

<sup>1</sup>  
<sup>2</sup>  
**ROAD DEFECT SEVERITY ASSESSMENT AND  
CLASSIFICATION**

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<sup>8</sup>  
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## Approval Sheet

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The Division of Physical Sciences and Mathematics, College of Arts and  
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22

### ROAD DEFECT SEVERITY ASSESSMENT AND 23 CLASSIFICATION

24

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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 unwavering love, patience, and support have been the foundation of their academic  
37        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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43        moments — this work is for them.

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## Abstract

69 Road surveying is a crucial part of the maintenance processes of roads in the  
70 Philippines that is carried out by the Department of Public Works and Highways.  
71 However, the current process of road surveying is time consuming which delays  
72 much needed maintenance operations. Existing studies involving automated pot-  
73 hole detection lack integration of the pothole's depth in assessing its severity which  
74 is essential for automating road surveying procedures. A system that incorporates  
75 estimated depth information in assessing pothole severity is developed in order to  
76 automate the manual process of depth measurement and severity assessment in  
77 road surveying. For depth estimation, stereo vision is favorable in this context  
78 as depth may be estimated through the disparity generated by a stereo pair. In  
79 obtaining a stereo view of the potholes, the StereoPi V2 is utilized along with  
80 some modifications that would make it eligible for outdoor use. To address cam-  
81 era imperfections, a fitted inverse model was applied to improve the accuracy of  
82 depth estimates. Linear regression analysis revealed a strong positive correlation  
83 ( $R = 0.978$ ) between estimated and actual depths, with the system measuring  
84 pothole depths mostly within 3 cm of the true values.

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

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<sup>158</sup> **Chapter 1**

<sup>159</sup> **Introduction**

<sup>160</sup> **1.1 Overview**

<sup>161</sup> According to the National Road Length by Classification, Surface Type, and Con-  
<sup>162</sup> dition of the Department of Public Works and Highways (DPWH), as of October  
<sup>163</sup> 2022 approximately 98.97% of roads in the Philippines is paved which is either  
<sup>164</sup> made of concrete or asphalt (DPWH, 2022). Since the DPWH is an institution  
<sup>165</sup> under the government, it is paramount to maintain such roads in order to avoid  
<sup>166</sup> accidents and congested traffic situations especially in heavily urbanized areas  
<sup>167</sup> where there are a lot of vehicles.

<sup>168</sup> In an interview with the Road Board of DPWH Region 6 it was stated that  
<sup>169</sup> road condition assessments are mostly done manually with heavy reliance on en-  
<sup>170</sup> gineering judgment (DPWH Regional Office 6 Road Board, Personal Interview.  
<sup>171</sup> 2024). In addition, manual assessment of roads is also time consuming which  
<sup>172</sup> leaves maintenance operations to wait for lengthy assessments (J. Chua, Personal  
<sup>173</sup> Interview. 16 September 2024). In a study conducted by Ramos, Dacanay, and  
<sup>174</sup> Bronuela-Ambrocio (2023), it was found that the Philippines' current method of  
<sup>175</sup> manual pavement surveying is considered as a gap since it takes an average of  
<sup>176</sup> 2-3 months to cover a 250 km road as opposed to a 1 day duration in the Aus-  
<sup>177</sup> tralian Road Research Board for the same road length. Ramos et al. (2023)  
<sup>178</sup> recommended that to significantly improve efficiency of surveying methods and  
<sup>179</sup> data gathering processes, automated survey tools are to be employed. It was also  
<sup>180</sup> added that use of such automated, surveying tools can also guarantee the safety  
<sup>181</sup> of road surveyors.

