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Remotely Operated Vehicles (ROV) for Corrosion Monitoring

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***Abstract*— Corrosion in underwater environments poses a significant risk to marine infrastructure, necessitating efficient and cost-effective monitoring solutions. Traditional inspection methods involving human divers are costly, time-consuming, and hazardous. This paper presents a remotely operated vehicle (ROV) designed for underwater corrosion detection. The proposed system integrates a FREDI HD PLUS ENDOSCOPE for high-definition video capture, a relay-controlled propulsion system, and a machine learning-based corrosion detection algorithm utilizing YOLOv11. The ROV is optimized for affordability and simplicity, making it accessible for small-scale operations and academic research. The results demonstrate the system's ability to provide real-time corrosion analysis, offering a viable alternative to traditional inspection techniques.**

I. INTRODUCTION

Corrosion in underwater environments poses a significant threat to the structural integrity of marine infrastructure. It is a critical issue faced by industries such as oil and gas, shipping, and marine construction. Submerged structures, including pipelines, ship hulls, and offshore platforms, are constantly exposed to harsh environmental conditions that accelerate material degradation. Factors such as salinity, dissolved oxygen levels, and marine organisms contribute to the corrosion process, leading to potential structural failures, increased maintenance costs, and environmental risks.

Traditional methods for detecting and mitigating corrosion rely heavily on manual inspections conducted by human divers. These inspections are not only time-consuming and costly but also present significant safety risks, especially in hazardous and deep-water environments. Human divers face challenges such as low visibility, strong underwater currents, and limited operational time due to depth and pressure constraints. As a result, there is a growing demand for alternative methods that can improve the efficiency, safety, and cost-effectiveness of underwater inspections. Remotely Operated Vehicles (ROVs) have emerged as a practical solution for underwater corrosion detection. ROVs are unmanned, remotely controlled submersibles equipped with tools to perform inspections and gather data in underwater environments. Unlike manual inspections, ROVs can operate for extended periods, access hard-to-reach areas, and function in environments that are hazardous for human divers. Advanced ROVs often come equipped with high-definition cameras, sensors, and manipulators to perform a wide range of tasks.[1]

This project focuses on the development of a simple and cost-effective ROV specifically designed for visual corrosion detection. The proposed system eliminates the need for complex sensor arrays and focuses on a minimalist design featuring two motors for propulsion and a single camera for visual inspection. By adopting this approach, the project aims to create a reliable and efficient ROV that can be utilized in smaller-scale operations and academic research.

II LITERATURE SURVEY

A. Importance of Corrosion Detection

Corrosion is a naturally occurring chemical process where metals react with environmental elements like oxygen, water, and other chemicals, leading to material degradation. It poses a significant threat to infrastructure and machinery in industries such as marine, oil and gas, and transportation. Corrosion can manifest as surface rust, pitting, or structural weakness, often resulting in costly repairs or catastrophic failures if undetected.[3]

Underwater environments exacerbate corrosion detection challenges due to factors like salinity, water pressure, temperature variations, and biofouling. Critical infrastructures like offshore oil rigs, pipelines, and ship hulls are particularly vulnerable, with minor corrosion potentially leading to severe consequences, including leaks, environmental hazards, and structural collapses.

Traditional corrosion detection methods rely on manual inspection and Non-Destructive Testing (NDT) techniques such as ultrasonic or radiographic testing. While effective, these methods have limitations: they are labor-intensive, time-consuming, and rely on human expertise, making them prone to subjectivity and inconsistency. Inspections in remote or hazardous locations, such as deep-sea pipelines, are also challenging and costly.[2]

B. Computer Vision for ROV-Assisted Inspections

Computer vision, a branch of artificial intelligence, has transformed industrial automation by enabling machines to interpret and process visual data. In underwater environments, ROV-mounted cameras capture image and video data, which are analyzed using computer vision algorithms to identify corrosion patterns.

Advanced techniques like Convolutional Neural Networks (CNNs) have been widely adopted for feature extraction and classification. CNNs excel at recognizing specific patterns in images, such as rust discoloration, pitting, or surface irregularities. These patterns often serve as early indicators of corrosion.

