In-Pipe Inspection Robot (IPIR)

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Poster

Autonomous Robot for In-Pipe Defect Detection

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Problem Statement

Companies like SGS in Saudi Arabia offer smart PIGs for pipeline [1]. Smart PIGs have upgraded features compared to regular PIGs, such as electronic sensors and ultrasonic sensors to Detect problems down the pipeline such as loss of metal, welding, cracking bending, and temperature anomaly [2]. Smart PIGs main issue is that it can only be performed by trained and qualified operators; it requires steps that carry safety and integrity risks for pigging, which is the operational procedure to launch a PIG [1]. Another disadvantage is that smart PIGs are very costly and difficult to afford, with no use of AI tools or cameras to capture defects in pipes. The project's goal is to address the previously discussed limitations associated with PIG.

Aims

This project aims to introduce an advanced, cost-effective in-pipe inspection robot that detects and localizes pipeline defects. The robot leverages AI, IOT, and real-time communication and notification to enable smart navigation and autonomous control, reducing manual intervention. This supports the transition to smart cities and helps prevent environmental damage.

Objectives

- Usecomputervisiontoclassifydefects.
- Semi Autonomous motion control of the robot.
- Real-time localization of defects in the pipeline.
- Collect images of identified defects and store them in a database.

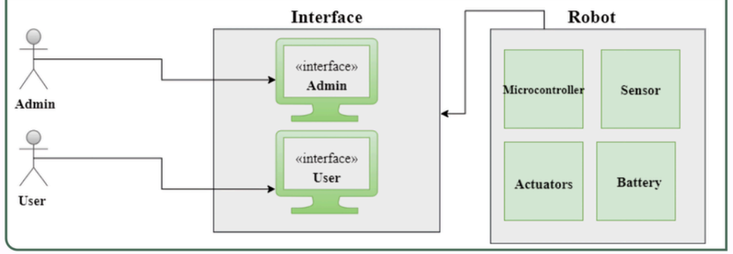
Abstract

This project presents the development of an Autonomous In-Pipe Inspection Robot (IPIR) designed to address the challenges of current pipeline inspection practices, which often rely on smart Pipeline Inspection Gauges (PIGs) offered by companies like SGS in Saudi Arabia. While these advanced technologies utilize electronic and ultrasonic sensors to detect issues such as metal loss and welding defects, their deployment presents significant challenges, including high costs, operational complexity, and inherent safety risks during the pigging process. Additionally, the lack of AI tools and cameras for defect visualization hinders efficient data analysis.
The IPIR integrates modern advancements in artificial intelligence and autonomous navigation. It features a Raspberry Pi 4 as the central processing unit running the YOLOv9t-based defect detection model and an OV5647 camera for visual inspections. The robot's movement is controlled by an Arduino microcontroller with an H-bridge motor driver, while a single optical encoder provides accurate navigation feedback.
Extensive testing has demonstrated that the IPIR effectively detects and classifies common pipeline defects, including cracks, holes, and obstacles, in real time, achieving a model accuracy of 0.77. A web-based dashboard enhances usability by visualizing defect types, locations, and captured images, allowing the maintenance team to make informed decisions. The robot can navigate effectively through T and L junction turns inside the pipe.
In conclusion, this research provides a scalable and cost-effective solution for pipeline inspections, addressing critical challenges in underground maintenance. Future work will focus on enhancing wireless communication for reliable data transmission, developing advanced control algorithms, and upgrading the robot's processing capabilities. This study contributes to improving pipeline integrity management and offers a safer alternative to traditional PIG technologies.

Conclusion

This research demonstrates significant progress in developing an Autonomous In-Pipe Inspection Robot (IPIR). Key achievements include accurate defect classification through computer vision, robust semi-autonomous motion control, and real-time defect localization within the pipeline.

Design: System Architecture



Implementation: Hardware And Software

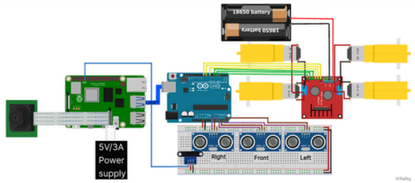


Figure 1: Hardware Circuit

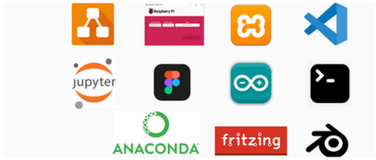


Figure 2: Software Used

FutureWork

- Investigate and implement advanced wireless communication technologies, such as long-range networks for robust and reliable data transmission in challenging pipe environments.
- Develop and implement sophisticated control algorithms, such as advanced PID controllers or model predictive control, to enhance the robot's navigation within complex pipe geometries.
- Development of a robust and standardized system for classifying pipe defects based on their severity. This system will provide a consistent framework for assessing the criticality of defects, enabling more informed decisions regarding maintenance and repair priorities.
- enhance the robot's capabilities by integrating a more powerful processor and a high-capacity power bank. This combination will enable the simultaneous execution of wall-following and defect-detection algorithms.

Prototype And Interfaces

Figure3: Robot Active view

Figure 4: Robot Dark view

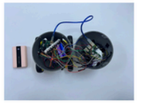


Figure 5: Interior view

Figure 6 : Dashboard defect

Figure 6: Fully Robot

References

[1] SmartpiggingSolutions.
[2] Content Seo Copilot. Intelligent Pigging procedure - How does it work? - Pigtek, 1 2024.
[3] Shin Takahashi Ayman Atia and Jiro Tanaka. Smart gesture sticker: Smart hand gestures profiles for daily objects interaction. In Computer and Information Science, ACIS International Conference on, 0:482–487, 2010.

Proposed Solution

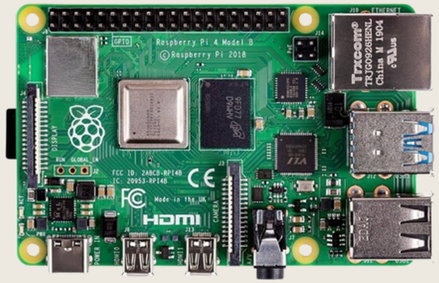
- Develop an **Semi-autonomous In-Pipe Inspection Robot (IPIR)** designed to inspect the internal surfaces of oil and gas underground pipelines.
- Key features include:
  - Deep learning defect detection using a camera as a non-traditional NDT (Non-Destructive Testing) technique for inspection process
  - Localization capabilities to accurately determine the defect's position within the pipeline.
  - Real-time data transmission to a dashboard for immediate analysis and action.

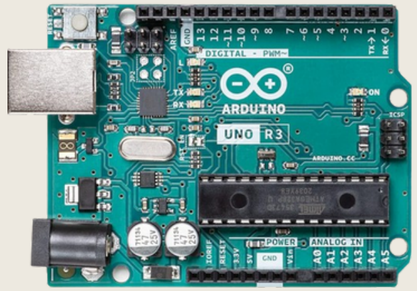
Objectives

- Use computer vision to classify defects.
- Semi Autonomous motion control of the robot.
- Real-time localization of defects in the pipeline.
- Collect images of identified defects and store them in a database.

