Inspection Of A Head Race Tunnel In HEPs Using Remote Operated Vehicle

Vishwas Bhatt[1], Prakriti Yadav[2], Suraj Singh[3]
[1, 2, 3] Dept of Electrical Engineering,
[1, 2, 3] Babu Banarasi Das Northern India Institute of Technology
Lucknow, India

Abstract- *- Inspection and upkeep of HRT (Head Race Tunnels) is a fundamental responsibility for the Hydro Electric Projects' (HEP) secure and efficient functioning. To be able to inspect the HRTs, the HRT must be emptied, flushed, and inspected—a painstaking procedure. In order to prevent disruption throughout the plant's operation, the assistance of a remotely operated vehicle (ROV) for the HRT's submerged state inspection could be taken into account for deployment.*

A specialized ROV featuring cameras, sensors, and instruments for inspection and maintenance duties that can navigate the HRT while operating in submerged conditions. Integrating Convolutional Neural Network (CNN) and other supervised AI algorithms into the ROV's control system to enable autonomous navigation, obstacle recognition, and path planning inside the HRT.

Furnished with AI analytics software, monitoring screens, and personnel qualified to supervise ROV operations. Save camera footage and inspection data for later review and analysis.

AI-based ROV monitoring in hydroelectric plants (HEPs) has the potential to revolutionize the way maintenance and inspections are carried out, ultimately improving the sustainability and dependability of hydroelectric power output. But it's crucial to carefully plan and carry out the deployment, taking regulatory, safety, and technical aspects into account.

Keywords- Artificial Intelligence, Head race Tunnel, Remote Operated Vehicle, Corrosion detection

I. INTRODUCTION

In the dynamic realm of hydroelectric power generation, the pursuit of efficiency and safety has led to the innovation of a cutting-edge Remote-Operated Vehicle (ROV). Inspired by the proven Seafox design, this ROV revolutionizes inspection and maintenance procedures within the head-race tunnels of hydroelectric power plants. Originally designed for naval applications, the Seafox-inspired ROV combines resilience and adaptability to navigate the complexities of submerged environments.

This hydroelectric-specific ROV surpasses conventional inspection tools, excelling in corrosion detection crucial for preserving tunnel structural integrity. Equipped with advanced sensors and imaging technology, it swiftly identifies even the smallest signs of corrosion, enabling timely intervention. Specialized scanning capabilities address crack detection, providing valuable insights for focused repairs through sophisticated imaging and machine learning algorithms.

The ROV's vigilance extends to sediment deposition, a common challenge in tunnel water flow. By detecting sediment presence, it facilitates effective scheduling of cleanup operations, pre-emptively mitigating issues like decreased water flow and surface wear on tunnels.

What sets this ROV apart is its autonomous route planning capability. Empowered by sophisticated navigation algorithms and artificial intelligence, the ROV adeptly navigates tunnel networks, optimizing inspection routes while minimizing the need for human intervention in potentially hazardous underwater environments.

In essence, the Seafox-inspired ROV signifies a paradigm shift in hydroelectric power plant inspection and maintenance. Its versatility, advanced capabilities, and autonomy position it as a crucial asset in the pursuit of reliable and sustainable energy production. This ROV, pushing the boundaries of what's achievable, stands as a testament to human ingenuity on our journey into the submerged depths of hydroelectric infrastructure, advancing towards a cleaner, safer, and more efficient energy future.

II. LITERATURE REVIEW

There are many opportunities and challenges associated with integrating artificial intelligence (AI) into the production of hydropower energy. The applications of artificial intelligence (AI) in hydropower plant operation and optimization have been thoroughly studied in research. The use of AI techniques, such as Artificial Neural Networks (ANN), Fuzzy Logic, and Deep Learning, to improve accuracy in site selection, parameter estimation, and operation optimization, is one important area of focus. These methods have demonstrated promise in raising the accuracy of site selection procedures and guaranteeing precise estimation of vital parameters like head and discharge, which are crucial in figuring out plant capacity (Kumar & Saini, 2021)[6].

