

<sup>1</sup>  
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**ROAD DEFECT SEVERITY ASSESSMENT AND  
CLASSIFICATION**

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<sup>8</sup>  
A Special Problem Proposal  
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<sup>12</sup>  
<sup>13</sup>  
<sup>14</sup>  
BELEBER, Benz Vrianne  
CATALAN, Perserose  
SENCIL, Kristian Lyle

<sup>15</sup>  
<sup>16</sup>  
Francis DIMZON, Ph.D.  
Adviser

<sup>17</sup>  
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18

## Approval Sheet

19

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

21

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

22

### ROAD DEFECT SEVERITY ASSESSMENT AND 23 CLASSIFICATION

24

#### Approved by:

25

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

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

29                                  **Declaration**

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

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

## Dedication

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

39        To their parents, for their endless sacrifices.

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41        wisdom.

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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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<sup>161</sup> **Chapter 1**

<sup>162</sup> **Introduction**

<sup>163</sup> **1.1 Overview of the Current State of Technology**

<sup>164</sup> According to the National Road Length by Classification, Surface Type, and Condition of the Department of Public Works and Highways (DPWH), as of October 2022 approximately 98.97% of roads in the Philippines is paved which is either made of concrete or asphalt (DPWH, 2022). 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.

<sup>171</sup> 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 (DPWH Regional Office 6 Road Board, Personal Interview. 2024). In addition, manual assessment of roads is also time consuming which leaves maintenance operations to wait for lengthy assessments (J. Chua, Personal Interview. 16 September 2024). 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.

<sup>185</sup> If the process of assessment on the severity of road defects can be automated

186 then the whole process of assessing the quality of roads can be hastened up which  
187 can also enable maintenance operations to commence as soon as possible if nec-  
188 essary. If not automated, the delay of assessments will continue and roads that  
189 are supposedly needing maintenance may not be properly maintained which can  
190 affect the general public that is utilizing public roads daily.

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

## 203 1.2 Problem Statement

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

## <sup>223</sup> 1.3 Research Objectives

### <sup>224</sup> 1.3.1 General Objective

<sup>225</sup> This special problem aims to develop a system that accurately estimates the depth  
<sup>226</sup> of potholes on road surfaces by using image analysis, depth measurement tech-  
<sup>227</sup> nologies, and computer vision techniques. The system will focus specifically on  
<sup>228</sup> measuring the depth of potholes to assess their severity, enabling faster and more  
<sup>229</sup> accurate road maintenance decisions, and there are no current practices in the  
<sup>230</sup> Philippines involving depth information of potholes in assessing their severity. In  
<sup>231</sup> accordance with the Department of Public Works and Highways Region 6's man-  
<sup>232</sup> ual for road maintenance, the study will classify potholes into different severity  
<sup>233</sup> levels such as low, medium, and high, which will be primarily based on their  
<sup>234</sup> depth. In order to measure the system's accuracy, linear regression in order to  
<sup>235</sup> represent the difference between the depth calculated from the disparity and the  
<sup>236</sup> actual depth of the pothole from ground truth data.

### <sup>237</sup> 1.3.2 Specific Objectives

<sup>238</sup> Specifically, this special problem aims:

- <sup>239</sup> 1. To collect high-quality stereo images of road surfaces that capture potholes  
<sup>240</sup> including their depth in favorable conditions
- <sup>241</sup> 2. To measure the accuracy of the system by comparing the depth measure-  
<sup>242</sup> ments against ground truth data collected from actual road inspections and  
<sup>243</sup> to utilize linear regression, root mean square error, and mean absolute error  
<sup>244</sup> as a metric for evaluation.
- <sup>245</sup> 3. To develop a prototype system that can detect and measure road potholes  
<sup>246</sup> from image input, analyze their depth, and assess their severity.

## <sup>247</sup> 1.4 Scope and Limitations of the Research

<sup>248</sup> This system focuses solely on detecting and assessing the severity of potholes  
<sup>249</sup> through image analysis and depth measurement technologies. The scope includes

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

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

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

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

## 268 1.5 Significance of the Research

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

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

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

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

<sup>283</sup>        *Future Researchers.* The special problem may serve as a baseline and guide of  
<sup>284</sup> researchers with the aim to pursue special problems similar or related to this.

