Defectra: Road Defect Severity Assessment and Classification

A Special Problem Proposal
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Abstract

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

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

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 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.

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

1.2 Problem Statement

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

1.3 Research Objectives

1.3.1 General Objective

This special problem aims to develop a system that will accurately estimate the depth of potholes on road surfaces by using image analysis, depth measurement technologies, and computer vision techniques. The system will focus specifically on measuring the depth of potholes to assess their severity, enabling faster and more accurate road maintenance decisions, and there are no current practices in the Philippines involving depth information of potholes in assessing their severity. 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 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 and Root Mean Square Error as a measure for perfomance since data is continuous.

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.
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, root mean square error, 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.

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

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

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

Chapter 2

Review of Related Literature

2.1 Frameworks

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.

2.1.3 Image and Video Processing

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

2.1.4 Stereo Vision

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

2.2 Related Studies

This section of the chapter presents related studies conducted by other researchers wherein the methodology and technologies used may serve as basis in the development of this special problem.

2.2.1 Deep Learning Studies

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

In the study of Bibi et al. (2021) it was noted that identification of active road defects are critical in maintaining smooth and safe flow of traffic. Detection and subsequent repair of such defects in roads are crucial in keeping vehicles using such roads away from mechanical failures. The study also emphasized the growth in use of autonomous vehicles in research data gathering which is what the researchers utilized in data gathering procedures. With the presence of autonomous vehicles, this allowed the researchers to use a combination of sensors and deep neural networks in deploying artificial intelligence. The study aimed to allow autonomous vehicles to avoid critical road defects that can possibly lead to dangerous situations. Researchers used Resnet-18 and VGG-11 in automatic detection and classification of road defects. Researchers concluded that the trained model was able to perform better than other techniques for road defect detection (Bibi et al., 2021). The study is able to provide the effectiveness of using deep learning models in training artificial intelligence for road defect detection and classification. However, the study lacks findings regarding the severity of detected defects which is crucial in automating manual procedures of road surveying in the Philippines.

2.2.1.2 Road Anomaly Detection through Deep Learning Approaches

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

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

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

2.2.1.4 Roadway pavement anomaly classification utilizing smartphones and artificial intelligence

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

2.2.2 Machine Learning Studies

2.2.2.1 Smartphones as Sensors for Road Surface Monitoring

In their study, Sattar, Li, and Chapman (2018) noted the rise of sensing capabilities of smartphones which they utilized in monitoring road surface to detect and identify anomalies. The researchers considered different approaches in detecting road surface anomalies using smartphone sensors. One of which are threshold-based approaches which was determined to be quite difficult due to several factors that are affecting the process of determining the interval length of a window function in spectral analysis (Sattar et al., 2018). The researchers also utilized a machine learning approach adapted from another study. It was stated that k-means was used in classifying sensor data and in training the SVM algorithm. Due to the requirement of training a supervised algorithm using a labeled sample data was required before classifying data from sensors, the approach was considered to be impractical for real-time situations (Sattar et al., 2018). In addition, Sattar et al. (2018) also noted various challenges when utilizing smartphones as sensors for 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, and 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 and 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 able to detect potholes that are deeper than 5 cm. The researchers concluded that such system can be utilized in commercial applications. However, it is also worth noting that despite the system being able to detect potholes and measure 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	SqueezNet, 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 were taken to address the problem of pothole depth estimation using StereoPi V2. The methodology is 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 is essential for accurately estimating the depth of potholes using StereoPi V2.

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. 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 used in the United States. The LTPP categorizes potholes based on depth thresholds, 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 DPWH Region 6. 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.

