

1                   ROAD DEFECT SEVERITY ASSESSMENT AND  
2                   CLASSIFICATION

3                   A Special Problem  
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18

**Approval Sheet**

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Sciences, University of the Philippines Visayas

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

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**ROAD DEFECT SEVERITY ASSESSMENT AND  
CLASSIFICATION**

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29                          **Declaration**

30        We, BENZ VRIANNE BELEBER, PERSEROSE CATALAN, and KRISTIAN  
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32        and is the record of work carried out by us. Any significant borrowings have been  
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**Dedication**

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

39        To their parents, for their endless sacrifices.

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

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71

## 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>174</sup> Chapter 1

## <sup>175</sup> Introduction

### <sup>176</sup> 1.1 Overview of the Current State of Technology

<sup>177</sup> According to the National Road Length by Classification, Surface Type, and Con-  
<sup>178</sup> dition of the Department of Public Works and Highways (DPWH), as of October  
<sup>179</sup> 2023 approximately 98.97% of roads in the Philippines is paved which is either  
<sup>180</sup> made of concrete or asphalt (Balita, 2024). Since the DPWH is an institution  
<sup>181</sup> under the government, it is paramount to maintain such roads in order to avoid  
<sup>182</sup> accidents and congested traffic situations especially in heavily urbanized areas  
<sup>183</sup> where there are a lot of vehicles.

<sup>184</sup> In an interview with the Road Board of DPWH Region 6 it was stated that road  
<sup>185</sup> condition assessments are mostly done manually with heavy reliance on engineer-  
<sup>186</sup> ing judgment (J. Chua, Personal Interview. 16 September 2024). In addition,  
<sup>187</sup> manual assessment of roads is also time consuming which leaves maintenance  
<sup>188</sup> operations to wait for lengthy assessments. In a study conducted by Ramos, Da-

189 canay, and Bronuela-Ambrocio (2023), it was found that the Philippines' current  
190 method of manual pavement surveying is considered as a gap since it takes an  
191 average of 2-3 months to cover a 250 km road as opposed to a 1 day duration  
192 in the Australian Road Research Board for the same road length. Ramos et al.  
193 (2023) recommended that to significantly improve efficiency of surveying methods  
194 and data gathering processes, automated survey tools are to be employed. It was  
195 also added that use of such automated, surveying tools can also guarantee the  
196 safety of road surveyors.

197 If the process of assessment on the severity of road defects can be automated then  
198 the whole process of assessing the quality of roads can be hastened up which can  
199 also enable maintenance operations to commence as soon as possible if necessary.  
200 If not automated, the delay of assessments will continue and roads that are sup-  
201 posedly needing maintenance may not be properly maintained which can affect  
202 the general public that is utilizing public roads daily.

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

<sup>214</sup> road condition monitoring.

## <sup>215</sup> 1.2 Problem Statement

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

## <sup>235</sup> 1.3 Research Objectives

### <sup>236</sup> 1.3.1 General Objective

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

### <sup>249</sup> 1.3.2 Specific Objectives

<sup>250</sup> Specifically, this special problem aims:

- <sup>251</sup> 1. To collect high-quality stereo images of road surfaces that capture potholes  
<sup>252</sup> including their depth in favorable conditions
- <sup>253</sup> 2. To measure the accuracy of the system by comparing the depth measure-  
<sup>254</sup> ments against ground truth data collected from actual road inspections and  
<sup>255</sup> to utilize linear regression, root mean square error, and mean absolute error

256 as a metric for evaluation.

- 257 3. To develop a prototype system that can detect and measure road potholes  
258 from image input, analyze their depth, and assess their severity.

## 259 1.4 Scope and Limitations of the Research

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

264 Depth-sensing tools, such as stereo cameras, will be used to record the depth of  
265 potholes specifically. The system will not address other road defects like cracks  
266 or other surface deformations; therefore, it will detect and analyze only potholes.

267 Additionally, only accessible potholes will be measured, meaning those that are  
268 filled with water or obscured by debris may not be accurately assessed.

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

275 Environmental factors such as lighting, road surface texture, and weather con-  
276 ditions may impact the system's performance. The accuracy and reliability of  
277 the system will depend on the quality of camera calibration and disparity map

278 finetuning. Its ability to measure the depth of pothole images needs careful vali-  
279 dation.

## 280 1.5 Significance of the Research

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

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

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

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

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

# <sup>297</sup> Chapter 2

## <sup>298</sup> Review of Related Literature

### <sup>299</sup> 2.1 Frameworks

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

#### <sup>302</sup> 2.1.1 Depth Estimation

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

#### <sup>306</sup> 2.1.2 Image and Video Processing

<sup>307</sup> Kumar (2024) defines image processing as a process of turning an image into its  
<sup>308</sup> digital form and extracting data from it through certain functions and operations.

<sup>309</sup> Usual processes are considered to treat images as 2D signals wherein different  
<sup>310</sup> processing methods utilize these signals. Like image processing, RICHES Project  
<sup>311</sup> (2014) defines video processing as being able to extract information and data from  
<sup>312</sup> video footage through signal processing methods. However, in video processing  
<sup>313</sup> due to the diversity of video formats, compression and decompression methods  
<sup>314</sup> are often expected to be performed on videos before processing methods to either  
<sup>315</sup> increase or decrease bitrate.

### <sup>316</sup> **2.1.3 Stereo Vision**

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

## <sup>323</sup> **2.2 Related Studies**

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

<sup>327</sup> **2.2.1 Deep Learning Studies**

<sup>328</sup> **Automated Detection and Classification of Road Anomalies  
329 in VANET Using Deep Learning**

<sup>330</sup>

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

<sup>348</sup> **Road Anomaly Detection through Deep Learning Approaches**

<sup>349</sup>

<sup>350</sup> The study of Luo, Lu, and Guo (2020) aimed to utilize deep learning models in

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

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

364

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

<sup>376</sup> higher accuracy rates. Furthermore, the researchers suggest incorporating depth  
<sup>377</sup> information in the models to further enhance results.

<sup>378</sup> **Roadway pavement anomaly classification utilizing smart-**  
<sup>379</sup> **phones and artificial intelligence**

<sup>380</sup>

<sup>381</sup> The study of Kyriakou, Christodoulou, and Dimitriou (2016) presented what is  
<sup>382</sup> considered as a low-cost technology which was the use of Artificial Neural Net-  
<sup>383</sup> works in training a model for road anomaly detection from data gathered by  
<sup>384</sup> smartphone sensors. The researchers were able to collect case study data us-  
<sup>385</sup> ing two-dimensional indicators of the smartphone's roll and pitch values. In the  
<sup>386</sup> study's discussion, the data collected displayed some complexity due to accelera-  
<sup>387</sup> tion and vehicle speed which lead to detected anomalies being not as conclusive as  
<sup>388</sup> planned. The researchers also added that the plots are unable to show parameters  
<sup>389</sup> that could verify the data's correctness and accuracy. Despite the setbacks, the  
<sup>390</sup> researchers still fed the data into the Artificial Neural Network that was expected  
<sup>391</sup> to produce two outputs which were "no defect" and "defect." The method still  
<sup>392</sup> yielded above 90% accuracy but due to the limited number of possible outcomes  
<sup>393</sup> in the data processing the researchers still needed to test the methodology with  
<sup>394</sup> larger data sets and roads with higher volumes of anomalies.