<sup>182</sup> If the process of assessment on the severity of road defects can be automated

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

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

## 200 1.2 Problem Statement

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

## <sup>220</sup> 1.3 Research Objectives

### <sup>221</sup> 1.3.1 General Objective

<sup>222</sup> This special problem aims to develop a system that accurately estimates the depth  
<sup>223</sup> of potholes on road surfaces by using image analysis, depth measurement tech-  
<sup>224</sup> nologies, and computer vision techniques. The system will focus specifically on  
<sup>225</sup> measuring the depth of potholes to assess their severity, enabling faster and more  
<sup>226</sup> accurate road maintenance decisions, and there are no current practices in the  
<sup>227</sup> Philippines involving depth information of potholes in assessing their severity. In  
<sup>228</sup> accordance with the Department of Public Works and Highways Region 6's man-  
<sup>229</sup> ual for road maintenance, the study will classify potholes into different severity  
<sup>230</sup> levels such as low, medium, and high, which will be primarily based on their  
<sup>231</sup> depth. In order to measure the system's accuracy, linear regression in order to  
<sup>232</sup> represent the difference between the depth calculated from the disparity and the  
<sup>233</sup> actual depth of the pothole from ground truth data.

### <sup>234</sup> 1.3.2 Specific Objectives

<sup>235</sup> Specifically, this special problem aims:

- <sup>236</sup> 1. To collect high-quality stereo images of road surfaces that capture potholes  
<sup>237</sup> including their depth in favorable conditions
- <sup>238</sup> 2. To measure the accuracy of the system by comparing the depth measure-  
<sup>239</sup> ments against ground truth data collected from actual road inspections and  
<sup>240</sup> to utilize linear regression, root mean square error, and mean absolute error  
<sup>241</sup> as a metric for evaluation.
- <sup>242</sup> 3. To develop a prototype system that can detect and measure road potholes  
<sup>243</sup> from image input, analyze their depth, and assess their severity.

## <sup>244</sup> 1.4 Scope and Limitations of the Research

<sup>245</sup> This system focuses solely on detecting and assessing the severity of potholes  
<sup>246</sup> through image analysis and depth measurement technologies. The scope includes

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

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

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

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

## 265 1.5 Significance of the Research

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

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

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

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

<sup>280</sup>        *Future Researchers.* The special problem may serve as a baseline and guide of  
<sup>281</sup> researchers with the aim to pursue special problems similar or related to this.

<sup>282</sup> **Chapter 2**

<sup>283</sup> **Review of Related Literature**

<sup>284</sup> **2.1 Frameworks**

<sup>285</sup> This section of the chapter presents related frameworks that is considered essential  
<sup>286</sup> for the development of this special problem.

<sup>287</sup> **2.1.1 Depth Estimation**

<sup>288</sup> Depth estimation as defined by Sanz, Mezcua, and Pena (2012) is a set of processes  
<sup>289</sup> that aims to extract a representation of a certain scene's spatial composition.  
<sup>290</sup> Stereo vision is stated to be among the depth estimation strategies.

<sup>291</sup> **2.1.2 Image and Video Processing**

<sup>292</sup> Kumar (2024) defines image processing as a process of turning an image into its  
<sup>293</sup> digital form and extracting data from it through certain functions and operations.  
<sup>294</sup> Usual processes are considered to treat images as 2D signals wherein different  
<sup>295</sup> processing methods utilize these signals. Like image processing, RICHES Project  
<sup>296</sup> (2014) defines video processing as being able to extract information and data from  
<sup>297</sup> video footage through signal processing methods. However, in video processing  
<sup>298</sup> due to the diversity of video formats, compression and decompression methods  
<sup>299</sup> are often expected to be performed on videos before processing methods to either  
<sup>300</sup> increase or decrease bitrate.