3.1.3.1 Materials and Equipment

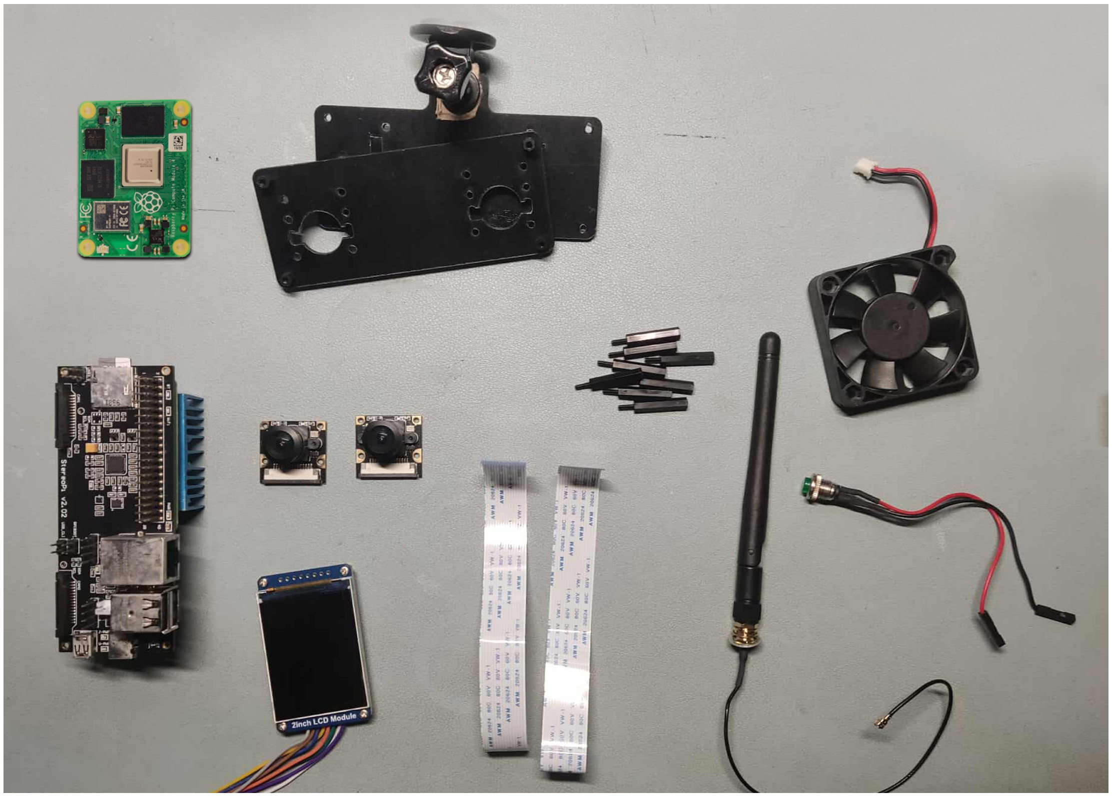

Figure 3.1: Components used in the prototype development.

The prototype system was constructed using the following materials and components:

- StereoPi V2 Board
- Raspberry Pi Compute Module 4 (CM4)
- Dual RaspberryPi Camera Modules with Fisheye Lens
- 3D Printed Custom Housing
- 2-inch LCD Module
- Micro SD Card
- Antenna
- Momentary Push Button

3.1.3.2 Prototype Building

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

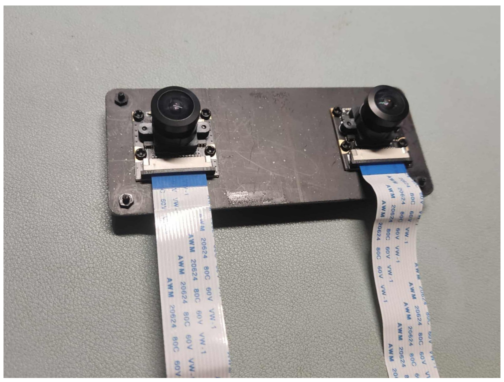

Figure 3.2: Dual RPi Camera Modules attached to the custom housing.

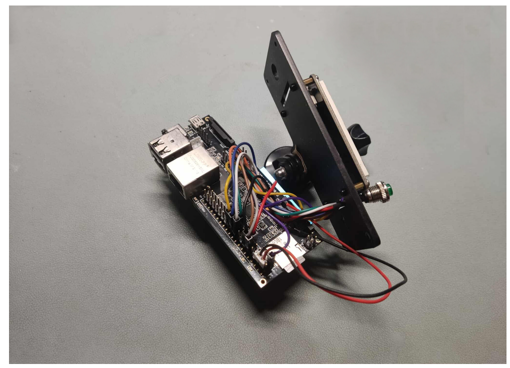

Figure 3.3: LCD Module connected to the StereoPi board.

