

1 DEFECTRA: ROAD DEFECT SEVERITY ASSESSMENT
2 AND CLASSIFICATION

3 A Special Problem Proposal
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Contents

21	1 Introduction	1
22	1.1 Overview	1
23	1.2 Problem Statement	2
24	1.3 Research Objectives	2
25	1.3.1 General Objective	2
26	1.3.2 Specific Objectives	2
27	1.4 Scope and Limitations of the Research	3
28	1.5 Significance of the Research	4
29	2 Review of Related Literature	5
30	2.1 Related Literature	5
31	2.1.1 Deep Learning	5
32	2.1.2 YOLOv5	5
33	2.1.3 Image and Video Processing	6
34	2.1.4 Stereo Vision	6
35	2.2 Related Studies	6
36	2.2.1 Automated Detection and Classification of Road Anomalies	
37	in VANET Using Deep Learning	6

38	2.2.2	Smartphones as Sensors for Road Surface Monitoring . . .	7
39	2.2.3	Road Anomaly Detection through Deep Learning Approaches	7
40	2.2.4	Road Surface Quality Monitoring Using Machine Learning	
41		Algorithms	8
42	2.2.5	Assessing Severity of Road Cracks Using Deep Learning-	
43		Based Segmentation and Detection	8
44	2.2.6	Roadway pavement anomaly classification utilizing smart-	
45		phones and artificial intelligence	9
46	2.2.7	Stereo Vision Based Pothole Detection System for Improved	
47		Ride Quality	9
48	2.3	Chapter Summary	10
49	3	Methodology	11
50	3.1	Research Activities	11
51	3.1.1	Data Collection	11
52	3.1.2	Algorithm Selection	12
53	3.1.3	Design, Testing, and Experimentation	12
54	3.1.4	Challenges and Limitations	14
55	3.2	Calendar of Activities	15
56	A	Resource Persons	18

57 List of Tables

<small>58</small>	2.1	Comparison of Related Studies on Road Anomaly Detection using	
<small>59</small>		Deep Learning Techniques and Stereo Vision	10
<small>60</small>	3.1	Timetable of Activities for 2024	15
<small>61</small>	3.2	Timetable of Activities for 2025	15

Chapter 1

Introduction

1.1 Overview

According to the National Road Length by Classification, Surface Type, and Condition of the Department of Public Works and Highways (DPWH), as of October 2022 approximately 98.97

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

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

87 1.2 Problem Statement

88 Roads support almost every aspect of daily life, from providing a way to transport
89 goods and services to allowing people to stay connected with their communities.
90 However, road defects such as cracks and potholes damage roads over time, and
91 they can increase accident risks and affect the overall transportation. The current
92 way of inspecting the roads for maintenance is often slow as it is done manually,
93 which makes it harder to detect and fix defects early. The delay in addressing
94 these problems can lead to even worse road conditions (J. Chua, Personal Inter-
95 view. 16 September 2024). There are several research studies into automated
96 road defect classification that have advanced in recent years but most of them
97 focus on identifying the types of defects rather than assessing their severity or
98 characteristics like depth. Without reliable data on the depth of the defect, road
99 maintenance authorities may underestimate the severity of certain defects. To ad-
100 dress these challenges, advancements are needed across various areas. An effective
101 solution should not only detect and classify road defects but also measure their
102 severity to better prioritize repairs. Failing to address this problem will require
103 more extensive repairs for damaged roads, which raises the cost and strains the
104 budget. Additionally, road maintenance would still be slow and cause disruptions
105 in daily activities. Using an automated system that accurately detects, classifies,
106 and assess the severity of road defects by incorporating depth are necessary to
107 efficiently monitor road quality.

108 1.3 Research Objectives

109 1.3.1 General Objective

110 This special problem aims to develop an automated system that will accurately
111 detect and assess the severity of potholes on road surfaces by using image ana-
112 lysis, depth measurement technologies, and a combination of machine learning and
113 computer vision techniques. The system will focus on measuring the depth of pot-
114 holes to assess their severity, enabling faster and more accurate road maintenance
115 decisions.