Object detection frameworks like YOLO (You Only Look Once) have gained popularity for real-time analysis. YOLO divides input images into grids and predicts bounding boxes, confidence scores, and class labels, allowing simultaneous detection and localization of multiple corrosion instances in a single pass. This approach makes it highly efficient for real-time ROV-assisted inspections.[4]

C. Advancements in Object Detection Models for ROVs

Over the years, object detection models have evolved to address the increasing complexity of real-world applications. The YOLO family has been at the forefront, with YOLOv11 introducing significant improvements for challenging underwater inspections:

1. Transformer-Based Architectures: Enhance the model's ability to capture global and local image features, improving detection of subtle corrosion patterns.
2. Improved Feature Pyramids: Advanced feature fusion techniques allow detection across varying corrosion scales, from microscopic pitting to large rust patches.
3. Dynamic Anchor Boxes: Adaptive anchors improve localization accuracy for irregularly shaped corroded areas.
4. Non-Maximum Suppression (NMS): Enhanced NMS algorithms reduce false positives by refining bounding box selection.[5]

D. Data Preparation for Corrosion Detection

Data preparation is a critical component of computer vision-based corrosion detection. Roboflow 3.0 simplifies dataset annotation, augmentation, and export, integrating seamlessly with object detection frameworks like YOLO. For corrosion detection, Roboflow provides tools to:

1. Annotate images with bounding boxes around corroded areas.
2. Apply augmentations such as flipping, rotation, and brightness adjustment to enhance dataset variability.
3. Export datasets in YOLO format for training.

Augmentations simulate real-world conditions like low lighting, turbidity, and reflections, ensuring model robustness for underwater applications.[6]

III. PROPOSED METHODOLOGY

DESIGN

1. Frame and Structure

The design of the remote-controlled underwater exploration ROV centers around a robust yet lightweight frame constructed from PVC pipes. The frame is designed with a 20 cm diameter to ensure structural integrity while maintaining buoyancy. The frame's design utilizes relative joints and silicon seal glue to provide watertight seals at the joints, ensuring that the system remains waterproof during operation in submerged environments.

The ROV incorporates a 62 cm diameter density balancer. This component is critical for ensuring the ROV's stability while submerged, preventing it from tipping or drifting in the water. The density balancer helps the ROV maintain a level position, ensuring that the camera remains properly aligned with the surfaces being inspected

2. Materials and Waterproofing

PVC pipes were selected for their lightweight properties and their resistance to corrosion in underwater environments. To prevent water ingress, silicon seal glue is applied at the joints to ensure that the frame remains watertight during operations. This is particularly important in an environment where pressure and water immersion could otherwise damage the internal components.[8]

3. Camera System

The ROV is equipped with a FREDI HD PLUS ENDOSCOPE camera, chosen for its 1080p resolution and compact design, measuring 5 x 2 x 1 cm and weighing 200 g. This camera allows for high-definition imaging of underwater surfaces, essential for corrosion detection. The camera is directly connected to a laptop for real-time video capture and image processing. The camera is capable of capturing detailed underwater images, which are processed by an onboard system (connected to the laptop) using real-time image processing algorithms.

4. Power System and Actuation

A. Power Supply

The ROV is powered by an 11.1V lithium-ion battery, which provides the necessary energy to drive the motors and power the camera system. The battery is chosen for its high energy density, ensuring longer operational times for the ROV.

B. Actuation and Control

The ROV uses relays and push buttons for actuation and control. The relays manage the distribution of power to the motors and other components, while the push buttons provide a simple user interface for manual control over movement and camera operation. The relay system allows for efficient power management, ensuring that the ROV operates optimally while minimizing power consumption.

5. Computer Vision and Corrosion Detection

A. Computer Vision and Preprocessing

The FREDI HD PLUS ENDOSCOPE camera captures underwater images at 1080p resolution, providing sufficient detail for the detection of corrosion features, such as rust, pitting, and cracks. The captured images are then pre-processed to enhance clarity. Techniques such as contrast enhancement, noise reduction, and edge detection are applied to improve the quality of the images, making corrosion features more distinguishable.