<sup>285</sup> **Chapter 2**

<sup>286</sup> **Review of Related Literature**

<sup>287</sup> **2.1 Frameworks**

<sup>288</sup> This section of the chapter presents related frameworks that is considered essential  
<sup>289</sup> for the development of this special problem.

<sup>290</sup> **2.1.1 Depth Estimation**

<sup>291</sup> Depth estimation as defined by Sanz, Mezcua, and Pena (2012) is a set of processes  
<sup>292</sup> that aims to extract a representation of a certain scene's spatial composition.  
<sup>293</sup> Stereo vision is stated to be among the depth estimation strategies.

<sup>294</sup> **2.1.2 Image and Video Processing**

<sup>295</sup> Kumar (2024) defines image processing as a process of turning an image into its  
<sup>296</sup> digital form and extracting data from it through certain functions and operations.  
<sup>297</sup> Usual processes are considered to treat images as 2D signals wherein different  
<sup>298</sup> processing methods utilize these signals. Like image processing, RICHES Project  
<sup>299</sup> (2014) defines video processing as being able to extract information and data from  
<sup>300</sup> video footage through signal processing methods. However, in video processing  
<sup>301</sup> due to the diversity of video formats, compression and decompression methods  
<sup>302</sup> are often expected to be performed on videos before processing methods to either  
<sup>303</sup> increase or decrease bitrate.

### **304 2.1.3 Stereo Vision**

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

## **311 2.2 Related Studies**

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

### **315 2.2.1 Deep Learning Studies**

#### **316 Automated Detection and Classification of Road Anomalies 317 in VANET Using Deep Learning**

318  
319 In the study of Bibi et al. (2021) it was noted that identification of active road  
320 defects are critical in maintaining smooth and safe flow of traffic. Detection and  
321 subsequent repair of such defects in roads are crucial in keeping vehicles using  
322 such roads away from mechanical failures. The study also emphasized the growth  
323 in use of autonomous vehicles in research data gathering which is what the re-  
324 searchers utilized in data gathering procedures. With the presence of autonomous  
325 vehicles, this allowed the researchers to use a combination of sensors and deep  
326 neural networks in deploying artificial intelligence. The study aimed to allow au-  
327 tonomous vehicles to avoid critical road defects that can possibly lead to dangerous  
328 situations. Researchers used Resnet-18 and VGG-11 in automatic detection and  
329 classification of road defects. Researchers concluded that the trained model was  
330 able to perform better than other techniques for road defect detection. The study  
331 is able to provide the effectiveness of using deep learning models in training arti-  
332 ficial intelligence for road defect detection and classification. However, the study  
333 lacks findings regarding the severity of detected defects and incorporation of pot-  
334 hole depth in their model which are both crucial in automating manual procedures  
335 of road surveying in the Philippines.

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

337

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

350 **Assessing Severity of Road Cracks Using Deep Learning-  
351 Based Segmentation and Detection**

352

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

366 **Roadway pavement anomaly classification utilizing smart-  
367 phones and artificial intelligence**

368

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

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

### 383 **2.2.2 Machine Learning Studies**

#### 384 **Smartphones as Sensors for Road Surface Monitoring**

385  
386 In their study, Sattar, Li, and Chapman (2018) noted the rise of sensing capabilities  
387 of smartphones which they utilized in monitoring road surface to detect and  
388 identify anomalies. The researchers considered different approaches in detecting  
389 road surface anomalies using smartphone sensors. One of which are threshold-  
390 based approaches which was determined to be quite difficult due to several factors  
391 that are affecting the process of determining the interval length of a window  
392 function in spectral analysis. The researchers also utilized a machine learning  
393 approach adapted from another study. It was stated that k-means was used in  
394 classifying sensor data and in training the SVM algorithm. Due to the requirement  
395 of training a supervised algorithm using a labeled sample data was required  
396 before classifying data from sensors, the approach was considered to be impractical  
397 for real-time situations. In addition, Sattar et al. (2018) also noted various  
398 challenges when utilizing smartphones as sensors for data gathering such as sensors  
399 being dependent on the device's placement and orientation, smoothness of  
400 captured data, and the speed of the vehicle it is being mounted on. Lastly, it was  
401 also concluded that the accuracy and performance of using smartphone sensors is  
402 challenging to compare due to the limited data sets and reported algorithms.