<sup>395</sup> **2.2.2 Machine Learning Studies**

<sup>396</sup> **Smartphones as Sensors for Road Surface Monitoring**

<sup>397</sup>

<sup>398</sup> In their study, Sattar, Li, and Chapman (2018) noted the rise of sensing capabil-  
<sup>399</sup> ities of smartphones which they utilized in monitoring road surface to detect and

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

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

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

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

434 **2.2.3 Computer Vision Studies**

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

437  
438 In the study of Ramaiah and Kundu (2021) it was stated that stereo vision has  
439 been earning attention due to its reliable obstacle detection and recognition. Fur-  
440 thermore, the study also discussed that such technology would be useful in improv-  
441 ing ride quality in automated vehicles by integrating it in a predictive suspension  
442 control system. The proposed study was to develop a novel stereo vision based  
443 pothole detection system which also calculates the depth accurately. However,  
444 the study focused on improving ride quality by using the 3D information from  
445 detected potholes in controlling the damping coefficient of the suspension system.  
446 Overall, the pothole detection system was able to achieve 84% accuracy and is  
447 able to detect potholes that are deeper than 5 cm. The researchers concluded  
448 that such system can be utilized in commercial applications. However, it is also

<sup>449</sup> worth noting that despite the system being able to detect potholes and measure  
<sup>450</sup> its depth, the overall severity of the pothole and road condition was not addressed.

## <sup>451</sup> 2.3 Chapter Summary

<sup>452</sup> The reviewed literature involved various techniques and approaches in road anomaly  
<sup>453</sup> detection and classification. These approaches are discussed and summarized be-  
<sup>454</sup> low 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>455</sup> Chapter 3

## <sup>456</sup> Research Methodology

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

### <sup>463</sup> 3.1 Research Activities

#### <sup>464</sup> 3.1.1 Data Collection

<sup>465</sup> The researchers conducted initial inquiries to understand the problem domain and  
<sup>466</sup> existing road maintenance practices. This phase included consulting the engineers  
<sup>467</sup> under the Road Maintenance Department of the government agency Department

468 of Public Works and Highways (DPWH). An interview with Engr. Jane Chua pro-  
469 vided a comprehensive overview of the DPWH's road maintenance manual, which  
470 was crucial in aligning this project with existing standards. This collaboration  
471 with DPWH provided insights into road pothole classification standards, ensuring  
472 that the collected data will align with industry standards. The DPWH manual  
473 primarily focuses on the volume of detected potholes within a road segment as a  
474 measure of severity. However, since depth is not explicitly measured in their cur-  
475 rent procedures, the study will supplement this by referencing international stan-  
476 dards such as the Long-Term Pavement Performance (LTPP) classification used  
477 in the United States (Miller & Bellinger, 2014). The LTPP categorizes potholes  
478 based on depth thresholds, which will be integrated with DPWH's volume-based  
479 assessment to provide a more comprehensive severity classification framework.  
480 The data collection involved capturing around 130 images of potholes from vari-  
481 ous locations within the UP Visayas Campus. Ground truth data of pothole depth  
482 were collected by the researchers by measuring the depth of different points in an  
483 individual pothole and then solving for its average depth. The researchers devel-  
484 oped a manual specifically designed for depth measurement, which underwent a  
485 review by Engr. Benjamin Javellana, Assistant Director of the Maintenance Divi-  
486 sion at the Department of Public Works and Highways (DPWH) Regional Office  
487 VI. The finalized version of the manual was subsequently validated by the DPWH  
488 First District Engineering Office. In order to individually locate or determine each  
489 pothole where the ground truth data is collected, images taken were labeled with  
490 their corresponding coordinates, street names, and nearby landmarks.

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

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



499

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

500

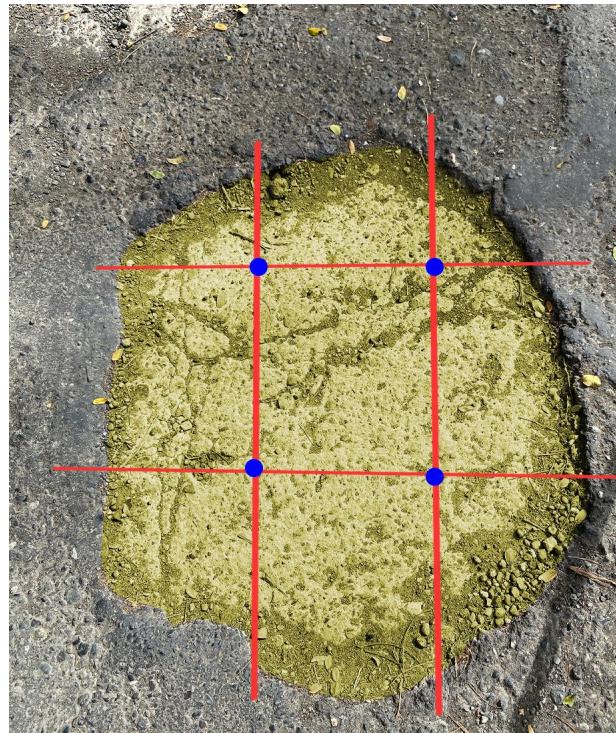


Figure 3.2: Four measure points of the pothole.

501

### 3.1.2 Design, Testing, and Experimentation

502

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

504

#### 3.1.2.1 Depth Measurement

505

Depth estimation is performed by generating disparity maps from the calibrated stereo image pairs captured by the StereoPi V2. In this process, two key measurement points are selected for each pothole: one targeting the pothole area itself, and another targeting the adjacent road surface considered as the reference plane. By calculating the difference in disparity values between these two points,

510 the system estimates the relative depth of the pothole. This approach improves  
511 accuracy by normalizing disparity measurements against the nearby road surface,  
512 effectively isolating the pothole's depth from overall scene variation.

513 The disparity-to-depth conversion utilizes an inverse model derived from calibra-  
514 tion data, ensuring that the depth estimates reflect real-world distances accurately  
515 within the effective operational range of the stereo camera setup.

