

1      DEFECTRA: ROAD DEFECT SEVERITY ASSESSMENT  
2      AND CLASSIFICATION

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## Abstract

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

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

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<sup>103</sup> **Chapter 1**

<sup>104</sup> **Introduction**

<sup>105</sup> **1.1 Overview**

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

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

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

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

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

## 144 1.2 Problem Statement

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

## <sup>164</sup> 1.3 Research Objectives

### <sup>165</sup> 1.3.1 General Objective

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

### <sup>178</sup> 1.3.2 Specific Objectives

<sup>179</sup> Specifically, this special problem aims:

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

## <sup>188</sup> 1.4 Scope and Limitations of the Research

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

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

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

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

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

## 209 1.5 Significance of the Research

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

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

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

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

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

# <sup>226</sup> Chapter 2

## <sup>227</sup> Review of Related Literature

### <sup>228</sup> 2.1 Frameworks

<sup>229</sup> This section of the chapter presents related frameworks that is considered essential  
<sup>230</sup> for the development of this special problem.

#### <sup>231</sup> 2.1.1 Depth Estimation

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

#### <sup>235</sup> 2.1.2 Image and Video Processing

<sup>236</sup> Kumar (2024) defines image processing as a process of turning an image into its  
<sup>237</sup> digital form and extracting data from it through certain functions and operations.  
<sup>238</sup> Usual processes are considered to treat images as 2D signals wherein different  
<sup>239</sup> processing methods utilize these signals. Like image processing, RICHES Project  
<sup>240</sup> (2014) defines video processing as being able to extract information and data from  
<sup>241</sup> video footage through signal processing methods. However, in video processing  
<sup>242</sup> due to the diversity of video formats, compression and decompression methods  
<sup>243</sup> are often expected to be performed on videos before processing methods to either  
<sup>244</sup> increase or decrease bitrate.

### **2.1.3 Stereo Vision**

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

## **2.2 Related Studies**

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

### **2.2.1 Deep Learning Studies**

#### **257 Automated Detection and Classification of Road Anomalies 258 in VANET Using Deep Learning**

259  
260 In the study of Bibi et al. (2021) it was noted that identification of active road  
261 defects are critical in maintaining smooth and safe flow of traffic. Detection and  
262 subsequent repair of such defects in roads are crucial in keeping vehicles using  
263 such roads away from mechanical failures. The study also emphasized the growth  
264 in use of autonomous vehicles in research data gathering which is what the re-  
265 searchers utilized in data gathering procedures. With the presence of autonomous  
266 vehicles, this allowed the researchers to use a combination of sensors and deep  
267 neural networks in deploying artificial intelligence. The study aimed to allow au-  
268 tonomous vehicles to avoid critical road defects that can possibly lead to dangerous  
269 situations. Researchers used Resnet-18 and VGG-11 in automatic detection and  
270 classification of road defects. Researchers concluded that the trained model was  
271 able to perform better than other techniques for road defect detection. The study  
272 is able to provide the effectiveness of using deep learning models in training arti-  
273 ficial intelligence for road defect detection and classification. However, the study  
274 lacks findings regarding the severity of detected defects and incorporation of pot-  
275 hole depth in their model which are both crucial in automating manual procedures  
276 of road surveying in the Philippines.

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

278

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

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

293

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

307 **Roadway pavement anomaly classification utilizing smart-  
308 phones and artificial intelligence**

309

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

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

### 324 **2.2.2 Machine Learning Studies**

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

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

#### 344 **Road Surface Quality Monitoring Using Machine Learning 345 Algorithms**

346  
347 The study of Singh, Bansal, Kamal, and Kumar (2021) aimed to utilize machine  
348 learning algorithms in classifying road defects as well as predict their locations.  
349 Another implication of the study was to provide useful information to commuters  
350 and maintenance data for authorities regarding road conditions. The researchers  
351 gathered data using various methods such as smartphone GPS, gyroscopes, and  
352 accelerometers. (Singh et al., 2021) also argued that early existing road monitoring  
353 models are unable to predict locations of road defects and are dependent  
354 on fixed roads and static vehicle speed. Neural and deep neural networks were