116 1.3.2 Specific Objectives

117 Specifically, this special problem aims:

- 118 1. To collect high-quality images of road surfaces that capture potholes includ-
119 ing their depth in various lighting and weather conditions.
- 120 2. To develop and train a machine learning model to detect and assess the
121 severity of potholes from images.
- 122 3. To measure the accuracy of the system by comparing the depth measure-
123 ments against ground truth data collected from actual road inspections
- 124 4. To develop a prototype system that can detect and measure road potholes
125 from image input, analyze their depth, and assess their severity.

126 1.4 Scope and Limitations of the Research

127 This system will focus solely on detecting and assessing the severity of potholes
128 through image analysis and depth measurement technologies. The scope includes
129 the collection of pothole images using cameras and depth-sensing tools under
130 various lighting and weather conditions, ensuring the data captures real-world
131 variations. High-quality and diverse image datasets will be crucial for training
132 the model to accurately assess pothole severity based on depth.

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

138 The machine learning model developed will focus exclusively on detecting pot-
139 holes and assessing their severity through depth measurement. The accuracy of
140 the model's depth measurements will be evaluated by comparing them against
141 data collected from actual field inspections. However, this comparison will be
142 limited to selected sample sites, as collecting field data over a large area can be
143 time-consuming and resource-intensive.

144 Environmental factors such as lighting, road surface texture, and weather con-
145 ditions may impact the model's performance. The accuracy and reliability of the
146 model will depend on the quality and variety of the training dataset. Its ability
147 to generalize to unseen pothole images will need to be carefully validated.

148 1.5 Significance of the Research

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

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

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

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

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

Chapter 2

Review of Related Literature

2.1 Related Literature

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

2.1.1 Deep Learning

Kelleher (2019) states that deep learning is inclined on making large-scale neural networks geared towards creating data-driven decisions. Furthermore, it was also argued that deep learning is oriented towards large-scale, complex data.

2.1.2 YOLOv5

According to Solawetz (2024), YOLOv5 is a model from a family of computer vision models used for object detection. YOLOv5 is reported to perform comparably to state-of-the-art techniques. It is designed to extract features from raw input images, used primarily in training object detection models alongside various data augmentation techniques.

180 **2.1.3 Image and Video Processing**

181 Kumar (2024) defines image processing as a process of turning an image into its
182 digital form and extracting data from it through certain functions and operations.
183 Usual processes are considered to treat images as 2D signals wherein different
184 processing methods utilize these signals. Like image processing, Riches Resources
185 (2020) defines video processing as being able to extract information and data from
186 video footage through signal processing methods. However, in video processing
187 due to the diversity of video formats, compression and decompression methods
188 are often expected to be performed on videos before processing methods to either
189 increase or decrease bitrate.

190 **2.1.4 Stereo Vision**

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

197 **2.2 Related Studies**

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

201 **2.2.1 Automated Detection and Classification of Road Anoma-** 202 **lies in VANET Using Deep Learning**

203 In the study of Bibi et al. (2021) it was noted that identification of active road
204 defects are critical in maintaining smooth and safe flow of traffic. Detection and
205 subsequent repair of such defects in roads are crucial in keeping vehicles using
206 such roads away from mechanical failures. The study also emphasized the growth
207 in use of autonomous vehicles in research data gathering which is what the re-
208 searchers utilized in data gathering procedures. With the presence of autonomous

209 vehicles, this allowed the researchers to use a combination of sensors and deep
210 neural networks in deploying artificial intelligence. The study aimed to allow au-
211 tonomous vehicles to avoid critical road defects that can possibly lead to dangerous
212 situations. Researchers used Resnet-18 and VGG-11 in automatic detection and
213 classification of road defects. Researchers concluded that the trained model was
214 able to perform better than other techniques for road defect detection (Bibi et al.,
215 2021). The study is able to provide the effectiveness of using deep learning models
216 in training artificial intelligence for road defect detection and classification. How-
217 ever, the study lacks findings regarding the severity of detected defects which is
218 crucial in automating manual procedures of road surveying in the Philippines.