516 **3.1.2.2 Severity Assessment**

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

524 **3.1.2.3 Materials and Equipment**

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

- 527     • StereoPi V2 Board
- 528     • Raspberry Pi Compute Module 4 (CM4)
- 529     • Dual RaspberryPi Camera Modules with Fisheye Lens

- 530      • 3D Printed Custom Housing
- 531      • 2-inch LCD Module
- 532      • Micro SD Card
- 533      • Antenna
- 534      • Momentary Push Button

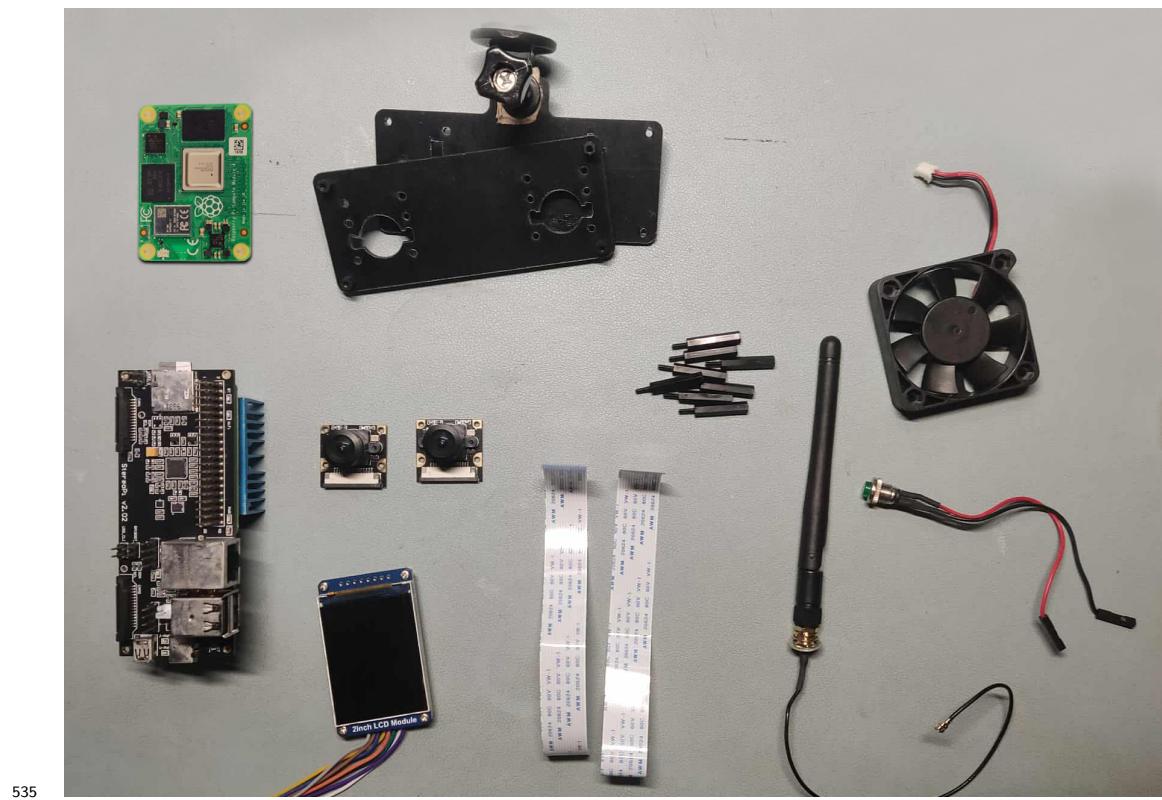


Figure 3.3: Components used in the prototype development.

#### 536 3.1.2.4 Prototype Building

- 537 The prototype involved the StereoPi V2 Kit which was acquired through an official  
538 international distributor. After assembling the camera, it was further modified to

- 539 address the it's heating by incorporating a heat sink and a small computer fan to  
540 make it suitable for outdoor use.

541



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

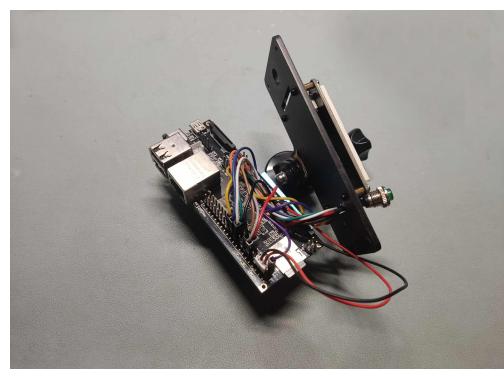


Figure 3.5: LCD Module connected to the StereoPi board.

542

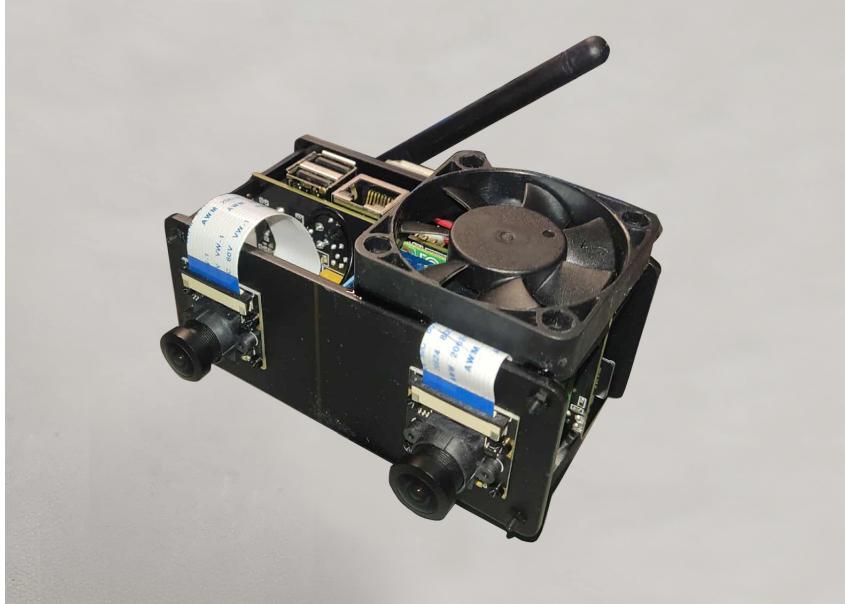


Figure 3.6: The finished prototype.

543 **3.1.2.5 Camera Calibration (Fisheye Distortion)**

- 544 The StereoPi V2 is first calibrated using a 9 by 6 checkerboard, with a checker  
545 size of 55mm, from different angles through calibration scripts that came with the

546 package. This process ensured that the camera is working properly in capturing  
547 stereo imagery. This removed distortion from captured images allowing depth  
548 estimation with more accuracy.