### **301 2.1.3 Stereo Vision**

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

## **308 2.2 Related Studies**

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

### **312 2.2.1 Deep Learning Studies**

#### **313 Automated Detection and Classification of Road Anomalies 314 in VANET Using Deep Learning**

315  
316 In the study of Bibi et al. (2021) it was noted that identification of active road  
317 defects are critical in maintaining smooth and safe flow of traffic. Detection and  
318 subsequent repair of such defects in roads are crucial in keeping vehicles using  
319 such roads away from mechanical failures. The study also emphasized the growth  
320 in use of autonomous vehicles in research data gathering which is what the re-  
321 searchers utilized in data gathering procedures. With the presence of autonomous  
322 vehicles, this allowed the researchers to use a combination of sensors and deep  
323 neural networks in deploying artificial intelligence. The study aimed to allow au-  
324 tonomous vehicles to avoid critical road defects that can possibly lead to dangerous  
325 situations. Researchers used Resnet-18 and VGG-11 in automatic detection and  
326 classification of road defects. Researchers concluded that the trained model was  
327 able to perform better than other techniques for road defect detection. The study  
328 is able to provide the effectiveness of using deep learning models in training arti-  
329 ficial intelligence for road defect detection and classification. However, the study  
330 lacks findings regarding the severity of detected defects and incorporation of pot-  
331 hole depth in their model which are both crucial in automating manual procedures  
332 of road surveying in the Philippines.

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

**334**

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

**347 Assessing Severity of Road Cracks Using Deep Learning-  
348 Based Segmentation and Detection**

**349**

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

**363 Roadway pavement anomaly classification utilizing smart-  
364 phones and artificial intelligence**

**365**

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

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

### 380 **2.2.2 Machine Learning Studies**

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

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

#### 400 **Road Surface Quality Monitoring Using Machine Learning 401 Algorithms**

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

<sup>411</sup> utilized in the classification of anomalies which was concluded by the researchers  
<sup>412</sup> to yield accurate results and are applicable on a larger scale of data. The study  
<sup>413</sup> of Singh et al. (2021) can be considered as an effective method in gathering data  
<sup>414</sup> about road conditions. However, it was stated in the study that relevant authori-  
<sup>415</sup> ties will be provided with maintenance operation and there is no presence of any  
<sup>416</sup> severity assessment in the study. This may cause confusion due to a lack of as-  
<sup>417</sup> sessment on what is the road condition that will require extensive maintenance or  
<sup>418</sup> repair.

<sup>419</sup> **2.2.3 Computer Vision Studies**

<sup>420</sup> **Stereo Vision Based Pothole Detection System for Improved**  
<sup>421</sup> **Ride Quality**

<sup>422</sup>

<sup>423</sup> In the study of Ramaiah and Kundu (2021) it was stated that stereo vision has  
<sup>424</sup> been earning attention due to its reliable obstacle detection and recognition. Fur-  
<sup>425</sup> thermore, the study also discussed that such technology would be useful in improv-  
<sup>426</sup> ing ride quality in automated vehicles by integrating it in a predictive suspension  
<sup>427</sup> control system. The proposed study was to develop a novel stereo vision based  
<sup>428</sup> pothole detection system which also calculates the depth accurately. However,  
<sup>429</sup> the study focused on improving ride quality by using the 3D information from  
<sup>430</sup> detected potholes in controlling the damping coefficient of the suspension system.  
<sup>431</sup> Overall, the pothole detection system was able to achieve 84% accuracy and is  
<sup>432</sup> able to detect potholes that are deeper than 5 cm. The researchers concluded  
<sup>433</sup> that such system can be utilized in commercial applications. However, it is also  
<sup>434</sup> worth noting that despite the system being able to detect potholes and measure  
<sup>435</sup> its depth, the overall severity of the pothole and road condition was not addressed.

## <sup>436</sup> 2.3 Chapter Summary

- <sup>437</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>440</sup> **Chapter 3**

<sup>441</sup> **Methodology**

<sup>442</sup> This chapter outlines the systematic approach that were taken to address the  
<sup>443</sup> problem of pothole depth estimation using StereoPi V2. The methodology is  
<sup>444</sup> divided into key phases: data collection, algorithm selection, design, testing and  
<sup>445</sup> experimentation, and challenges and limitations. Each phase will play a crucial  
<sup>446</sup> role in accurately classifying and assessing road defects. Each phase is essential  
<sup>447</sup> for accurately estimating the depth of potholes using StereoPi V2.