Furthermore, the effectiveness of machine learning (ML) models in maximizing energy output from hydropower plants throughout various operating stages has been thoroughly examined. River flow forecasting, reservoir operation optimization, scheduling, and real-time adjustments and post-operation analysis are just a few of the tasks for which machine learning (ML), and especially supervised learning methods, have been used. Short-term, medium-term, and long-term scheduling have all benefited from these applications, which also point to areas that need more study, particularly real-time schedule forecasting and low-head hydropower plant optimization (Bernardes et al., 2022)[7].

A. ROV Design Consideration

When creating a remotely operated vehicle (ROV) for underwater operations, the selection of structural components and materials is essential for guaranteeing optimal performance and establishing the maximum depth capability as studied by Oscar Adrian Aguirre-Castro et al (2019) . The use of polyvinyl chloride (PVC) pipe reinforced with steel satisfies the mechanical requirements for the operation of the ROV. With a fracture point pressure of 1724 kPa, the maximum depth that can be reached with this material is estimated to be 125.65 meters.

The Seafox concept has become well-known in ROV design. The hydrodynamic benefits of the Seafox design are examined in a study by R. Frank Busby (2018), who emphasize the design's streamlined shape for best underwater maneuverability. Ranuga et al. (2021) investigates further the structural advantages and adaptability of the Seafox design (Ranuga et al., 2021).

Hydrostatics and buoyancy are taken into account in the design to accommodate both controlled (freshwater) and marine (saltwater) environments. Utilizing a weight-balanced arrangement to support motor topology, a 3D model was created with SolidWorks software. The ROV measures 18.41 cm by 29.50 cm by 33.50 cm in size. It weighs 5.64 kg and has an estimated volume of 18.19 x 10^(-3) m^3.

$$E = -\rho \, g \, V \tag{1}$$

Equation (1) is used to determine the buoyancy force, which is 249.6 N given a saltwater density of 1400 kg/m^3. The variables E stands for total thrust, ρ for fluid density, g for gravity, and V for volume. As such, the three motors in the ROV's suggested motor topology have a minimum thrust force of 9.82 kg.

Aguirre-Castro, Oscar Adrian et al. (2019) examine the use of PVC pipes in ROV construction, highlighting their value as reasonably priced but robust structural elements and their contribution to buoyancy control (Aguirre-Castro, Oscar Adrian et al, 2019).

B. Related work

According to S. Lopez & F. Micheli et al. (2023) while doing the survey of Paute HPP Phase C part of Ecuador’s largest hydroelectric complex in the year 2016 and 2021 it was found that The geometric properties of the headrace tunnel, such as variations like holes, cracks, outcrops, and debris, are revealed by the 3D model analysis. These characteristics point to changes in the tunnel profile, which may be an indication of problems such as material deposits, over-excavations, or discontinuities in the structure. Interestingly, void volumes show up as important markers of recent degradation, especially in regions with poor granodiorite rock quality.

Quantitative comparisons between the ROV inspections conducted in 2016 and 2021 show significant alterations in the amount of debris accumulation and voids along the tunnel. Variations in volume per meter indicate that a number of factors, such as material fragmentation, transportation to unmonitored zones, and variations in sonar resolution, may be contributing to the ongoing increase in voids and deposits.

Interestingly, negative values for debris per meter signify situations in which deposits have been moved, highlighting the necessity of treating debris quantifications as a secondary factor when identifying critical degradation areas. On the other hand, areas prone to deterioration are indicated by voids, which consistently increase, especially in highly fractured granodiorite rock sections.

Similarly, another inspection done by D. Brox et al. (2023) at The Tala headrace tunnel located along the Wangchu River in Bhutan gave that the observations and interpretations made by the ROV are in close agreement with the results of manual inspections, especially when it comes to the relative locations of cracks in the concrete lining. Even though opinions regarding the size and severity of these cracks are fairly divided, ROV inspections are still an essential tool, particularly in situations where precise as-built records are not available.

It's crucial to be aware of the limitations of the sonar technology that is currently available, as it can identify construction joints and detached concrete blocks along the tunnel floor but may not be able to detect tiny cracks caused by shrinking concrete. Furthermore, the ROV can detect steel ribs even if it might not be able to detect exposed reinforcing rebar.