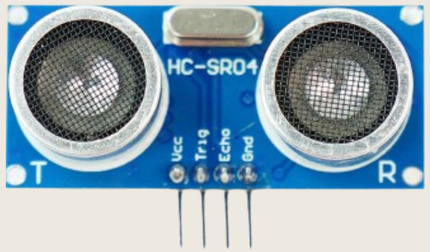
Hardware Used

Proccessing and Control

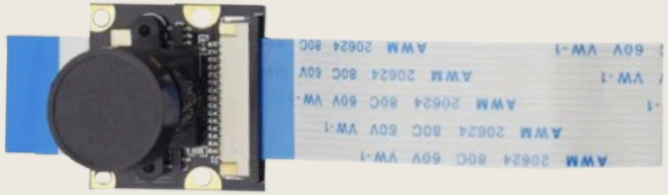




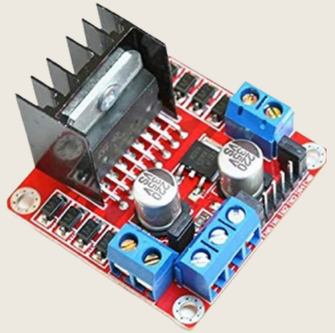
Navigation and Localization



Inspection Camera



Movement and Actuation



Software Used

Coding

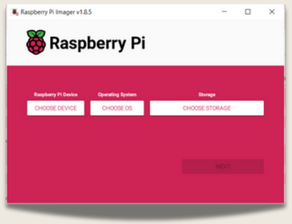
Database & Web Page

AI

3D Modeling

Design Diagram

Hardware & AI

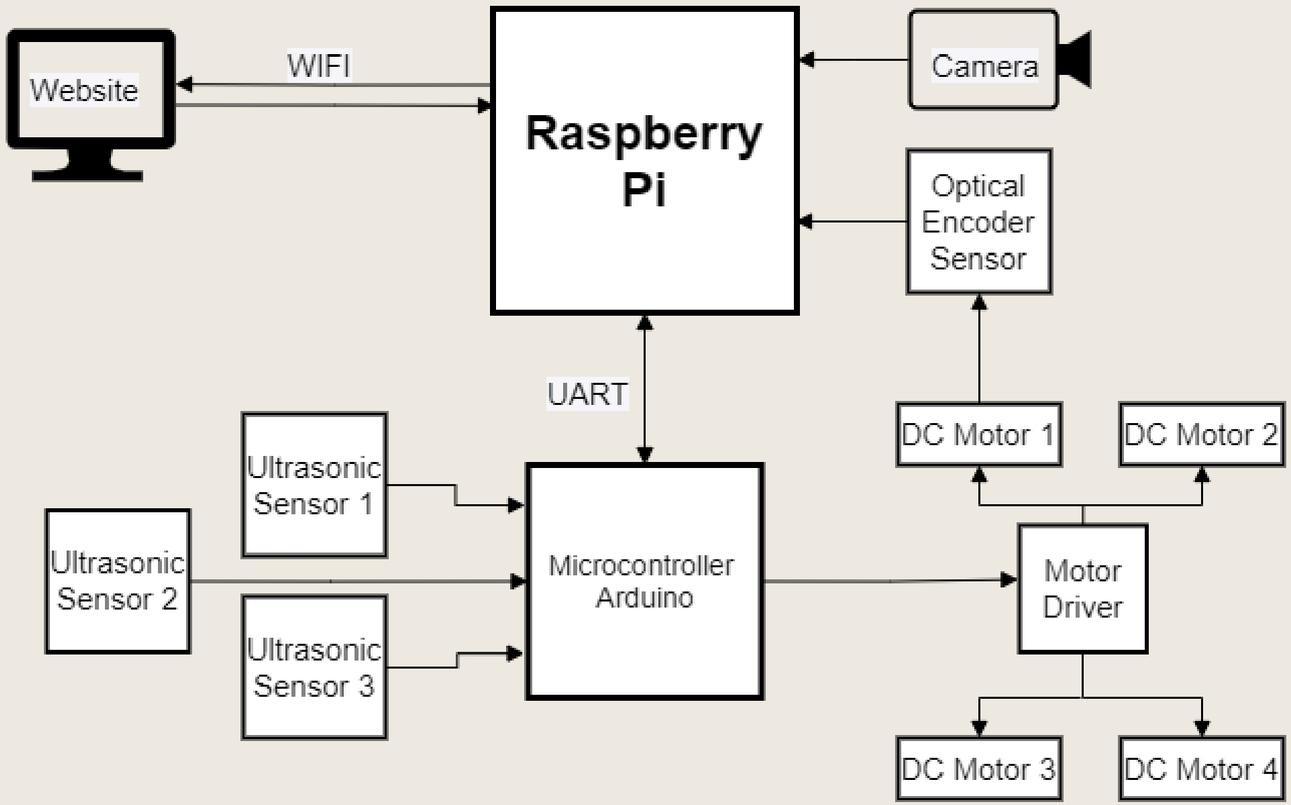


Design Interface

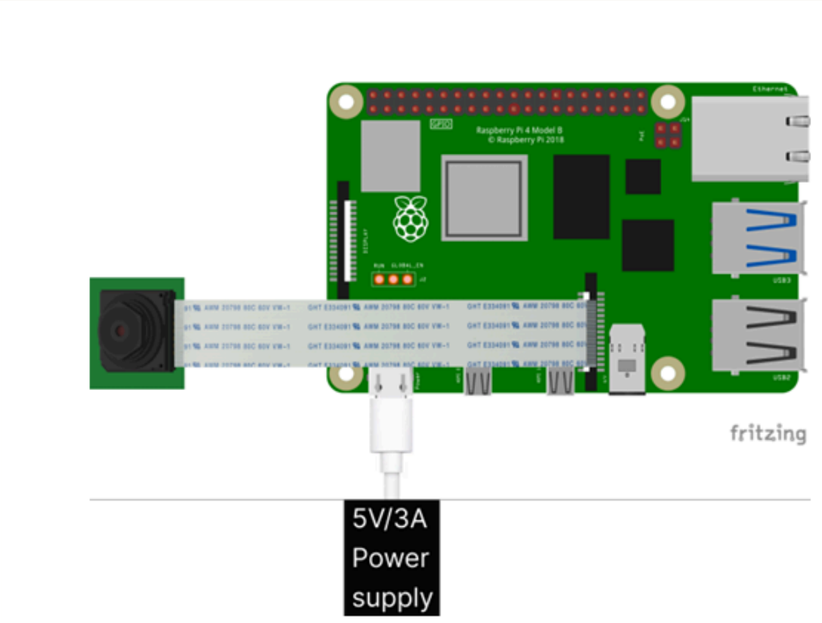
Dataset Augmentation

Prototyping

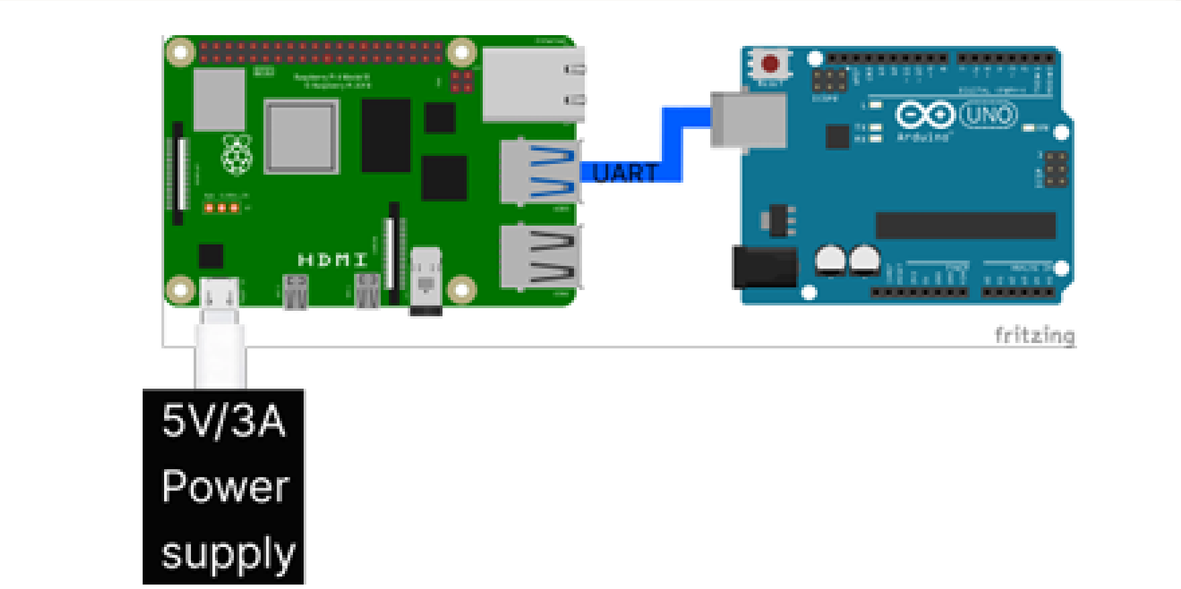
Block Diagram



Circuit

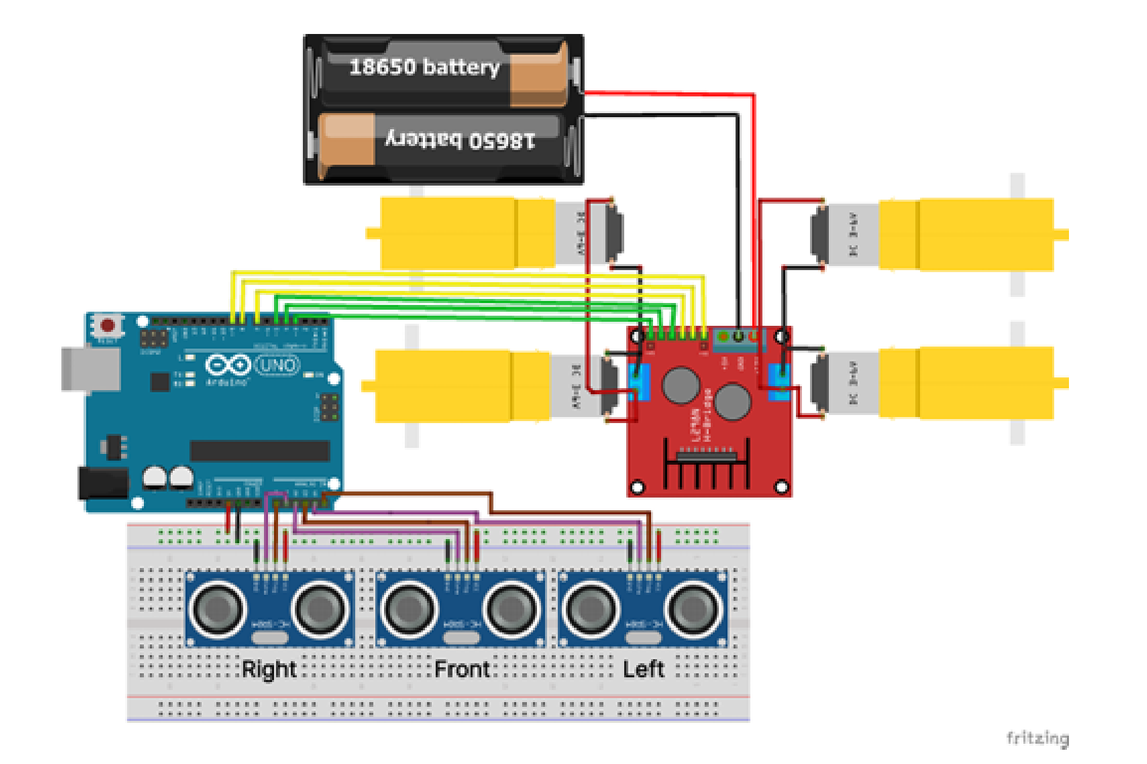


camera inspection system

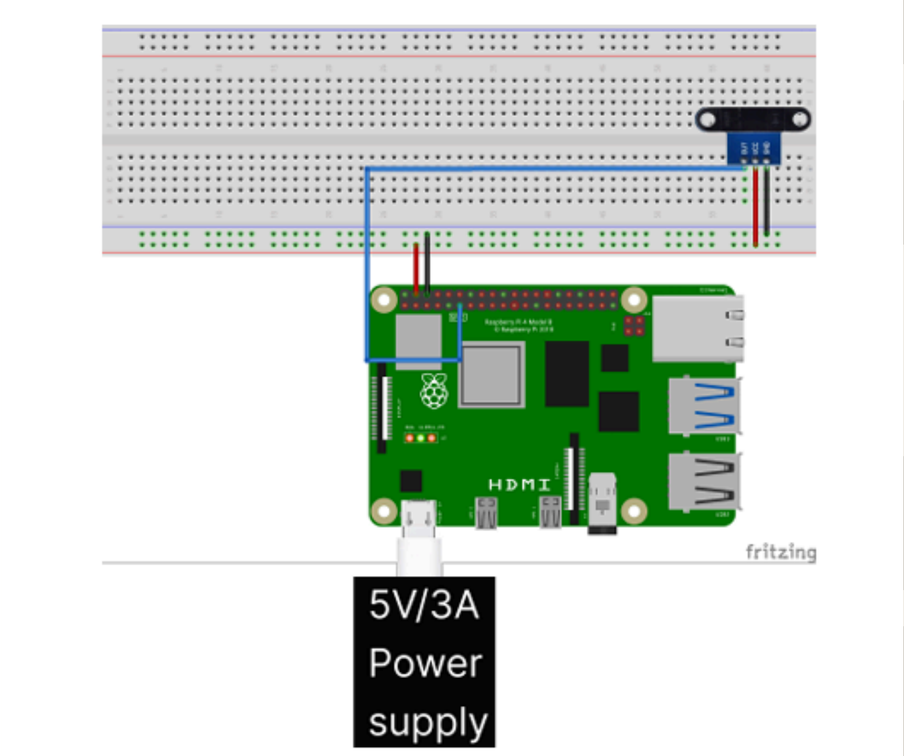


serial communication between the RPI and Arduino

Circuit

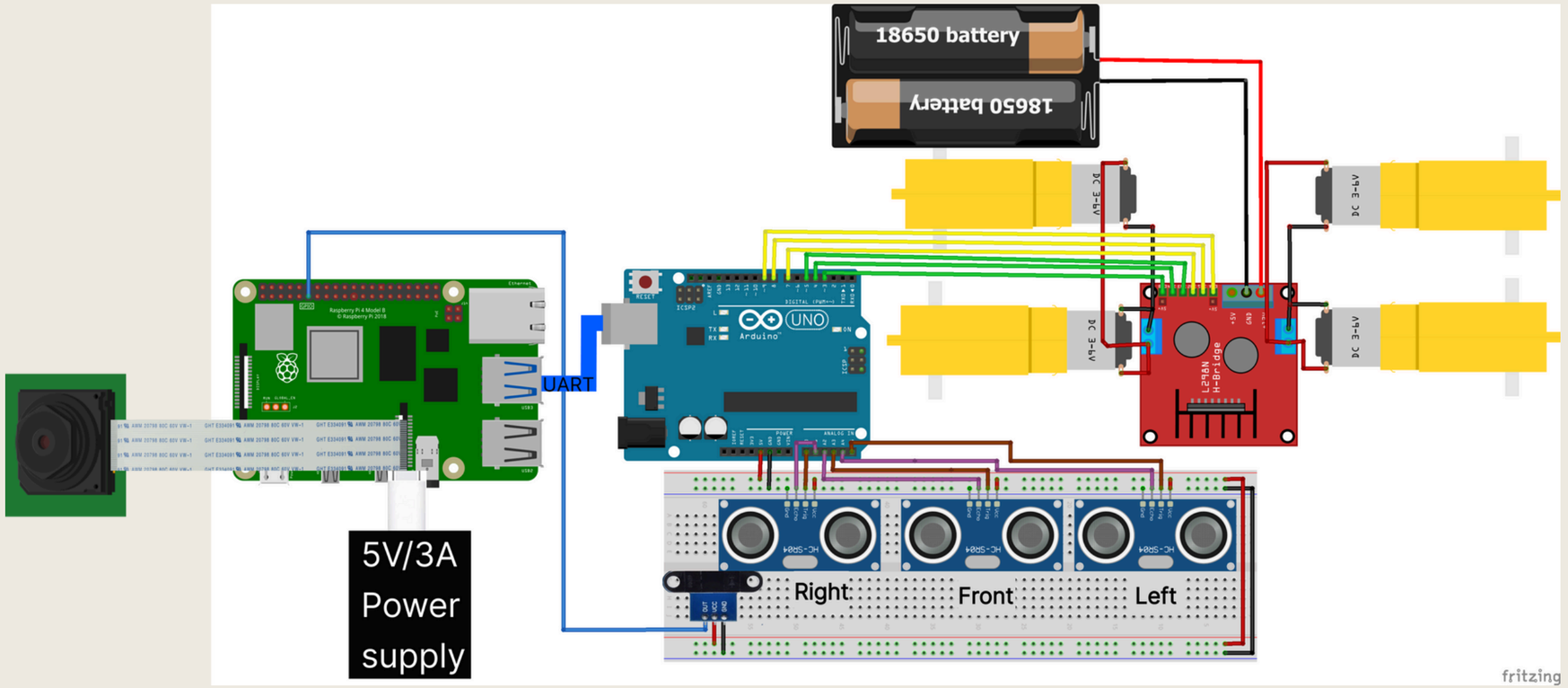


Circuit diagram for robot navigation system



Circuit diagram for robot localization system

Circuit



Full robot navigation system

Prototype

Implementation Details

- **Dataset Acquisition**

- We used multiple sources to gather a better defect sample.

- we selected the types of defects commonly found in oil and gas pipelines

NO.	pipeline type	Link	NO. of images in dataset
1	storm drain	com/new-workspac	1k
2	not mention	ık/browse?queryTex	
3	not mention	low.com/tongji/pipe	804
4	not mention	ı/quickwork-qxpmp/	278
5	not mention	latasets/manaidu/pi	19,908