#### 403 **Road Surface Quality Monitoring Using Machine Learning 404 Algorithms**

405  
406 The study of Singh, Bansal, Kamal, and Kumar (2021) aimed to utilize machine  
407 learning algorithms in classifying road defects as well as predict their locations.  
408 Another implication of the study was to provide useful information to commuters  
409 and maintenance data for authorities regarding road conditions. The researchers  
410 gathered data using various methods such as smartphone GPS, gyroscopes, and  
411 accelerometers. (Singh et al., 2021) also argued that early existing road monitoring  
412 models are unable to predict locations of road defects and are dependent  
413 on fixed roads and static vehicle speed. Neural and deep neural networks were

<sup>414</sup> utilized in the classification of anomalies which was concluded by the researchers  
<sup>415</sup> to yield accurate results and are applicable on a larger scale of data. The study  
<sup>416</sup> of Singh et al. (2021) can be considered as an effective method in gathering data  
<sup>417</sup> about road conditions. However, it was stated in the study that relevant authori-  
<sup>418</sup> ties will be provided with maintenance operation and there is no presence of any  
<sup>419</sup> severity assessment in the study. This may cause confusion due to a lack of as-  
<sup>420</sup> sessment on what is the road condition that will require extensive maintenance or  
<sup>421</sup> repair.

<sup>422</sup> **2.2.3 Computer Vision Studies**

<sup>423</sup> **Stereo Vision Based Pothole Detection System for Improved**  
<sup>424</sup> **Ride Quality**

<sup>425</sup>

<sup>426</sup> In the study of Ramaiah and Kundu (2021) it was stated that stereo vision has  
<sup>427</sup> been earning attention due to its reliable obstacle detection and recognition. Fur-  
<sup>428</sup> thermore, the study also discussed that such technology would be useful in improv-  
<sup>429</sup> ing ride quality in automated vehicles by integrating it in a predictive suspension  
<sup>430</sup> control system. The proposed study was to develop a novel stereo vision based  
<sup>431</sup> pothole detection system which also calculates the depth accurately. However,  
<sup>432</sup> the study focused on improving ride quality by using the 3D information from  
<sup>433</sup> detected potholes in controlling the damping coefficient of the suspension system.  
<sup>434</sup> Overall, the pothole detection system was able to achieve 84% accuracy and is  
<sup>435</sup> able to detect potholes that are deeper than 5 cm. The researchers concluded  
<sup>436</sup> that such system can be utilized in commercial applications. However, it is also  
<sup>437</sup> worth noting that despite the system being able to detect potholes and measure  
<sup>438</sup> its depth, the overall severity of the pothole and road condition was not addressed.

## <sup>439</sup> 2.3 Chapter Summary

- <sup>440</sup> 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

<sup>443</sup> **Chapter 3**

<sup>444</sup> **Methodology**

<sup>445</sup> This chapter outlines the systematic approach that were taken to address the  
<sup>446</sup> problem of pothole depth estimation using StereoPi V2. The methodology is  
<sup>447</sup> divided into key phases: data collection, algorithm selection, design, testing and  
<sup>448</sup> experimentation, and challenges and limitations. Each phase will play a crucial  
<sup>449</sup> role in accurately classifying and assessing road defects. Each phase is essential  
<sup>450</sup> for accurately estimating the depth of potholes using StereoPi V2.

<sup>451</sup> **3.1 Research Activities**

<sup>452</sup> **3.1.1 Data Collection**

<sup>453</sup> The researchers conducted initial inquiries to understand the problem domain and  
<sup>454</sup> existing road maintenance practices. This phase included consulting the engineers  
<sup>455</sup> under the Road Maintenance Department of the government agency Department  
<sup>456</sup> of Public Works and Highways (DPWH). An interview with Engr. Jane Chua pro-  
<sup>457</sup> vided a comprehensive overview of the DPWH's road maintenance manual, which  
<sup>458</sup> was crucial in aligning this project with existing standards. This collaboration  
<sup>459</sup> with DPWH provided insights into road pothole classification standards, ensuring  
<sup>460</sup> that the collected data will align with industry standards. The DPWH manual  
<sup>461</sup> primarily focuses on the volume of detected potholes within a road segment as  
<sup>462</sup> a measure of severity. However, since depth is not explicitly measured in their  
<sup>463</sup> current procedures, the study will supplement this by referencing international  
<sup>464</sup> standards such as the Long-Term Pavement Performance (LTPP) classification  
<sup>465</sup> used in the United States (Miller et al., 2014). The LTPP categorizes potholes

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

#### 477 **3.1.1.1 Data Collection (Ground Truth Data)**

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

#### 484 **3.1.2 Design, Testing, and Experimentation**

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

##### 487 **3.1.2.1 Depth Measurement**

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

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

<sup>497</sup> bration data, ensuring that the depth estimates reflect real-world distances accu-  
<sup>498</sup> rately within the effective operational range of the stereo camera setup.

