

1 DEFECTRA: ROAD DEFECT SEVERITY ASSESSMENT
2 AND CLASSIFICATION

3 A Special Problem Proposal
4 Presented to
5 the Faculty of the Division of Physical Sciences and Mathematics
6 College of Arts and Sciences
7 University of the Philippines Visayas
8 Miag-ao, Iloilo

9 In Partial Fulfillment
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11 Bachelor of Science in Computer Science by

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Abstract

21 From 150 to 200 words of short, direct and complete sentences, the abstract should
22 be informative enough to serve as a substitute for reading the entire SP document
23 itself. It states the rationale and the objectives of the research. In the final Special
24 Problem document (i.e., the document you'll submit for your final defense), the
25 abstract should also contain a description of your research results, findings, and
26 contribution(s).

27 Suggested keywords based on ACM Computing Classification system can be
28 found at https://dl.acm.org/ccs/ccs_flat.cfm

29 **Keywords:** Keyword 1, keyword 2, keyword 3, keyword 4, etc.

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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% of roads in the Philippines is paved which is either made of concrete or asphalt (DPWH, 2022). Since the DPWH is an institution under the government, it is paramount to maintain such roads in order to avoid accidents and congested traffic situations especially in heavily urbanized areas where there are a lot of vehicles.

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, & Bronuela-Ambrocio, 2023), it was found that the Philippines' current method of manual pavement surveying is considered as a gap since it takes an average of 2-3 months to cover a 250 km road as opposed to a 1 day duration in the Australian Road Research Board for the same road length. Ramos et al. (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., 2023).

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

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

96 Existing studies involving road defects such as potholes mainly focus on the
97 detection of potholes using deep learning models such as CNN and almost not
98 considering the severity of detected potholes. In addition, for studies that in-
99 clude severity assessment on potholes, the main goal of the study is not directed
100 towards road maintenance automation but other factors such as improvement
101 of ride quality for the vehicle. Another issue found in existing solutions is the
102 lack of incorporation to the context of Philippine roads. With these issues in
103 mind, the study aims to utilize stereo vision from StereoPi V2 in order to obtain
104 multi-perspective views of detected potholes to be used in severity assessment
105 by focusing on estimating the depth of individual potholes for automated road
106 condition monitoring.

107 1.2 Problem Statement

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

1.3 Research Objectives

1.3.1 General Objective

This special problem aims to develop an automated system that will accurately detect and assess the severity of potholes on road surfaces by using image analysis, depth measurement technologies, and a combination of machine learning and computer vision techniques. The system will focus on measuring the depth of potholes to assess their severity, enabling faster and more accurate road maintenance decisions. In accordance with the Department of Public Works and Highways Region 6's manual for road maintenance, the study will classify potholes into different severity levels such as low, medium, and high, which will be primarily based on their area and depth. In order to measure the system's accuracy, precision and recall will be used in order to determine the number of true positives and true positive rate and also the number of false positives and negatives detected by the system. In addition, in order to calculate the average precision and recall of the system the F-1 Score will also be used. Lastly, the Mean Absolute Error will be utilized in order to provide a straightforward measure of average error magnitude.

1.3.2 Specific Objectives

Specifically, this special problem aims:

1. To collect high-quality images of road surfaces that capture potholes including their depth in various lighting, camera distance and orientation, and weather conditions.
2. To measure the accuracy of the system by comparing the depth measurements against ground truth data collected from actual road inspections and to utilize precision and recall, F1-score and mean absolute error as metrics for evaluation.
3. To develop a prototype system that can detect and measure road potholes from image input, analyze their depth, and assess their severity that will be deployed through stereo camera mounted vehicles used for road surveying.

1.4 Scope and Limitations of the Research

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

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

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

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

1.5 Significance of the Research

This special problem aims to be significant to the following:

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

Concerned Government Agencies. This system offers a valuable tool for road safety and maintenance. Not only can this detect and classify anomalies, it can

188 also assess the defect's severity which allows them to prioritize repairs, optimal
189 project expenditures, and better overall road safety and quality.

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

193 *Future Researchers.* The special problem can serve as a baseline and guide of
194 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.

210 **2.1.3 Image and Video Processing**

211 (Kumar, 2024) defines image processing as a process of turning an image into its
212 digital form and extracting data from it through certain functions and operations.
213 Usual processes are considered to treat images as 2D signals wherein different
214 processing methods utilize these signals. Like image processing, (Resources, 2020)
215 defines video processing as being able to extract information and data from video
216 footage through signal processing methods. However, in video processing due to
217 the diversity of video formats, compression and decompression methods are often
218 expected to be performed on videos before processing methods to either increase
219 or decrease bitrate.