C. *Integrating AI algorithms*

1) *Crack detection using Deep Learning*: In concrete structures, visible indications of cracks frequently point to years of stress and wear and tear. Expert inspectors' manual inspections take a lot of time and are subjective. In order to overcome this constraint, scientists have developed an autonomous crack detection technique based on deep learning (DL) and convolutional neural networks (CNNs). In a recent study, various CNN models were created by processing RGB images and fine-tuning a pretrained VGG16 architecture. Grayscale models outperformed RGB models, proving that color is not a factor in DL crack detection. This method may improve structural integrity and reliability by automatically detecting cracks in concrete infrastructures.[1]

2) *Under-Deposit Corrosion (UDC) on Steel Pipeline Surfaces:*Many industries, including boiler tubes, cooling systems, heat exchangers, oil and gas pipelines, and wastewater treatment facilities, are at serious risk from UDC. In contrast to uniform corrosion, UDC is caused by differences in local chemistry and happens beneath solid deposits. System parameters and deposit features determine the precise mechanism. To make matters more complicated, UDC frequently coexists with MIC, or microbiologically influenced corrosion. Although various mechanical and physical strategies have been investigated by researchers to counteract UDC, mitigation is still difficult. Effective UDC management requires an understanding of the species involved, the makeup of the deposits, and the underlying mechanisms[2]

*3) Corrosion Monitoring Techniques:*There are now a number of in-situ monitoring technologies available for corrosion detection. These consist of acoustic emission (AE), microwave imaging, infrared thermography, eddy current detection, and ultrasonic thickness measurement. In particular, AE offers insightful information about the occurrence time, sites of initiation, and intensity of corrosion damage. Due to their diversity, testing field deposits in the lab is still difficult. Scholars are still investigating the best ways to test UDC corrosion.[3]

D. Setting Up a communication system

The core objective of an integrated communication system for UAVs is to establish seamless connectivity. Whether it’s a surveillance drone, a search and rescue quadcopter, or an environmental monitoring UAV, effective communication is critical.

The system typically comprises two essential components:

1) *Unidirectional Broadcast Transmission:* This component ensures real-time information flow from the UAV to the ground station. Video feeds, audio data, and telemetry are transmitted unidirectionally. Operators within a mobile command center receive this broadcast, allowing them to monitor the UAV’s activities.

2) *Two-Way Communication:* In addition to the broadcast, the system enables bidirectional communication. Operators can send commands to the UAV and receive telemetry data in return. This two-way link enhances control, situational awareness, and responsiveness during UAV operations.
Both components are integrated into a single chassis, which is strategically placed on the UAV. The compact design ensures minimal interference with flight dynamics. [5]

We can thus conclude with confidence that the hydroelectric-specific ROV project represents the best option for transforming the inspection and maintenance procedures used in hydroelectric power plants, having undergone extensive research and development. This ROV, painstakingly built with state-of-the-art technologies and inspired by the renowned Seafox design, is the result of our quest for the best underwater engineering performance. Its unmatched capacities for autonomous navigation, sediment analysis, corrosion detection, and crack identification represent a paradigm shift in the management of hydroelectric infrastructure. In the most demanding underwater environments, the ROV offers unparalleled resilience and adaptability thanks to its strong structural design, which is supported by cutting-edge sensors and intelligent systems. This innovation and sustainability come together to create a hydroelectric energy production process that redefines safety, efficiency, and environmental responsibility.

III. METHODOLOGY (HARDWARE)

Our proposed autonomous underwater remotely operated vehicle (ROV), which provides an innovative approach to head-race tunnel inspection, possesses the potential to transform underwater assessments. This novel method makes use of cutting-edge technology to negotiate the complex and difficult conditions of head race tunnels, guaranteeing thorough inspections with the least amount of human involvement. With its sophisticated sensors and imaging powers, our ROV seeks to deliver unmatched data precision and effectiveness, boosting the dependability of tunnel inspections. With its robust solution for the careful inspection of head race tunnels under various operating conditions, this proposed methodology is a major advancement in underwater inspection practices.