6. Corrosion Detection Process Using Roboflow YoloV11

1) Collect And Prepare Dataset

- Collect Images: Capture or source images of the objects you want to detect.
- Label Images: Use tools like [Roboflow Annotate] (https://roboflow.com/annotate) or other annotation tools to label objects in your images by drawing bounding boxes around the objects and assigning them class names.[6]

2) Upload And Prepare Dataset in Roboflow

- Create a Roboflow Project:
  1. Log in to your Roboflow account.
  2. Create a new project and name it.
- Upload Images:
  1. Upload your labeled images (e.g., in COCO, Pascal VOC, or YOLO format).
  2. Ensure annotations match your desired format.
- Augment and Preprocess:
  1. Apply augmentation techniques (e.g., flipping, rotation, brightness adjustment) to expand your dataset and improve model robustness.
  2. Resize images to match YOLOv11's requirements (e.g., 640x640 pixels).
- Export Dataset:
  1. Select YOLO format when exporting.
  2. Generate a download link or API key for direct integration.

3) Set Up Yolov11 Environment

- Install Required Tools:
  1. Install Python 3.8+ and create a virtual environment:

  bash

python -m venv yolov11_env
source yolov11_env/bin/activate

- Install dependencies:
  bash
  pip install torch torch vision numpy matplotlib
- Clone YOLOv11 Repository:
  bash
  git clonhttps://github.com/ultralytics/yolov11.git
  cd yolov11
- Install YOLOv11 Requirements:
  bash
  pip install -r requirements.txt

4) CONFIG. YOLOV11 FOR TRAINING

- Download Pretrained Weights:
  1. Download YOLOv11 pretrained weights (if available) or use YOLOv8 weights as a starting point.
  2. Place them in the designated directory (e.g., weights/).
- Edit ConFig. File:
  1. Modify the data.yaml file to point to your Roboflow dataset:
  yaml
  train: path/to/roboflow/train/images
  val: path/to/roboflow/valid/images
  nc: <1>
  names: [Corrosion]

5) Train The Model

- Run Training Command:
  bash
  python train.py --img 640 --batch 16 --epochs 50 --data data.yaml --weights yolov11.pt --device 0
- Monitor Training:
  1. YOLOv11 will display metrics like mAP (mean Average Precision) and loss during training. [Fig. 1.1]

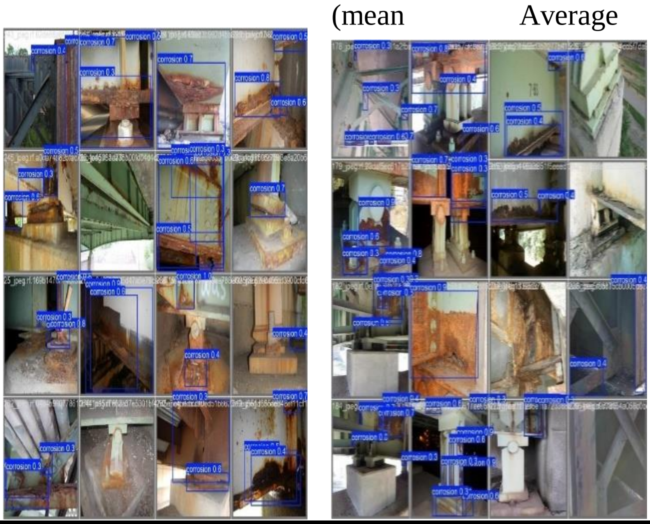


Fig. 3.1 Trained Data Set

6) Test And Validate The Model

- Evaluate on Validation Set:
  bash
  python val.py --data data.yaml –weights runs/train/exp/weights/best.pt --img 640 –device 0
- Analyze Results:
  a. Check validation metrics (e.g., precision, recall, and mAP).
  b. Visualize predictions on validation images.