355 utilized in the classification of anomalies which was concluded by the researchers  
356 to yield accurate results and are applicable on a larger scale of data. The study  
357 of Singh et al. (2021) can be considered as an effective method in gathering data  
358 about road conditions. However, it was stated in the study that relevant authori-  
359 ties will be provided with maintenance operation and there is no presence of any  
360 severity assessment in the study. This may cause confusion due to a lack of as-  
361 sessment on what is the road condition that will require extensive maintenance or  
362 repair.

363 **2.2.3 Computer Vision Studies**

364 **Stereo Vision Based Pothole Detection System for Improved**  
365 **Ride Quality**

366

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

## 380 2.3 Chapter Summary

- 381 The reviewed literature involved various techniques and approaches in road anomaly  
 382 detection and classification. These approaches are discussed and summarized below along with their limitations and research gaps.

<b>Study</b>	<b>Technology/ Techniques Used</b>	<b>Key Findings</b>	<b>Limitations</b>
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>384</sup> **Chapter 3**

<sup>385</sup> **Methodology**

<sup>386</sup> This chapter outlines the systematic approach that were taken to address the  
<sup>387</sup> problem of pothole depth estimation using StereoPi V2. The methodology is  
<sup>388</sup> divided into key phases: data collection, algorithm selection, design, testing and  
<sup>389</sup> experimentation, and challenges and limitations. Each phase will play a crucial  
<sup>390</sup> role in accurately classifying and assessing road defects. Each phase is essential  
<sup>391</sup> for accurately estimating the depth of potholes using StereoPi V2.

<sup>392</sup> **3.1 Research Activities**

<sup>393</sup> **3.1.1 Data Collection**

<sup>394</sup> The researchers conducted initial inquiries to understand the problem domain and  
<sup>395</sup> existing road maintenance practices. This phase included consulting the engineers  
<sup>396</sup> under the Road Maintenance Department of the government agency Department  
<sup>397</sup> of Public Works and Highways (DPWH). An interview with Engr. Jane Chua pro-  
<sup>398</sup> vided a comprehensive overview of the DPWH's road maintenance manual, which  
<sup>399</sup> was crucial in aligning this project with existing standards. This collaboration  
<sup>400</sup> with DPWH provided insights into road pothole classification standards, ensuring  
<sup>401</sup> that the collected data will align with industry standards. The DPWH manual  
<sup>402</sup> primarily focuses on the volume of detected potholes within a road segment as  
<sup>403</sup> a measure of severity. However, since depth is not explicitly measured in their  
<sup>404</sup> current procedures, the study will supplement this by referencing international  
<sup>405</sup> standards such as the Long-Term Pavement Performance (LTPP) classification  
<sup>406</sup> used in the United States. The LTPP categorizes potholes based on depth thresh-