<sup>448</sup> **3.1 Research Activities**

<sup>449</sup> **3.1.1 Data Collection**

<sup>450</sup> The researchers conducted initial inquiries to understand the problem domain and  
<sup>451</sup> existing road maintenance practices. This phase included consulting the engineers  
<sup>452</sup> under the Road Maintenance Department of the government agency Department  
<sup>453</sup> of Public Works and Highways (DPWH). An interview with Engr. Jane Chua pro-  
<sup>454</sup> vided a comprehensive overview of the DPWH's road maintenance manual, which  
<sup>455</sup> was crucial in aligning this project with existing standards. This collaboration  
<sup>456</sup> with DPWH provided insights into road pothole classification standards, ensuring  
<sup>457</sup> that the collected data will align with industry standards. The DPWH manual  
<sup>458</sup> primarily focuses on the volume of detected potholes within a road segment as  
<sup>459</sup> a measure of severity. However, since depth is not explicitly measured in their  
<sup>460</sup> current procedures, the study will supplement this by referencing international  
<sup>461</sup> standards such as the Long-Term Pavement Performance (LTPP) classification  
<sup>462</sup> used in the United States (Miller et al., 2014). The LTPP categorizes potholes

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

#### 474 **3.1.1.1 Data Collection (Ground Truth Data)**

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

### 481 **3.1.2 Design, Testing, and Experimentation**

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

#### 484 **3.1.2.1 Depth Measurement**

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

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

<sup>494</sup> bration data, ensuring that the depth estimates reflect real-world distances accu-  
<sup>495</sup> rately within the effective operational range of the stereo camera setup.

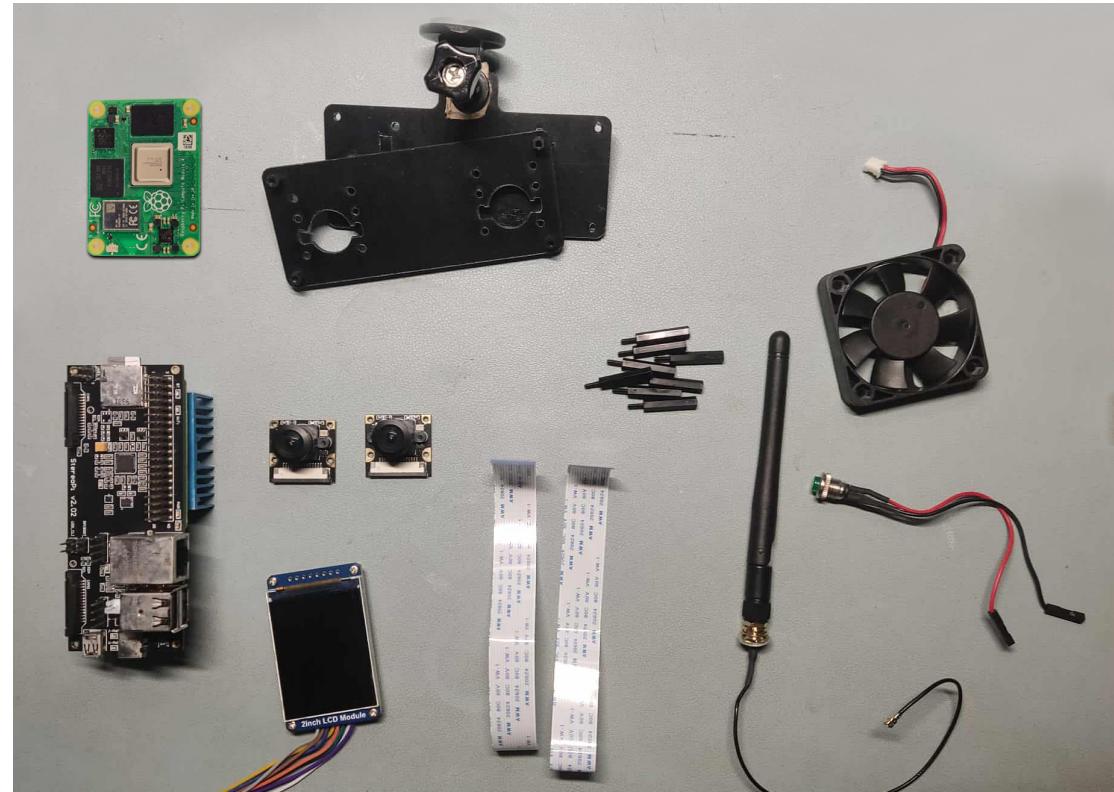
<sup>496</sup> **3.1.2.2 Severity Assessment**