219 **2.2.2 Smartphones as Sensors for Road Surface Monitor-** 220 **ing**

221 In their study, Chapman, Li, and Sattar (2018) noted the rise of sensing capabil-
222 ities of smartphones which they utilized in monitoring road surface to detect and
223 identify anomalies. The researchers considered different approaches in detecting
224 road surface anomalies using smartphone sensors. One of which are threshold-
225 based approaches which was determined to be quite difficult due to several factors
226 that are affecting the process of determining the interval length of a window func-
227 tion in spectral analysis (Chapman et al., 2018). The researchers also utilized
228 a machine learning approach adapted from another study. It was stated that k-
229 means was used in classifying sensor data and in training the SVM algorithm. Due
230 to the requirement of training a supervised algorithm using a labeled sample data
231 was required before classifying data from sensors, the approach was considered
232 to be impractical for real-time situations (Chapman et al., 2018). In addition,
233 Chapman et al. (2018) also noted various challenges when utilizing smartphones
234 as sensors for data gathering such as sensors being dependent on the device's
235 placement and orientation, smoothness of captured data, and the speed of the
236 vehicle it is being mounted on. Lastly, it was also concluded that the accuracy
237 and performance of using smartphone sensors is challenging to compare due to
238 the limited data sets and reported algorithms.

239 **2.2.3 Road Anomaly Detection through Deep Learning** 240 **Approaches**

241 The study of Guo, Luo, and Lu (2020) aimed to utilize deep learning models in
242 classifying road anomalies. The researchers used three deep learning approaches
243 namely Convolutional Neural Network, Deep Feedforward Network, and Recurrent

244 Neural Network from data collected through the sensors in the vehicle’s suspension
245 system. In comparing the performance of the three deep learning approaches, the
246 researchers fixed some hyperparameters. Results revealed that the RNN model
247 was the most stable among the three and in the case of the CNN and DFN
248 models, the researchers suggested the use of wheel speed signals to ensure accuracy.
249 And lastly, the researchers concluded that the RNN model was best due to high
250 prediction performance with small set parameters (Guo et al., 2020).

251 **2.2.4 Road Surface Quality Monitoring Using Machine Learn-** 252 **ing Algorithms**

253 The study of Bansal et al. (2021) aimed to utilize machine learning algorithms in
254 classifying road defects as well as predict their locations. Another implication of
255 the study was to provide useful information to commuters and maintenance data
256 for authorities regarding road conditions. The researchers gathered data using
257 various methods such as smartphone GPS, gyroscopes, and accelerometers. Bansal
258 et al. (2021) also argued that early existing road monitoring models are unable
259 to predict locations of road defects and are dependent on fixed roads and static
260 vehicle speed. Neural and deep neural networks were utilized in the classification
261 of anomalies which was concluded by the researchers to yield accurate results and
262 are applicable on a larger scale of data (Bansal et al., 2021). The study of Bansal
263 et al. (2021) can be considered as an effective method in gathering data about
264 road conditions. However, it was stated in the study that relevant authorities will
265 be provided with maintenance operation and there is no presence of any severity
266 assessment in the study. This may cause confusion due to a lack of assessment on
267 what is the road condition that will require extensive maintenance or repair.

268 **2.2.5 Assessing Severity of Road Cracks Using Deep Learning-** 269 **Based Segmentation and Detection**

270 In the study of Ha, Kim, and Kim (2022), it was argued that the detection, clas-
271 sification, and severity assessment of road cracks should be automated due to the
272 bottleneck it causes during the entire process of surveying. For the study, the
273 researchers utilized SqueezeNet, U-Net, and MobileNet-SSD models for crack clas-
274 sification and severity assessment. Furthermore, the researchers also employed
275 separate U-nets for linear and area cracking cases. For crack detection, the re-
276 searchers followed the process of pre-processing, detection, classification. Dur-
277 ing preprocessing images were smoothed out using image processing techniques.
278 The researchers also utilized YOLOv5 object detection models for classification of

279 pavement cracking wherein the YOLOv51 model recorded the highest accuracy.
280 The researchers however stated images used for the study are only 2D images
281 which may have allowed higher accuracy rates. Furthermore, the researchers sug-
282 gest incorporating depth information in the models to further enhance results.

283 **2.2.6 Roadway pavement anomaly classification utilizing** 284 **smartphones and artificial intelligence**

285 The study of Christodoulou, Dimitrio, and Kyriakou (2016) presented what is con-
286 sidered as a low-cost technology which was the use of Artificial Neural Networks
287 in training a model for road anomaly detection from data gathered by smart-
288 phone sensors. The researchers were able to collect case study data using two-
289 dimensional indicators of the smartphone’s roll and pitch values. In the study’s
290 discussion, the data collected displayed some complexity due to acceleration and
291 vehicle speed which lead to detected anomalies being not as conclusive as planned.
292 The researchers also added that the plots are unable to show parameters that could
293 verify the data’s correctness and accuracy. Despite the setbacks, the researchers
294 still fed the data into the Artificial Neural Network that was expected to produce
295 two outputs which were “no defect” and “defect.” The method still yielded above
296 90% accuracy but due to the limited number of possible outcomes in the data
297 processing the researchers still needed to test the methodology with larger data
298 sets and roads with higher volumes of anomalies.