7) Deploy And Inference

- Run Inference on New Images:
  bash
  pythondetect.py--sourcepath/to/test/images—weight runs/train/exp/weights/best.pt --img 640 --device
- Deploy Model:
  a. Export the model to ONNX or TensorRT for edge devices.
  b. Use APIs or custom scripts to deploy the model in production.[7]

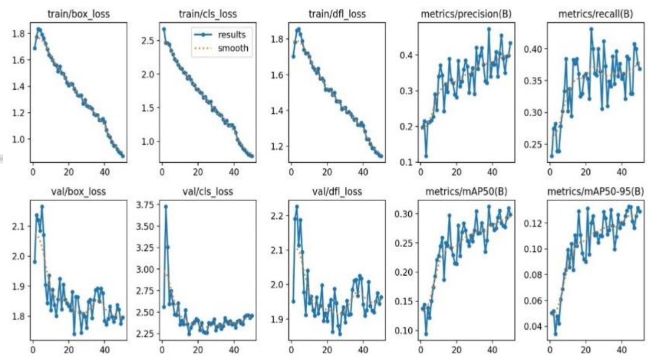


Fig. 3.2 Graphical Representation of Trained Data Set

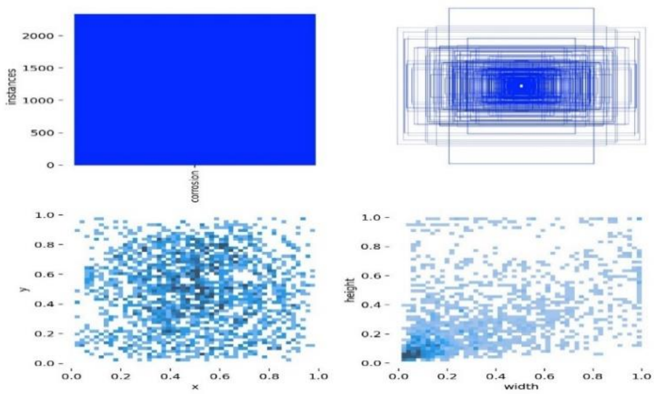


Fig. 3.3 Pixel Representation of Trained Data Set

7. ITERATE AND IMPROVE

a. Collect new data from edge cases or errors.
b. Retrain the model with updated datasets using transfer learning.

IV. SOFTWARE INTERFACE

1) CAD Model

Fig:4.1 3D CAD model

Computer-Aided Design (CAD) plays a crucial role in the development of the Remotely Operated Vehicle (ROV), particularly in visualizing the structural design before physical assembly. In this project, Autodesk Fusion 360 is utilized to create a detailed 3D model of the ROV. This modelling process allows for precise dimensioning of components, ensuring accurate placement of PVC pipes, T-joints, buoyancy tubes, and camera mounting locations. By using CAD, potential design flaws can be identified and corrected before fabrication, minimizing material waste and structural inefficiencies. Additionally, Fusion 360 enables simulation and stress analysis, allowing the team to evaluate the ROV's stability, buoyancy, and structural integrity under different underwater conditions. The software provides a visual representation of how different components interact, making it easier to refine the design before implementation. (Fig. 4.1)

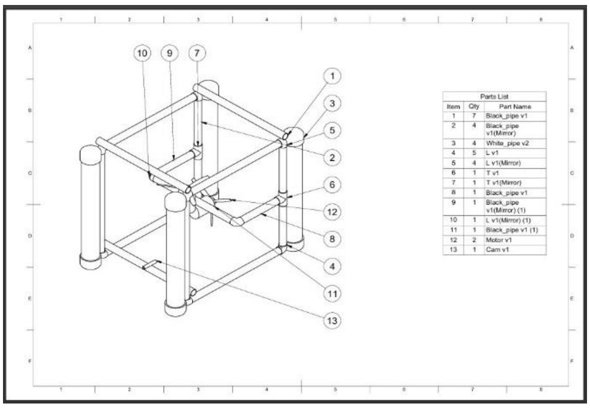


Fig:4.2 Parts of ROV

Fusion 360 is a powerful cloud-based CAD tool that combines parametric, direct, and surface modelling capabilities, making it an ideal choice for ROV design. It enables the creation of complex assemblies where multiple components, such as the frame pipes (370 cm length, 20.2 cm diameter), buoyancy pipes (425.51 cm length, 62 cm diameter), and T-joints, can be modelled and tested for proper alignment.(Fig. 4.2)

2) Corrosion Detection Algorithm

The ROV employs YOLO (You Only Look Once), a cutting-edge object detection algorithm, to identify corrosion in real-time. YOLO is highly effective for real-time object detection because it processes images quickly and efficiently, identifying multiple features within a single pass. This capability makes it ideal for underwater applications, where fast and accurate detection is critical to minimize operational delays. "Fig. 1.2, Fig. 1.3"

The algorithm is specifically trained to recognize various corrosion patterns, such as rust and pitting, by analysing labelled datasets of corrosion images. Once identified, these areas are marked for further inspection, enabling precise maintenance planning. YOLO's ability to detect multiple corrosion features simultaneously enhances the ROV's performance, making it a reliable tool for monitoring structural integrity in challenging environments.