220 **2.1.4 Stereo Vision**

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

227 **2.2 Related Studies**

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

231 **2.2.1 Deep Learning Studies**

232 **2.2.1.1 Automated Detection and Classification of Road Anomalies in** 233 **VANET Using Deep Learning**

234 In the study of Bibi et al. (2021) it was noted that identification of active road
235 defects are critical in maintaining smooth and safe flow of traffic. Detection and
236 subsequent repair of such defects in roads are crucial in keeping vehicles using
237 such roads away from mechanical failures. The study also emphasized the growth

238 in use of autonomous vehicles in research data gathering which is what the re-
 239 searchers utilized in data gathering procedures. With the presence of autonomous
 240 vehicles, this allowed the researchers to use a combination of sensors and deep
 241 neural networks in deploying artificial intelligence. The study aimed to allow au-
 242 tonomous vehicles to avoid critical road defects that can possibly lead to dangerous
 243 situations. Researchers used Resnet-18 and VGG-11 in automatic detection and
 244 classification of road defects. Researchers concluded that the trained model was
 245 able to perform better than other techniques for road defect detection (Bibi et al.,
 246 2021). The study is able to provide the effectiveness of using deep learning models
 247 in training artificial intelligence for road defect detection and classification. How-
 248 ever, the study lacks findings regarding the severity of detected defects which is
 249 crucial in automating manual procedures of road surveying in the Philippines.

250 **2.2.1.2 Road Anomaly Detection through Deep Learning Approaches**

251 The study of (Luo, Lu, & Guo, 2020) aimed to utilize deep learning models in
 252 classifying road anomalies. The researchers used three deep learning approaches
 253 namely Convolutional Neural Network, Deep Feedforward Network, and Recurrent
 254 Neural Network from data collected through the sensors in the vehicle’s suspension
 255 system. In comparing the performance of the three deep learning approaches, the
 256 researchers fixed some hyperparameters. Results revealed that the RNN model
 257 was the most stable among the three and in the case of the CNN and DFN
 258 models, the researchers suggested the use of wheel speed signals to ensure accuracy.
 259 And lastly, the researchers concluded that the RNN model was best due to high
 260 prediction performance with small set parameters (Luo et al., 2020).

261 **2.2.1.3 Assessing Severity of Road Cracks Using Deep Learning-Based** 262 **Segmentation and Detection**

263 In the study of (Ha, Kim, & Kim, 2022), it was argued that the detection, classi-
 264 fication, and severity assessment of road cracks should be automated due to the
 265 bottleneck it causes during the entire process of surveying. For the study, the
 266 researchers utilized SqueezeNet, U-Net, and MobileNet-SSD models for crack clas-
 267 sification and severity assessment. Furthermore, the researchers also employed
 268 separate U-nets for linear and area cracking cases. For crack detection, the re-
 269 searchers followed the process of pre-processing, detection, classification. Dur-
 270 ing preprocessing images were smoothed out using image processing techniques.
 271 The researchers also utilized YOLOv5 object detection models for classification of
 272 pavement cracking wherein the YOLOv51 model recorded the highest accuracy.
 273 The researchers however stated images used for the study are only 2D images

274 which may have allowed higher accuracy rates. Furthermore, the researchers sug-
275 gest incorporating depth information in the models to further enhance results.

276 **2.2.1.4 Roadway pavement anomaly classification utilizing smartphones** 277 **and artificial intelligence**

278 The study of (Kyriakou, Christodoulou, & Dimitriou, 2016) presented what is
279 considered as a low-cost technology which was the use of Artificial Neural Net-
280 works in training a model for road anomaly detection from data gathered by
281 smartphone sensors. The researchers were able to collect case study data us-
282 ing two-dimensional indicators of the smartphone’s roll and pitch values. In the
283 study’s discussion, the data collected displayed some complexity due to accelera-
284 tion and vehicle speed which lead to detected anomalies being not as conclusive as
285 planned. The researchers also added that the plots are unable to show parameters
286 that could verify the data’s correctness and accuracy. Despite the setbacks, the
287 researchers still fed the data into the Artificial Neural Network that was expected
288 to produce two outputs which were “no defect” and “defect.” The method still
289 yielded above 90% accuracy but due to the limited number of possible outcomes
290 in the data processing the researchers still needed to test the methodology with
291 larger data sets and roads with higher volumes of anomalies.