One promising way to increase safety, efficiency, and cost-effectiveness is to monitor and inspect head race tunnels (HRTs) in hydroelectric projects (HEPs) using artificial intelligence (AI) and remote access vehicles (ROVs). Here is how we envision this kind of system operating:

A. ROV Design and Deployment:

Our advanced Remotely Operated Vehicle (ROV) for Head Race Tunnel (HRT) maintenance and inspection is specifically built for submerged operations. With its sophisticated sensors, cameras, and multifunctional toolkit, this remotely controlled robot takes pride in its ability to manoeuvre through complex, high-resolution thermal environments. Its ability to send video and data feeds in real-time to a central monitoring station guarantees effective remote operation and prompt tunnel condition assessment. This cutting-edge technology is essential for maintaining the integrity and dependability of HRT systems because it not only improves inspection accuracy but also makes timely maintenance task decisions easier.

1) The Seafox Design

Inspired by its marine namesake, the Seafox design is a well-known feature in the field of remote-operated vehicles (ROVs) that provides optimal performance underwater. The Seafox design, which has a torpedo-shaped body and is streamlined, has several advantages for building and using ROVs. One particularly useful feature of the Seafox design is its hydrodynamic efficiency, which guarantees the ROV's manoeuvrability and low resistance when navigating through complex underwater environments. The vehicle's precision is improved by its streamlined configuration, which makes it especially skilled in difficult operational situations.

Figure 1: Modified Seafox Design

2) Use of PVC Pipes in Seafox-Designed ROVs

The strategic integration of PVC (polyvinyl chloride) pipes is a crucial element in Seafox-designed remotely operated vehicles (ROVs). PVC pipes in ROV construction provide a cost-effective and versatile solution, offering a sturdy yet lightweight framework. They safeguard sensitive electronic components during underwater missions, ensuring protection from external elements. Additionally, PVC pipes enable precise buoyancy control, allowing engineers to modify depth and stability, contributing to the production of highly capable underwater vehicles at a low cost.

Figure 2: Framework of the ROV

B. AI Integration

Our state-of-the-art Remotely Operated Vehicle (ROV) is more than just an underwater vehicle; it's an intelligent system that incorporates Artificial Intelligence (AI) algorithms for autonomous navigation, obstacle detection, and accurate path planning inside the difficult Head Race Tunnels (HRT). Through the use of sophisticated computer vision algorithms, the ROV's cameras are able to record visual information that extends beyond the surface.

This involves using unmatched accuracy to find cracks, corrosion, sediment accumulation, and other anomalies. By combining AI-driven autonomy with advanced image analysis, the ROV can make well-informed decisions in real-time, which guarantees a thorough and effective inspection process and raises the bar for HRT maintenance and monitoring.

Figure 3: Integrating AI algorithms into the ROV

C. Data Transmission and Communication System

With its effective communication system, the ROV is capable of connecting with the control centre without any problems. Sensitive data is protected by using secure data transmission protocols. Ensuring the integrity and efficiency of inspection and maintenance operations in demanding underwater environments, our communication infrastructure can operate at significant depths and reliably transmit data over long distances.

D. Data Storage and Analysis

Our system has a thorough data storage mechanism that archives inspection data and video footage for later use and analysis in order to improve operational efficiency. Through the integration of AI algorithms, wear patterns and potential problems are identified in historical data, allowing for a thorough examination and predictive maintenance. A cost-benefit analysis shows that although there are some initial costs associated with deploying and operating a ROV, these are greatly outweighed by the potential savings from improved maintenance and decreased downtime. In addition to maximizing resource utilization, this innovative strategy guarantees the durability and dependability of head race tunnel systems.

E. Monitoring and Control Centre

To ensure smooth ROV operations, a sophisticated control centre must be established. This centralized hub guarantees effective oversight with its monitoring screens, AI analytics software, and human operators with training. The intuitive interface makes it easy to operate the ROV and gives operators access to real-time data and inspection outcomes. This configuration facilitates human-machine collaboration while optimizing the use of AI capabilities and enabling operators to make well-informed decisions.

IV. METHODOLOGY (SOFTWARE)

A. *Jupyter Notebook*

With the integration of advanced algorithms, our innovative ROV system unlocks the potential of Artificial Intelligence (AI) in hydroelectric infrastructure. With the help of Convolutional Neural Networks (CNN), the Crack Detection, Corrosion Detection, and Sediment Deposition algorithms redefine inspection precision, guaranteeing the efficiency, safety, and dependability of hydroelectric head race tunnels (HRTs).