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

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

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

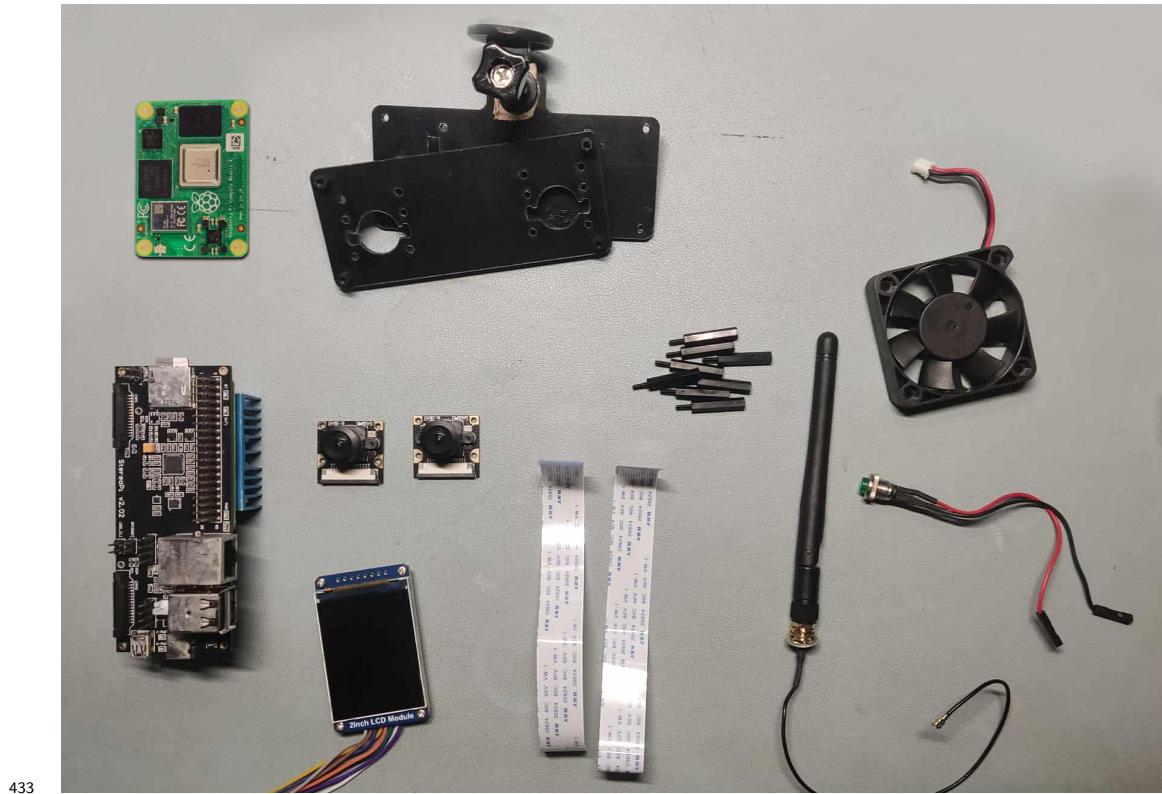
#### 3.1.2 Algorithm Selection

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

#### 3.1.3 Design, Testing, and Experimentation

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

432    **3.1.3.1 Materials and Equipment**



433

Figure 3.1: Components used in the prototype development.

434    The prototype system was constructed using the following materials and com-  
435    ponents:

- 436    • StereoPi V2 Board
- 437    • Raspberry Pi Compute Module 4 (CM4)
- 438    • Dual RaspberryPi Camera Modules with Fisheye Lens
- 439    • 3D Printed Custom Housing
- 440    • 2-inch LCD Module
- 441    • Micro SD Card
- 442    • Antenna
- 443    • Momentary Push Button

444 **3.1.3.2 Prototype Building**

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

449

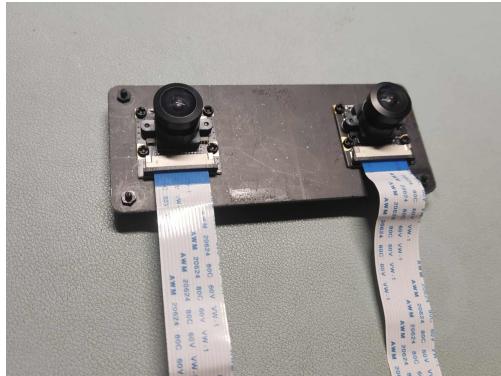


Figure 3.2: Dual RPi Camera Modules attached to the custom housing.

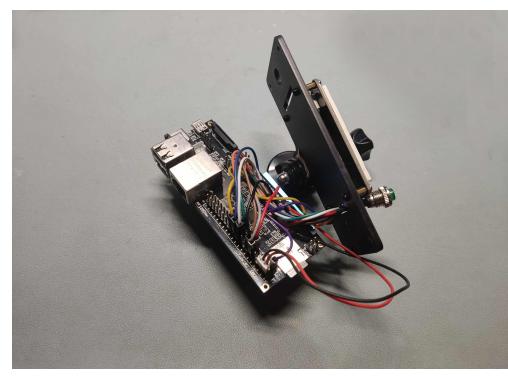


Figure 3.3: LCD Module connected to the StereoPi board.