6	not mention	asets/simplexitypip	22,120
7	drain pipe	w.com/drainimage/	338
8	not mention	low.com/project-c2s	2,022
9	sewer	oflow.com/sewage/	2400

Various sources for collecting datasets

Implementation Details

- **Dataset Acquisition**

- To collect more datasets and improve accuracy, we created our own datasets using the pipe.

Type of defect	Number of images
crack	**1.083**
holes	**166**
obstacle	**605**
total	**1.612**

Full dataset number

Create our dataset

Implementation Details

- **Model Training**

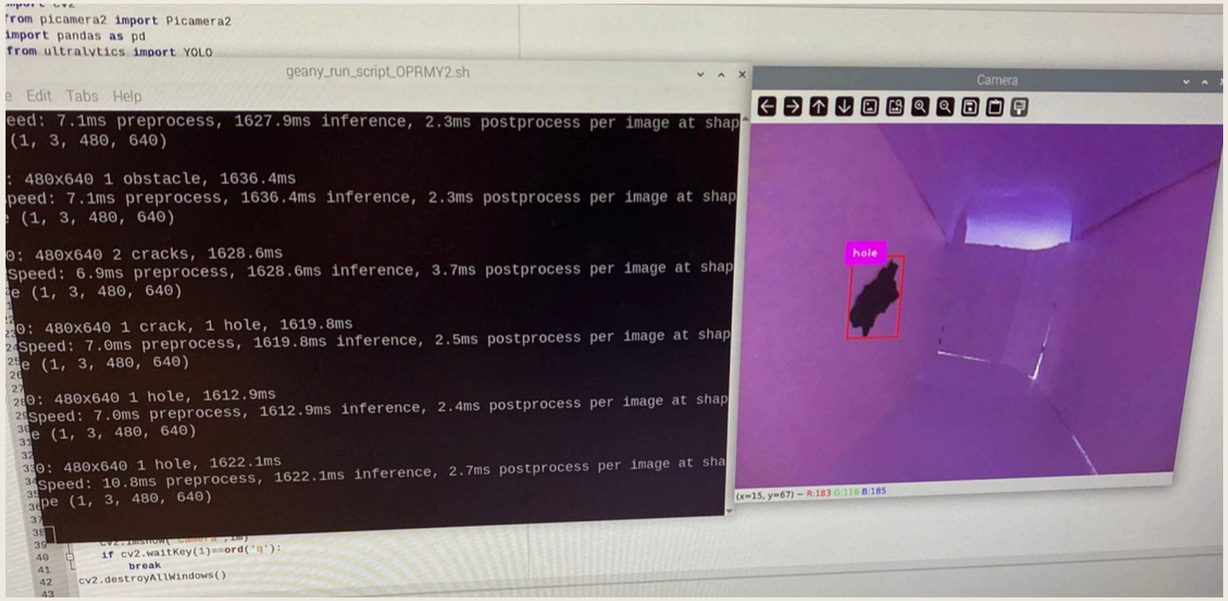
- The dataset was trained using YOLOv9t with the following parameters:

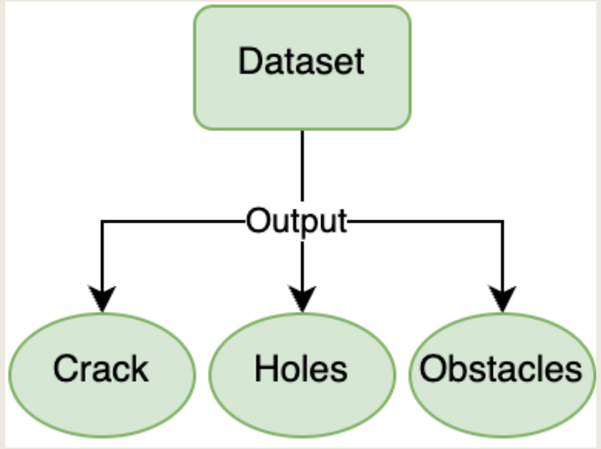
Parameters	Input
epochs	**100**
Images size	**640**
freeze	**9**
Multiscale	**True**

Implementation Details

- **Classification and detection results**

- The camera immediately detects, captures, and classifies the defect as a hole within 1.7 seconds.



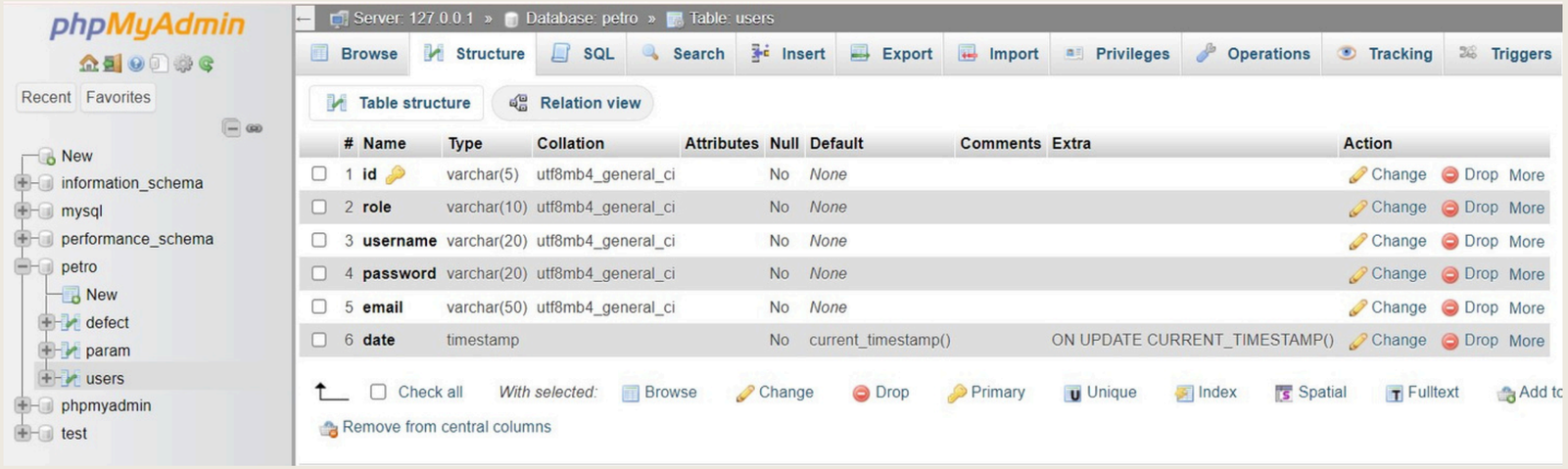


Implementation Details

- **Database tables**

- **Users Table**

- This table stores information about the users who interact with the robot system,

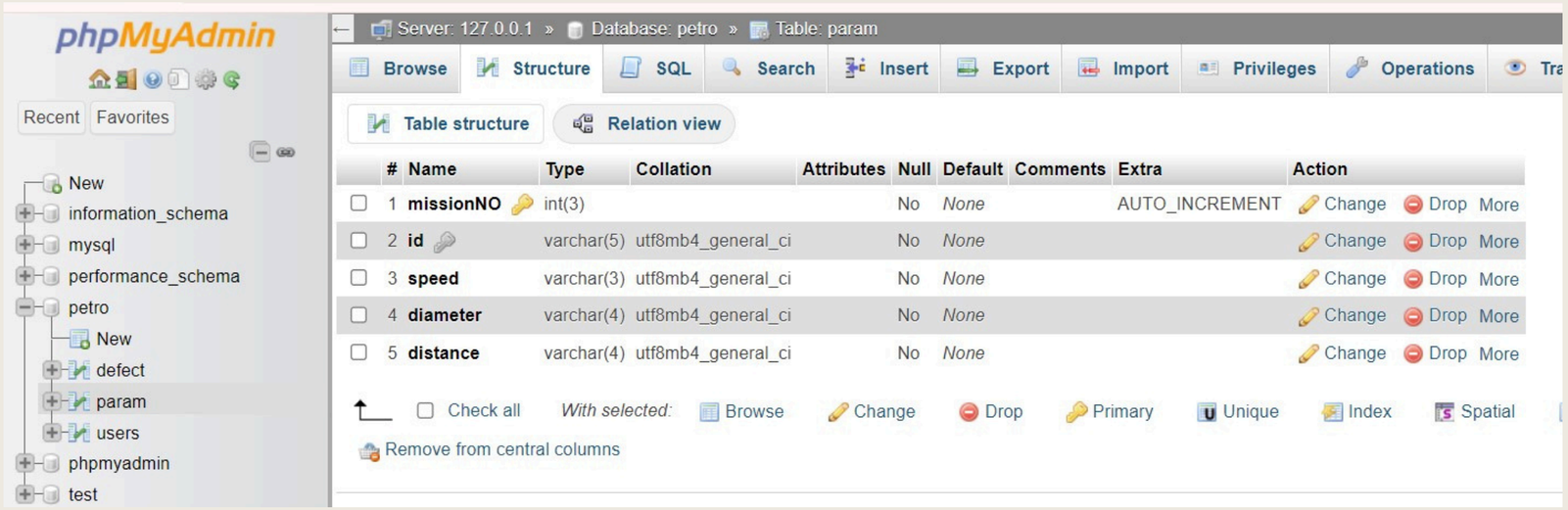


Implementation Details

- **Database tables**

- **Parameters Table**

- The Parameters table is designed to store various operational settings for the robot, which are provided by the admin.