<sup>497</sup> The estimated pothole depths were classified using the Long-Term Pavement Per-  
<sup>498</sup> formance (LTPP) depth thresholds, an internationally recognized framework for  
<sup>499</sup> pavement distress evaluation. This classification provides standardized criteria  
<sup>500</sup> to assess pothole severity objectively based on measured depth values. Specifi-  
<sup>501</sup> cally, potholes with depths less than 2.5 cm are categorized as low severity, those  
<sup>502</sup> between 2.5 cm and 5 cm as medium severity, and potholes exceeding 5 cm are  
<sup>503</sup> classified as high severity (Miller et al., 2014)

<sup>504</sup> **3.1.2.3 Materials and Equipment**

<sup>505</sup> The prototype system was constructed using several hardware components, which  
<sup>506</sup> include the items listed below and shown in Figure 3.1:

- <sup>507</sup> • StereoPi V2 Board
- <sup>508</sup> • Raspberry Pi Compute Module 4 (CM4)
- <sup>509</sup> • Dual RaspberryPi Camera Modules with Fisheye Lens
- <sup>510</sup> • 3D Printed Custom Housing
- <sup>511</sup> • 2-inch LCD Module
- <sup>512</sup> • Micro SD Card
- <sup>513</sup> • Antenna
- <sup>514</sup> • Momentary Push Button



515

Figure 3.1: Components used in the prototype development.

#### 516 3.1.2.4 Prototype Building

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

521

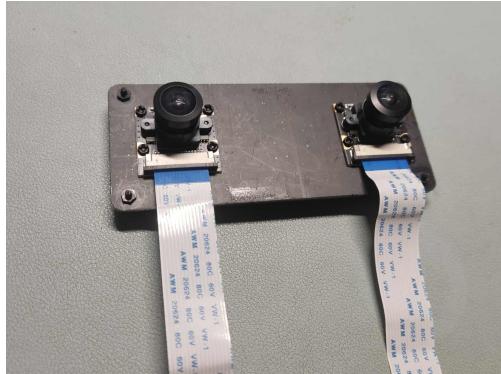


Figure 3.2: Dual RPi Camera Modules attached to the custom housing.

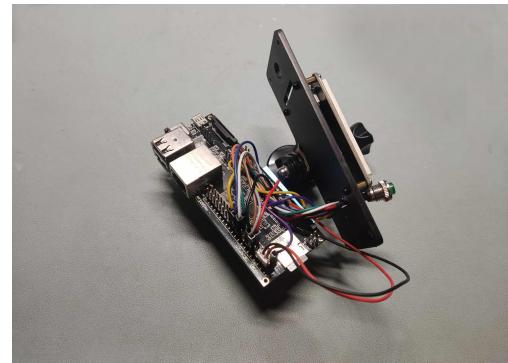


Figure 3.3: LCD Module connected to the StereoPi board.

522



Figure 3.4: The finished prototype.

### 523 3.1.2.5 Camera Calibration (Fisheye Distortion)

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

529



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

530

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

531

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.

