

1 DEFECTRA: ROAD DEFECT SEVERITY ASSESSMENT
2 AND CLASSIFICATION

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

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

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Abstract

21 From 150 to 200 words of short, direct and complete sentences, the abstract should
22 be informative enough to serve as a substitute for reading the entire SP document
23 itself. It states the rationale and the objectives of the research. In the final Special
24 Problem document (i.e., the document you'll submit for your final defense), the
25 abstract should also contain a description of your research results, findings, and
26 contribution(s).

27 Suggested keywords based on ACM Computing Classification system can be
28 found at https://dl.acm.org/ccs/ccs_flat.cfm

29 **Keywords:** Keyword 1, keyword 2, keyword 3, keyword 4, etc.

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⁸⁶ **Chapter 1**

⁸⁷ **Introduction**

⁸⁸ **1.1 Overview**

⁸⁹ According to the National Road Length by Classification, Surface Type, and Con-
⁹⁰ dition of the Department of Public Works and Highways (DPWH), as of October
⁹¹ 2022 approximately 98.97% of roads in the Philippines is paved which is either
⁹² made of concrete or asphalt (DPWH, 2022). Since the DPWH is an institution
⁹³ under the government, it is paramount to maintain such roads in order to avoid
⁹⁴ accidents and congested traffic situations especially in heavily urbanized areas
⁹⁵ where there are a lot of vehicles.

⁹⁶ In an interview with the Road Board of DPWH Region 6 it was stated that
⁹⁷ road condition assessments are mostly done manually with heavy reliance on en-
⁹⁸ gineering judgment. In addition, manual assessment of roads is also time con-
⁹⁹ suming which leaves maintenance operations to wait for lengthy assessments (J.
¹⁰⁰ Chua, Personal Interview. 16 September 2024). In a study conducted by (Ramos,
¹⁰¹ Dacanay, & Bronuela-Ambrocio, 2023), it was found that the Philippines' current
¹⁰² method of manual pavement surveying is considered as a gap since it takes an
¹⁰³ average of 2-3 months to cover a 250 km road as opposed to a 1 day duration
¹⁰⁴ in the Australian Road Research Board for the same road length. Ramos et al.
¹⁰⁵ (2022) recommended that to significantly improve efficiency of surveying methods
¹⁰⁶ and data gathering processes, automated survey tools are to be employed. It was
¹⁰⁷ also added that use of such automated, surveying tools can also guarantee the
¹⁰⁸ safety of road surveyors (Ramos et al., 2023).

¹⁰⁹ If the process of assessment on the severity of road defects can be automated
¹¹⁰ then the whole process of assessing the quality of roads can be hastened up which

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

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

127 **1.2 Problem Statement**

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

¹⁴⁷ 1.3 Research Objectives

¹⁴⁸ 1.3.1 General Objective

¹⁴⁹ This special problem aims to develop a system that accurately estimates the depth
¹⁵⁰ of potholes on road surfaces by using image analysis, depth measurement tech-
¹⁵¹ nologies, and computer vision techniques. The system will focus specifically on
¹⁵² measuring the depth of potholes to assess their severity, enabling faster and more
¹⁵³ accurate road maintenance decisions, and there are no current practices in the
¹⁵⁴ Philippines involving depth information of potholes in assessing their severity. In
¹⁵⁵ accordance with the Department of Public Works and Highways Region 6's man-
¹⁵⁶ ual for road maintenance, the study will classify potholes into different severity
¹⁵⁷ levels such as low, medium, and high, which will be primarily based on their
¹⁵⁸ depth. In order to measure the system's accuracy, linear regression in order to
¹⁵⁹ represent the difference between the depth calculated from the disparity and the
¹⁶⁰ actual depth of the pothole from ground truth data.