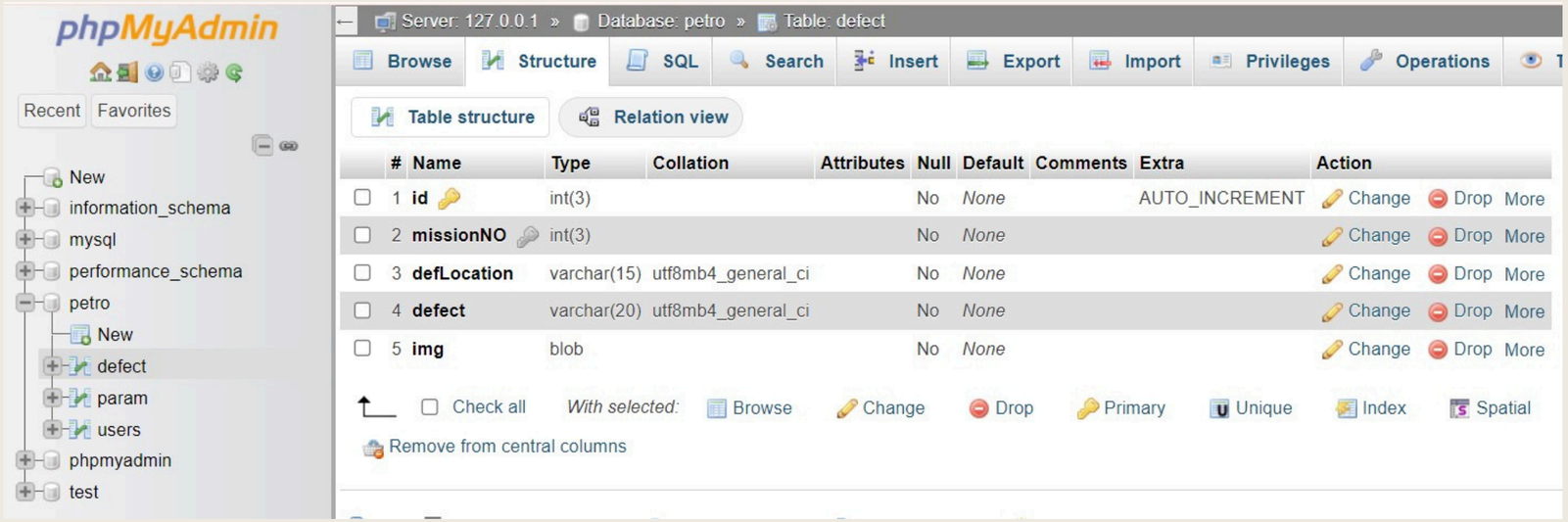


Implementation Details

- **Database tables**

- **Defects Table**

- The Defects Table is designed to record any defects detected by the robot during its operation,



Implementation Details

Pseudocode for Robot Motion

```
START
LOOP:
  IF SerialInputAvailable THEN
    ReadInputString a

    IF a == "0" THEN
      frontSensor = ReadFrontSensor()

      IF frontSensor <= 15 THEN  // Obstacle detected
        leftSensor = ReadLeftSensor()
        rightSensor = ReadRightSensor()
        WAIT 1 second

        IF rightSensor > leftSensor THEN
          SoftRight()
          WAIT 580 ms
        ELSE IF leftSensor > rightSensor THEN
          SoftLeft()
          WAIT 850 ms

        END IF
      ELSE
        // No obstacle in front
        Forward()
        WAIT 300 ms
        Stop()

        frontSensor = ReadFrontSensor()
        IF frontSensor <= 15 THEN

          RETURN
        END IF
      END IF

    ELSE
      Stop()
      WAIT 2000 ms

    ELSE IF a == "1" THEN
      Stop()
      WAIT 5000 ms

    ELSE
      Stop()
    END IF
  END IF
```

Scenarios Details

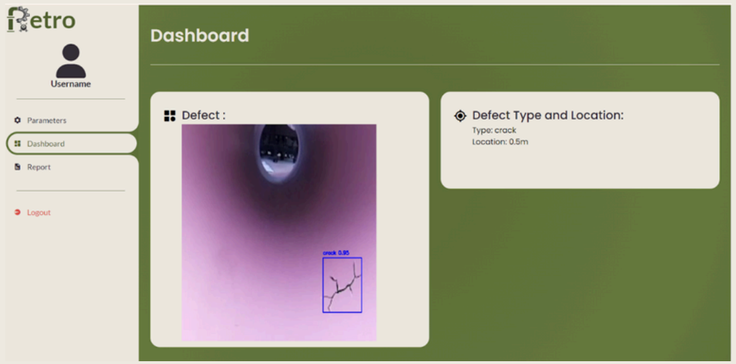
- Unit testing scenarios
- Integration testing scenarios
- Validation and system testing scenarios

Testing Details

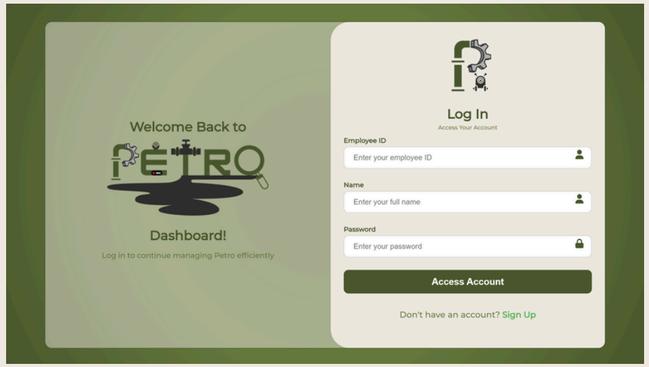
- **Unit testing details :**
  - Web pages testing
  - Camera testing
  - Ultrasonic testing
  - Encoder testing

Testing Details

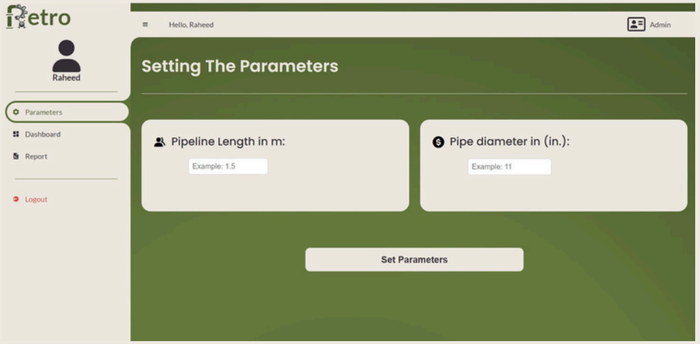
Web page testing:



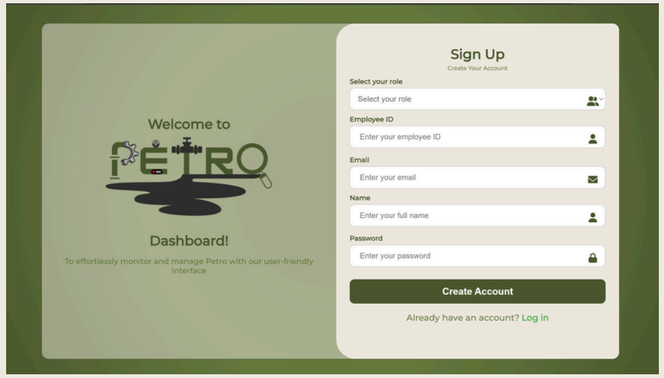
Dashboard Page



Login Page



Parameter Page

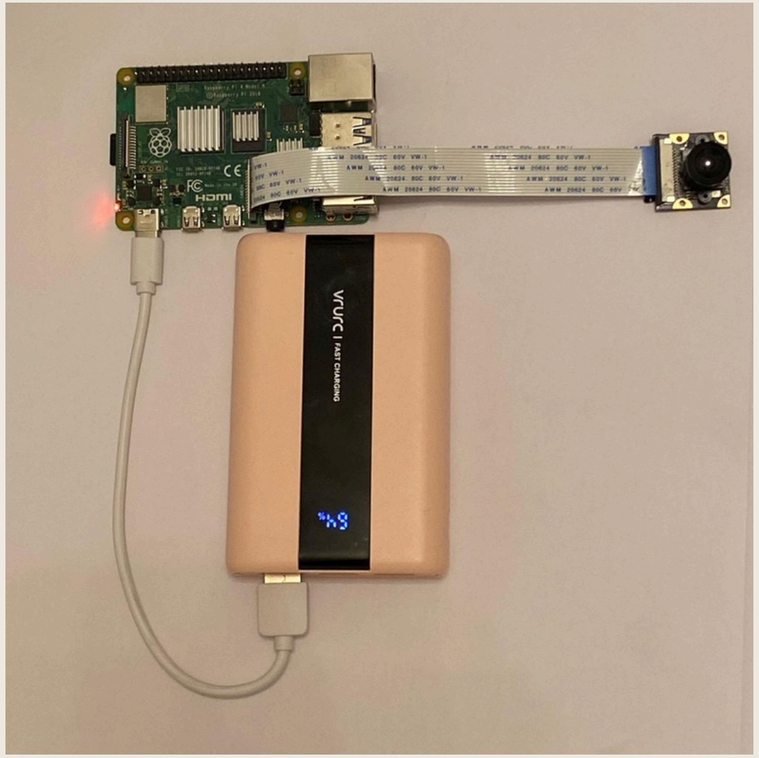


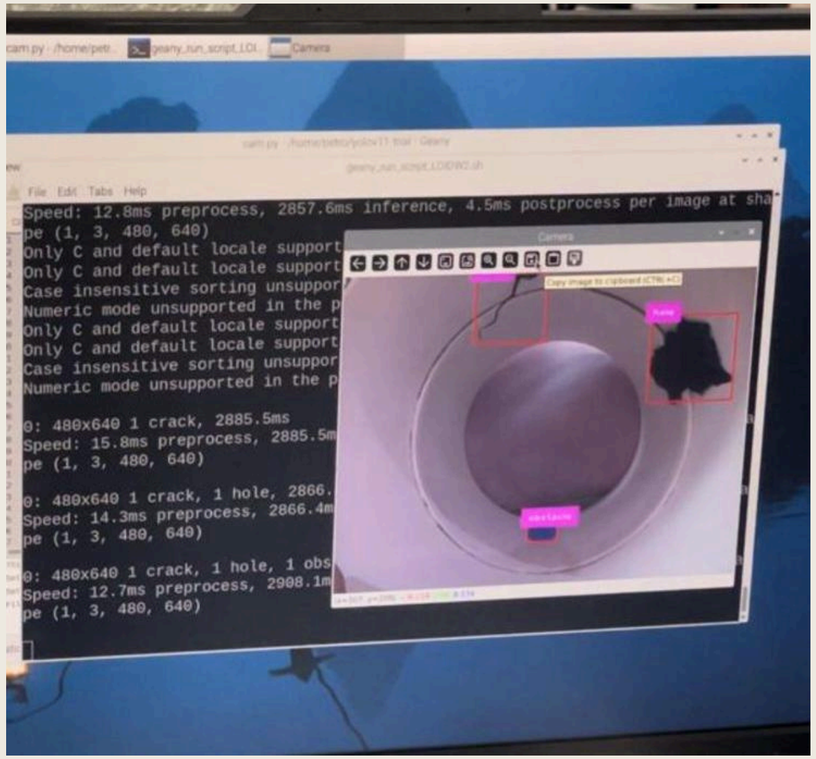
Sign up Page

Report Page

Testing Details

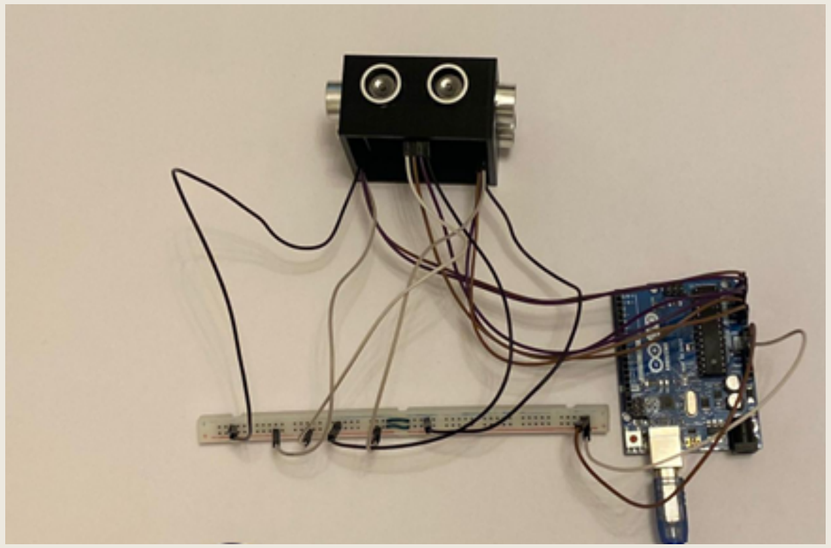
Camera testing details:

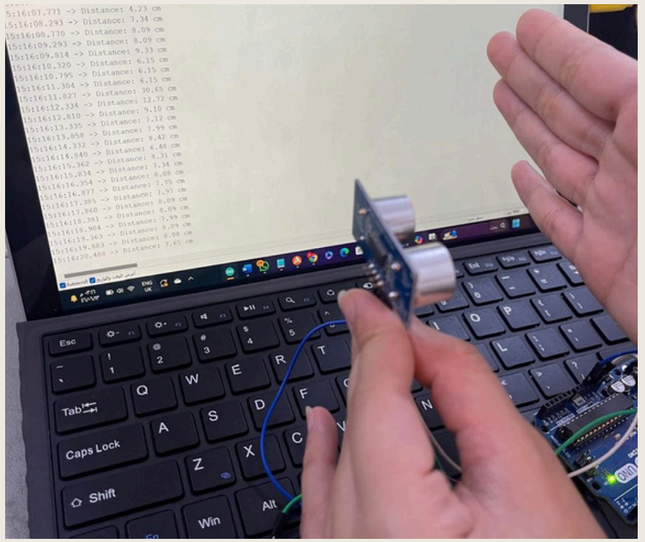


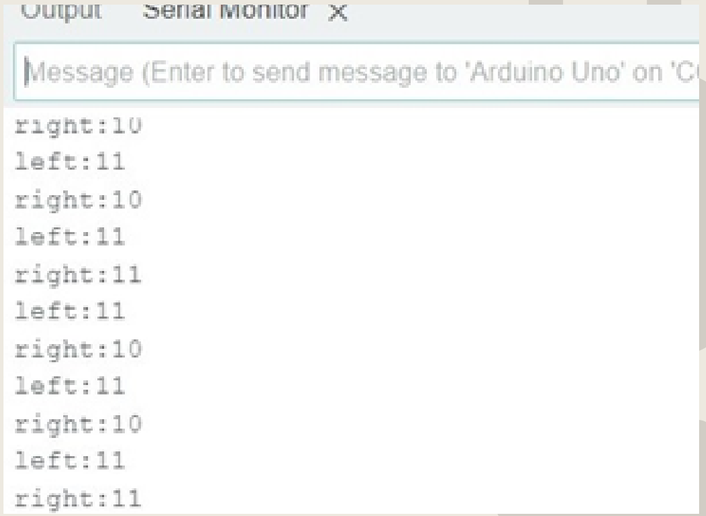


Testing Details

Ultrasonic testing details:

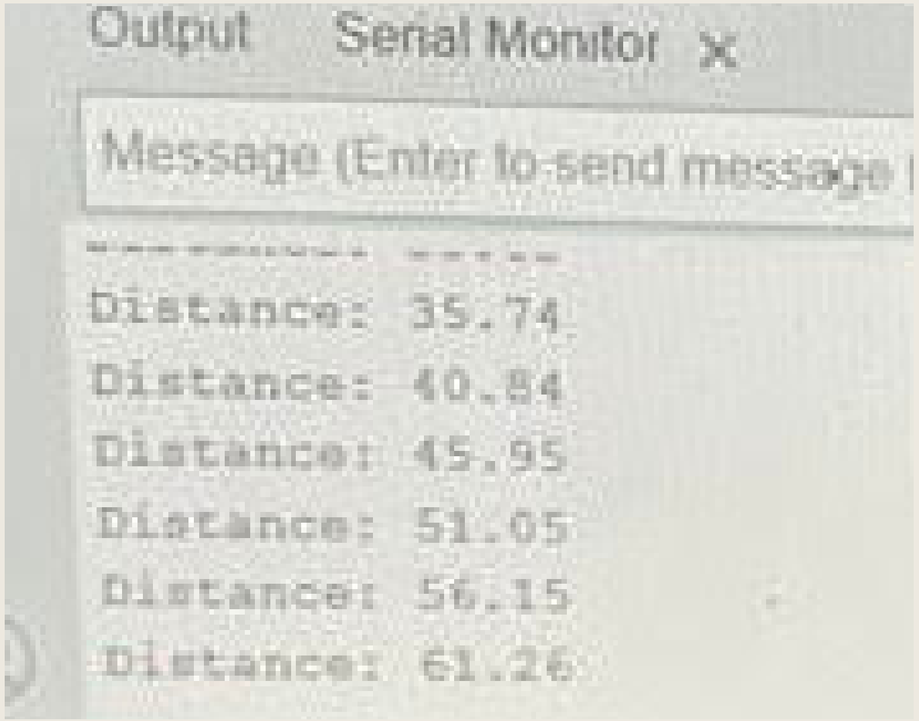






Testing Details

- **Encoder testing details:**

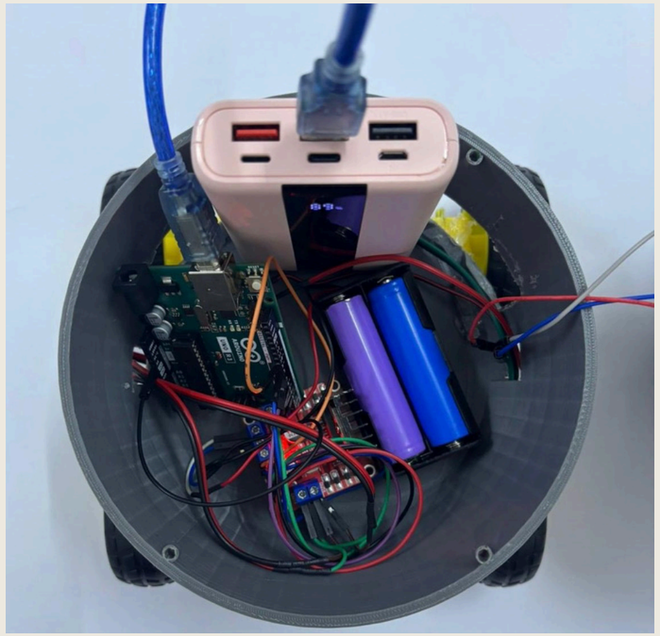


Testing Details

- **Integration testing details:**
  - Robot motion integration testing
  - Defect detection and classification integration testing
  - Localization integration testing
  - Website communication integration testing

