truth data collected from manual inspections.

⁴⁸⁸ 3.1.3.8 Documentation

⁴⁸⁹ Throughout the research activities, thorough documentation was maintained.
⁴⁹⁰ This documentation captured all methods, results, challenges, and adjustments
⁴⁹¹ made during the experimentation phases. It ensured the reproducibility of the
⁴⁹² work and provided transparency for future research endeavors.

493 **3.1.4 Challenges and Limitations**

494 **3.1.4.1 Camera Limitations**

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

502 **3.2 Calendar of Activities**

503 Table 1 shows a Gantt chart of the activities. Each bullet represents approximately
504 one week's worth of activity.

Table 3.1: Timetable of Activities for 2024

Activities (2024)	Aug	Sept	Oct	Nov	Dec
Pre-proposal Preparation	W4				
Literature Review	W3	W1			
Data Collection	W2	W2			
Algorithm Selection		W2			
System Design		W1	W2	W2	
Preliminary Testing				W2	W1
Documentation and SP Writing	W4	W4	W4	W4	W2

Table 3.2: Timetable of Activities for 2025

Activities (2025)	Jan	Feb	Mar	Apr	May	Jun
Data Collection	W4					
System Design	W3	W2	W2			
Model testing	W3	W4	W4			
Results Analysis			W2	W4		
Conclusion Formulation				W2	W3	
Documentation and SP Writing	W4	W4	W4	W4	W4	W2

505 **Chapter 4**

506 **Preliminary Results/System
507 Prototype**

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

515 **4.1 System Calibration and Model Refinement**

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

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

520 where:

- 521 • f is the focal length in pixels,
522 • B is the baseline distance between the two cameras,

- 523 • d is the disparity.

524 However, preliminary observations revealed that the relationship between measured disparity and depth was shifted from the ideal. Their relationship is inherently nonlinear, specifically an inverse relationship (of the form $y=1/x$). As disparity decreases, depth increases rapidly and nonlinearly. However, due to real-world factors such as lens distortion, imperfect calibration, stereo matching errors, and pixel quantization, the actual relationship between measured disparity and true depth often deviates from the theoretical ideal (Scharstein & Szeliski, 531 2002).

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

535 An inverse function of the form:

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

536 where:

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

540 4.2 Model Refinement Using Regression

541 The regression analysis produced the following model parameters:

- 542 • $a = \dots$
543 • $b = \dots$

544 The model achieved the following performance on the test data:

Metric	Value
Mean Absolute Error (MAE)	X cm
Root Mean Square Error (RMSE)	X cm

Table 4.1: Performance Metrics for the Regression Model

545 The relatively low MAE and RMSE indicate that the fitted model signifi-
 546 cantly improved the accuracy of depth estimation compared to the original stereo
 547 formula.

548 4.3 Error Analysis

549 Despite the improvements, minor estimation errors remained. These errors were
 550 primarily attributed to:

- 551 • Low-light imaging conditions affecting disparity computation,
- 552 • Shallow potholes with depths less than 1 cm, where disparity resolution
 553 becomes a limiting factor,
- 554 • Perspective distortion when the stereo camera was not parallel to the ground
 555 plane.

556 4.4 Testing Results

557 Following calibration, actual potholes located around the University of the Philip-
 558 pines Visayas (UPV) campus were tested. The ground truth depths of the potholes
 559 were measured manually and compared with the depths estimated by the camera.
 560 Based on the results, the StereoPi camera was able to estimate the depths fairly
 561 close to the ground truth values. The smallest difference was seen in Pothole 5,
 562 where the estimated depth was only 0.24 cm away from the ground truth. The
 563 largest difference was found in Pothole 1, where the error was 3.45 cm. For the
 564 other potholes, the differences were 0.67 cm for Pothole 2, 2.07 cm for Pothole
 565 3, and 2.66 cm for Pothole 4. Most of the time, the camera's estimated depths
 566 were only off by about one to three centimeters. Table 4.2 shows the comparison
 567 between the manually measured ground truth depths and the depths estimated
 568 by the StereoPi camera for each simulated pothole.