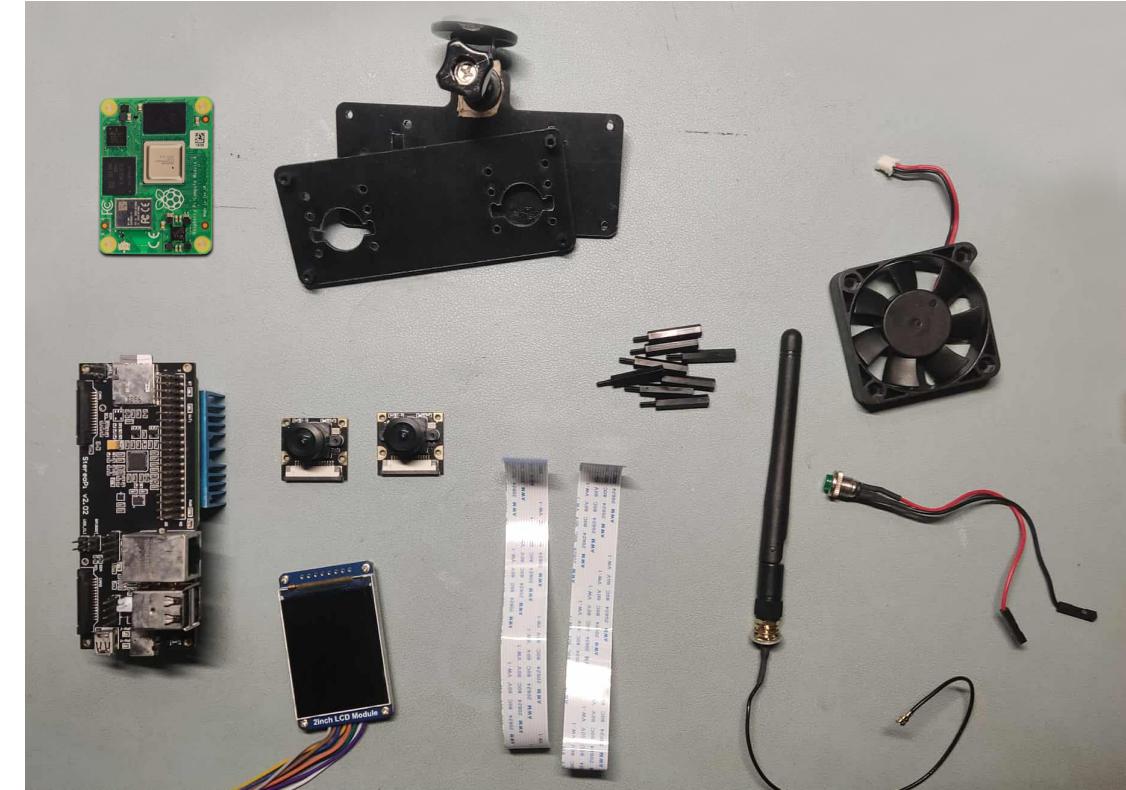
<sup>499</sup> **3.1.2.2 Severity Assessment**

<sup>500</sup> The estimated pothole depths were classified using the Long-Term Pavement Per-  
<sup>501</sup> formance (LTPP) depth thresholds, an internationally recognized framework for  
<sup>502</sup> pavement distress evaluation. This classification provides standardized criteria  
<sup>503</sup> to assess pothole severity objectively based on measured depth values. Specifi-  
<sup>504</sup> cally, potholes with depths less than 2.5 cm are categorized as low severity, those  
<sup>505</sup> between 2.5 cm and 5 cm as medium severity, and potholes exceeding 5 cm are  
<sup>506</sup> classified as high severity (Miller et al., 2014)