1) Crack Detection Algorithm

The Crack Detection Algorithm, which uses Convolutional Neural Networks (CNN) for reliable image analysis, places a high value on precision. It reduces false positives and negatives by identifying cracks with a high degree of accuracy, having been trained on a variety of datasets. The algorithm's increasing accuracy is demonstrated in Fig. No.

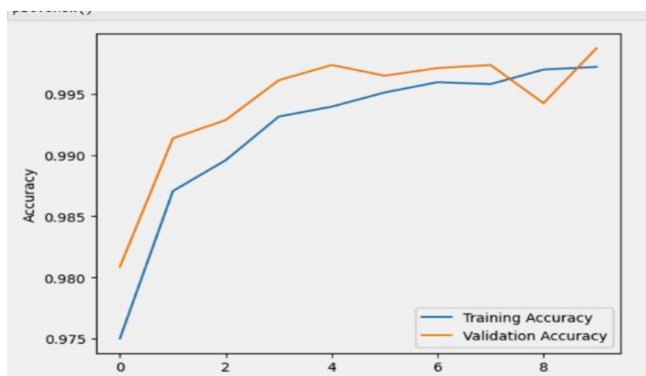


Figure 4: Variation of accuracy throughout testing

2) Corrosion detection algorithm

In order to accurately identify corrosion patterns, the Corrosion Detection Algorithm makes use of CNN architecture. It exhibits high accuracy in separating corrosion from other irregularities, having been trained on a large dataset. The accuracy of the algorithm across different levels of corrosion severity is shown in Figure .

Figure 5: Corrosion detection system

3) Sediment Deposition Detection Algorithm

Using CNN, the Sediment Deposition Algorithm examines photos to detect sediment accumulation. It attains high accuracy in identifying various types and quantities of sediment after being trained on a variety of sediment compositions.

B. Integration with the ROV System

These algorithms offer real-time image analysis during inspections and are seamlessly integrated into the ROV's control system. The ROV's capabilities are improved by the CNN-based models, which enable accurate and autonomous identification of corrosion, cracks, and sediment. An anticipatory maintenance strategy is guaranteed by this integration.

C. *Validation and Ongoing Improvement*

Extensive testing and validation guarantee algorithm correctness under various HRT scenarios. Iterative improvements are made possible by continuous monitoring and feedback loops, guaranteeing adaptability to changing tunnel conditions. This promise guarantees the inspection system's ongoing dependability.

In summary, the creation of CNN-based algorithms for the analysis of sediment deposition, corrosion detection, and crack detection in underwater structures necessitates a methodical software development process that includes a number of phases, from requirements collecting to testing and assessment. Developers make sure that their work is in line with operational requirements and environmental conditions by involving stakeholders and carefully crafting use cases. To train reliable CNN models with accurate detection capabilities, data collection, preprocessing, and model selection are essential. Model parameters are iteratively improved and generalization ability is evaluated during the training and validation phases. Testing and assessment guarantee dependability in practical situations and validate performance metrics. CNN-based algorithms improve the capabilities of remotely operated vehicles (ROVs) by means of these structured processes. This allows for accurate anomaly detection and efficient underwater inspection and maintenance operations.

V. RESULT & CONCLUSION

The AI-based Remote Operated Vehicle (ROV) for monitoring Hydroelectric Head Race Tunnels (HRTs) has improved hydroelectric infrastructure management with remarkable success after painstaking planning, rigorous testing, and seamless integration.

A. Hardware Integration

During the hardware integration stage, careful consideration is given to building a sturdy PVC pipe structure for the Remote Operated Vehicle (ROV). The vehicle's backbone is made up of these precisely drilled, cut, and assembled pipes, which provide the buoyancy and support needed for underwater operations. Every PVC part, including elbows, T-junctions, and end caps, is painstakingly assembled to guarantee structural stability and integrity in demanding underwater conditions.

Figure 6: Installing bilge pump to the structure

Electronic parts like sensors, actuators, and microcontrollers are concurrently and smoothly incorporated into the PVC framework. To maximize accessibility and functionality, these parts are positioned and fastened inside the structure in a deliberate manner. The brains of the ROV are microcontrollers, which direct its many operations and react to sensor input. Actuators allow the ROV to move and grasp objects, while sensors—such as cameras, temperature, depth, and depth sensors—collect vital information about the underwater environment.