549



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

#### 550 3.1.2.6 Camera Calibration (Disparity Map Fine-tuning)

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

558

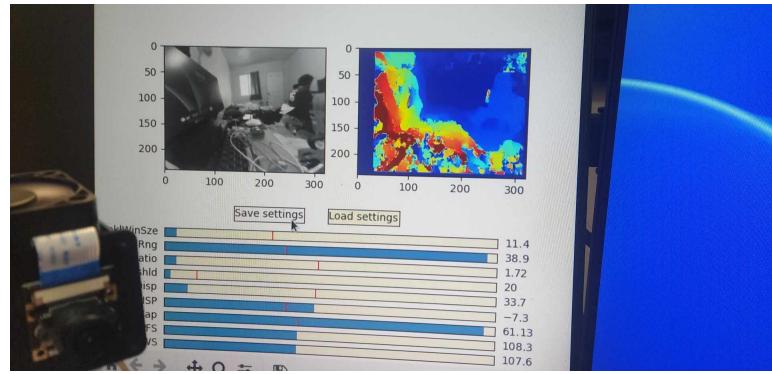


Figure 3.8: Parameter tuning process to achieve cleaner and more accurate disparity maps.

559

### 3.1.2.7 Initial Testing

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

565

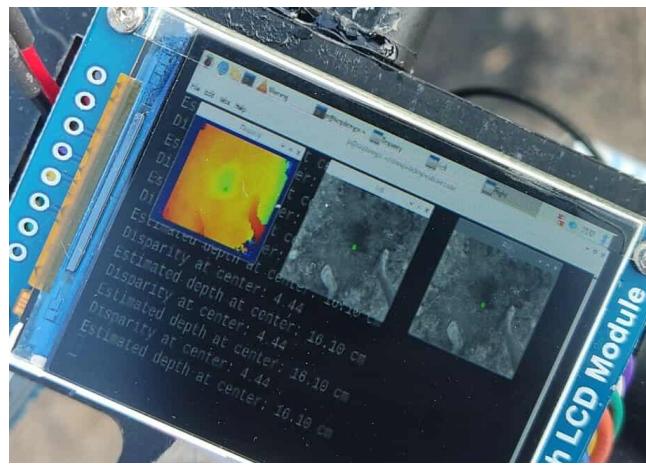


Figure 3.9: The system tested on a simulated pothole.

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

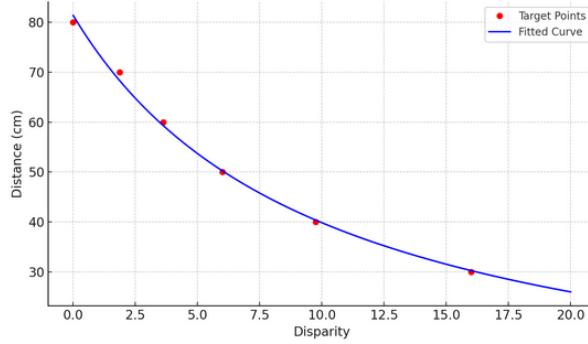


Figure 3.10: Inverse Model Fit to Disparity vs. Distance.

### 573 3.1.2.8 Performance Metrics

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

### 577 3.1.2.9 Final Testing and Validation

578 The testing process began with a detailed testing plan that includes both simu-  
 579 lated and real-world testing scenarios. Initially, the system is tested in controlled  
 580 environments to verify its capability to estimate pothole depth effectively. Fol-

581 lowing this, real-world testing was conducted using the StereoPi kit on previously  
582 located potholes, specifically at the University of the Philippines Visayas Mia-  
583 gao Campus. The procedure for estimating pothole depth closely followed the  
584 validated depth measurement manual where the system captured depth measure-  
585 ments at four designated points within each pothole, corresponding to the measure-  
586 points used in the manual measurement data. These four estimated depths were  
587 then averaged to determine the final depth estimate for each pothole. The sys-  
588 tem's performance was validated by comparing its predictions with ground-truth  
589 data collected from manual inspections.

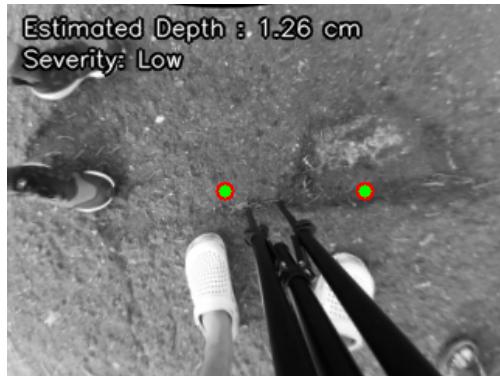


Figure 3.11: First measure point



Figure 3.12: Second measure point



Figure 3.13: Third measure point



Figure 3.14: Fourth measure point

590 **3.1.2.10 Documentation**

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

595 **3.1.3 Challenges and Limitations**

596 **3.1.3.1 Camera Limitations**

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

608 **Chapter 4**

609 **Results and Discussion**

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

617 **4.1 System Calibration and Model Refinement**

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

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

622 where:

623 •  $f$  is the focal length in pixels,

624 •  $B$  is the baseline distance between the two cameras,

625 •  $d$  is the disparity.

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

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

637 An inverse function of the form:

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

638 where:

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

## 642 4.2 Testing Results

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

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

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

655 The results show that the StereoPi system provides highly accurate estimates  
656 of pothole depth. The strong correlation ( $R=0.978$ ) and high coefficient of de-  
657 termination ( $R^2=0.956$ ) indicate that the actual depth significantly predicts the

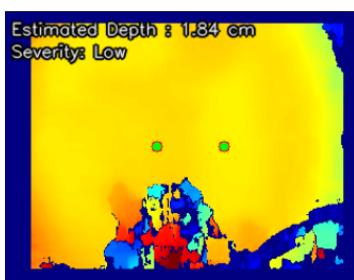


Figure 4.1: Disparity Map



Figure 4.2: Left Stereo Image



Figure 4.3: Right Stereo Image

658 estimated values. The regression coefficient for actual depth was statistically sig-  
 659 nificant ( $p < 0.001$ ), suggesting that the relationship is not due to chance. While  
 660 the RMSE of 0.844 cm and MAE of 0.945 cm suggest generally small errors, the  
 661 presence of a maximum error of 3.45 cm indicates that there may be occasional  
 662 outliers or limitations in specific scenarios. Nonetheless, the overall model per-  
 663 formance demonstrates that the StereoPi system is suitable for practical pothole  
 664 depth estimation.

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

Table 4.1: Linear Regression Model Fit Summary

Predictor	Estimate	SE	t	p
Intercept	0.159	0.2544	0.625	0.536
Actual Depth	0.848	0.0317	26.752	<0.001

Table 4.2: Model Coefficients - Estimated Depth

665 In figure 4.4, a linear relationship between actual and estimated depth is observed  
 666 with points closely clustered around the regression line. Indicating the accurate

667 depth estimation. The close alignment of most data points with the fitted line  
668 and narrow confidence interval suggest high predictive accuracy and minimal de-  
669 viation, especially at lower depth values.