<sup>507</sup> **3.1.2.3 Materials and Equipment**

<sup>508</sup> The prototype system was constructed using several hardware components, which  
<sup>509</sup> include the items listed below and shown in Figure 3.1:

- <sup>510</sup> • StereoPi V2 Board
- <sup>511</sup> • Raspberry Pi Compute Module 4 (CM4)
- <sup>512</sup> • Dual RaspberryPi Camera Modules with Fisheye Lens
- <sup>513</sup> • 3D Printed Custom Housing
- <sup>514</sup> • 2-inch LCD Module
- <sup>515</sup> • Micro SD Card
- <sup>516</sup> • Antenna
- <sup>517</sup> • Momentary Push Button



518

Figure 3.1: Components used in the prototype development.

#### 519    3.1.2.4    Prototype Building

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

524

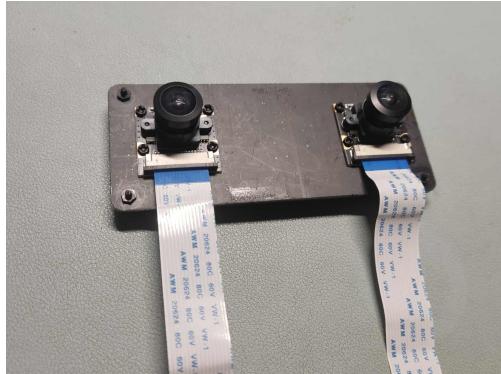


Figure 3.2: Dual RPi Camera Modules attached to the custom housing.

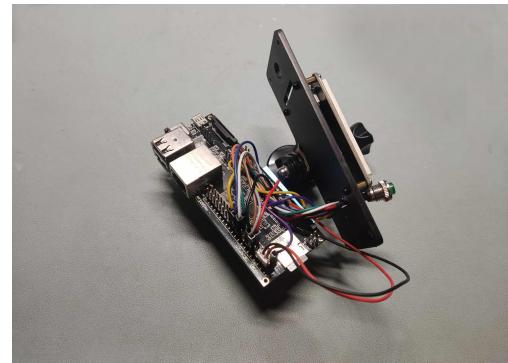


Figure 3.3: LCD Module connected to the StereoPi board.

525



Figure 3.4: The finished prototype.

### 526 3.1.2.5 Camera Calibration (Fisheye Distortion)

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

532

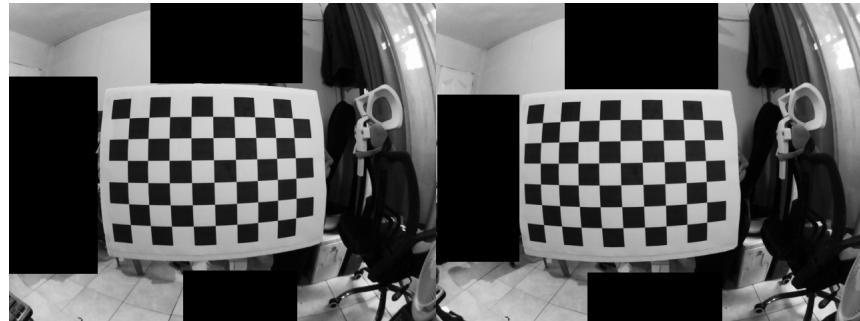


Figure 3.5: Calibration process with a checkerboard to correct fisheye lens distortion.

533

### 3.1.2.6 Camera Calibration (Disparity Map Fine-tuning)

534

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

541

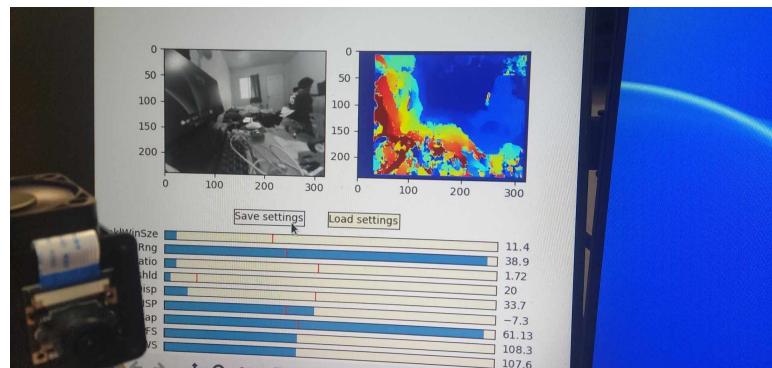


Figure 3.6: Parameter tuning process to achieve cleaner and more accurate disparity maps.