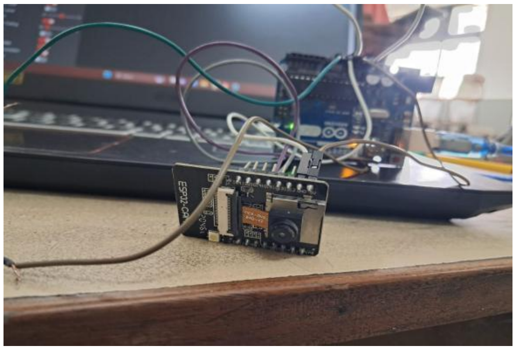


Figure 7: Initializing the ESP32 Camera

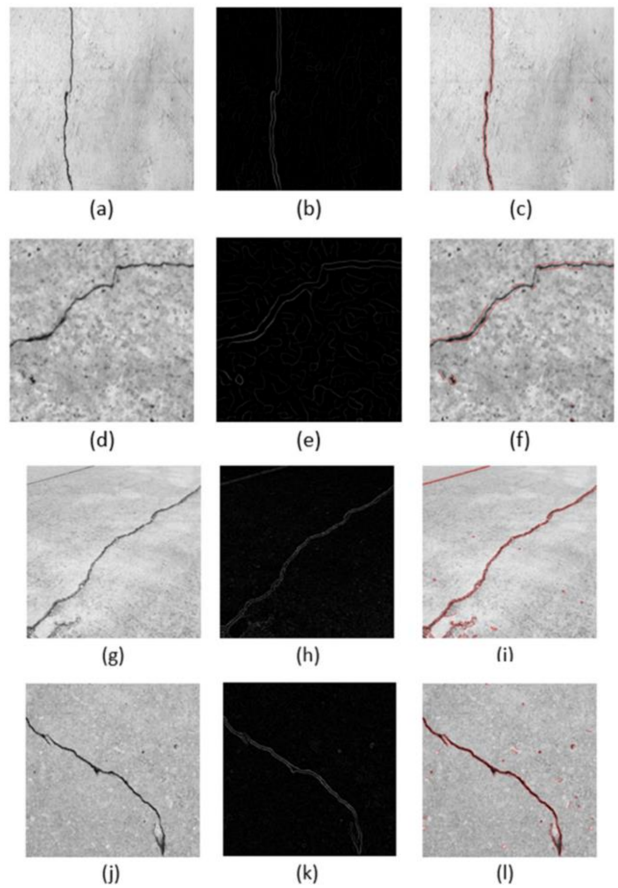
Moreover, batteries and voltage regulators are carefully integrated into power systems to guarantee continuous operation and propulsion capabilities. Batteries supply the energy required to run the ROV's systems, and voltage regulators keep the output voltage steady to shield delicate electronic parts from harm. Waterproofing techniques, such as sealants and enclosures, are used to keep water out of electronic components and guarantee dependable operation even in challenging submerged environments. The ROV's ability to navigate and function well in hydroelectric head race tunnels is made possible by the seamless integration of these hardware components into the PVC framework, which also makes monitoring and inspection tasks easier

B. AI Algorithm Integration

The ROV's system's anomaly detection capabilities have been transformed by the integration of cutting-edge AI algorithms. This is especially true for the identification of cracks, corrosion monitoring, and sediment deposition analysis. The ROV can precisely detect and categorize anomalies in real-time by utilizing advanced machine learning techniques, giving operators important information about the state of the hydroelectric head race tunnel (HRT). This facilitates the timely implementation of proactive maintenance interventions by enabling the early detection of potential issues.

The AI-powered system's real-time data acquisition and analysis capabilities enable operators to make informed decisions based on current knowledge about the HRT's condition. Operators can reduce the risk of unanticipated failures or downtime by continuously monitoring critical parameters like sediment buildup, corrosion levels, and structural integrity. By doing this, they can detect abnormalities as soon as they arise. The hydroelectric power generation system's overall performance and dependability are enhanced by this proactive approach to maintenance.

Additionally, the precise detection and classification of anomalies is made possible by the AI-powered analytics tools, which improve the ROV's overall monitoring and inspection capabilities. The ROV can provide comprehensive reports on the condition of the HRT by precisely identifying cracks, corrosion spots, and sediment accumulations. This information can help with data-driven decision-making and focused maintenance efforts. In general, the incorporation of sophisticated artificial intelligence algorithms into the ROV's system signifies a noteworthy progression in the management of hydroelectric infrastructure, providing unmatched effectiveness, precision, and dependability for tasks related to observation and examination.