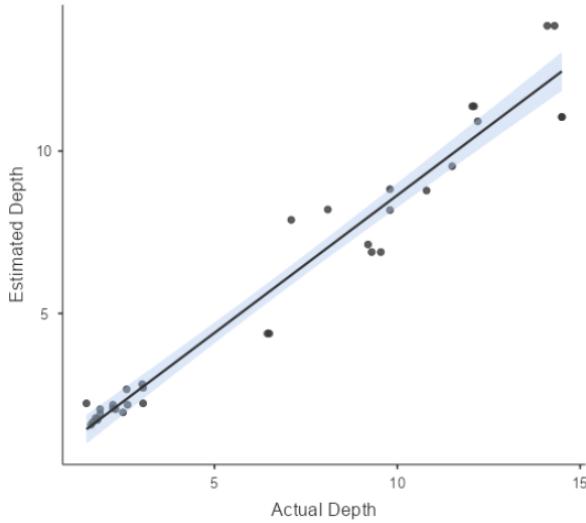


Figure 4.4: Linear Regression Fit Between Actual and Estimated Depth

### 670 4.3 Discussion

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

680 research.

681 A strong positive correlation ( $R = 0.978$ ) and coefficient of determination ( $R^2$   
682 = 0.956) indicate that the actual pothole depths strongly predict the estimated  
683 values. The regression model's significant predictor ( $p < 0.001$ ) further supports  
684 the robustness of the depth estimation approach. This level of accuracy and model  
685 performance highlights the suitability of the StereoPi system for practical field  
686 applications in pothole monitoring and maintenance prioritization. This finding  
687 is significant because earlier machine learning-based road detection studies such as  
688 those by Bibi et al. (2021) focused mostly on classifying the existence of defects,  
689 not measuring their severity.

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

698 However, the study also highlighted limitations affecting system performance, in-  
699 cluding sensitivity to camera calibration quality, lighting conditions, road surface  
700 texture, and the camera's vertical positioning during image capture. Outdoor  
701 testing revealed that low lighting and shallow potholes made it difficult to gen-  
702 erate clean disparity maps, sometimes causing minor estimation errors. These  
703 observations are consistent with Sattar et al. (2018), who reported that mobile

<sup>704</sup> road sensing systems often struggle in low-light or highly variable surface condi-  
<sup>705</sup> tions. Understanding these challenges is important because it points to practical  
<sup>706</sup> improvements, such as using better cameras, adding lighting support, or applying  
<sup>707</sup> more robust image enhancement methods in future versions of the system.



# <sup>708</sup> Chapter 5

## <sup>709</sup> Conclusion

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

### <sup>714</sup> 5.1 Summary

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

<sup>722</sup> regression analysis, and to build a working prototype using stereo vision that can  
<sup>723</sup> detect, measure, and assess potholes.

<sup>724</sup> To achieve these objectives, a hardware prototype was built using the StereoPi  
<sup>725</sup> V2 board and Raspberry Pi Compute Module 4, equipped with dual fisheye-lens  
<sup>726</sup> cameras. Camera calibration was performed using a 9x6 checkerboard pattern  
<sup>727</sup> with known square sizes to correct for fisheye lens distortion and ensure proper  
<sup>728</sup> alignment of the stereo pair. After calibration, disparity map generation was  
<sup>729</sup> fine-tuned by adjusting block matching parameters to produce clearer and more  
<sup>730</sup> reliable disparity maps. Initial testing was conducted using simulated potholes  
<sup>731</sup> with known depths to verify the functionality of the system and identify the non-  
<sup>732</sup> linear behavior present in stereo vision depth measurements. It was observed that  
<sup>733</sup> using the standard stereo depth formula led to inaccuracies, particularly at greater  
<sup>734</sup> distances.

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

## <sup>742</sup> 5.2 Conclusions

<sup>743</sup> The researchers conclude the following based on the findings:

- 744     ● The system effectively captures and analyzes depth information from stereo  
745       images, providing a viable method for automated pothole severity assess-  
746       ment.
  
  - 747     ● Incorporating depth measurements significantly improves pothole repair pri-  
748       oritization compared to traditional visual-only inspections, allowing main-  
749       tenance decisions to be based on objective, measurable data.
  
  - 750     ● The system achieved an acceptable regression model fit, with a strong posi-  
751       tive correlation ( $R = 0.978$ ) and a coefficient of determination ( $R^2 = 0.956$ ),  
752       confirming that the depth estimates closely align with the ground truth  
753       measurements. The system obtained satisfactory error metrics, with a Mean  
754       Absolute Error (MAE) of 0.945 cm and a Root Mean Square Error (RMSE)  
755       of 0.844 cm, indicating reliable performance for both pothole detection and  
756       depth estimation tasks.
  
  - 757     ● The proposed approach fills a critical gap in current road maintenance prac-  
758       tices, especially within the Philippine context where depth-based severity  
759       classification is not yet systematically implemented.
- 
- 760     This special project has successfully developed a system that addresses the prob-  
761     lem of pothole severity assessment using depth measurement. The research shows  
762     that stereo vision, even using accessible and affordable technology, holds strong  
763     potential for future development in road maintenance automation. By building  
764     upon the foundation laid by this project, future systems can become even more  
765     accurate, efficient, and practical for real-world deployment

### **766 5.3 Recommendations for Practice**

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

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

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

### **778 5.4 Suggestions for Further Research**

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

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

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

791 *Use of multi-camera arrays.* Instead of relying solely on a two-camera stereo setup,  
792 future research could explore the use of multi-point or multi-angle camera arrays.  
793 These systems can offer improved depth perception and coverage, particularly for  
794 complex or uneven road surfaces, by capturing more comprehensive 3D data.