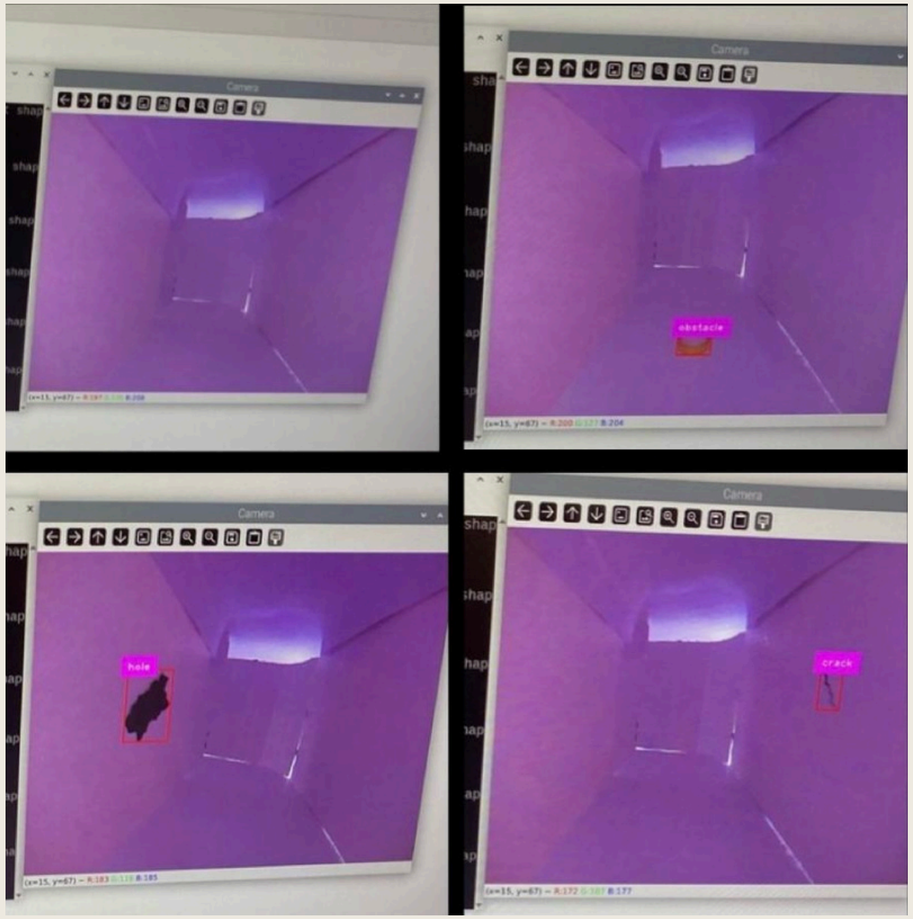
Testing Details

- **Robot motion integration testing**



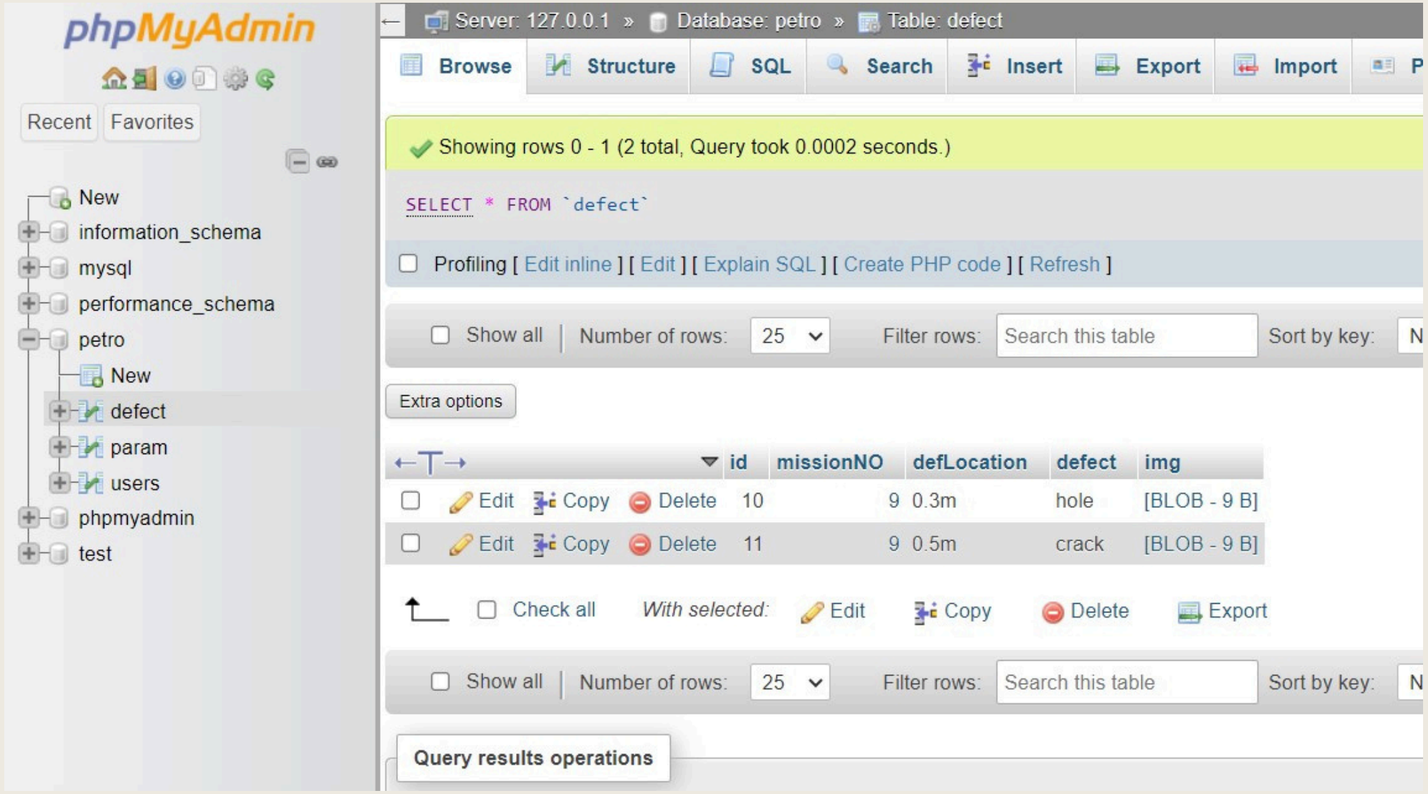
Testing Details

- **Defect detection and classification integration testing**



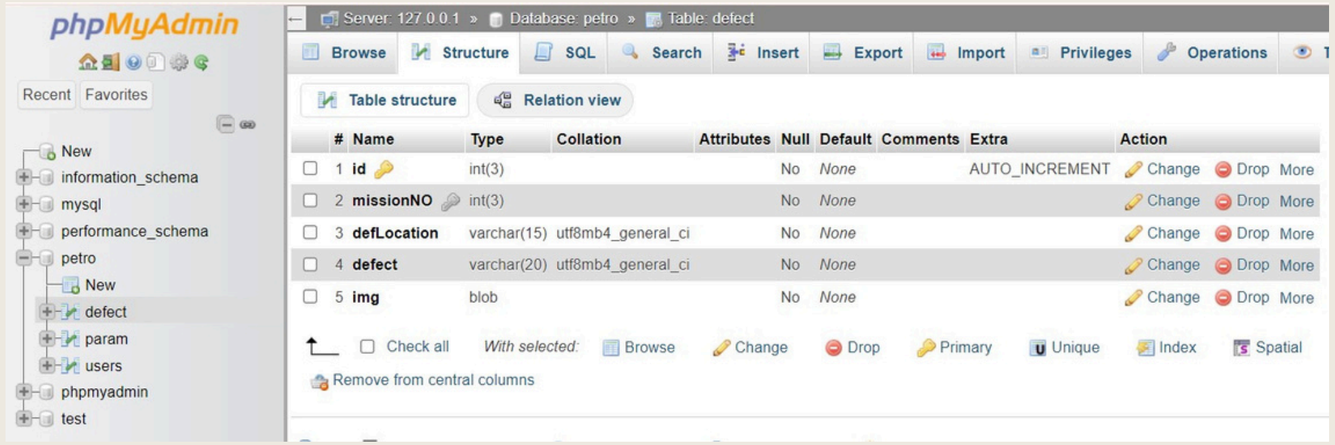
Testing Details

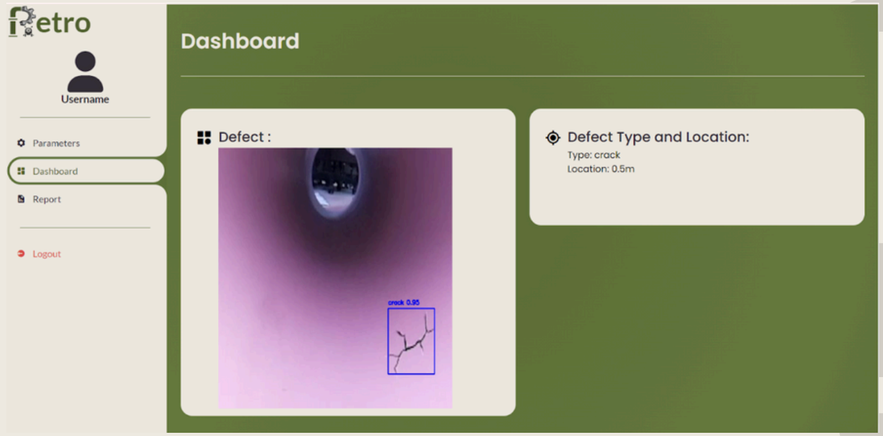
LOCALIZATION INTEGRATION TESTING



Testing Details

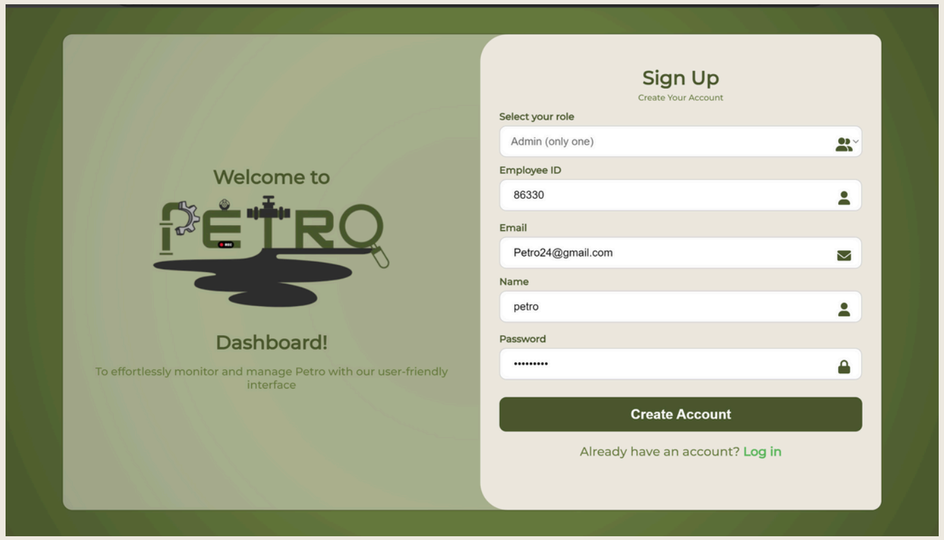
Website communication integration testing