538

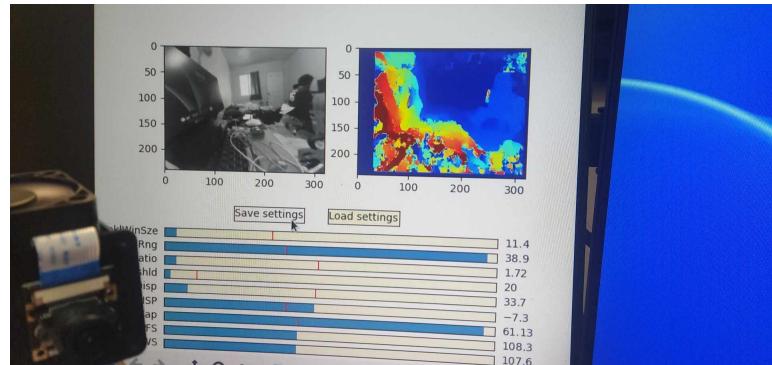


Figure 3.6: Parameter tuning process to achieve cleaner and more accurate disparity maps.

539

### 3.1.2.7 Initial Testing

540

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

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

545

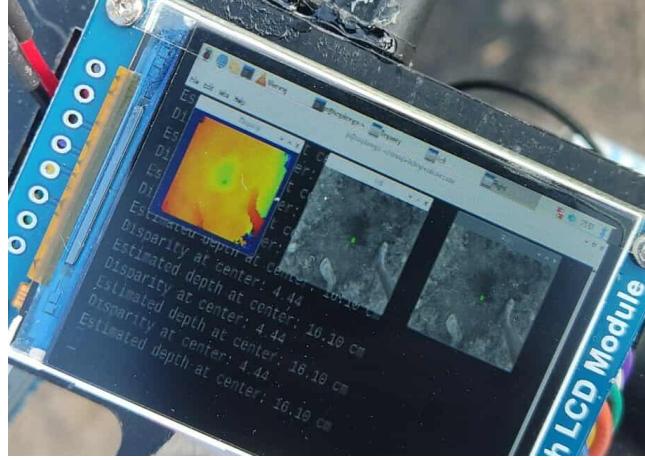


Figure 3.7: The system tested on a simulated pothole.

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

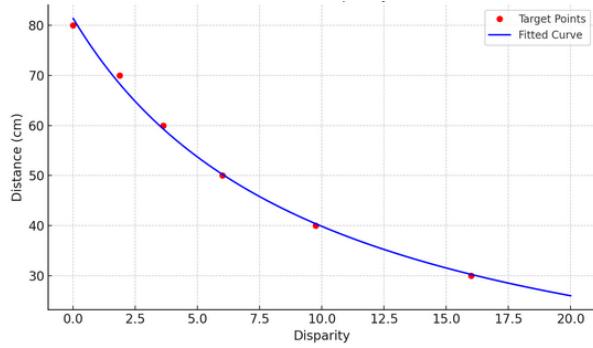


Figure 3.8: Inverse Model Fit to Disparity vs. Distance.

553 **3.1.2.8 Performance Metrics**

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

557 **3.1.2.9 Final Testing and Validation**

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

565 **3.1.2.10 Documentation**

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

570 **3.1.3 Challenges and Limitations**

571 **3.1.3.1 Camera Limitations**

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

579 **Chapter 4**

580 **Results and Discussion**

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

588 **4.1 System Calibration and Model Refinement**

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

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

593 where:

- 594 •  $f$  is the focal length in pixels,  
595 •  $B$  is the baseline distance between the two cameras,  
596 •  $d$  is the disparity.

597        However, preliminary observations revealed that the relationship between mea-  
598        sured disparity and depth was shifted from the ideal. Their relationship is in-  
599        herently nonlinear, specifically an inverse relationship (of the form  $y=1/x$ ). As  
600        disparity decreases, depth increases rapidly and nonlinearly. However, due to  
601        real-world factors such as lens distortion, imperfect calibration, stereo matching  
602        errors, and pixel quantization, the actual relationship between measured disparity  
603        and true depth often deviates from the theoretical ideal (Scharstein & Szeliski,  
604        2002).