Table 4.2: Ground Truth and StereoPi Depth Measurements

Pothole	Ground Truth 1 (cm)	Ground Truth 2 (cm)	Ground Truth Avg (cm)	Est Depth 1(cm)	Est Depth 2 (cm)	Est Depth Avg(cm)	Diff(cm)
1	14.6	14.4	14.5	11.16	10.94	11.05	3.45
2	12.0	12.1	12.05	12.36	10.4	11.38	0.67
3	6.4	6.5	6.45	4.76	4.0	4.38	2.07
4	9.8	9.3	9.55	6.16	7.62	6.89	2.66
5	13.9	14.3	14.1	13.04	14.68	13.86	0.24

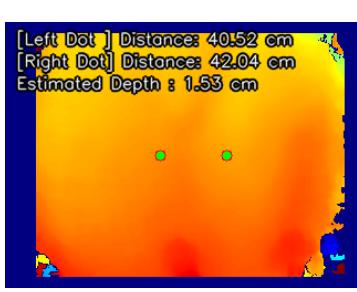


Figure 4.1: Disparity Map

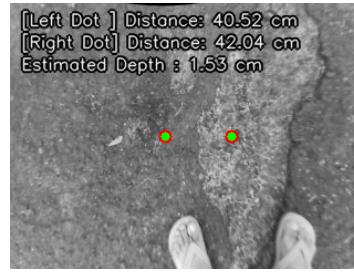


Figure 4.2: Left Stereo Image



Figure 4.3: Right Stereo Image

569 4.5 Discussion

570 The Linear Regression test on the collected data revealed a strong positive linear
 571 relationship between the estimated and ground truth depths ($R = 0.937$). The co-
 572 efficient of determination ($R^2 = 0.878$) also indicates that 87.8% of the differences
 573 in the estimated depth are correctly predicted based on the ground truth data.
 574 After calculating for the Mean Absolute Error, it was also found that estimated
 575 pothole depths differ from the actual ground truth data by around 1.82 cm. In
 576 addition, the Root Mean Square Error also revealed that the typical error size is
 577 at 1.19 cm.

R	R ²	Root Mean Square Error	Mean Absolute Error
0.937	0.878	1.19	1.82

Table 4.3: Linear Regression Model for Pothole Depth Estimation

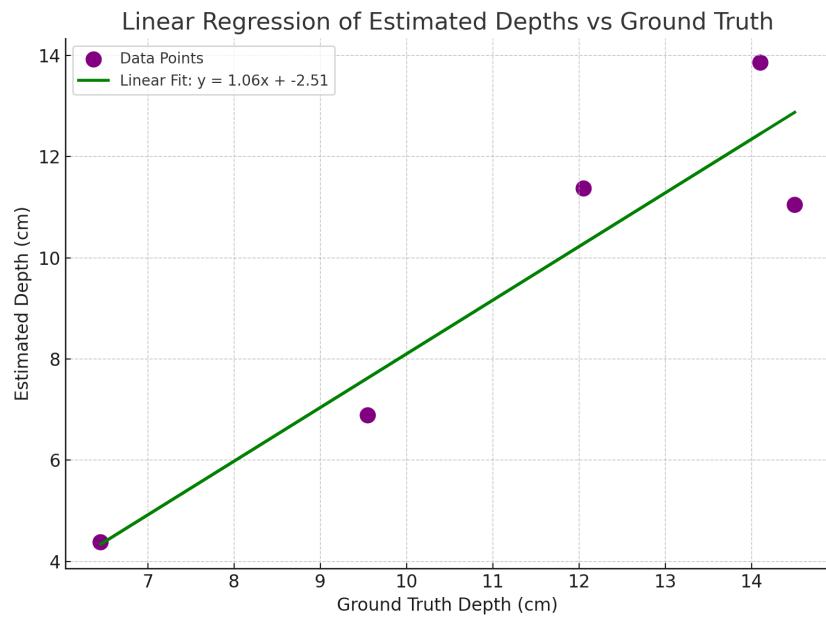


Figure 4.4: Inverse Model Fit to Disparity vs. Distance.

⁵⁷⁸ Chapter 5

⁵⁷⁹ **Summary, Conclusions, 580 Discussion, and 581 Recommendations**

⁵⁸² This chapter provides conclusions based on the research findings from data collected on the development of a pothole depth estimation system using stereo vision technology. It also presents a discussion and recommendations for future research.
⁵⁸³ This chapter reviews the purpose of the study, research questions, related literature, methodology, and findings. It then presents the conclusions, a discussion of the results, recommendations for practice, suggestions for further research, and ⁵⁸⁴ ⁵⁸⁵ ⁵⁸⁶ ⁵⁸⁷ ⁵⁸⁸ the final conclusion of the study.

⁵⁸⁹ **5.1 Summary**

⁵⁹⁰ This special project addressed the critical issue of road maintenance by developing ⁵⁹¹ a system capable of estimating the depth of potholes to help prioritize repairs. ⁵⁹² The purpose of the project was to create an automated method that not only ⁵⁹³ detects potholes but also assesses their severity based on depth, responding to ⁵⁹⁴ the current manual and slow road inspection practices. The researchers aimed to ⁵⁹⁵ collect high-quality images of potholes under varying conditions, to validate the ⁵⁹⁶ system's depth estimation accuracy using ground truth measurements and linear ⁵⁹⁷ regression analysis, and to build a working prototype using stereo vision that can ⁵⁹⁸ detect, measure, and assess potholes.