¹⁶¹ 1.3.2 Specific Objectives

¹⁶² Specifically, this special problem aims:

- ¹⁶³ 1. To collect high-quality images of road surfaces that capture potholes includ-
¹⁶⁴ ing their depth in various lighting, camera distance and orientation.
- ¹⁶⁵ 2. To measure the accuracy of the system by comparing the depth measure-
¹⁶⁶ ments against ground truth data collected from actual road inspections and
¹⁶⁷ to utilize linear regression as a metric for evaluation.
- ¹⁶⁸ 3. To develop a prototype system that can detect and measure road potholes
¹⁶⁹ from image input, analyze their depth, and assess their severity.

¹⁷⁰ 1.4 Scope and Limitations of the Research

¹⁷¹ This system focuses solely on detecting and assessing the severity of potholes
¹⁷² through image analysis and depth measurement technologies. The scope includes
¹⁷³ the collection of pothole images using cameras and depth-sensing tools under a
¹⁷⁴ favorable weather condition.

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

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

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

191 1.5 Significance of the Research

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

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

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

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

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

²⁰⁸ **Chapter 2**

²⁰⁹ **Review of Related Literature**

²¹⁰ **2.1 Frameworks**

²¹¹ This section of the chapter presents related literature that is considered essential
²¹² for the development of this special problem.

²¹³ **2.1.1 Depth Estimation**

²¹⁴ Depth estimation as defined by Sanz, Mezcua, and Pena (2012) as a set of processes
²¹⁵ that aims to extract a representation of a certain scene's spatial composition.
²¹⁶ Stereo vision is stated to be among the depth estimation strategies (Sanz et al.,
²¹⁷ 2012).

²¹⁸ **2.1.2 Image and Video Processing**

²¹⁹ Kumar (2024) defines image processing as a process of turning an image into its
²²⁰ digital form and extracting data from it through certain functions and operations.
²²¹ Usual processes are considered to treat images as 2D signals wherein different
²²² processing methods utilize these signals. Like image processing, Resources (2020)
²²³ defines video processing as being able to extract information and data from video
²²⁴ footage through signal processing methods. However, in video processing due to
²²⁵ the diversity of video formats, compression and decompression methods are often
²²⁶ expected to be performed on videos before processing methods to either increase
²²⁷ or decrease bitrate.

2.1.3 Stereo Vision

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

2.2 Related Studies

This section of the chapter presents related studies conducted by other researchers wherein the methodology and technologies used may serve as basis in the development of this special problem.

2.2.1 Deep Learning Studies

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

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

259 **2.2.1.2 Road Anomaly Detection through Deep Learning Approaches**

260 The study of Luo, Lu, and Guo (2020) aimed to utilize deep learning models in
261 classifying road anomalies. The researchers used three deep learning approaches
262 namely Convolutional Neural Network, Deep Feedforward Network, and Recurrent
263 Neural Network from data collected through the sensors in the vehicle's suspension
264 system. In comparing the performance of the three deep learning approaches, the
265 researchers fixed some hyperparameters. Results revealed that the RNN model
266 was the most stable among the three and in the case of the CNN and DFN
267 models, the researchers suggested the use of wheel speed signals to ensure accuracy.
268 And lastly, the researchers concluded that the RNN model was best due to high
269 prediction performance with small set parameters (Luo et al., 2020). However,
270 proper severity assessment through depth information was not stated to be utilized
271 in any of the three approaches used in the study.

272 **2.2.1.3 Assessing Severity of Road Cracks Using Deep Learning-Based
273 Segmentation and Detection**

274 In the study of Ha et al. (2022), it was argued that the detection, classification,
275 and severity assessment of road cracks should be automated due to the bottleneck
276 it causes during the entire process of surveying. For the study, the researchers
277 utilized SqueezeNet, U-Net, and MobileNet-SSD models for crack classification and
278 severity assessment. Furthermore, the researchers also employed separate U-nets
279 for linear and area cracking cases. For crack detection, the researchers followed
280 the process of pre-processing, detection, classification. During preprocessing im-
281 ages were smoothed out using image processing techniques. The researchers also
282 utilized YOLOv5 object detection models for classification of pavement cracking
283 wherein the YOLOv51 model recorded the highest accuracy. The researchers how-
284 ever stated images used for the study are only 2D images which may have allowed
285 higher accuracy rates. Furthermore, the researchers suggest incorporating depth
286 information in the models to further enhance results.