450

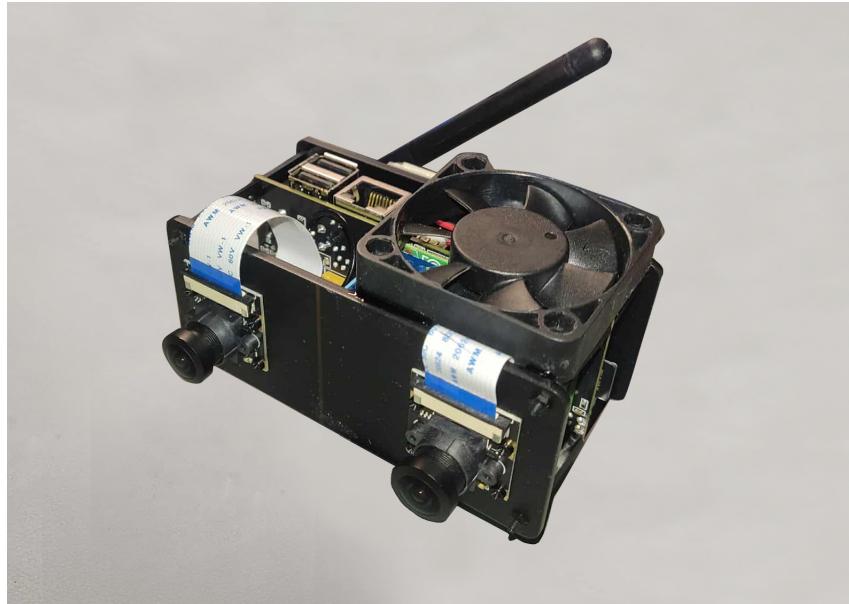


Figure 3.4: The finished prototype.

451 **3.1.3.3 Camera Calibration (Fisheye Distortion)**

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

457

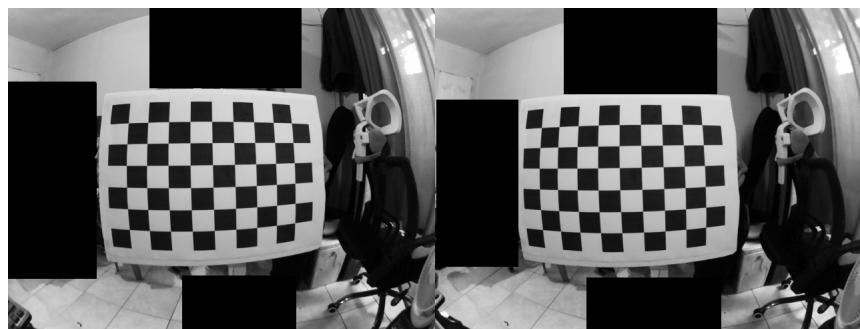


Figure 3.5: Calibration process with a checkerboard to correct fisheye lens distortion.

458 **3.1.3.4 Camera Calibration (Disparity Map Fine-tuning)**

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

466

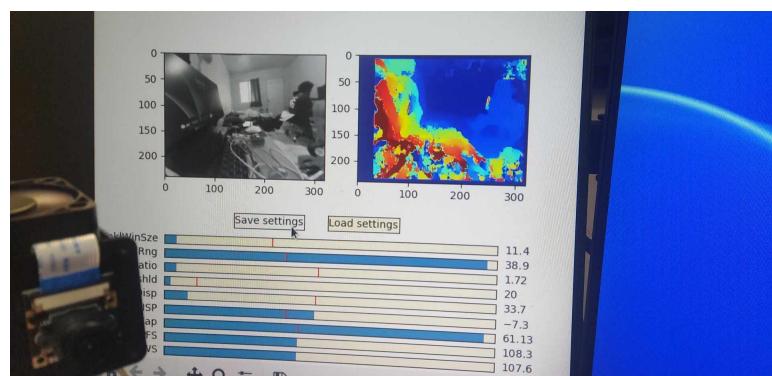


Figure 3.6: Parameter tuning process to achieve cleaner and more accurate disparity maps.