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



<sup>801</sup> **Chapter 6**

<sup>802</sup> **References**

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852 **Appendix A**

853 **Code Snippets**

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

```
854     def stereo_depth_map(rectified_pair ,  
855         save_path_prefix=None):  
856         global disp_max , disp_min  
857         dmLeft , dmRight = rectified_pair  
858  
859         disparity_raw = sbm.compute(dmLeft , dmRight) .  
860             astype(np.float32)  
861         disparity_raw /= 16.0    # normalize disparity  
862  
863         local_max , local_min = disparity_raw.max() ,  
864             disparity_raw.min()  
865  
866         if dm_colors_autotune:
```

```

867     disp_max = max(local_max , disp_max)
868     disp_min = min(local_min , disp_min)
869     local_max , local_min = disp_max , disp_min
870
871     # Normalize for visualization
872     disparity_vis = (disparity_raw - local_min) *
873         (255.0 / (local_max - local_min))
874     disparity_vis = np.uint8(np.clip(disparity_vis , 0 ,
875         255))
876     disparity_color = cv2.applyColorMap(disparity_vis ,
877         cv2.COLORMAP_JET)
878
879     # Calculate depth
880     depth_map = calculate_depth(disparity_raw)
881
882     # Define two points
883     center_y , center_x = depth_map.shape[0] // 2 ,
884     depth_map.shape[1] // 2 - 20
885     second_y = center_y
886     second_x = center_x + offset_x
887
888     # Read depth and disparity values
889     center_depth_cm = (depth_map[center_y , center_x])
890     second_depth_cm = (depth_map[second_y , second_x])
891     estimated_depth_cm = abs(center_depth_cm -

```

```

892     second_depth_cm)

893

894     # Define severity based on estimated depth
895     if estimated_depth_cm < 2.5:
896         severity = "Low"
897     elif estimated_depth_cm >= 2.5 and
898         estimated_depth_cm < 5.0:
899         severity = "Medium"
900     elif estimated_depth_cm > 5.0:
901         severity = "High"
902     else:
903         severity = "Unknown"

```

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

```

904     for frame in camera.capture_continuous(capture ,
905         format="bgra", use_video_port=True, resize=
906             img_width, img_height)):
907
908         pair_img = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
909
910         imgLeft = pair_img[:, :img_width // 2]
911
912         imgRight = pair_img[:, img_width // 2:]
913
914         imgL = cv2.remap(imgLeft, leftMapX, leftMapY,
915                         interpolation=cv2.INTER_LINEAR, borderMode=cv2.
916                         BORDER_CONSTANT)

```

```

915     imgR = cv2.remap(imgRight, rightMapX, rightMapY,
916                        interpolation=cv2.INTER_LINEAR, borderMode=cv2.
917                        BORDER_CONSTANT)
918
919     if useStripe:
920         imgL = imgL[80:160,:]
921         imgR = imgR[80:160,:]
922
923         stereo_depth_map((imgL, imgR), save_path_prefix=
924                           None)
925
926         button_held_time = 0
927         HOLD_THRESHOLD = 1.0 # seconds
928
929         if GPIO.input(BUTTON_PIN) == GPIO.LOW:
930             press_start = time.time()
931             while GPIO.input(BUTTON_PIN) == GPIO.LOW:
932                 time.sleep(0.01)
933                 button_held_time = time.time() - press_start
934
935             if button_held_time < HOLD_THRESHOLD:
936                 timestamp = datetime.now().strftime("%Y%m%d_%H%M%S
937 ")
938                 prefix = f"./captures/capture_{timestamp}"
939                 print(f"\n[!] - Capturing - snapshot - at - {timestamp} ..."

```

```
940         ” )  
941     stereo_depth_map( (imgL, imgR) , save_path_prefix=  
942             prefix)  
943     time.sleep(0.5)  
944     else:  
945         cycle_offset()  
946         time.sleep(0.5)
```



<sup>947</sup> **Appendix B**

<sup>948</sup> **Resource Persons**

<sup>949</sup> **Prof. Jumar Cadondon**

<sup>950</sup> Assistant Professor

<sup>951</sup> Division of Physical Sciences and Mathematics

<sup>952</sup> University of the Philippines Visayas

<sup>953</sup> [jgcadondon@up.edu.ph](mailto:jgcadondon@up.edu.ph)

<sup>954</sup>

<sup>955</sup> **Engr. Jane Chua**

<sup>956</sup> Engineer

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<sup>972</sup>

<sup>973</sup> **Mr. Cris Beleber**

<sup>974</sup> Engineering Assistant

<sup>975</sup> Planning and Design

<sup>976</sup> DPWH Region 6

<sup>977</sup> [beleber.cris@dpwh.gov.ph](mailto:beleber.cris@dpwh.gov.ph)

<sup>978</sup>

<sup>979</sup> Appendix C

<sup>980</sup> Data Table and Pothole Images

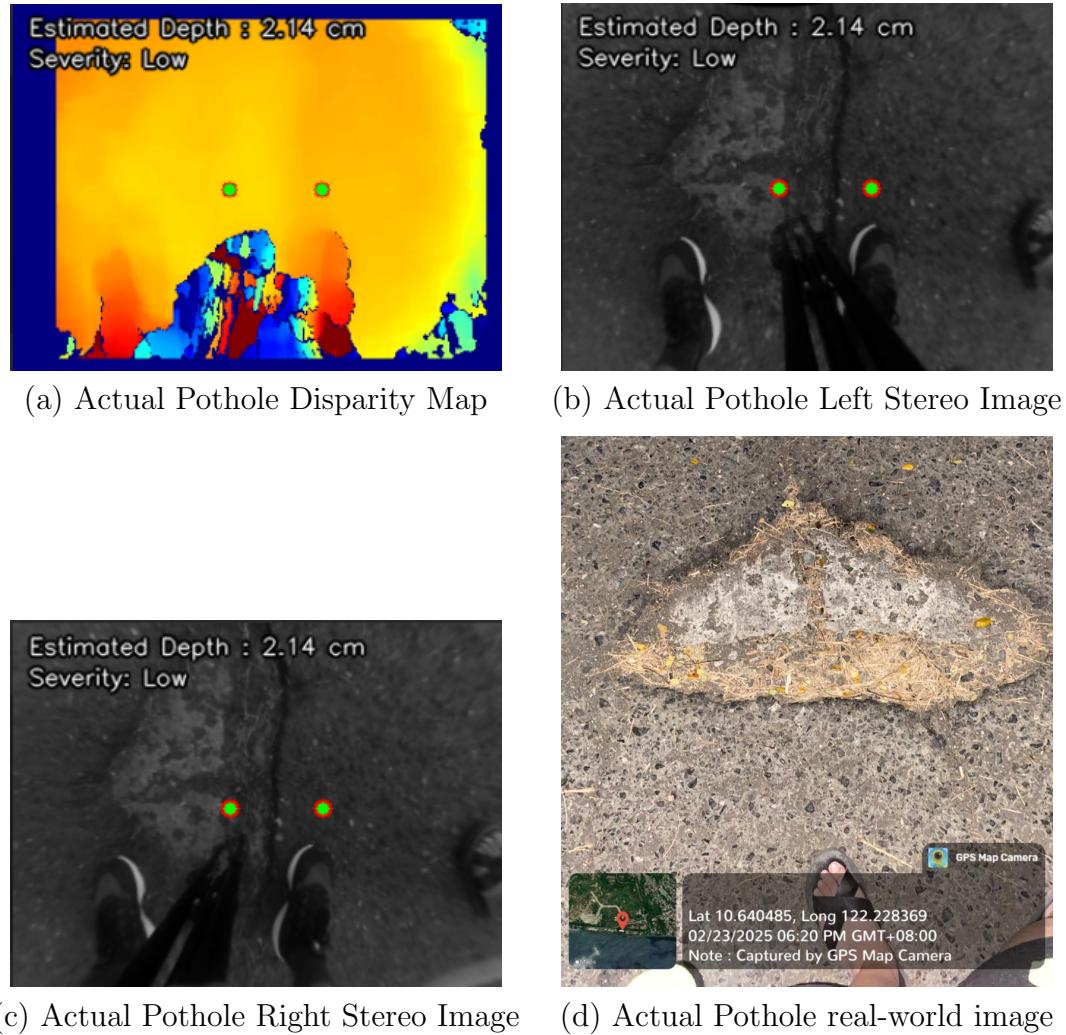
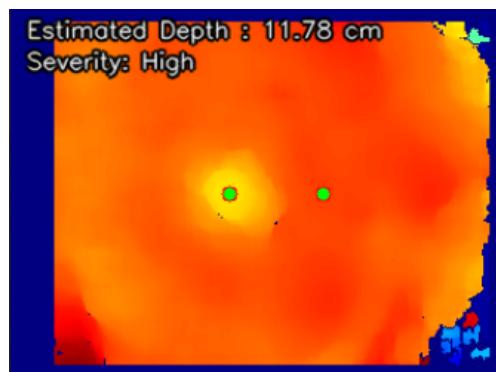