3) Real-Time Processing and Feedback

The system processes images in real-time, enabling immediate detection of corrosion on submerged structures. This rapid analysis is essential for efficient inspections, as it allows operators to identify corrosion as soon as it appears in the camera feed. By leveraging YOLO's fast processing speed, the model can analyses multiple frames per second, ensuring that no critical damage is overlooked.

Real-time feedback is particularly crucial for underwater inspections, where environmental conditions such as water currents and visibility can make manual detection challenging. The system continuously scans and highlights corrosion spots, reducing the chances of missing defects and minimizing the need for repeated inspections.

This instant feedback mechanism improves decision-making, allowing inspectors to take immediate action, whether it be closer examination, maintenance planning, or preventive measures. By integrating real-time corrosion accuracy of structural inspections, ensuring the longevity and safety of critical assets.detection, the system enhances the efficiency and

4) Program:

```python
from inference import get_model
import supervision as sv
import cv2

# define the image url to use for inference
image_file = "taylor-swift-album-1989.jpeg"
image = cv2.imread(image_file)

# load a pre-trained yolov8n model
model = get_model(model_id="taylor-swift-records/3")

# run inference on our chosen image, image can be a url, a numpy array, a PIL image, etc.
results = model.infer(image)[0]

# load the results into the supervision Detections api
detections = sv.Detections.from_inference(results)

# create supervision annotators
bounding_box_annotator = sv.BoxAnnotator()
label_annotator = sv.LabelAnnotator()

# annotate the image with our inference results
annotated_image = bounding_box_annotator.annotate(
    scene=image, detections=detections)
annotated_image = label_annotator.annotate(
    scene=annotated_image, detections=detections)

# display the image
sv.plot_image(annotated_image)
```

Fig. 4.3 YOLOv8 Program

The provided code can be directly applied to your corrosion detection project by adapting it for real-time image analysis from the ROV's camera. Similar to how the code loads and processes an image for object detection with a pre-trained YOLOv8 model, your system would capture frames from the FREDI HD Plus Endoscope camera mounted on the ROV. The captured images would then be fed into a corrosion detection model, trained to recognize corroded areas. The YOLOv8 model would identify and annotate the corrosion, drawing bounding boxes around affected areas and labelling them for clarity. (Fig. 4.3)
Just like the code uses Supervision's Box Annotator and Label Annotator to visualize object detection results, these annotations could be used to highlight corroded regions in the captured images. This would allow you to monitor corrosion in real-time during ROV operations. The results could be displayed on your laptop interface, providing immediate feedback about the presence and location of corrosion, helping operators make data-driven decisions during the inspection process

1) Testing Methodology

A. Test Environment

The ROV was tested in both a controlled environment (swimming pool) and on a corroded metallic plate to validate its functionality and the effectiveness of the corrosion detection algorithm. The controlled environments provide an opportunity to evaluate the ROV's performance under different conditions and verify the accuracy of the corrosion detection system.

B. Test Procedure

The test procedure was designed to simulate real-world underwater inspections. The tests lasted approximately 45 minutes, providing enough time for the ROV to capture a range of images and for the algorithm to identify corrosion patterns. During the tests, the ROV was navigated manually using the relays and push buttons to move it through different sections of the test environment.