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

608        An inverse function of the form:

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

609        where:

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

## 613        4.2 Testing Results

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

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

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

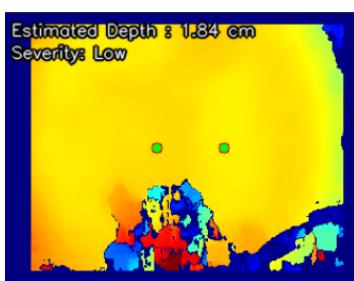


Figure 4.1: Disparity Map



Figure 4.2: Left Stereo Image



Figure 4.3: Right Stereo Image

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

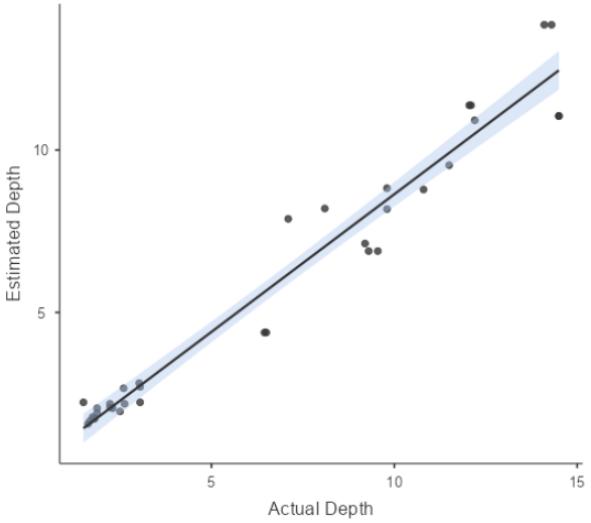


Figure 4.4: Linear Regression Fit Between Actual and Estimated Depth

### 636 4.3 Discussion

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

647 A strong positive correlation ( $R = 0.978$ ) and coefficient of determination ( $R^2$   
 648 = 0.956) indicate that the actual pothole depths strongly predict the estimated  
 649 values. The regression model's significant predictor ( $p < 0.001$ ) further supports  
 650 the robustness of the depth estimation approach. This level of accuracy and model  
 651 performance highlights the suitability of the StereoPi system for practical field  
 652 applications in pothole monitoring and maintenance prioritization. This finding  
 653 is significant because earlier machine learning-based road detection studies such as  
 654 those by Bibi et al. (2021) focused mostly on classifying the existence of defects,  
 655 not measuring their severity.

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

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

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

682 **Chapter 5**

683 **Conclusion**

684 This chapter provides conclusions based on the research findings from data collected on the development of a pothole depth estimation system using stereo 685 vision technology. It then presents recommendations for practice and suggestions 686 for further research.

688 **5.1 Summary**

689 This special project addressed the critical issue of road maintenance by developing 690 a system capable of estimating the depth of potholes to help prioritize repairs. 691 The purpose of the project was to create an automated method that not only 692 detects potholes but also assesses their severity based on depth, responding to 693 the current manual and slow road inspection practices. The researchers aimed to 694 collect high-quality images of potholes under varying conditions, to validate the 695 system's depth estimation accuracy using ground truth measurements and linear 696 regression analysis, and to build a working prototype using stereo vision that can 697 detect, measure, and assess potholes.

698 To achieve these objectives, a hardware prototype was built using the StereoPi 699 V2 board and Raspberry Pi Compute Module 4, equipped with dual fisheye-lens 700 cameras. Camera calibration was performed using a 9x6 checkerboard pattern 701 with known square sizes to correct for fisheye lens distortion and ensure proper 702 alignment of the stereo pair. After calibration, disparity map generation was 703 fine-tuned by adjusting block matching parameters to produce clearer and more 704 reliable disparity maps. Initial testing was conducted using simulated potholes 705 with known depths to verify the functionality of the system and identify the non-

<sup>706</sup> linear behavior present in stereo vision depth measurements. It was observed that  
<sup>707</sup> using the standard stereo depth formula led to inaccuracies, particularly at greater  
<sup>708</sup> distances.