287 **2.2.1.4 Roadway pavement anomaly classification utilizing smartphones
288 and artificial intelligence**

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

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

303 **2.2.2 Machine Learning Studies**

304 **2.2.2.1 Smartphones as Sensors for Road Surface Monitoring**

305 In their study, Sattar, Li, and Chapman (2018) noted the rise of sensing capabilities
306 of smartphones which they utilized in monitoring road surface to detect and
307 identify anomalies. The researchers considered different approaches in detecting
308 road surface anomalies using smartphone sensors. One of which are threshold-based
309 approaches which was determined to be quite difficult due to several factors
310 that are affecting the process of determining the interval length of a window
311 function in spectral analysis (Sattar et al., 2018). The researchers also utilized
312 a machine learning approach adapted from another study. It was stated that k-means
313 was used in classifying sensor data and in training the SVM algorithm. Due
314 to the requirement of training a supervised algorithm using a labeled sample data
315 was required before classifying data from sensors, the approach was considered to
316 be impractical for real-time situations (Sattar et al., 2018). In addition, Sattar
317 et al. (2018) also noted various challenges when utilizing smartphones as sensors
318 for data gathering such as sensors being dependent on the device's placement and
319 orientation, smoothness of captured data, and the speed of the vehicle it is being
320 mounted on. Lastly, it was also concluded that the accuracy and performance of
321 using smartphone sensors is challenging to compare due to the limited data sets
322 and reported algorithms.

323 **2.2.2.2 Road Surface Quality Monitoring Using Machine Learning Al-** 324 **gorithms**

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

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

341 **2.2.3 Computer Vision Studies**

342 **2.2.3.1 Stereo Vision Based Pothole Detection System for Improved 343 Ride Quality**

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

³⁵⁷ 2.3 Chapter Summary

- ³⁵⁸ The reviewed literature involved various techniques and approaches in road anomaly
³⁵⁹ 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

³⁶¹ **Chapter 3**

³⁶² **Methodology**

³⁶³ This chapter outlines the systematic approach that were taken to address the
³⁶⁴ problem of pothole depth estimation using StereoPi V2. The methodology is
³⁶⁵ divided into key phases: data collection, algorithm selection, design, testing and
³⁶⁶ experimentation, and challenges and limitations. Each phase will play a crucial
³⁶⁷ role in accurately classifying and assessing road defects. Each phase is essential
³⁶⁸ for accurately estimating the depth of potholes using StereoPi V2.

³⁶⁹ **3.1 Research Activities**

³⁷⁰ **3.1.1 Data Collection**

³⁷¹ The researchers conducted initial inquiries to understand the problem domain and
³⁷² existing road maintenance practices. This phase included consulting the engineers
³⁷³ under the Road Maintenance Department of the government agency Department
³⁷⁴ of Public Works and Highways (DPWH). An interview with Engr. Jane Chua pro-
³⁷⁵ vided a comprehensive overview of the DPWH's road maintenance manual, which
³⁷⁶ was crucial in aligning this project with existing standards. This collaboration
³⁷⁷ with DPWH provided insights into road pothole classification standards, ensuring
³⁷⁸ that the collected data will align with industry standards. The DPWH manual
³⁷⁹ primarily focuses on the volume of detected potholes within a road segment as
³⁸⁰ a measure of severity. However, since depth is not explicitly measured in their
³⁸¹ current procedures, the study will supplement this by referencing international
³⁸² standards such as the Long-Term Pavement Performance (LTPP) classification
³⁸³ used in the United States. The LTPP categorizes potholes based on depth thresh-

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

3.1.1.1 Data Collection (Ground Truth Data)

The researchers collected depth information from 130 potholes around the University of the Philippines Visayas Miagao Campus. During data collection, the researchers are equipped with safety vests and an early warning device to give caution to incoming vehicles. To measure the depth of each pothole, the researchers recorded four depth points within the pothole and calculated their average.