5) FLOW CHART:

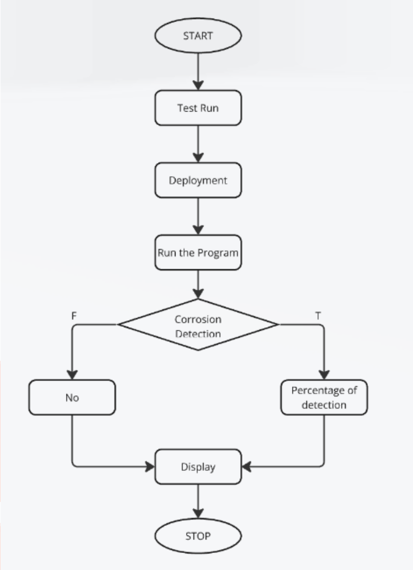


Fig. 4.4 Flow Chat

The ROV's camera captured high-resolution images of the submerged surfaces, and these images were processed using the corrosion detection algorithm. The system was evaluated on its ability to accurately detect corrosion features such as rust and pitting, and its effectiveness in providing real-time feedback to the user. The flowchart begins with the START phase, where the ROV system is initialized. This step involves powering up all hardware components, such as the 11.1V battery, camera, relays, and push buttons, ensuring they are fully functional. The operator verifies the connections between the camera and laptop via USB and the manual control setup through wired connections. At this stage, all systems are checked for readiness before proceeding to the next phase. This includes verifying the integrity of the ROV's frame, buoyancy pipes, and seals to ensure the unit can withstand underwater conditions without failure.

The next step is the Test Run, which is crucial for validating the performance of the system. The ROV is submerged in a controlled environment, such as a swimming pool, to assess its movement, stability, and buoyancy. The operator tests the push buttons to confirm manual directional control (front, back, left, and right) through the relay system. The camera feed is monitored on Roboflow.com, where the real-time video is displayed to ensure image quality and clarity. This phase allows any technical issues, such as faulty connections or insufficient stability, to be identified and addressed before full deployment.

After a successful test run, the ROV proceeds to the Deployment phase. The ROV is carefully placed in the target environment, typically underwater near metallic surfaces prone to corrosion. During deployment, the operator ensures that the buoyancy and stability are maintained and that all components are functioning optimally. The ROV begins operation, and the video feed is displayed on the laptop. At this stage, the operator triggers image captures manually, as required, while the Roboflow interface processes the video feed in real time to detect corrosion. This manual control setup ensures precision in navigating the ROV and targeting specific areas for inspection. (Fig. 4.4)

The core functionality is captured in the Corrosion Detection phase. As the ROV navigates, the corrosion detection model on Roboflow.com analyses the video feed and determines whether corrosion is present. If detected, the system calculates the percentage of the corroded area and displays the results on the interface. If no corrosion is detected, the system outputs "No" for that segment. This data is vital for assessing the extent of corrosion and planning necessary maintenance or repairs. The results are displayed clearly, providing the operator with actionable insights. The process concludes with the STOP step, where the program is terminated, and the ROV is retrieved from the water for post-operation analysis. This structured approach ensures efficient and precise corrosion detection.

V. RESULTS AND DISCUSSIONS

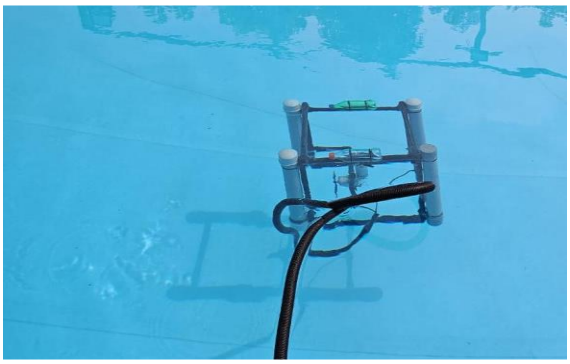
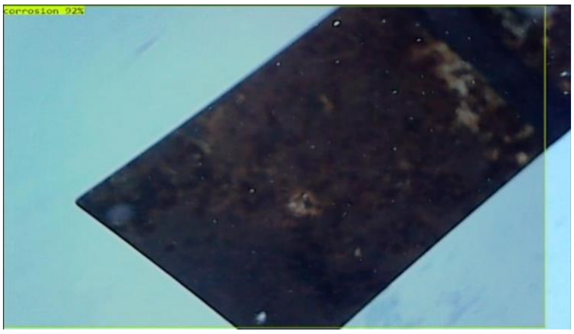
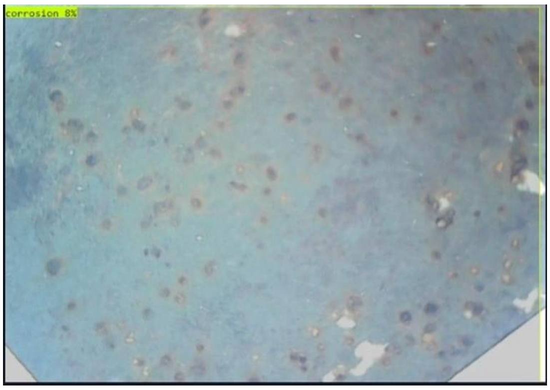