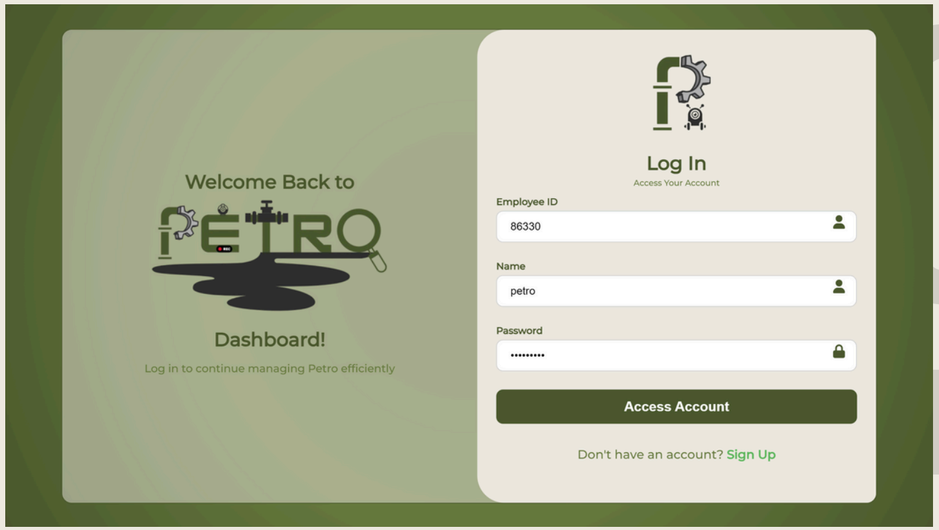


Testing Details

- **Validation and system testing details :**
  - Testing the whole system



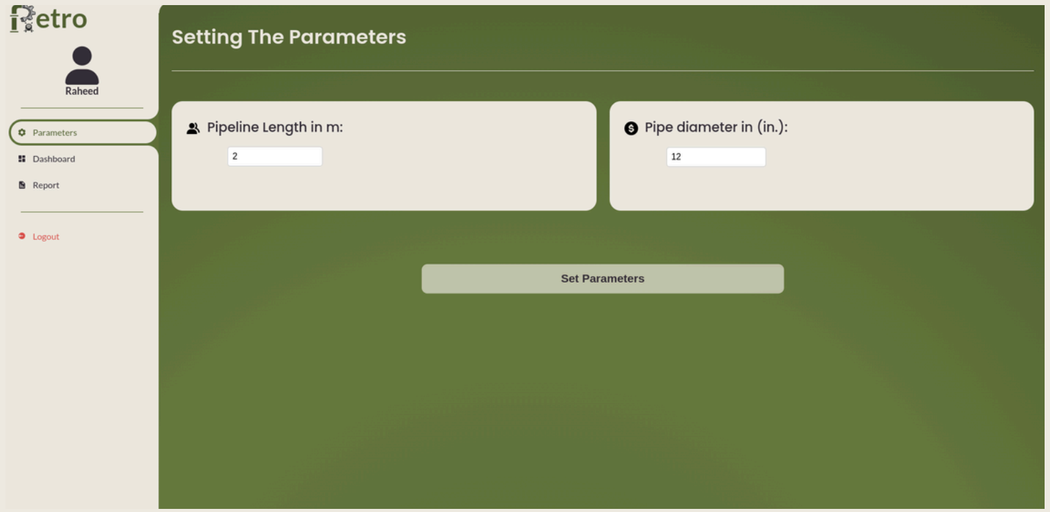
1-SIGN UP PAGE REGISTRATION



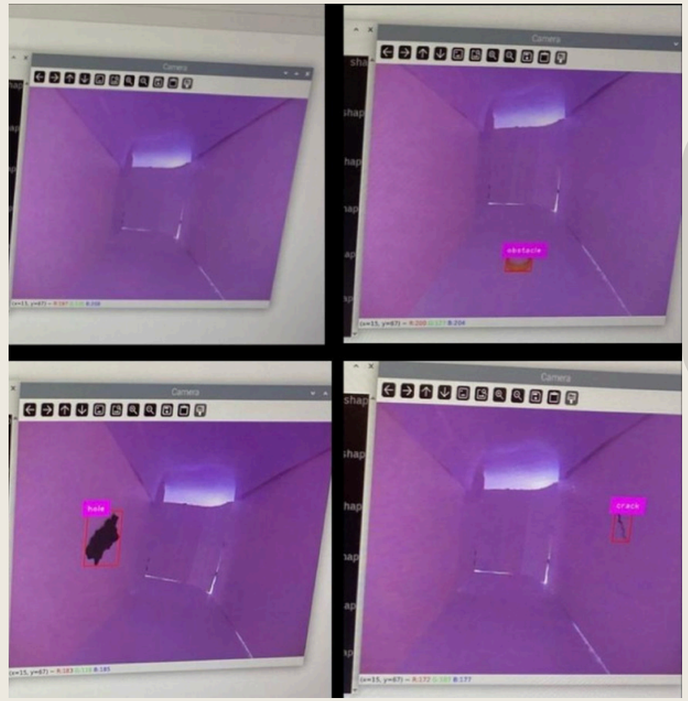
2-LOGIN PAGE REGISTRATION

Testing Details

- **Validation and system testing details :**
  - Testing the whole system



3-PARAMETER PAGE INFORMATION

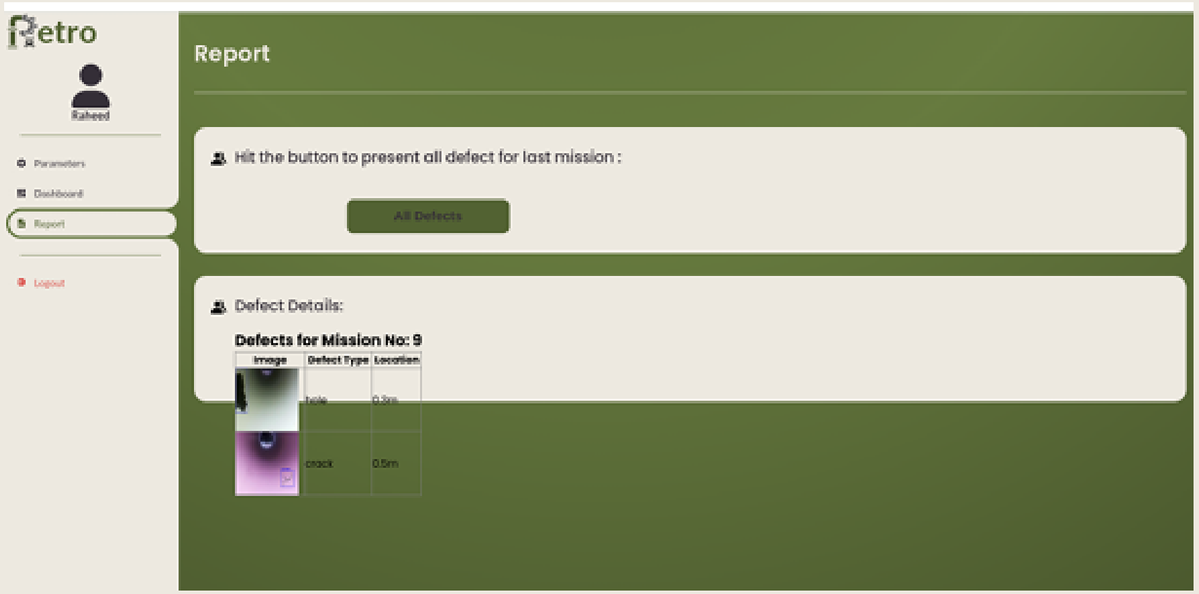


4-ALL POSSIBLE DEFECTS INSIDE THE PIPE

Testing Details

- **Validation and system testing details :**
  - Testing the whole system

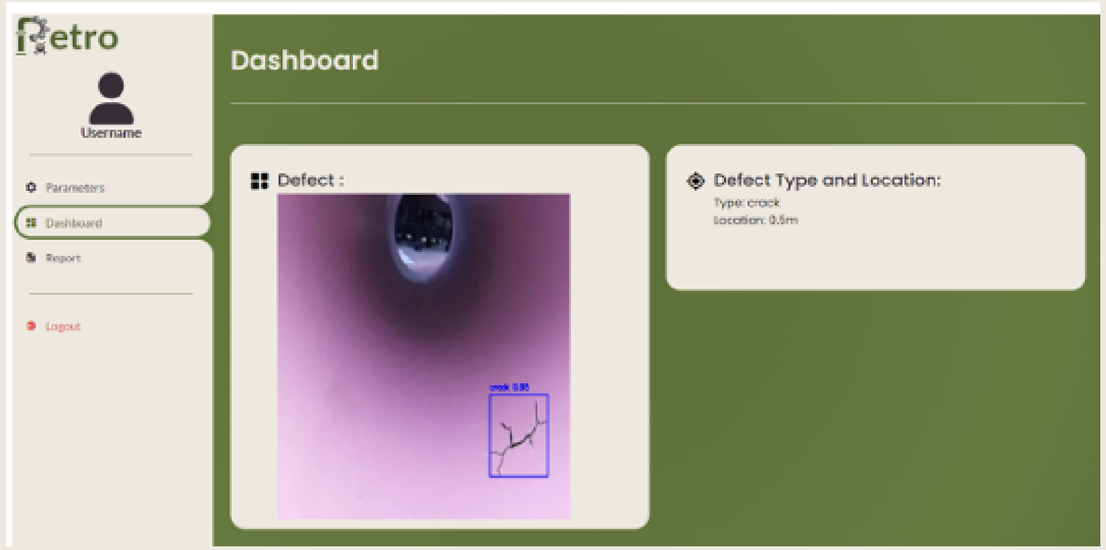
5-THE ROBOT MOVEMENT TESTING



6-REPORT PAGE INFORMATION

Testing Details

- **Validation and system testing details :**
  - Testing the whole system



7-DASHBOARD PAGE INFORMATION

Conclusion

- **Key Findings:**
  - YOLOv9t excels: Achieved 77% accuracy, balancing precision and robustness. Approved for future development.
  - Robot Semi-Automation: Minimal human intervention, boosting efficiency and reducing oversight.
  - Defect Location Identification: Improves accuracy, saving time and resources.
  - Real-world Dataset: Enhanced model performance through realistic training data.

Conclusion

Challenges and Limitations

Environmental Factors:

- The project requires pipes exceeding 10 inches in diameter.
- Suitable 16-inch pipes are only available in bulk.

Data Collection:

- Lack of a dedicated dataset for oil and gas pipe defects
- Limited access to real defect images from companies like Aramco and SAPIC
- A general pipe defect dataset was used but required significant cleaning and augmentation.

Operational Limitations:

- The semi-automated mode requires initial user interaction to position the robot at the center.
- Proper positioning is essential for ensuring correct orientation during movement.

Conclusion

Future Work for Enhancing the semi-autonomous In-Pipe Inspection Robot (IPIR)

- **Expanded Defect Categories:** Add corrosion, erosion, and pipe displacement to the defect classification system.
- **Enhanced Hardware:** Upgrade to a powerful processor and high-capacity power bank to support simultaneous execution of wall-following and defect-detection algorithms.
- **Advance Wireless Communication**: Implement long-range networks for reliable data transmission i pipelines.
- **Improve Control Algorithms:** Use advanced PID or model predictive control for better navigation complex pipe geometries.
- **Defect Classification System:** Standardize defect severity assessment for effective maintenance prioritization.

THANK YOU

ANY QUESTIONS?

Why YOLOv9t

- Comparison Result

Models name	MAP50
Yolov5n	0.699
Yolov8s	0.643
Yolov9t	0.69
Yolov10n	0.524
Yolov11n	0.656

Why YOLOv9t

- Result Yolov 5n

```
100 epochs completed in 1.983 hours.
Optimizer stripped from runs\detect\train2\weights\last.pt, 5.3MB
Optimizer stripped from runs\detect\train2\weights\best.pt, 5.3MB

Validating runs\detect\train2\weights\best.pt...
Ultralytics 8.3.28  Python-3.12.7 torch-2.5.1 CUDA:0 (NVIDIA GeForce GTX 1060, 6144MiB)
YOLOv5n summary (fused): 193 layers, 2,503,529 parameters, 0 gradients, 7.1 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 4/4 [00:0
                   all        114        186      0.836      0.686      0.734      0.531
                 crack         44         97      0.755      0.309      0.394      0.246
                  hole         14         14      0.854      0.929      0.945      0.743
              obstacle         38         75      0.898      0.821      0.863      0.602
Speed: 1.1ms preprocess, 7.2ms inference, 0.0ms loss, 3.0ms postprocess per image
Results saved to runs\detect\train2
```

- Result Yolov 11

```
100 epochs completed in 1.465 hours.
Optimizer stripped from runs\detect\train\weights\last.pt, 5.5MB
Optimizer stripped from runs\detect\train\weights\best.pt, 5.5MB

Validating runs\detect\train\weights\best.pt...
Ultralytics 8.3.28  Python-3.12.7 torch-2.5.1 CUDA:0 (NVIDIA GeForce GTX 1060, 6144MiB)
YOLO11n summary (fused): 238 layers, 2,582,737 parameters, 0 gradients, 6.3 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 4/4 [00:02<0
                   all        114        186      0.816      0.707      0.728      0.526
                 crack         44         97      0.628      0.366      0.375      0.216
                  hole         14         14      0.974      0.929      0.934      0.739
              obstacle         38         75      0.845      0.827      0.874      0.624
Speed: 0.9ms preprocess, 9.7ms inference, 0.0ms loss, 2.4ms postprocess per image
Results saved to runs\detect\train
```

Why YOLOv9t

- yolov9t Architecture

```yaml
# YOLOv9

# parameters
nc: 80  # number of classes
depth_multiple: 1.0  # model depth multiple
width_multiple: 1.0  # layer channel multiple
#activation: nn.LeakyReLU(0.1)
#activation: nn.ReLU()

# anchors
anchors: 3

# gelan backbone
backbone:
  [
   # conv down
   [-1, 1, Conv, [16, 3, 2]],  # 0-P1/2
   # conv down
   [-1, 1, Conv, [32, 3, 2]],  # 1-P2/4
   # elan-1 block
   [-1, 1, ELAN1, [32, 32, 16]],  # 2
   # avg-conv down
   [-1, 1, AConv, [64]],  # 3-P3/8
   # elan-2 block
   [-1, 1, RepNCSPELAN4, [64, 64, 32, 3]],  # 4
   # avg-conv down
   [-1, 1, AConv, [96]],  # 5-P4/16
   # elan-2 block
   [-1, 1, RepNCSPELAN4, [96, 96, 48, 3]],  # 6
   # avg-conv down
   [-1, 1, AConv, [128]],  # 7-P5/32
   # elan-2 block
   [-1, 1, RepNCSPELAN4, [128, 128, 64, 3]],  # 8
```