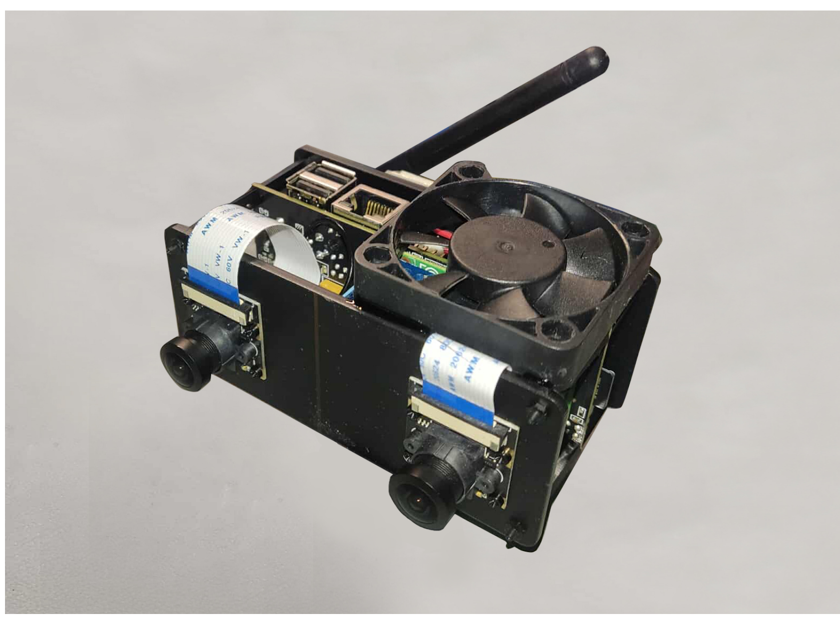

Figure 3.4: The finished prototype.

3.1.3.3 Camera Calibration (Fisheye Distortion)

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

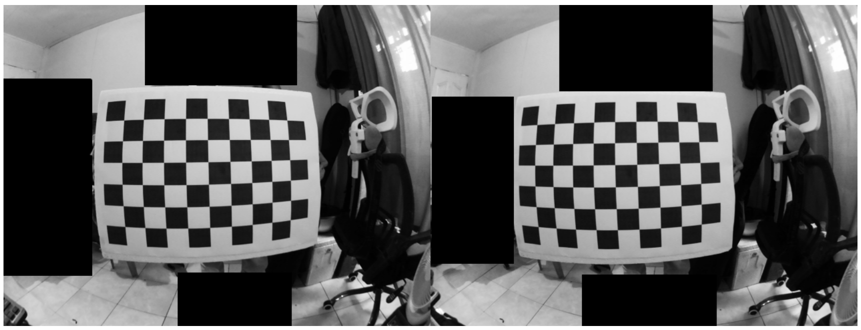

Figure 3.5: Calibration process with a checkerboard to correct fisheye lens distortion.

3.1.3.4 Camera Calibration (Disparity Map Fine-tuning)

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

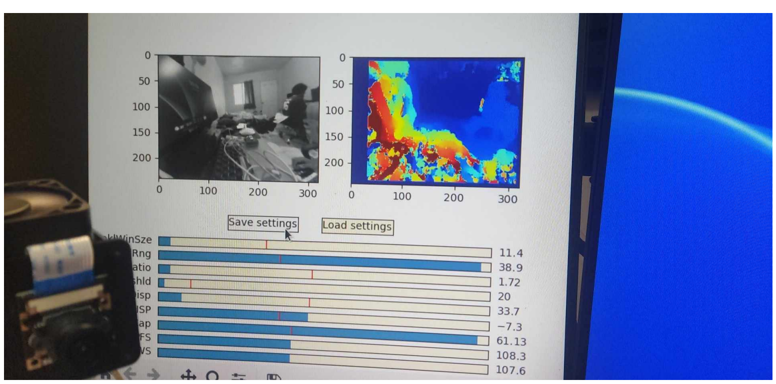

Figure 3.6: Parameter tuning process to achieve cleaner and more accurate disparity maps.