Fig:5.1 Structural Integrity and Buoyancy



(a)



(b)

Fig:5.2 Corrosion Detection Output

The testing and evaluation of the Remotely Operated Vehicle (ROV) were conducted in a controlled swimming pool environment and on a corroded metallic plate to assess its overall performance, including its structural integrity, maneuverability, camera efficiency, and corrosion detection accuracy. The results obtained from these tests provide insights into the system's capabilities and highlight areas for potential improvement.

Structural Integrity and Buoyancy: The frame of the ROV is constructed using PVC pipes with a length of 370 cm and a diameter of 20.2 cm. The frame provides the necessary rigidity and stability, ensuring that the ROV can withstand underwater pressure without deforming. The buoyancy system consists of a buoyancy pipe with a total length of 425.51 cm and a diameter of 62 cm, which helps the ROV maintain neutral buoyancy underwater. (Fig. 5.1)

To ensure water-tight joints, silicon seal glue was used to secure the T-joints and pipe caps. This method effectively prevented water leakage, ensuring that the ROV remained stable throughout its operation. The overall structural design allowed for smooth movement without excessive tilting or sinking, making it suitable for corrosion inspection in various underwater environments.

Camera and Image Capture: The ROV utilizes a FREDI HD PLUS ENDOSCOPE with 1080p video capture resolution for visual inspection. The camera feed is transmitted via USB to a laptop, where it is displayed in real time on Roboflow.com. The manual image capture system allows the operator to take snapshots at specific locations where corrosion is suspected.

During testing, the camera provided clear and detailed footage of submerged surfaces, making it effective for corrosion detection. However, the fixed positioning of the camera limited its field of view, requiring frequent adjustments in ROV orientation. The image clarity was adequate for corrosion detection, but underwater lighting conditions could impact the quality of captured images, indicating a need for additional illumination in darker environments. (Fig. 5.2)

1. Manual Control and Power Management:

The ROV is manually controlled using push buttons connected to a 4-relay module, which allows movement in four directions: forward, backward, left, and right. The control system is wired, meaning the operator must be in proximity to the ROV during operation.

The power system includes an HW 131 mini power supply module and a Bonka 11.1V 2200mAh 35C 3S Lithium Polymer Battery Pack. This setup provided sufficient energy for continuous operation for approximately 45 minutes without noticeable performance drops. However, the battery's limited runtime suggests that a higher-capacity battery or an alternative power management system could improve operational efficiency in long-duration inspections.

Corrosion Detection and Output: The corrosion detection model was deployed using Roboflow.com, which analyses the captured images and provided a confidence ratio box indicating the percentage of corrosion present in the detected area. This output served as a quantitative assessment, enabling the operator to determine the severity of corrosion on different surfaces.

During testing, the model successfully identified corroded areas with a high confidence score, making it a valuable tool for underwater structural monitoring. However, environmental factors such as water clarity, lighting conditions, and camera angle influenced detection accuracy. Future improvements could involve enhancing the dataset with more diverse corrosion samples to increase the robustness of the detection model.

2. Discussion

The ROV-based corrosion detection system demonstrated its effectiveness in providing real-time underwater inspection while maintaining structural stability and functional reliability. The results highlight its potential as a cost-effective alternative to traditional underwater inspection methods, particularly in marine infrastructure, offshore platforms, and industrial pipelines.