299 **2.2.7 Stereo Vision Based Pothole Detection System for** 300 **Improved Ride Quality**

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

2.3 Chapter Summary

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	YOLOv51 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

318 Chapter 3

319 Methodology

320 This chapter outlines the systematic approach that will be taken to address the
321 problem of classifying and assessing road defects using artificial intelligence. The
322 methodology will be divided into key phases: data collection, algorithm selection,
323 design, testing and experimentation, and challenges and limitations. Each phase
324 will play a crucial role in accurately classifying and assessing road defects. Each
325 phase will be essential for accurately classifying and assessing road defects.

326 3.1 Research Activities

327 3.1.1 Data Collection

328 The researchers conducted initial inquiries to understand the problem domain and
329 existing road maintenance practices. This phase included consulting the engineers
330 under the Road Maintenance Department of the government agency Department
331 of Public Works and Highways (DPWH). An interview with Engr. Jane Chua pro-
332 vided a comprehensive overview of the DPWH's road maintenance manual, which
333 was crucial in aligning this project with existing standards. This collaboration
334 with DPWH provided insights into road pothole classification standards, ensuring
335 that the collected data will align with industry standards. The researchers will
336 also manually annotate the pilot dataset based on these standards, ensuring local
337 relevance.

338 3.1.2 Algorithm Selection

339 Potential solutions, algorithms, and system architectures were discussed by the re-
340 searchers and the special problem adviser in this phase. These sessions, conducted
341 in class and virtually via Zoom, helped narrow down the overview of the system,
342 leading to the selection of the main architecture YOLOv5 for pothole detection
343 and Epipolar Spatio-Temporal Networks (ESTN) for depth estimation.

344 Pothole Detection

345 YOLOv5 was selected due to its high accuracy and ability to process images in
346 real-time, making it suitable for detecting road defects in dynamic environments.
347 Its architecture is optimized for speed and performance, which is crucial for large-
348 scale deployment in road inspections.

349 Severity Assessment

350 The Multi-view Depth Estimation using Epipolar Spatio-Temporal Networks was
351 selected due to the high cost and limited accessibility of LiDAR technology. By
352 applying epipolar geometry and temporal consistency across sequential frames,
353 this approach provides an accurate depth estimation from standard video footage
354 (Long et al., 2021).

355 3.1.3 Design, Testing, and Experimentation

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

358 Model Design

359 The system was designed to operate with two core components: YOLOv5 for
360 pothole detection and ESTN for severity assessment. The model architecture was
361 chosen based on the real-time processing capabilities and the need for accurate
362 depth estimation from standard video footage. The design ensures that the system
363 can detect defects and provide severity assessments in a seamless workflow.

364 Data Set

365 The YOLOv5 model was trained using two datasets from Universe Roboflow. One
366 of the data sets was posted by a user named Eric Tam. It was also stated that
367 the images from the dataset are sourced from a Crowdsensing-based Road Damage
368 Detection Challenge from 2022 in Japan. The challenge involves contestants being
369 required to submit road damage datasets, shortlist their data set, and use the data
370 set for road damage detection and classification models. The use of this data set
371 in training models for road damage detection and classification ensures that the
372 data is viable for training the YOLOv5 model. The dataset contains various road
373 defects in Japan. Another data set used in training the YOLOv5 model was also
374 uploaded in Universe Roboflow by a user named Atikur Rahman Chitholian which
375 was stated to be part of his undergraduate thesis. The dataset is comprised of 665
376 images with potholes being labeled. It was also stated that the data set can be
377 utilized in automatically detecting and categorizing potholes found in the streets
378 of cities. Data preprocessing techniques were applied to both datasets to improve
379 model accuracy and generalization. These included resizing images to a uniform
380 size, applying augmentation techniques (flipping, rotation, and color adjustment)
381 to increase dataset variability, and normalizing pixel values to ensure consistency
382 across images.