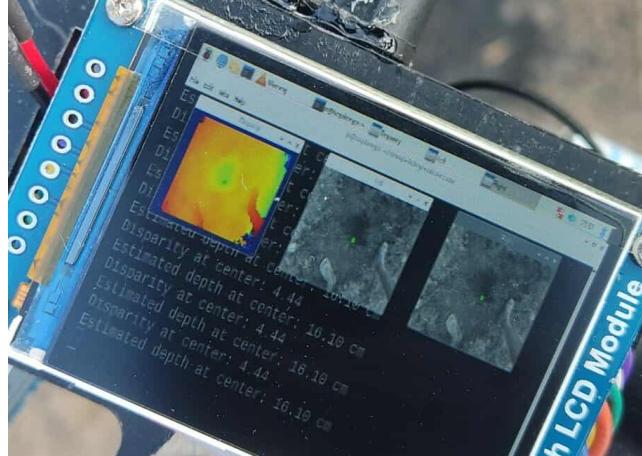
542

### 3.1.2.7 Initial Testing

543

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

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



548

Figure 3.7: The system tested on a simulated pothole.

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

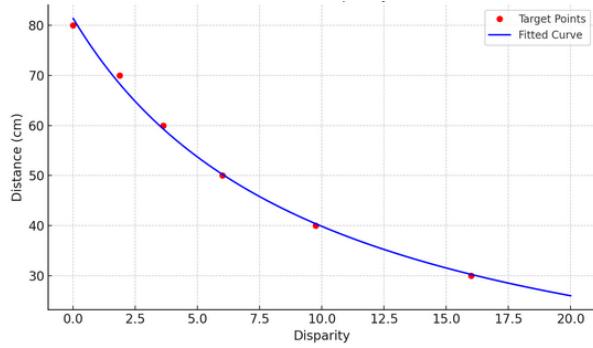


Figure 3.8: Inverse Model Fit to Disparity vs. Distance.

556 **3.1.2.8 Performance Metrics**

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

560 **3.1.2.9 Final Testing and Validation**

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

568 **3.1.2.10 Documentation**

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

573 **3.1.3 Challenges and Limitations**

574 **3.1.3.1 Camera Limitations**

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

582 **Chapter 4**

583 **Results and Discussion**

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

591 **4.1 System Calibration and Model Refinement**

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

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

596 where:

- 597 •  $f$  is the focal length in pixels,  
598 •  $B$  is the baseline distance between the two cameras,  
599 •  $d$  is the disparity.

600        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, 2002).

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

611        An inverse function of the form:

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

612        where:

- 613        •  $y$  is the estimated distance (in cm),  
614        •  $x$  is the measured disparity,  
615        •  $a$  and  $b$  are coefficients obtained through regression analysis.

## 616        4.2 Testing Results

617        Following calibration, actual potholes located around the University of the Philippines Visayas (UPV) campus were tested. The ground truth depths of the potholes were measured manually and compared with the depths estimated by the StereoPi camera. Based on the results, the StereoPi camera was able to estimate the depths fairly close to the actual measurements.

622        The smallest error occurred in one pothole, where the estimated depth was only 0.02 cm off from the ground truth. The largest observed error was 3.45 cm.  
623        Most of the time, the camera's estimated depths were within approximately 1 to  
624        3 centimeters of the actual depths. This demonstrates reasonable accuracy given  
625        the hardware setup and environmental conditions.

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

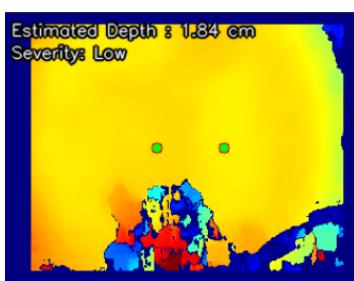


Figure 4.1: Disparity Map



Figure 4.2: Left Stereo Image



Figure 4.3: Right Stereo Image

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

<b>R</b>	<b>R<sup>2</sup></b>	<b>Root Mean Square Error (cm)</b>	<b>Mean Absolute Error (cm)</b>
0.978	0.956	0.844	0.945