3.1.3.5 Initial Testing

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

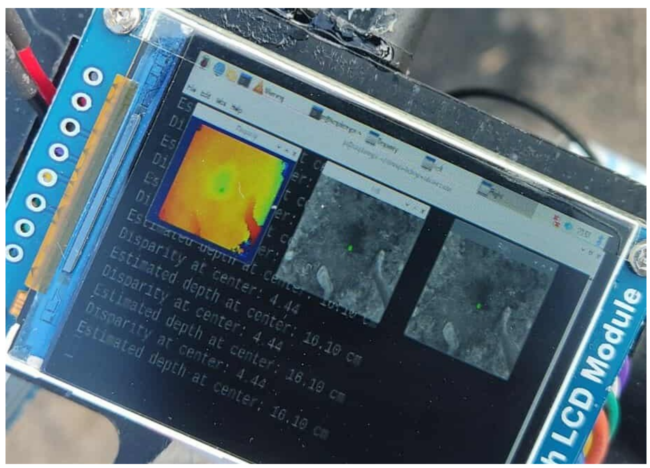

Figure 3.7: The system tested on a simulated pothole.

However, the results revealed a non-linear relationship between the computed disparity values and the actual distances. This discrepancy indicated that the traditional depth estimation method was insufficient for our setup. To address this, we collected multiple data points correlating known distances to their respective disparity readings and fitted an inverse model to better represent the system's behavior (see 3.8). This updated disparity-to-depth model was subsequently used in the final testing phase.

3.1.3.6 Performance Metrics

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

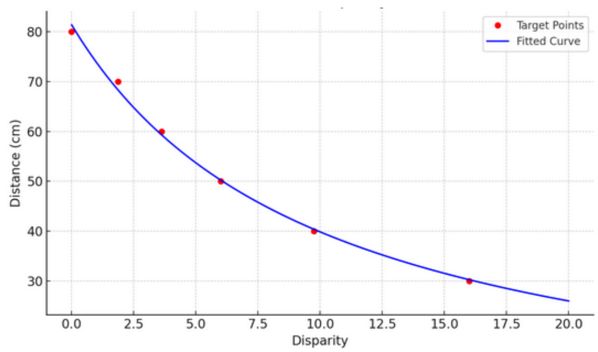

Figure 3.8: Inverse Model Fit to Disparity vs. Distance.

3.1.3.7 Final Testing and Validation

The testing process began with a detailed testing plan that includes both simulated and real-world testing scenarios. Initially, the model is tested in controlled environments to ensure it can estimate pothole depth effectively. Following this, real-world testing was conducted using the StereoPi kit on previously located pot holes, specifically at the University of the Philippines Visayas Miagao Campus. The system's performance was validated by comparing its predictions with ground-truth data collected from manual inspections.

3.1.3.8 Documentation

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

3.1.4 Challenges and Limitations

3.1.4.1 Camera Limitations

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

3.2 Calendar of Activities

Table 1 shows a Gantt chart of the activities. Each bullet represents approximately 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**

Chapter 4

Preliminary Results/System Prototype

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

4.1 System Calibration and Model Refinement

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

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

where:

- f is the focal length in pixels,
- B is the baseline distance between the two cameras,

- d is the disparity.

However, preliminary observations revealed that the relationship between measured disparity and true depth was nonlinear, particularly for small disparities corresponding to greater distances. As a result, a direct application of the stereo formula led to systematic errors, especially at the extremes of the depth range.

To address the nonlinear 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.

An inverse function of the form:

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

where:

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

4.2 Model Refinement Using Regression

The regression analysis produced the following model parameters:

- a = . . .
- b = ...

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

The relatively low MAE and RMSE indicate that the fitted model significantly improved the accuracy of depth estimation compared to the original stereo formula.

4.3 Error Analysis

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

- Low-light imaging conditions affecting disparity computation,
- Shallow potholes with depths less than 3 cm, where disparity resolution becomes a limiting factor,
- Perspective distortion when the stereo camera was not parallel to the ground plane.

4.4 Testing Results

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

4.5 Discussion

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Appendix A

Appendix Title

Appendix B

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