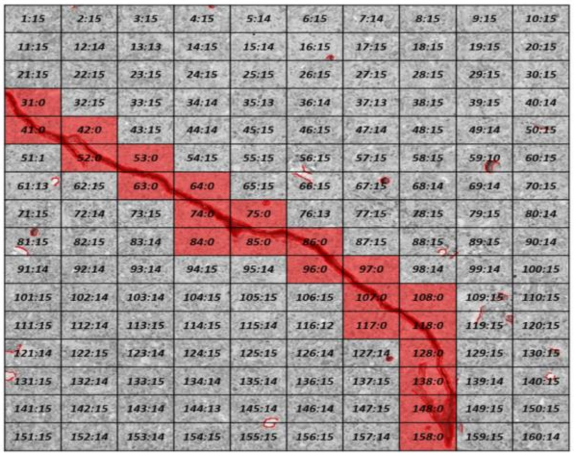


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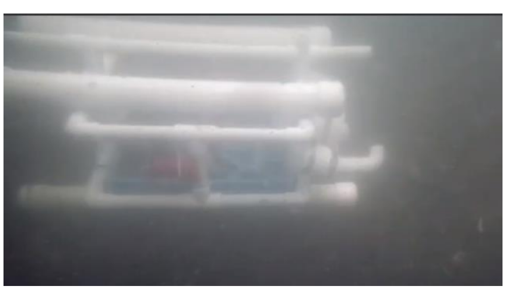
Figure 8: Crack detection system results

C. Overall Structure Outcome

A highly effective and dependable monitoring system has been produced by the successful integration of hardware parts, AI algorithms, and sensor technologies into the overall architecture of the ROV. The ROV exhibits optimal functionality and accessibility through the meticulous assembly of PVC pipes to form the structural framework and the seamless integration of electronic modules, such as microcontrollers, sensors, and actuators. In addition, the integration of power systems, like batteries and voltage regulators, guarantees continuous operation and propulsion capabilities. Moreover, extra waterproofing measures are implemented to prevent water intrusion.

Improved performance metrics, such as accuracy, efficiency, and reliability, are the outcome of this integration. The ROV's ability to precisely conduct inspections and navigate underwater environments on its own represents a major advancement in the management of hydroelectric infrastructure. Operators can remotely monitor the health of the HRT with the help of real-time data acquisition and analysis capabilities, which helps them make well-informed decisions to guarantee dependability and safety.