Table 4.1: Linear Regression Model Fit Summary

<b>Predictor</b>	<b>Estimate</b>	<b>SE</b>	<b>t</b>	<b>p</b>
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

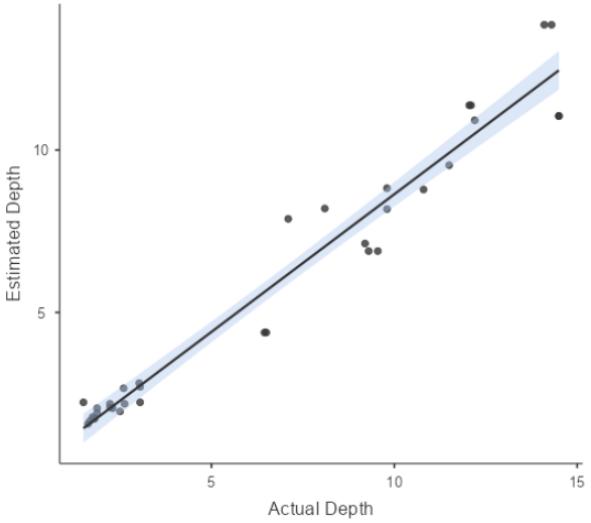


Figure 4.4: Linear Regression Fit Between Actual and Estimated Depth

### 639 4.3 Discussion

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

650 A strong positive correlation ( $R = 0.978$ ) and coefficient of determination ( $R^2$   
651 = 0.956) indicate that the actual pothole depths strongly predict the estimated  
652 values. The regression model's significant predictor ( $p < 0.001$ ) further supports  
653 the robustness of the depth estimation approach. This level of accuracy and model  
654 performance highlights the suitability of the StereoPi system for practical field  
655 applications in pothole monitoring and maintenance prioritization. This finding  
656 is significant because earlier machine learning-based road detection studies such as  
657 those by Bibi et al. (2021) focused mostly on classifying the existence of defects,  
658 not measuring their severity.

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

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

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

685 **Chapter 5**

686 **Conclusion**

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

691 **5.1 Summary**

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

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

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

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

## 719 5.2 Conclusions

720 The researchers conclude the following based on the findings:

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

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

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

### 743 5.3 Recommendations for Practice

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

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

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

### 755 5.4 Suggestions for further research

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

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

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

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

<sup>771</sup> arrays. These systems can offer improved depth perception and coverage, partic-  
<sup>772</sup> ularly for complex or uneven road surfaces, by capturing more comprehensive 3D  
<sup>773</sup> data.

<sup>774</sup> *Integration of stereo vision with motion-based analysis.* Incorporating frame  
<sup>775</sup> differencing techniques, similar to motion detection algorithms, could be beneficial  
<sup>776</sup> for dynamic environments or mobile applications. This approach may simulate  
<sup>777</sup> the effect of a moving vehicle and allow the system to detect and estimate potholes  
<sup>778</sup> more robustly in real time, enhancing its applicability for onboard vehicle-mounted  
<sup>779</sup> systems.