<sup>467</sup> **3.1.3.5 Initial Testing**

<sup>468</sup> Initial testing was conducted to verify the functionality and basic accuracy of the  
<sup>469</sup> stereoscopic camera system in a controlled environment. Artificial potholes with  
<sup>470</sup> known depths were created to simulate varying real-world scenarios. The system  
<sup>471</sup> captured disparity maps, and estimated depths were computed using the standard  
<sup>472</sup> stereo camera depth formula.

<sup>473</sup>

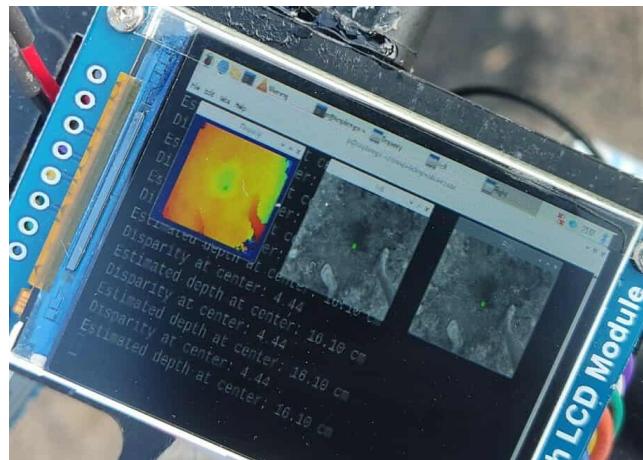


Figure 3.7: The system tested on a simulated pothole.

<sup>474</sup> However, the results revealed a non-linear relationship between the computed  
<sup>475</sup> disparity values and the actual distances. This discrepancy indicated that the  
<sup>476</sup> traditional depth estimation method was insufficient for the current setup. To  
<sup>477</sup> address this, the researchers collected multiple data points and correlating known  
<sup>478</sup> distances to their respective disparity readings and fitted an inverse model to  
<sup>479</sup> better represent the system's behavior (see Figure 4.4). This updated disparity-  
<sup>480</sup> to-depth model was subsequently used in the final testing phase.

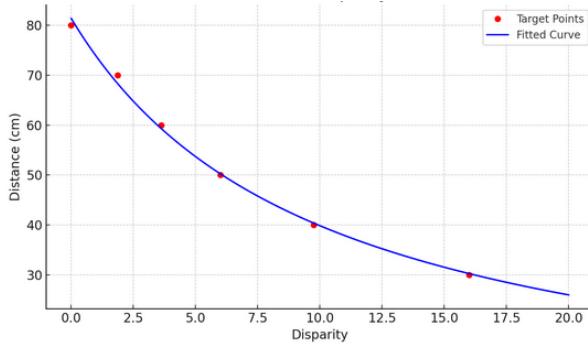


Figure 3.8: Inverse Model Fit to Disparity vs. Distance.

#### **481 3.1.3.6 Performance Metrics**

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

#### **485 3.1.3.7 Final Testing and Validation**

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

#### **493 3.1.3.8 Documentation**

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

498 **3.1.4 Challenges and Limitations**

499 **3.1.4.1 Camera Limitations**

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

507 **3.2 Calendar of Activities**

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

Table 3.1: Timetable of Activities for 2024

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

Table 3.2: Timetable of Activities for 2025

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

# 510 Chapter 4

## 511 Preliminary Results/System 512 Prototype

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

### 520 4.1 System Calibration and Model Refinement

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

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

525 where:

- 526 •  $f$  is the focal length in pixels,
- 527 •  $B$  is the baseline distance between the two cameras,

- 528     •  $d$  is the disparity.