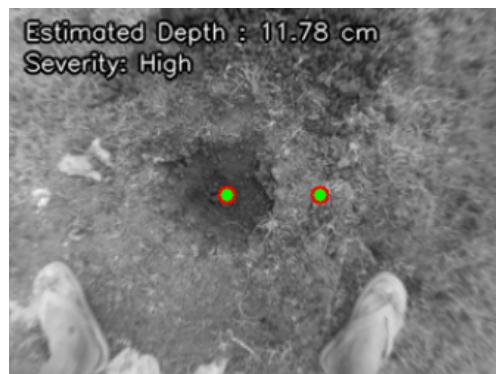
Figure C.1: Actual Pothole Images



(a) Simulated Pothole Disparity Map



(b) Simulated Pothole Left Stereo Image



(c) Simulated Pothole Right Stereo Image



(d) Simulated Pothole StereoPi capture

Figure C.2: Simulated Pothole Images

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>981</sup> **Appendix D**

<sup>982</sup> **Supplementary Documents**

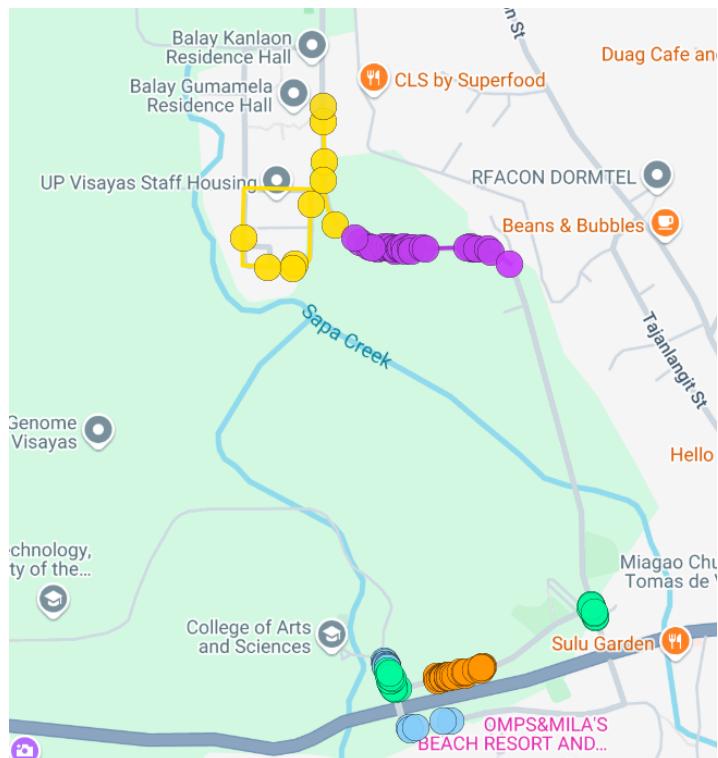


Figure D.1: Visualized pothole locations during the ground truth data collection within the UPV campus.

January 31, 2025

**ENGR. ETHEL B. MORALES**  
 OIC – District Engineer  
 Department of Public Works and Highways (DPWH)  
 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*

  
**PERSEROCE CATALAN**  
*Team Member*

Figure D.2: Letter requesting validation of data collection procedures.

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

RECEIVED

January 31, 2025

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

UP VISAYAS  
(through channels) OFFICE OF THE CHANCELLOR

NOA 25-0226  
REF. NO. FEB 01 2025

Dear Vice Chancellor Bagsit,  
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,

*CLEMENT O. CAMPASANO*  
CLEMENT O. CAMPASANO  
CHANCELLOR

*Benz Vrianne Beleber*  
Benz Vrianne Beleber  
Team Member

*Perserose Catalan*  
Perserose Catalan  
Team Leader

*Kent Christian A. Castor*  
Kent Christian A. Castor  
Chairperson, DPM

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

*Kristian Lyle Sencil*  
Kristian Lyle Sencil  
Team Member

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

*09614415782*

**RECOMMENDING APPROVAL/DISAPPROVAL:**  
PEPITO R. FERNANDEZ JR.,  
Dean, College of Arts & Sciences  
UP VISAYAS

**RECOMMENDING APPROVAL:**  
31 JAN 2025  
REF NO. PRF 2025-003

Figure D.3: Letter requesting permission for ground truth data collection within the UPV campus.

January 17, 2025

**ENGR. SANNY BOY O. OROPEL, CES E**  
 Regional Director  
 Department of Public Works and Highways (DPWH)  
 Regional Office VI  
 Fort San Pedro, Iloilo City

Dear Engr. Oropel:

Greetings of Honor and Excellence!



We are Computer Science students from the University of the Philippines Visayas, currently working on a special problem for our CMSC 198.2 course. Our project focuses on developing a system for the depth estimation of potholes.

In line with this, we kindly request an opportunity to interview representatives from your esteemed agency to gain insights into the process of verifying our research data, including ground truth data. This will greatly assist us in ensuring that our system adheres to the standards and requirements upheld by your agency.

We would also greatly appreciate your advice on the specific procedures, documentation, and requirements necessary for submitting our data for review. Your expertise and assistance would be invaluable to the success of our project, and we are eager to learn from your knowledge and experience.

Your support will not only guide our research but also ensure our system could one day be a valuable tool in improving road maintenance practices. We understand the importance of these standards, and we assure you that any information provided will be strictly used for academic purposes.