292 **2.2.2 Machine Learning Studies**

293 **2.2.2.1 Smartphones as Sensors for Road Surface Monitoring**

294 In their study, (Sattar, Li, & Chapman, 2018) noted the rise of sensing capabilities
295 of smartphones which they utilized in monitoring road surface to detect and iden-
296 tify anomalies. The researchers considered different approaches in detecting road
297 surface anomalies using smartphone sensors. One of which are threshold-based
298 approaches which was determined to be quite difficult due to several factors that
299 are affecting the process of determining the interval length of a window function
300 in spectral analysis (Sattar et al., 2018). The researchers also utilized a machine
301 learning approach adapted from another study. It was stated that k-means was
302 used in classifying sensor data and in training the SVM algorithm. Due to the
303 requirement of training a supervised algorithm using a labeled sample data was
304 required before classifying data from sensors, the approach was considered to be
305 impractical for real-time situations (Sattar et al., 2018). In addition, (Sattar et
306 al., 2018) also noted various challenges when utilizing smartphones as sensors for
307 data gathering such as sensors being dependent on the device’s placement and

orientation, smoothness of captured data, and the speed of the vehicle it is being mounted on. Lastly, it was also concluded that the accuracy and performance of using smartphone sensors is challenging to compare due to the limited data sets and reported algorithms.

2.2.2.2 Road Surface Quality Monitoring Using Machine Learning Algorithms

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

2.2.3 Computer Vision Studies

2.2.3.1 Stereo Vision Based Pothole Detection System for Improved Ride Quality

In the study of (Ramaiah & Kundu, 2021) it was stated that stereo vision has been earning attention due to its reliable obstacle detection and recognition. Furthermore, the study also discussed that such technology would be useful in improving ride quality in automated vehicles by integrating it in a predictive suspension control system. The proposed study was to develop a novel stereo vision based pothole detection system which also calculates the depth accurately. However, the study focused on improving ride quality by using the 3D information from detected potholes in controlling the damping coefficient of the suspension system. Overall, the pothole detection system was able to achieve 84% accuracy and is

342 able to detect potholes that are deeper than 5 cm. The researchers concluded
343 that such system can be utilized in commercial applications. However, it is also
344 worth noting that despite the system being able to detect potholes and measure
345 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

Chapter 3

Methodology

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

3.1 Research Activities

3.1.1 Data Collection

The researchers conducted initial inquiries to understand the problem domain and existing road maintenance practices. This phase included consulting the engineers under the Road Maintenance Department of the government agency Department of Public Works and Highways (DPWH). An interview with Engr. Jane Chua provided a comprehensive overview of the DPWH's road maintenance manual, which was crucial in aligning this project with existing standards. This collaboration with DPWH provided insights into road pothole classification standards, ensuring that the collected data will align with industry standards. Pothole severity will be classified based on a combination of area and depth. The DPWH manual primarily focuses on the volume of detected potholes within a road segment as a measure of severity. However, since depth is not explicitly measured in their current procedures, the study will supplement this by referencing international standards such as the Long-Term Pavement Performance (LTPP) classification

373 used in the United States. The LTPP categorizes potholes based on depth thresh-
374 olds, which will be integrated with DPWH’s volume-based assessment to provide
375 a more comprehensive severity classification framework. In order to individually
376 locate or determine each pothole where the ground truth data is collected, im-
377 ages taken will be labeled with their corresponding coordinates, street names,
378 and nearby landmarks. The data collection will involve capturing at least 500
379 images of potholes from various locations within the UP Visayas Campus and the
380 Province of Iloilo. These locations were selected based on reports of road dete-
381 rioration and input from the DPWH to ensure the dataset represents real-world
382 conditions. In addition to locally collected data, open-source datasets such as
383 the Dataset by Eric Tam from the Crowdsensing-based Road Damage Detection
384 Challenge focusing on road defects and the Dataset by Atikur Rahman Chitho-
385 lian, featuring 665 labeled pothole images from urban streets will be reviewed to
386 supplement the model training and improve generalization.