<sup>709</sup> The calibrated system and fitted regression model were validated by comparing  
<sup>710</sup> the estimated depths with the manually measured depths. The findings showed  
<sup>711</sup> that the system was able to estimate pothole depths within approximately  $\pm 3$   
<sup>712</sup> cm of actual measurements, achieving a Mean Absolute Error (MAE) of 0.945 cm  
<sup>713</sup> and a Root Mean Square Error (RMSE) of 0.844 cm. A strong positive linear  
<sup>714</sup> relationship was observed between the estimated and actual depths ( $R = 0.978$ ,  
<sup>715</sup>  $R^2 = 0.956$ ).

## <sup>716</sup> 5.2 Conclusions

<sup>717</sup> The researchers conclude the following based on the findings:

- <sup>718</sup> • The system effectively captures and analyzes depth information from stereo  
<sup>719</sup> images, providing a viable method for automated pothole severity assess-  
<sup>720</sup> ment.
- <sup>721</sup> • Incorporating depth measurements significantly improves pothole repair pri-  
<sup>722</sup> oritization compared to traditional visual-only inspections, allowing main-  
<sup>723</sup> tenance decisions to be based on objective, measurable data.
- <sup>724</sup> • The system achieved an acceptable regression model fit, with a strong posi-  
<sup>725</sup> tive correlation ( $R = 0.978$ ) and a coefficient of determination ( $R^2 = 0.956$ ),  
<sup>726</sup> confirming that the depth estimates closely align with the ground truth  
<sup>727</sup> measurements. The system obtained satisfactory error metrics, with a Mean  
<sup>728</sup> Absolute Error (MAE) of 0.945 cm and a Root Mean Square Error (RMSE)  
<sup>729</sup> of 0.844 cm, indicating reliable performance for both pothole detection and  
<sup>730</sup> depth estimation tasks.
- <sup>731</sup> • The proposed approach fills a critical gap in current road maintenance prac-  
<sup>732</sup> tices, especially within the Philippine context where depth-based severity  
<sup>733</sup> classification is not yet systematically implemented.

<sup>734</sup> This special project has successfully developed a system that addresses the  
<sup>735</sup> problem of pothole severity assessment using depth measurement. The research  
<sup>736</sup> shows that stereo vision, even using accessible and affordable technology, holds  
<sup>737</sup> strong potential for future development in road maintenance automation. By

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

### 740 5.3 Recommendations for Practice

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

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

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

### 752 5.4 Suggestions for further research

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

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

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

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

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

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

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<sup>815</sup> **Appendix A**

<sup>816</sup> **Code Snippets**

<sup>817</sup> **Appendix B**

<sup>818</sup> **Resource Persons**

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<sup>838</sup> javellana.benjamin@dpwh.gov.ph

<sup>839</sup> **Appendix C**

<sup>840</sup> **Data Table and Stereo Pi Images**

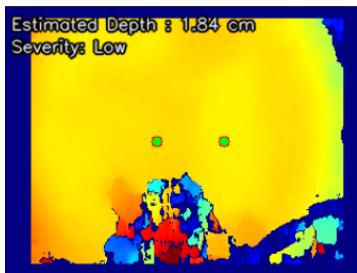


Figure C.1: Disparity Map



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>841</sup> **Appendix D**

<sup>842</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

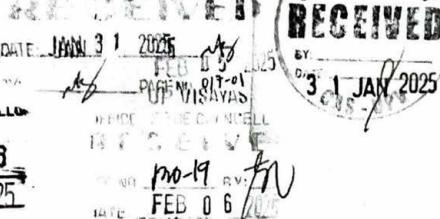
**Dr. Farisal U. Bagsit**  
*Vice Chancellor for Administration*

(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, DPM

*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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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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**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