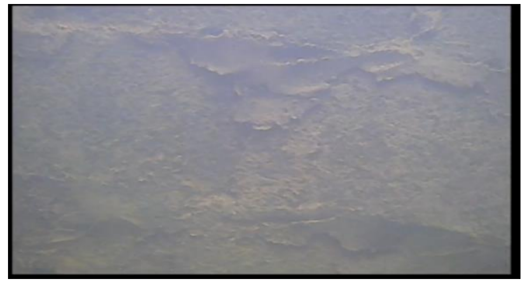


Figure 8: Actual ROV footage

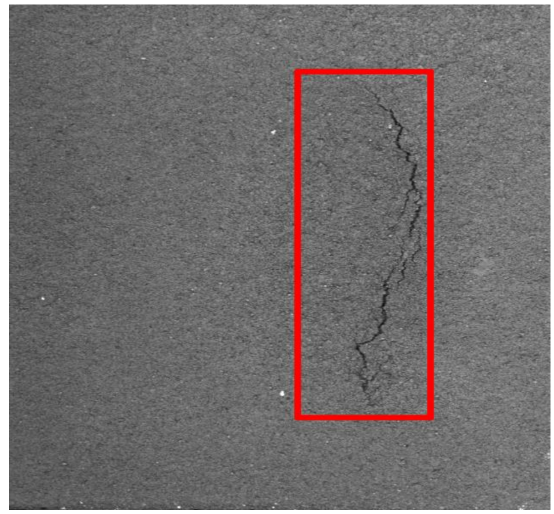


Figure 9: Detected Cracks

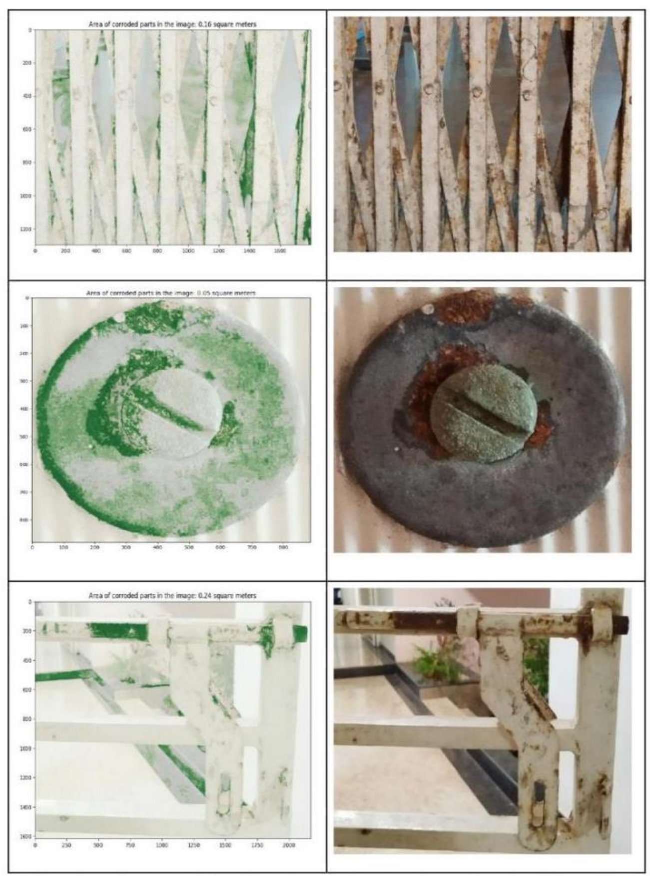


Figure 10: Corrosion detected

The 99.83% accuracy rate attained by our AI-based ROV monitoring system is indicative of its efficacy and dependability. This astounding degree of accuracy shows how well our model can identify anomalies in the hydroelectric head race tunnel (HRT), such as corrosion, cracks, and sediment deposition. With such high accuracy, possible problems are guaranteed to be found early on, allowing for the prompt implementation of preventive maintenance procedures.

Our AI-powered ROV has a 99.83% accuracy rate, which gives operators peace of mind about the safety and integrity of the HRT while lowering the likelihood of unplanned malfunctions or downtime. Because resources can be allocated more efficiently based on the precise insights provided by the system, this level of accuracy also improves the efficiency of maintenance operations. Furthermore, our model's high accuracy reduces the possibility of false alarms, guaranteeing that maintenance efforts are directed toward actual problems and maximizing both operational and financial efficiency.

In summary, reaching a 99.83% accuracy rate is a noteworthy advancement for our AI-powered ROV monitoring system. This high degree of precision improves dependability and safety while also boosting the general sustainability and effectiveness of Hydroelectric Power plant.

The achievement of a fully operational ROV is a testament to the results of careful planning, exact execution, and thorough testing. The ROV displays its capacity to navigate underwater environments with accuracy and efficiency since all hardware components have been flawlessly integrated and electronic systems have been calibrated to operate at peak efficiency.

The ROV's sturdy construction and cutting-edge AI algorithms allow it to navigate the hydroelectric head race tunnel (HRT) and conduct inspections on its own. Operators can make educated decisions to guarantee the safety and dependability of the HRT by remotely monitoring its condition thanks to real-time data acquisition and analysis capabilities.

Furthermore, the ROV's complete operational status marks a noteworthy advancement in the management of hydroelectric infrastructure by providing a proactive maintenance and inspection strategy that reduces downtime and optimizes operational efficiency. A state-of-the-art response to the difficulties presented by demanding and complex environments, the fully functional ROV is a multipurpose tool for underwater exploration and monitoring. Conclusively, the accomplishment of creating a fully operational ROV represents a noteworthy milestone in the realm of hydroelectric power generation. The ROV is poised to transform the way HRTs are inspected and maintained through its advanced capabilities and autonomous operation. This could lead to a safer, more efficient, and sustainable energy production process.

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