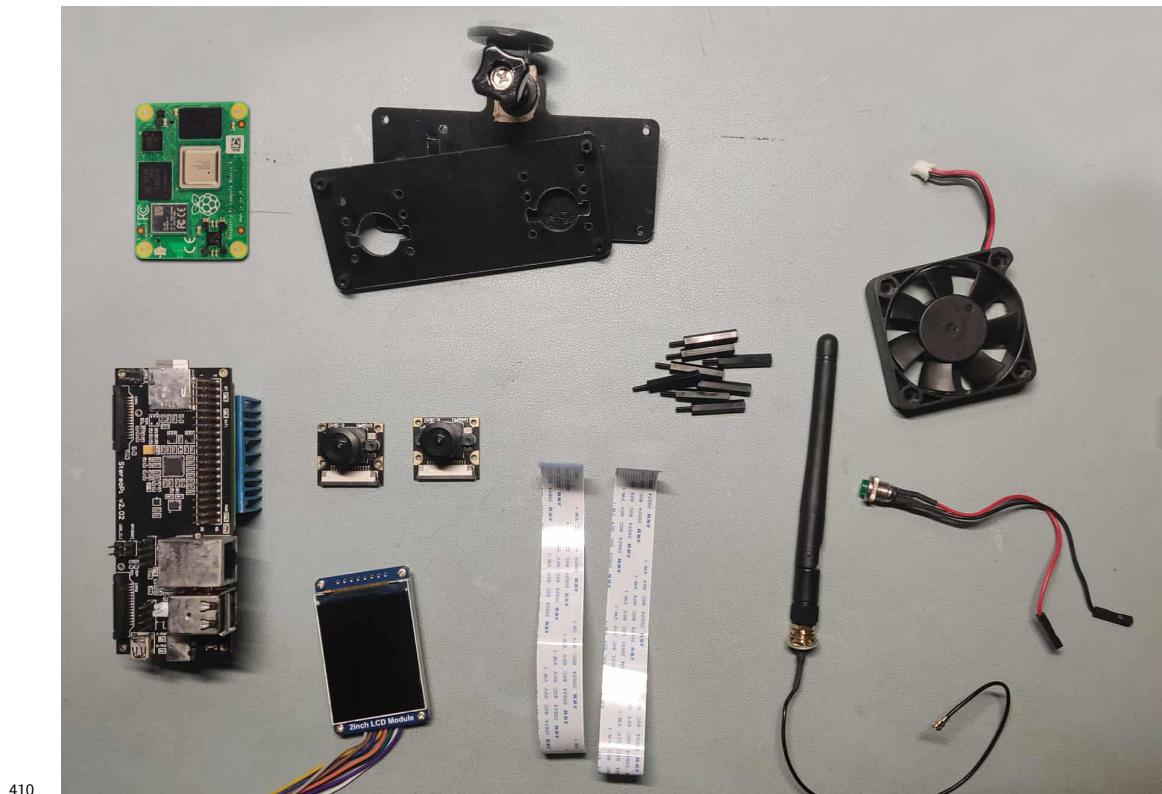
3.1.2 Algorithm Selection

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

3.1.3 Design, Testing, and Experimentation

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

409 **3.1.3.1 Materials and Equipment**



410 Figure 3.1: Components used in the prototype development.

411 The prototype system was constructed using the following materials and com-
412 ponents:

- 413 • StereoPi V2 Board
- 414 • Raspberry Pi Compute Module 4 (CM4)
- 415 • Dual RaspberryPi Camera Modules with Fisheye Lens
- 416 • 3D Printed Custom Housing
- 417 • 2-inch LCD Module
- 418 • Micro SD Card
- 419 • Antenna
- 420 • Momentary Push Button

421 **3.1.3.2 Prototype Building**

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

426

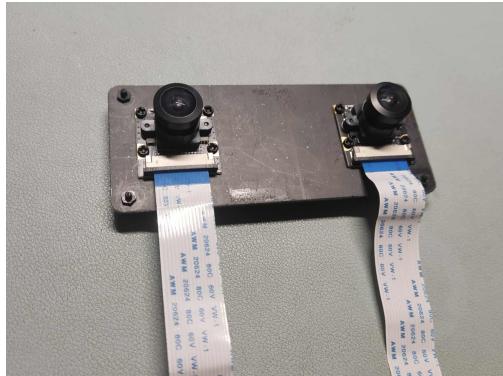


Figure 3.2: Dual RPi Camera Modules attached to the custom housing.