529     However, preliminary observations revealed that the relationship between measured disparity and depth was shifted from the ideal. Their relationship is inherently nonlinear, specifically an inverse relationship (of the form  $y=1/x$ ). As disparity decreases, depth increases rapidly and nonlinearly. However, due to real-world factors such as lens distortion, imperfect calibration, stereo matching errors, and pixel quantization, the actual relationship between measured disparity and true depth often deviates from the theoretical ideal (Scharstein & Szeliski, 536 2002).

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

540     An inverse function of the form:

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

541     where:

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

## 545     4.2 Model Refinement Using Regression

546     The regression analysis produced the following model parameters:

- 547     •  $a = \dots$   
548     •  $b = \dots$

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

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

Table 4.1: Performance Metrics for the Regression Model

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

### 553 4.3 Error Analysis

554 Despite the improvements, minor estimation errors remained. These errors were  
 555 primarily attributed to:

- 556 • Low-light imaging conditions affecting disparity computation,
- 557 • Shallow potholes with depths less than 1 cm, where disparity resolution  
 558 becomes a limiting factor,
- 559 • Perspective distortion when the stereo camera was not parallel to the ground  
 560 plane.

### 561 4.4 Testing Results

562 Following calibration, actual potholes located around the University of the Philip-  
 563 pines Visayas (UPV) campus were tested. The ground truth depths of the potholes  
 564 were measured manually and compared with the depths estimated by the camera.  
 565 Based on the results, the StereoPi camera was able to estimate the depths fairly  
 566 close to the ground truth values. The smallest difference was seen in Pothole 5,  
 567 where the estimated depth was only 0.24 cm away from the ground truth. The  
 568 largest difference was found in Pothole 1, where the error was 3.45 cm. For the  
 569 other potholes, the differences were 0.67 cm for Pothole 2, 2.07 cm for Pothole  
 570 3, and 2.66 cm for Pothole 4. Most of the time, the camera's estimated depths  
 571 were only off by about one to three centimeters. Table 4.2 shows the comparison  
 572 between the manually measured ground truth depths and the depths estimated  
 573 by the StereoPi camera for each simulated pothole.

Table 4.2: Ground Truth and StereoPi Depth Measurements

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

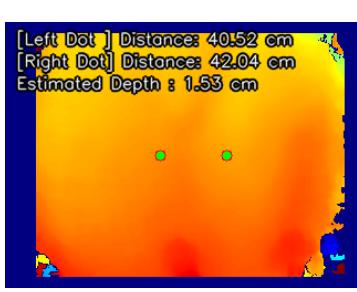


Figure 4.1: Disparity Map

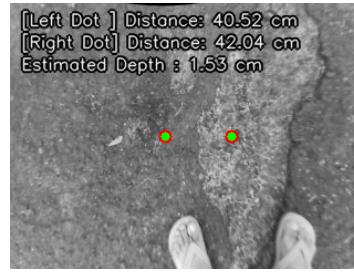


Figure 4.2: Left Stereo Image



Figure 4.3: Right Stereo Image

## 574 4.5 Discussion

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

R	R <sup>2</sup>	Root Mean Square Error	Mean Absolute Error
0.937	0.878	1.19	1.82