387 **3.1.2 Algorithm Selection**

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

393 **3.1.2.1 Pothole Detection**

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

398 **3.1.2.2 Severity Assessment**

399 The Multi-view Depth Estimation using Epipolar Spatio-Temporal Networks was
400 selected due to the high cost and limited accessibility of LiDAR technology. By
401 applying epipolar geometry and temporal consistency across sequential frames,
402 this approach provides an accurate depth estimation from standard video footage
403 (Long, Wang, Zhang, Mei, & Shen, 2021).

404 **3.1.3 Design, Testing, and Experimentation**

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

407 **3.1.3.1 Model Design**

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

413 **3.1.3.2 Data Set**

414 The YOLOv5 model was trained using two datasets from Universe Roboflow. One
415 of the data sets was posted by a user named Eric Tam. It was also stated that
416 the images from the dataset are sourced from a Crowdsensing-based Road Damage
417 Detection Challenge from 2022 in Japan. The challenge involves contestants being
418 required to submit road damage datasets, shortlist their data set, and use the data
419 set for road damage detection and classification models. The use of this data set
420 in training models for road damage detection and classification ensures that the
421 data is viable for training the YOLOv5 model. The dataset contains various road
422 defects in Japan. Another data set used in training the YOLOv5 model was also
423 uploaded in Universe Roboflow by a user named Atikur Rahman Chitholian which
424 was stated to be part of his undergraduate thesis. The dataset is comprised of 665
425 images with potholes being labeled. It was also stated that the data set can be
426 utilized in automatically detecting and categorizing potholes found in the streets
427 of cities. Data preprocessing techniques were applied to both datasets to improve
428 model accuracy and generalization. These included resizing images to a uniform
429 size, applying augmentation techniques (flipping, rotation, and color adjustment)
430 to increase dataset variability, and normalizing pixel values to ensure consistency
431 across images.

432 **3.1.3.3 Performance Metrics**

433 The performance of the YOLOv5 model will be evaluated using mean Average
434 Precision (mAP). mAP is a widely used metric in object detection tasks and is

435 particularly useful for assessing models that need to detect and classify multiple
436 object categories. In this case, mAP will provide a comprehensive evaluation of the
437 model’s ability to detect and classify potholes, offering an aggregated score across
438 the relevant detection thresholds. This ensures a balanced assessment of both
439 detection accuracy and classification performance, which is essential for accurately
440 identifying potholes across varying conditions. The effectiveness of mAP for this
441 task is well-established in object detection literature (Everingham et al., 2015; Lin
442 et al., 2014).

443 For the accuracy of depth estimation using the Epipolar Spatio-Temporal Net-
444 works (ESTN), Root Mean Squared Error (RMSE) and Mean Absolute Error
445 (MAE) will be used. RMSE is chosen for its ability to penalize larger errors more
446 heavily, making it suitable for assessing depth estimation performance where larger
447 deviations from the ground truth are more significant (Zhang et al., 2018). MAE is
448 also employed to provide a straightforward measure of average error magnitude,
449 offering a complementary evaluation of depth estimation without emphasizing
450 larger errors as much (Zhang et al., 2020).

451 **3.1.3.4 Testing and Validation**

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

459 **3.1.3.5 Documentation**

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

464 **3.1.4 Challenges and Limitations**

465 **3.1.4.1 Availability of Local Datasets**

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

473 **3.1.4.2 Data Quality and Variability**

474 Variations in the quality and resolution of the data collected from different sources
475 may impact the performance of the trained models. In particular, images captured
476 under varying weather conditions or lighting may affect the accuracy of pothole
477 detection. To address this, the researchers plan to use the StereoPi kit to capture
478 images under optimal weather and lighting conditions, such as mid-morning or
479 early afternoon on clear days, ensuring consistent image quality for stereo vision
480 analysis. The kit’s stereo cameras will be calibrated for uniform resolution and
481 focus. Data augmentation techniques will also be applied to simulate varying con-
482 ditions, and pre-processing steps like noise reduction and contrast enhancement
483 will be used to improve the quality of the captured data. This approach aims
484 to minimize the impact of environmental factors on the accuracy of road pothole
485 detection and depth estimation.

486 **3.2 Calendar of Activities**

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

Table 3.1: Timetable of Activities for 2024

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

Table 3.2: Timetable of Activities for 2025

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

489 Chapter 4

490 Preliminary Results/System 491 Prototype

492 This chapter presents the preliminary results or the system prototype of your SP.
493 Include screenshots, tables, or graphs and provide the discussion of results.

References

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⁵⁴³ **Appendix A**

⁵⁴⁴ **Appendix Title**

545 **Appendix B**

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