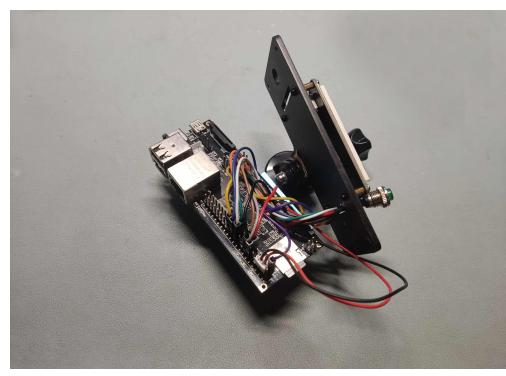


Figure 3.3: LCD Module connected to the StereoPi board.

427

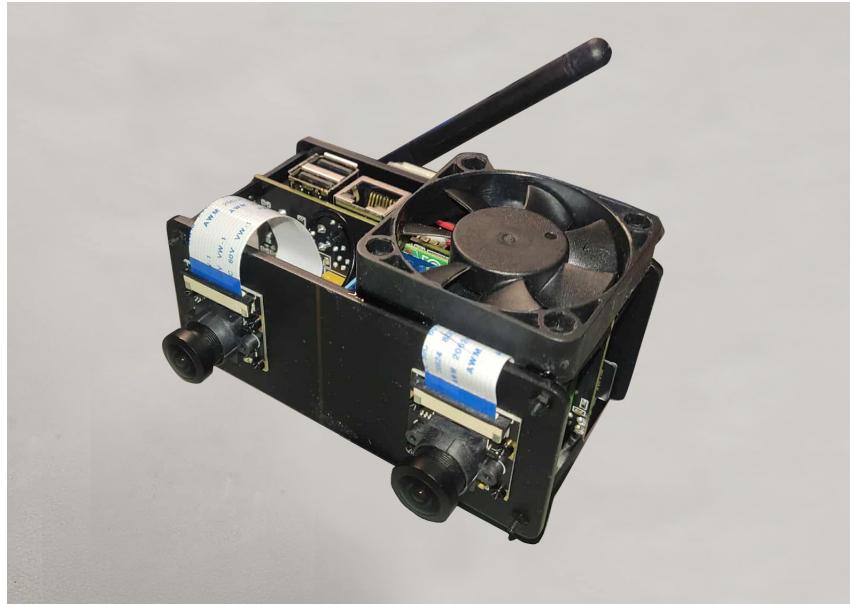


Figure 3.4: The finished prototype.

428 **3.1.3.3 Camera Calibration (Fisheye Distortion)**

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

434

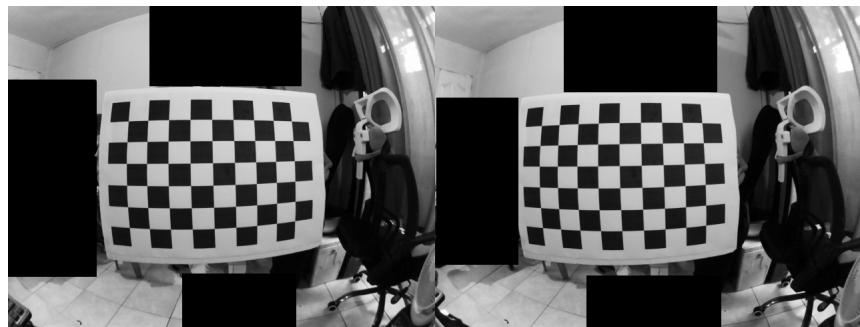


Figure 3.5: Calibration process with a checkerboard to correct fisheye lens distortion.