780      

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822

<sup>823</sup> **Appendix A**

<sup>824</sup> **Code Snippets**

<sup>825</sup> **Appendix B**

<sup>826</sup> **Resource Persons**

<sup>827</sup> **Prof. Jumar Cadondon**

<sup>828</sup> Assistant Professor

<sup>829</sup> Division of Physical Sciences and Mathematics

<sup>830</sup> University of the Philippines Visayas

<sup>831</sup> jgcadondon@up.edu.ph

<sup>832</sup> **Engr. Jane Chua**

<sup>833</sup> Engineer

<sup>834</sup> DPWH Region 6

<sup>835</sup> chua.jane@dpwh.gov.ph

<sup>836</sup>

<sup>837</sup> **Engr. Marilou Zamora**

<sup>838</sup> Chief

<sup>839</sup> Planning and Design

<sup>840</sup> DPWHRegion6

<sup>841</sup> zamora.marilou@dpwh.gov.ph

<sup>842</sup> **Engr. Benjamin Javellana**

<sup>843</sup> Assistant Director

<sup>844</sup> Maintenance

<sup>845</sup> DPWHRegion6

<sup>846</sup> javellana.benjamin@dpwh.gov.ph

<sup>847</sup> **Appendix C**

<sup>848</sup> **Data Table and Stereo Pi Images**

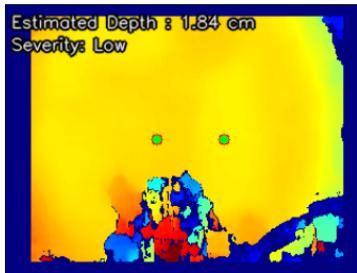


Figure C.1: Disparity Map

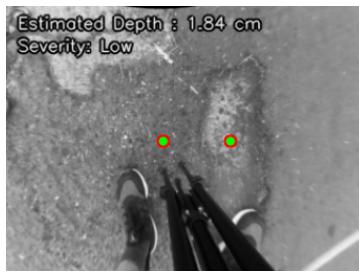


Figure C.2: Left Stereo Image

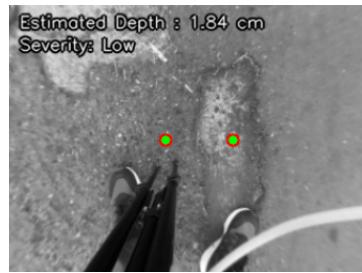


Figure C.3: Right Stereo Image

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

<sup>849</sup> **Appendix D**

<sup>850</sup> **Supplementary Documents**

January 31, 2025

**ENGR. ETHEL B. MORALES**  
OIC – District Engineer  
Department of Public Works and Highways (DPWH)  
1<sup>st</sup> District Engineering Office  
Rizal St., Guimbal, Iloilo



Dear Engr. Morales:

Greetings of Honor and Excellence!

We are 4<sup>th</sup> 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 1<sup>st</sup> 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.1: Letter requesting validation of data collection procedures.

University Of The Philippines Visayas  
College Of Arts And Sciences  
Division Of Physical Sciences And Mathematics

January 31, 2025

**Dr. Farisal U. Bagsit**  
*Vice Chancellor for Administration*

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

**25-0226**  
Dear Vice Chancellor Bagsit

REF. NO. **FEB 07 2025**

Good day!



We, Benz Vrianne Beleber, Kristian Lyle Sencil, and Perserose Catalan, are currently conducting our Special Problem study as a requirement for our Bachelor of Science in Computer Science at the University of the Philippines Visayas.

Our study focuses on detecting potholes and assessing their severity through depth measurement estimation utilizing stereo vision and machine learning.. As part of our data collection process, we need to conduct manual measurement of potholes within the campus roads which will serve as ground truth data to validate our methodology. Our procedures have been validated by the Department of Public Works and Highways (DPWH), ensuring that our approach aligns with their standards. This will involve recording the depth and dimensions of potholes using standard measuring tools while ensuring minimal disruption to pedestrian and vehicular movement.

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

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

We sincerely hope for your kind consideration of our request.

**APPROVED / DISAPPROVED**

Thank you very much.

Sincerely yours,

*Benz Vrianne Beleber*  
Team Member

*CLEMENT G. CAMPOSANO*  
CHANCELLOR *2.6.2025*

*Perserose Catalan*  
Team Leader

Noted:

*Francis Dimzon, Ph.D.*  
BSCS Special Problem Adviser

09614415782

**RECOMMENDING APPROVAL/DISAPPROVAL:**  
*Farisal U. Bagsit 2.6.2025*  
FARISAL U. BAGSIT, Ph.D.  
Vice Chancellor for Administration

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

**RECOMMEND APPROVAL/DISAPPROVAL:**  
*31 JAN 2025*  
DATE **31 JAN 2025**  
REF NO. PRF **2025-103**  
**RECOMMEND APPROVAL:**

*Kent Christian A. Castor*  
Chairperson, DPSM

*PEPITO R. FERNANDEZ JR.*  
DEAN, COLLEGE OF ARTS & SCIENCES  
IP VISAYAS

Figure D.2: Letter requesting permission for ground truth data collection within the UPV campus.



**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.3: Validated pothole measurement procedural manual, reviewed by Engr. Ethel B. Morales, District Engineer, DPWH 1st District Engineering Office.



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**COLLEGE OF ARTS AND SCIENCES**  
DIVISION OF PHYSICAL SCIENCES AND MATHEMATICS

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**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.4: Second page of the pothole measurement procedural manual



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**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.5: 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.6: Fourth page of the pothole measurement procedural manual



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**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.7: Fifth page of the pothole measurement procedural manual