We sincerely hope that you accept our humble request, as it will play a crucial role in our project.

Thank you very much for your time and consideration. We look forward to your positive response.

Sincerely,

  
 BENZ VRIANNE BELEBER

  
 KRISTIAN LYLE SENCIL

  
 PERSE ROSE P. CATALAN

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

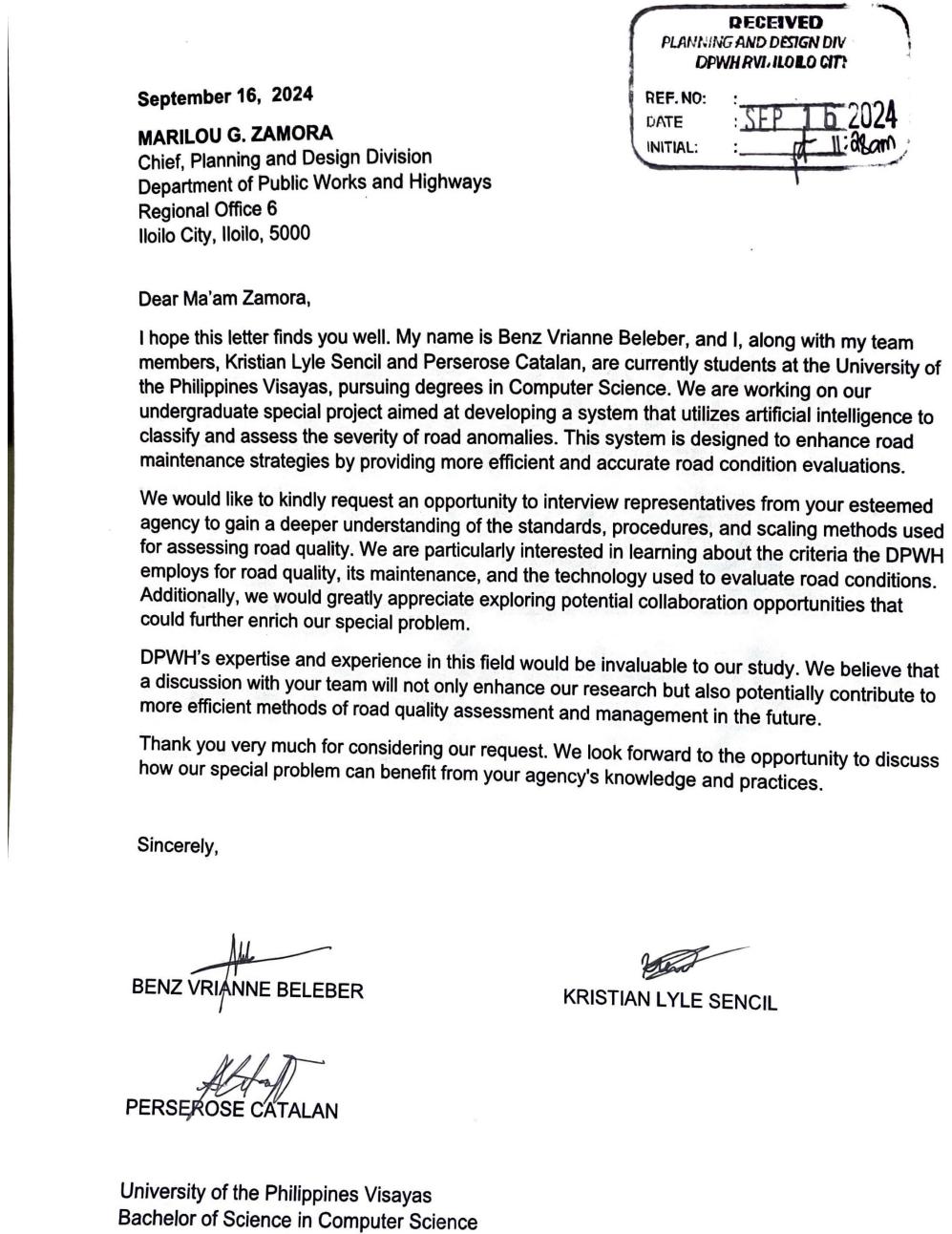


Figure D.5: Letter requesting an interview with DPWH representatives for the standard operating procedures of the agency for assessing road quality.



UNIVERSITY OF THE PHILIPPINES VISAYAS  
COLLEGE OF ARTS AND SCIENCES  
DIVISION OF PHYSICAL SCIENCES AND MATHEMATICS

**POTHOLE MEASUREMENT PROCEDURAL MANUAL**

Prepared by:

Benz Vrianne BELEBER  
Perserose CATALAN  
Kristian Lyle SENCIL



Figure D.6: Validated pothole measurement procedural manual, reviewed by Engr. Ethel B. Morales, District Engineer, DPWH 1st District Engineering Office.



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

---

**I. PURPOSE**

This manual is developed as part of the special project *Defectra: Road Defect Severity Assessment and Classification* at the University of the Philippines Visayas. The study focuses on evaluating road defects, particularly potholes, by assessing their severity based on the depth measurements. This manual establishes a standardized procedure for measuring pothole depth, ensuring consistency, accuracy, and compliance with engineering best practices.

**II. SCOPE**

This procedure applies to research personnel, faculty members, and students involved in pothole assessment and measurement activities within the University of the Philippines Visayas and designated research sites.

**III. PROCEDURE**

**a. Preparation and Safety Measures**

- Ensure the availability and functionality of required equipment, including a GPS-enabled camera for location tagging, rulers, and measuring tape.
- Wear appropriate personal protective equipment (PPE), such as reflective vests and hard hats, to ensure visibility and safety.
- Set up early warning device if working on active roads to alert motorists and pedestrians
- Ensure all equipment is in optimal working condition before use.

Figure D.7: Second page of the pothole measurement procedural manual



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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.8: Third page of the pothole measurement procedural manual



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DIVISION OF PHYSICAL SCIENCES AND MATHEMATICS**

---

**c. Data Documentation**



- Capture photographs of the pothole from multiple angles, ensuring that measurement tools are visible in the images for scale reference.
- Record depth measurements alongside GPS coordinates for accurate geotagging.
- Save the data in organized format and proper identification using unique identifiers for easy tracking and analysis.

**IV. SAFETY CONSIDERATIONS**

Compliance with university guidelines on safety is mandatory throughout the measurement process. Ensuring safety during pothole measurement is essential to protect personnel and road users. All team members must wear the required personal protective equipment (PPE), including reflective vests and hard hats, to enhance visibility and minimize risk. Researchers must remain aware of their surroundings and avoid working in high-traffic areas without proper traffic control measures.

Figure D.9: Fourth page of the pothole measurement procedural manual



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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.10: Fifth page of the pothole measurement procedural manual