⁵⁹⁹ To achieve these objectives, a hardware prototype was built using the StereoPi

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

610 The calibrated system and fitted regression model were validated by comparing
611 the estimated depths with the manually measured depths. The findings showed
612 that the system was able to estimate pothole depths within approximately ± 2
613 cm of actual measurements, achieving a Mean Absolute Error (MAE) of 1.82 cm
614 and a Root Mean Square Error (RMSE) of 1.19 cm. A strong positive linear
615 relationship was observed between the estimated and actual depths ($R = 0.937$,
616 $R^2 = 0.878$).

617 5.2 Conclusions

618 The researchers conclude the following based on the findings:

- 619 • The system effectively captures and analyzes depth information from stereo
620 images, providing a viable method for automated pothole severity assess-
621 ment.
- 622 • Incorporating depth measurements significantly improves pothole repair pri-
623 oritization compared to traditional visual-only inspections, allowing main-
624 tenance decisions to be based on objective, measurable data.
- 625 • The system achieved an acceptable regression model fit, with a strong posi-
626 tive correlation ($R = 0.937$) and a coefficient of determination ($R^2 = 0.878$),
627 confirming that the depth estimates closely align with the ground truth
628 measurements. The system obtained satisfactory error metrics, with a Mean
629 Absolute Error (MAE) of 1.82 cm and a Root Mean Square Error (RMSE)
630 of 1.19 cm, indicating reliable performance for both pothole detection and
631 depth estimation tasks.
- 632 • The proposed approach fills a critical gap in current road maintenance prac-
633 tices, especially within the Philippine context where depth-based severity

634 classification is not yet systematically implemented.

635 5.3 Discussion

636 The study found that stereo vision works effectively in helping estimate the depth
637 of road potholes. The system built using the StereoPi V2 camera was able to
638 measure pothole depths with results mostly within ± 2 cm of the actual ground
639 truth values. This matches the general observation in earlier studies (e.g., Ra-
640 maiah and Kundu, 2021), which showed that stereo vision can provide useful 3D
641 information for road obstacle detection. However, this study advances previous
642 work by focusing not just on detection, but on depth-based severity classification,
643 which was largely missing in earlier research.

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

652 It was also observed that incorporating depth measurements into pothole de-
653 tection greatly improves how potholes are prioritized for repairs compared to
654 traditional visual-only inspections. This insight fills a notable gap in current
655 practices, especially in the Philippine context where depth measurements are not
656 typically part of road surveys (Ramos et al., 2023). Depth-based severity clas-
657 sification enables road maintenance teams to make more informed and objective
658 decisions on which potholes to prioritize for immediate repair, helping to optimize
659 resource allocation and improve public road safety.

660 The system achieved a strong positive regression model fit ($R = 0.937$, R^2
661 = 0.878) and satisfactory error measures (MAE = 1.82 cm, RMSE = 1.19 cm).
662 These results confirm that stereo vision, when combined with simple regression
663 modeling, can reliably estimate pothole depths. This finding is significant because
664 earlier machine learning-based road detection studies (such as Bibi et al., 2021)
665 focused mostly on classifying the existence of defects, not measuring their severity.

666 However, the study also highlighted limitations affecting system performance,
667 including sensitivity to camera calibration quality, lighting conditions, road sur-
668 face texture, and the camera's vertical positioning during image capture. Outdoor

669 testing revealed that low lighting and shallow potholes made it difficult to generate
670 clean disparity maps, sometimes causing minor estimation errors. These observations are
671 consistent with Sattar et al. (2018), who reported that mobile road sensing systems often
672 struggle in low-light or highly variable surface conditions. Understanding these challenges is
673 important because it points to practical improvements, such as using better cameras, adding lighting support, or applying
674 more robust image enhancement methods in future versions of the system.
675

676 5.4 Recommendations for Practice

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

679 *Use stereo vision systems for road surveys.* Road maintenance agencies should
680 consider using calibrated stereo vision systems to estimate pothole depth, allowing
681 for better prioritization of road repairs compared to visual inspections alone.

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

685 5.5 Suggestions for further research

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

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

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

699 5.6 Conclusion

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

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⁷⁵⁰ **Appendix A**

⁷⁵¹ **Appendix Title**

⁷⁵² **Appendix B**

⁷⁵³ **Resource Persons**

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