Table 4.3: Linear Regression Model for Pothole Depth Estimation

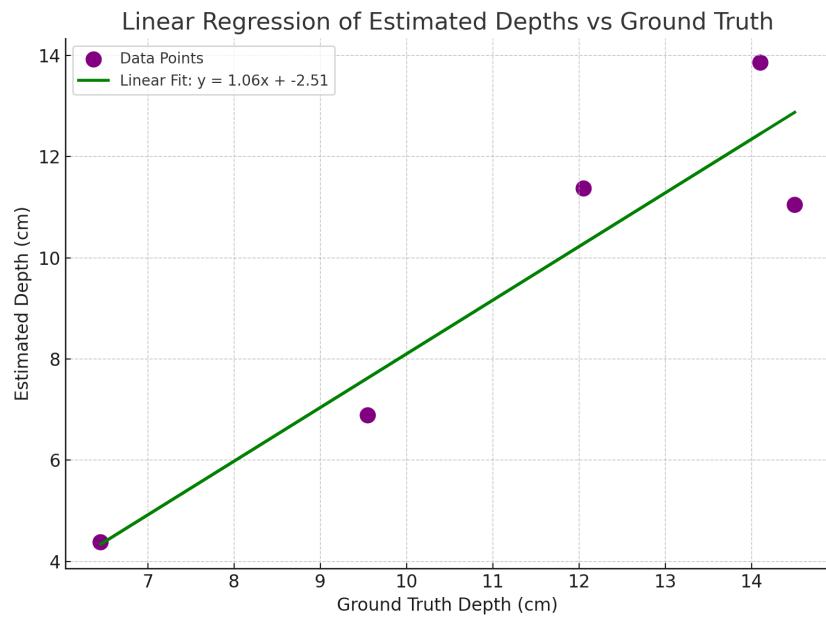


Figure 4.4: Inverse Model Fit to Disparity vs. Distance.

# <sup>583</sup> Chapter 5

## <sup>584</sup> Summary, Conclusions, <sup>585</sup> Discussion, and <sup>586</sup> Recommendations

<sup>587</sup> This chapter provides conclusions based on the research findings from data col-  
<sup>588</sup> lected on the development of a pothole depth estimation system using stereo vision  
<sup>589</sup> technology. It also presents a discussion and recommendations for future research.  
<sup>590</sup> This chapter reviews the purpose of the study, research questions, related liter-  
<sup>591</sup> ature, methodology, and findings. It then presents the conclusions, a discussion  
<sup>592</sup> of the results, recommendations for practice, suggestions for further research, and  
<sup>593</sup> the final conclusion of the study.

### <sup>594</sup> 5.1 Summary

<sup>595</sup> This special project addressed the critical issue of road maintenance by developing  
<sup>596</sup> a system capable of estimating the depth of potholes to help prioritize repairs.  
<sup>597</sup> The purpose of the project was to create an automated method that not only  
<sup>598</sup> detects potholes but also assesses their severity based on depth, responding to  
<sup>599</sup> the current manual and slow road inspection practices. The researchers aimed to  
<sup>600</sup> collect high-quality images of potholes under varying conditions, to validate the  
<sup>601</sup> system's depth estimation accuracy using ground truth measurements and linear  
<sup>602</sup> regression analysis, and to build a working prototype using stereo vision that can  
<sup>603</sup> detect, measure, and assess potholes.

<sup>604</sup> To achieve these objectives, a hardware prototype was built using the StereoPi

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

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

## 622 5.2 Conclusions

623 The researchers conclude the following based on the findings:

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

639 classification is not yet systematically implemented.

### 640 5.3 Discussion

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

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

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

665 The system achieved a strong positive regression model fit ( $R = 0.937$ ,  $R^2$   
666 = 0.878) and satisfactory error measures (MAE = 1.82 cm, RMSE = 1.19 cm).  
667 These results confirm that stereo vision, when combined with simple regression  
668 modeling, can reliably estimate pothole depths. This finding is significant because  
669 earlier machine learning-based road detection studies (such as Bibi et al., 2021)  
670 focused mostly on classifying the existence of defects, not measuring their severity.

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

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

## 681 5.4 Recommendations for Practice

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

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

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

## 690 5.5 Suggestions for further research

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

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

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

<sup>704</sup> **5.6 Conclusion**

<sup>705</sup> This special project has successfully developed a system that addresses the prob-  
<sup>706</sup> lem of pothole severity assessment using depth measurement. The research shows  
<sup>707</sup> that stereo vision, even using accessible and affordable technology, holds strong  
<sup>708</sup> potential for future development in road maintenance automation. By building  
<sup>709</sup> upon the foundation laid by this project, future systems can become even more  
<sup>710</sup> accurate, efficient, and practical for real-world deployment.

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<sup>754</sup> **Appendix A**

<sup>755</sup> **Appendix Title**

<sup>756</sup> **Appendix B**

<sup>757</sup> **Resource Persons**

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