383 Performance Metrics

384 The performance of the YOLOv5 model will be evaluated using mean Average
385 Precision (mAP). mAP is a widely used metric in object detection tasks and is
386 particularly useful for assessing models that need to detect and classify multiple
387 object categories. In this case, mAP will provide a comprehensive evaluation of the
388 model’s ability to detect and classify potholes, offering an aggregated score across
389 the relevant detection thresholds. This ensures a balanced assessment of both
390 detection accuracy and classification performance, which is essential for accurately
391 identifying potholes across varying conditions. The effectiveness of mAP for this
392 task is well-established in object detection literature (Everingham et al., 2015; Lin
393 et al., 2014).

394 For the accuracy of depth estimation using the Epipolar Spatio-Temporal Net-
395 works (ESTN), Root Mean Squared Error (RMSE) and Mean Absolute Error
396 (MAE) will be used. RMSE is chosen for its ability to penalize larger errors more
397 heavily, making it suitable for assessing depth estimation performance where larger
398 deviations from the ground truth are more significant (Zhang et al., 2018). MAE is
399 also employed to provide a straightforward measure of average error magnitude,
400 offering a complementary evaluation of depth estimation without emphasizing

401 larger errors as much (Zhang et al., 2020).

402 **Testing and Validation**

403 The testing process will begin with a detailed testing plan that includes both
404 simulated and real-world testing scenarios. Initially, the model will be tested in
405 controlled environments to ensure it can detect and assess road defects accurately.
406 Following this, real-world testing will be conducted using the StereoPi kit on local
407 roads, specifically at the University of the Philippines Visayas Miagao Campus.
408 The system’s performance will be validated by comparing its predictions with
409 ground-truth data collected from manual inspections.

410 **Documentation**

411 Throughout the research activities, thorough documentation will be maintained.
412 This documentation will capture all methods, results, challenges, and adjustments
413 made during the experimentation phases. It ensures the reproducibility of the
414 work and provides transparency for future research endeavors.

415 **3.1.4 Challenges and Limitations**

416 **Availability of Local Datasets**

417 The lack of locally labeled datasets for road defects has posed a challenge in
418 training accurate models. The majority of available datasets are sourced from
419 international locations, which may not fully represent the road conditions found
420 in the study area. To address the lack of locally labeled datasets, the researchers
421 will create a pilot dataset from local roads within the University of the Philippines
422 Visayas Miagao Campus. This dataset will be manually annotated according to
423 DPWH’s classification standards, ensuring local relevance.

424 **Data Quality and Variability**

425 Variations in the quality and resolution of the data collected from different sources
426 may impact the performance of the trained models. In particular, images captured
427 under varying weather conditions or lighting may affect the accuracy of pothole

428 detection. To address this, the researchers plan to use the StereoPi kit to capture
 429 images under optimal weather and lighting conditions, such as mid-morning or
 430 early afternoon on clear days, ensuring consistent image quality for stereo vision
 431 analysis. The kit’s stereo cameras will be calibrated for uniform resolution and
 432 focus. Data augmentation techniques will also be applied to simulate varying con-
 433 ditions, and pre-processing steps like noise reduction and contrast enhancement
 434 will be used to improve the quality of the captured data. This approach aims
 435 to minimize the impact of environmental factors on the accuracy of road pothole
 436 detection and depth estimation.

437 3.2 Calendar of Activities

438 Table 1 shows a Gantt chart of the activities. Each bullet represents approximately
 439 one week’s worth of activity.

Table 3.1: Timetable of Activities for 2024

Activities (2024)	Aug	Sept	Oct	Nov	Dec
Pre-proposal Preparation	••••				
Literature Review	•••	•			
Data Collection	••	••			
Algorithm Selection		••			
System Design		•	••	••	
Preliminary Testing				••	•
Documentation and SP Writing	••••	••••	••••	••••	••

Table 3.2: Timetable of Activities for 2025

Activities (2025)	Jan	Feb	Mar	Apr	May	Jun
Data Collection	••••					
System Design	•••	••	••			
Model testing	•••	••••	••••			
Results Analysis			••	••••		
Conclusion Formulation				••	•••	
Documentation and SP Writing	••••	••••	••••	••••	••••	••

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476 **Appendix A**

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