435 **3.1.3.4 Camera Calibration (Disparity Map Fine-tuning)**

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

443

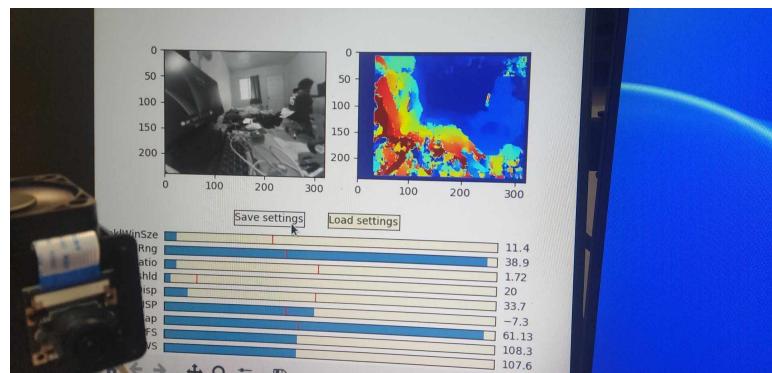


Figure 3.6: Parameter tuning process to achieve cleaner and more accurate disparity maps.

444 3.1.3.5 Initial Testing

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

450

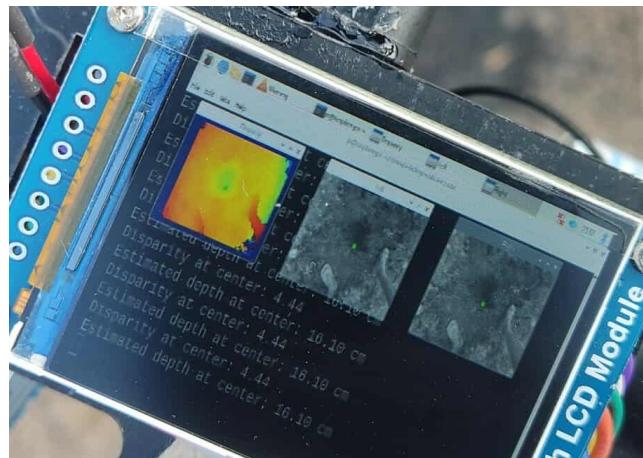


Figure 3.7: The system tested on a simulated pothole.

451 However, the results revealed a non-linear relationship between the computed
452 disparity values and the actual distances. This discrepancy indicated that the
453 traditional depth estimation method was insufficient for the current setup. To
454 address this, the researchers collected multiple data points and correlating known
455 distances to their respective disparity readings and fitted an inverse model to
456 better represent the system's behavior (see Figure 3.8). This updated disparity-
457 to-depth model was subsequently used in the final testing phase.

458 3.1.3.6 Performance Metrics

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

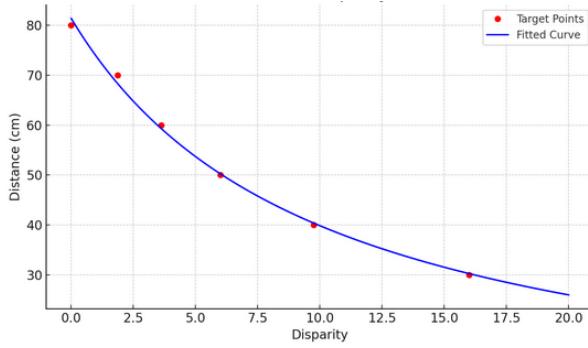


Figure 3.8: Inverse Model Fit to Disparity vs. Distance.

462 3.1.3.7 Final Testing and Validation

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

470 3.1.3.8 Documentation

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

475 3.1.4 Challenges and Limitations

476 3.1.4.1 Camera Limitations

477 During the data collection process, the researchers were faced with various issues
 478 involving the StereoPi V2 kit. Issues like inaccuracies in the rectified image pair
 479 and generated disparity map were very apparent in the early stages of data collec-
 480 tion due to limited related studies and literature involving the camera. In addition,
 481 the camera also yielded some inaccurate depth estimation and over reliance on

⁴⁸² controlled environments which prompted the researchers to further improve its
⁴⁸³ tuning and calibration.