- Parameter Yolov 9t

```python
from ultralytics import YOLO

# Load a model
model = YOLO("yolov9t.pt")

# Train the model
train_results = model.train(
   data="C:/Users/pca/Desktop/yolo9/yolov9Dataset/data.yaml",  # path to dataset YAML
    epochs=100,  # number of training epochs
    imgsz=640,  # training image size
    freeze = 9,
    device=0,  # device to run on
)
```

Why YOLOv9t

- yolov9t multi-scale parameter tuning

```python
from ultralytics import YOLO

# Load a model
model = YOLO("C:/Users/pca/Desktop/yolo9/runs/detect/train5/weights/best.pt")

# Train the model
train_results = model.train(
    data="C:/Users/pca/Desktop/yolo9/yolov9Dataset/data.yaml",  # path to dataset YAML
    epochs=100,  # number of training epochs
    imgsz=640,  # training image size
    multi_scale=True, #Multi-Resolution
)
```

Why YOLOv9t

- yolov9t Result

```
100 epochs completed in 4.082 hours.
Optimizer stripped from runs\detect\train5\weights\last.pt, 4.6MB
Optimizer stripped from runs\detect\train5\weights\best.pt, 4.6MB

Validating runs\detect\train5\weights\best.pt...
Ultralytics 8.3.28  Python-3.12.7 torch-2.5.1 CUDA:0 (NVIDIA GeForce GTX 1060, 6144MiB)
YOLOv9t summary (fused): 486 layers, 1,971,369 parameters, 0 gradients, 7.6 GFLOPs
```

Class	Images	Instances	Box(P	R	mAP50	mAP50-95): 100%|| 4/4 [00:04<0
all	123	197	0.813	0.711	0.736	0.553
crack	46	99	0.67	0.323	0.375	0.25
hole	14	14	0.889	0.929	0.924	0.745
obstacle	47	84	0.879	0.881	0.909	0.666

```
Speed: 1.4ms preprocess, 22.6ms inference, 0.0ms loss, 2.1ms postprocess per image
Results saved to runs\detect\train5
```

- Final Reslut Yolov 9t

```
100 epochs completed in 8.837 hours.
Optimizer stripped from runs\detect\train6\weights\last.pt, 4.6MB
Optimizer stripped from runs\detect\train6\weights\best.pt, 4.6MB

Validating runs\detect\train6\weights\best.pt...
Ultralytics 8.3.28  Python-3.12.7 torch-2.5.1 CUDA:0 (NVIDIA GeForce GTX 1060, 6144MiB)
YOLOv9t summary (fused): 486 layers, 1,971,369 parameters, 0 gradients, 7.6 GFLOPs
```

Class	Images	Instances	Box(P	R	mAP50	mAP50-95): 100%|| 4/4 [00:04<0
all	123	197	0.86	0.727	0.768	0.573
crack	46	99	0.742	0.384	0.403	0.247
hole	14	14	0.939	0.929	0.972	0.78
obstacle	47	84	0.897	0.869	0.93	0.692

```
Speed: 0.8ms preprocess, 13.1ms inference, 0.0ms loss, 6.3ms postprocess per image
Results saved to runs\detect\train6
```

Why RPI4

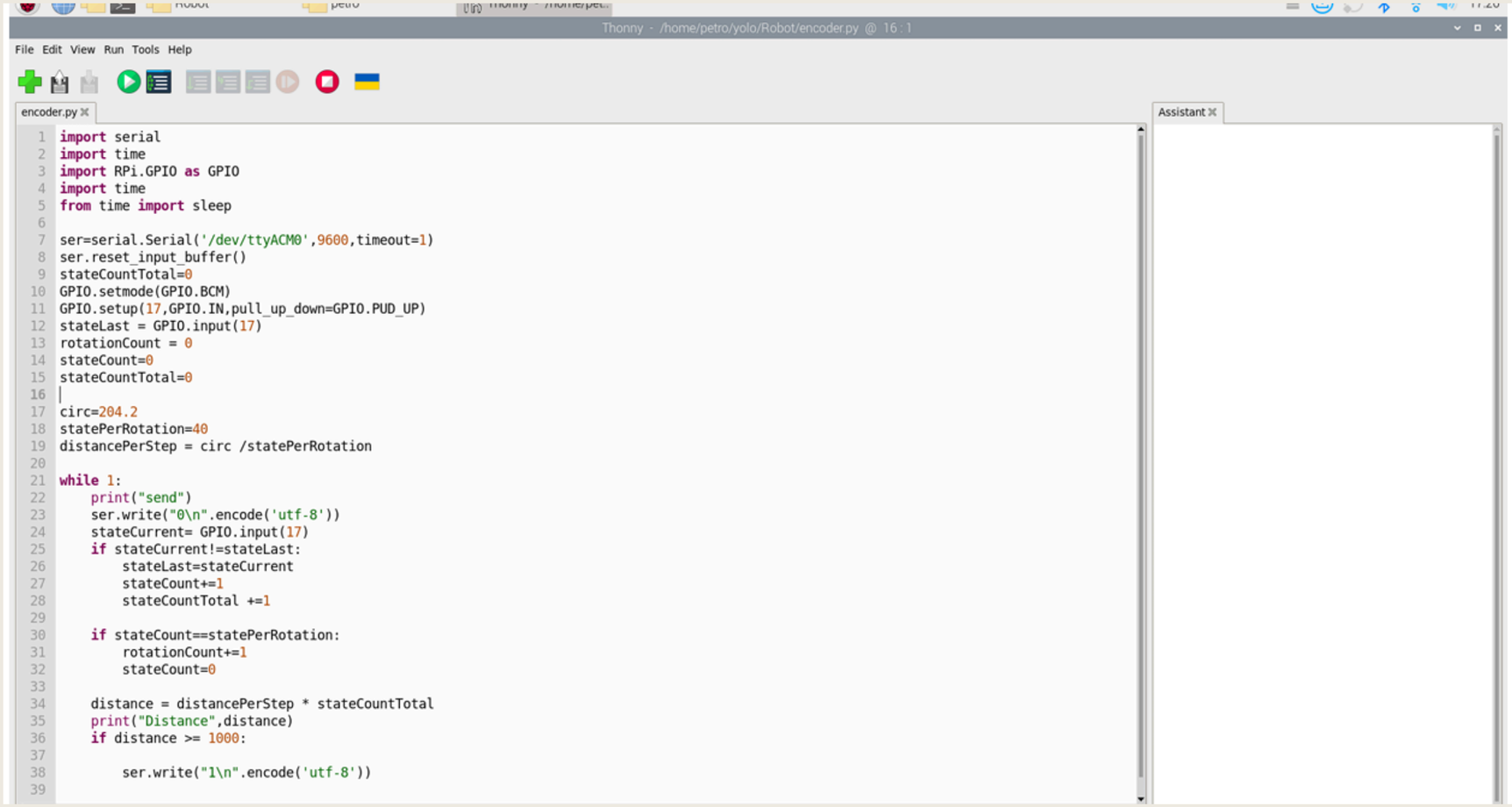
Feature	Raspberry Pi 2	Raspberry Pi 3	Raspberry Pi 4	Raspberry Pi 5
Processors (Quad-core)	ARM Cortex-A7	ARM Cortex-A53	ARM Cortex-A72	Arm Cortex-A76
Clock Speed	900 MHz	1.2 GHz	1.5 GHz	2.4 GHz
Wi-Fi	No	Yes	Yes	Yes
Bluetooth	No	Yes	Yes	Yes
USB Ports	4 × USB 2.0	4 × USB 2.0	2 × USB 2.0 2 × USB 3.0	2 × USB 2.0 2 × USB 3.0
Ethernet Port	Yes	Yes	Yes	Yes
Power Supply	5V/2A	5V/2.5∼3A	5V/3A	5V/5A

Why Ultrasonic

Feature	HC-SR04	JSN-SR04T	A02YYUW
Type	Non-waterproof	Waterproof	Waterproof
Operating Voltage	5V	5V	3.3V-5V
Measuring Range	2 cm to 400 cm	20 cm to 600 cm	3cm m to 450 cm
Accuracy	±0.3 cm	±1 cm	±1 cm
Weight	Lightweight	Heavier	Lightweight
Cost	Lower cost	Higher cost	Higher cost
Availability	Available	Available	Unavailable

Implementation Details

Robot Navigation and Localization Code:




```python
import serial
import time
import RPi.GPIO as GPIO
import time
from time import sleep

ser=serial.Serial('/dev/ttyACM0',9600,timeout=1)
ser.reset_input_buffer()
stateCountTotal=0
GPIO.setmode(GPIO.BCM)
GPIO.setup(17,GPIO.IN,pull_up_down=GPIO.PUD_UP)
stateLast = GPIO.input(17)
rotationCount = 0
stateCount=0
stateCountTotal=0

circ=204.2
statePerRotation=40
distancePerStep = circ /statePerRotation

while 1:
    print("send")
    ser.write("0\n".encode('utf-8'))
    stateCurrent= GPIO.input(17)
    if stateCurrent!=stateLast:
        stateLast=stateCurrent
        stateCount+=1
        stateCountTotal +=1

    if stateCount==statePerRotation:
        rotationCount+=1
        stateCount=0

    distance = distancePerStep * stateCountTotal
    print("Distance",distance)
    if distance >= 1000:

        ser.write("1\n".encode('utf-8'))
```

Implementation Details

- **Functions to control motors speed and direction**

```
81  void left() {
82  analogWrite(enA, 255);
83  analogWrite(enB, 255);
84    digitalWrite(in1, LOW);
85    digitalWrite(in2, HIGH);
86    digitalWrite(in3, HIGH);
87    digitalWrite(in4, LOW);
88  }
89  void right() {
90  analogWrite(enA, 255);
91  analogWrite(enB, 255);
92    digitalWrite(in1, HIGH);
93    digitalWrite(in2, LOW);
94    digitalWrite(in3, LOW);
95    digitalWrite(in4, HIGH);
96  }
97  void Stop() {
98  analogWrite(enA, 0);
99  analogWrite(enB, 0);
100   digitalWrite(in1, LOW);
101   digitalWrite(in2, LOW);
102   digitalWrite(in3, LOW);
103   digitalWrite(in4, LOW);
104 }
105 void forward(){
106 analogWrite(enA, 150);
107 analogWrite(enB, 150);
108   digitalWrite(in1, HIGH);
109   digitalWrite(in2, LOW);
110   digitalWrite(in3, HIGH);
111   digitalWrite(in4, LOW);
112 }
113 void backward(){
114 analogWrite(enA, 200);
115 analogWrite(enB, 200);
116   digitalWrite(in1, LOW);
```

Implementation Details

- **navigation with localization code:**

```
void loop() {
 if  (Serial.available()>0){
    String a = Serial.readStringUntil('\n');
    if( a == "0")
    {
int frontSensor = sensorFront();
if(frontSensor <= threshold){
int leftSensor = sensorLeft();
int rightSensor = sensorRight();
delay(1000);
if(rightSensor>leftSensor){
    right();
    delay(690);
  }
else if(leftSensor>rightSensor){
  left();
  delay(780);
  }
  else{
    Stop();
  }
}
 else{
   frontSensor = sensorFront();
  forward();
  delay(300);
  Stop();
if(frontSensor <= threshold){
  return;
}
else{
  Stop();
  delay(3000);
}
 }
    }else if ( a == "1"){
  Stop();
  delay(5000);
 }
  }
    else {
    Stop();
    }
}
```