1) **Advantages of the System**:

The system's modular design using PVC pipes ensures ease of assembly and maintenance, making it scalable for various applications. The integration of Roboflow.com for corrosion detection provides automated image analysis, reducing the reliance on manual visual inspection. The wired control system ensures instantaneous response without communication delays, which is beneficial for precise maneuvering.
Additionally, the manual image capture feature gives the operator the ability to focus on specific areas of interest, rather than relying on automated snapshots that might miss crucial corrosion points. The battery power supply was sufficient for short-duration missions, allowing for effective corrosion detection within a controlled timeframe.

2) **Limitations and Areas for Improvement:**

While the wired control system provides reliable actuation, it also restricts the movement range of the ROV. This limits its usability in large underwater environments where extensive coverage is needed. A wireless or semi-autonomous navigation system could improve flexibility.
The fixed-position camera restricted the field of view, requiring frequent adjustments to inspect different angles of a structure. Implementing a servo-controlled camera mount would allow for dynamic positioning, improving coverage without excessive ROV movement.
Additionally, lighting conditions significantly impact image clarity. In low-light environments, corrosion detection accuracy was affected due to poor visibility. The integration of underwater LED lights could enhance image quality, improving model performance under various conditions. [9]
The absence of safety measures, such as automatic shutdown mechanisms or waterproofing of electrical components, poses risks in long-duration missions. Implementing protective enclosures for electronic parts and fail-safe mechanisms would enhance reliability and prevent potential damage during operation.

3) Future Enhancements:

For real-world applications, the system could be improved by:

a) Developing an autonomous navigation system that allows the ROV to move independently along predefined paths, reducing operator workload.
b) Upgrading the camera system with a pan-tilt mechanism for better field-of-view control.
c) Enhancing battery capacity for longer operational times.
d) Improving corrosion detection algorithms by training the model on larger, more diverse datasets to increase accuracy in different underwater conditions.
e) Implementing a real-time wireless data transmission system, eliminating the need for wired connections.

4) Advantages:

a) Cost-Effective: The ROV's PVC-based modular design makes it an affordable alternative to traditional underwater inspection methods.
b) Remote Operation: Eliminates the need for human divers, enhancing safety and reducing risks.
c) Real-Time Corrosion Analysis: The integration of Roboflow.com enables AI-based corrosion detection with instant results.
d) Ease of Assembly and Maintenance: The system's modular construction ensures quick repairs and easy upgradability.
e) Compact Design: The lightweight and compact nature of the ROV allows for easier deployment and transport.

5) Applications

1. Marine Infrastructure Inspection: Monitoring the condition of bridges, piers, and offshore platforms for corrosion or damage.
2. Industrial Pipelines: Inspecting underwater oil, gas, and water pipelines for structural integrity.
3. Environmental Research: Studying underwater ecosystems and monitoring the condition of submerged structures.
4. Ship Hull Maintenance: Inspecting the underwater parts of ships for corrosion, biofouling, or structural damage.
5. Reservoirs and Dams: Assessing the condition of submerged components in reservoirs, dams, and hydroelectric facilities.

6) Limitations:

a) Manual Control Constraints: The wired manual control system restricts the ROV's range and makes it unsuitable for large-scale underwater environments.
b) Field of View: The fixed camera limits coverage, requiring frequent adjustments to capture different angles.
c) Lighting Dependence: Poor lighting conditions underwater can affect image clarity and detection accuracy.
d) Short Runtime: The battery allows only 45 minutes of operation, which may not be sufficient for long-duration inspections.
e) Safety Features: The system lacks safety mechanisms, such as waterproofing for electrical components or emergency shutoff functions, increasing risks during operation.
f) Limited Corrosion Dataset: The detection model is currently trained on a limited dataset, which may not perform optimally in varied conditions.

V. CONCLUSION

The various hardware parts, software, and neural network setup are all explained in detail. An effective model that performed as planned was created with the use of image processing and machine learning. Autonomous car technology needs to get over a lot of social obstacles, despite its apparent advantages. The effect of metal models can obstruct technological advancement, much like the problem with the first cars. Nonetheless, new laws are giving these vehicles a chance to demonstrate their feasibility. The biggest transformation in personal transportation since the invention of autos will be possible when more governments legalize driverless cars, removing social barriers in the process.

VI. ACKNOWLEDGMENT

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VII. REFERENCE

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