⁴⁸⁴ 3.2 Calendar of Activities

⁴⁸⁵ Table 1 shows a Gantt chart of the activities. Each bullet represents approximately
⁴⁸⁶ 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

⁴⁸⁷ **Chapter 4**

⁴⁸⁸ **Preliminary Results/System
Prototype**

⁴⁹⁰ This chapter presents the results on estimating the depth of potholes using the
⁴⁹¹ StereoPi system. It details the prototype construction, calibration of the system,
⁴⁹² and the application of regression analysis to improve depth estimation. It also
⁴⁹³ contains the measurements taken during the testing phases, comparing the ground
⁴⁹⁴ truth depths with the value estimated by the camera. Findings are presented
⁴⁹⁵ systematically, supported by tables showing the collected data, images of the
⁴⁹⁶ outputs, and discussion on the analysis of results.

⁴⁹⁷ **4.1 System Calibration and Model Refinement**

⁴⁹⁸ After the initial testing, the system was calibrated using a controlled setup, where
⁴⁹⁹ artificial potholes with known depths were created. The stereo camera system
⁵⁰⁰ captured disparity maps, from which depth was calculated using the standard
⁵⁰¹ stereo vision formula:

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

⁵⁰² where:

- ⁵⁰³ • f is the focal length in pixels,
⁵⁰⁴ • B is the baseline distance between the two cameras,

- 505 • d is the disparity.

506 However, preliminary observations revealed that the relationship between measured disparity and true depth was nonlinear, particularly for small disparities corresponding to greater distances. As a result, a direct application of the stereo formula led to systematic errors, especially at the extremes of the depth range.

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

513 An inverse function of the form:

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

514 where:

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

518 4.2 Model Refinement Using Regression

519 The regression analysis produced the following model parameters:

- 520 • $a = \dots$
521 • $b = \dots$

522 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

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

526 **4.3 Error Analysis**

527 Despite the improvements, minor estimation errors remained. These errors were
528 primarily attributed to:

- 529 • Low-light imaging conditions affecting disparity computation,
- 530 • Shallow potholes with depths less than 3 cm, where disparity resolution
531 becomes a limiting factor,
- 532 • Perspective distortion when the stereo camera was not parallel to the ground
533 plane.

534 **4.4 Testing Results**

535 Following calibration, actual potholes located around the University of the Philip-
536 pines Visayas (UPV) campus were tested. The ground truth depths of the potholes
537 were measured manually and compared with the depths estimated by the camera.
538 Based on the results, the StereoPi camera was able to estimate the depths fairly
539 close to the ground truth values. The smallest difference was seen in Pothole 5,
540 where the estimated depth was only 0.24 cm away from the ground truth. The
541 largest difference was found in Pothole 1, where the error was 3.45 cm. For the
542 other potholes, the differences were 0.67 cm for Pothole 2, 2.07 cm for Pothole
543 3, and 2.66 cm for Pothole 4. Most of the time, the camera's estimated depths
544 were only off by about one to three centimeters. Table 4.2 shows the comparison
545 between the manually measured ground truth depths and the depths estimated
546 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

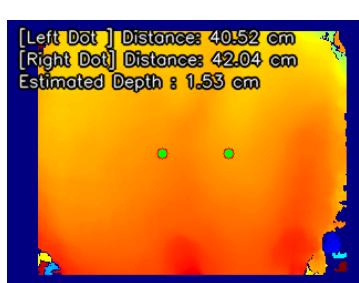


Figure 4.1: Disparity Map



Figure 4.2: Left Stereo Image



Figure 4.3: Right Stereo Image

547 4.5 Discussion

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⁵⁸⁸ **Appendix A**

⁵⁸⁹ **Appendix Title**

⁵⁹⁰ **Appendix B**

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