Unmanned surface vehicle with deep learning-based obstacle avoidance for water quality monitoring

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Abstract. This study presents the design, implementation, and critical evaluation of an unmanned surface vehicle (USV) for real-time water quality monitoring in harbour environments equipped with an AI-based vision system for obstacle avoidance. The primary objective was to develop a mobile platform capable of gathering multi-parameter water data (pH, temperature, turbidity, total dissolved solids) at 30-second intervals and transmitting it remotely while autonomously navigating and avoiding collisions. Key findings indicate that the USV successfully integrates environmental sensing with deep learning-based obstacle detection, achieving a maximum obstacle detection range of 3.4m in optimal daylight and meeting water sampling frequency requirements. Strengths of the system include a stable catamaran hull design that exceeded payload capacity targets (15 kg carried vs 10 kg target) and an innovative vision approach using semantic segmentation to distinguish water and sky from obstacles. The research's main contributions lie in combining reliable water monitoring with AI-driven navigation on a low-cost platform. Overall, the USV demonstrates the viability of combining deep learning vision with environmental monitoring, but further refinement is recommended in obstacle avoidance algorithms, sensor calibration, and extended field testing to ensure robust operation under diverse real-world conditions.

1 Introduction

Coastal harbours and inland waterways often suffer from localised pollution that threatens marine ecosystems and human health. Up to 80% of ocean pollution is estimated to originate from land-based runoff accumulating in semi-enclosed harbours [2]. The confined geometry of harbours can create pollution "hotspots" where contaminants concentrate rather than disperse [2]. Traditional water quality monitoring methods in these environments face significant drawbacks. Fixed sensor stations and manual sampling campaigns provide high-accuracy data, but only at discrete locations and time points, leading to gaps in spatial coverage and delayed responses [2, 3]. Laboratory analysis of grabbed samples introduces further delays of days to weeks, by which time transient pollution events may have passed [2].

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There is a critical need for mobile, real-time monitoring solutions that can dynamically cover the water area and promptly detect pollution incidents [2].

Autonomous surface vehicles (ASVs) or unmanned surface vehicles (USVs) offer a promising platform to address this need. These robotic boats can navigate waterways continuously, carrying sensors to map water quality in situ. Prior deployments of USVs for environmental monitoring have demonstrated the potential to automate data collection over large areas [4, 5]. However, ensuring reliable autonomous operation in busy harbour conditions remains challenging. A major concern is obstacle avoidance, the USV must detect and avoid various obstacles, such as piers, boats, buoys, and floating debris, to prevent collisions.

Traditional sensor-based navigation (e.g. radar, sonar, LiDAR) can detect obstacles but often requires expensive hardware and struggles with water surface reflections and clutter [6, 7]. Vision-based approaches have emerged as an attractive alternative due to the rich information content of camera images and lower cost, but they must overcome difficulties with changing lighting, wave motion, and distinguishing true obstacles from reflections [1, 8]. Recent advances in computer vision and deep learning have significantly improved obstacle detection for USVs. Classical vision methods (edge detection, horizon finding) achieved only moderate reliability (75–85% in controlled tests [8]), whereas modern convolutional neural networks (CNNs) and segmentation models have pushed accuracy above 90% in specialised tasks [1].

For example, the Water Obstacle Detection and Identification System (WODIS) network achieved 91.3% accuracy in sea-surface obstacle segmentation [1]. Similarly, [9] integrated inertial data with semantic segmentation to improve detection robustness against platform motion. These studies illustrate that deep learning-based semantic segmentation (classifying each camera image pixel as water, sky, or obstacle) is a promising strategy for robust obstacle avoidance on USVs [1]. Still, challenges remain in achieving real-time processing on embedded hardware and maintaining performance in adverse conditions (glare, low light) [9].

This paper reports on an autonomous catamaran-type USV for harbour water quality monitoring, integrating a deep-learning vision system for obstacle avoidance. The USV, approximately 0.8 m in length, carries sensors for pH, temperature, turbidity, and total dissolved solids (TDS) to characterise water quality. A Raspberry Pi 4 on-board handles data acquisition and runs a pre-trained CNN segmentation model to detect obstacles from the video feed [1, 9]. The vehicle communicates via a 4G cellular network, enabling remote monitoring and control through a custom mobile application. Field trials evaluated water sampling performance in a controlled pool environment at the Nelson Mandela University and obstacle detection in the Swartkops River under varying lighting conditions.

2 Related work

2.1 Water quality monitoring in harbours

Monitoring programs traditionally rely on stationary stations or vessel-based manual sampling to track parameters such as pH, dissolved oxygen, and pollutants in harbour water [4, 10]. While laboratory analysis of collected samples yields accurate measurements, it introduces latency that hampers timely response to pollution events [2]. Fixed in-situ sensors provide continuous data but only at limited locations [3]. As a result, significant portions of the water body can go unmonitored between stations, potentially missing pollutant plumes or illegal discharge events [4, 10]. There is growing interest in using autonomous platforms to complement traditional methods by covering the gaps.

Unmanned surface vehicles have been proposed as environmental monitoring and assessment tools since at least the mid-2000s [4]. Early prototypes demonstrated the ability to carry basic water sensors and navigate pre-set routes but lacked sophisticated autonomy or real-time communication [4]. Recent projects have advanced these concepts – for instance, [13] developed a USV with a hybrid control architecture for water quality monitoring, emphasising stable navigation and reliable data logging. Similarly, [11] built an affordable USV for estuary research, highlighting the educational potential of such platforms. These efforts underline the importance of robust platform design (hull stability, propulsion) and effective control systems for successful environmental data collection.

2.2 Wireless communication for USVs

A key aspect of modern monitoring systems is the ability to transmit data in real-time to remote servers or user interfaces. Several wireless technologies have been explored in marine contexts. Long-range low-power radio (LoRa) has been tested for transmitting sensor data from buoys or USVs [5]. LoRa can achieve communication over many kilometres with low energy consumption, but it has drawbacks such as requiring gateway infrastructure, low bandwidth, and high latency [5]. These limitations make it less suitable for streaming rich data, such as images, or supporting teleoperation in real time.

Wi-Fi-based solutions offer high data rates and were adopted in some UAV/USV systems [13], but the Wi-Fi range of typically a few hundred meters is insufficient for wide harbour coverage unless a mesh of access points is present. Satellite communication provides global coverage and has been used on oceanic drifters, but satellite modems are expensive and power-hungry for a small USV [5]. Cellular 4G/LTE networks present a compelling option for harbour scenarios, as infrastructure is usually available in populated coastal areas. Cellular modules can offer broadband data speeds allowing live video or frequent sensor updates with moderate power draw and have the benefit of established two-way connectivity (TCP/IP) for control commands [5].

Prior studies have implemented cellular links in environmental monitoring drones, such as in [12], which used an LTE module on a UAV to transmit atmospheric data, and [13] achieved bi-directional SMS command and data communication in a greenhouse IoT system using GSM. These demonstrate the feasibility of leveraging cellular networks for reliable remote operations. In the research presented here, a 4G LTE modem was chosen for the USV to ensure real-time data upload and remote control capability across the entire harbour without needing custom infrastructure.

3 Methodology

3.1 USV hull and propulsion design

For a monitoring USV, stability and endurance are critical design considerations. Twin-hull catamaran configurations are widely favoured for small USVs due to their high transverse stability and payload capacity relative to monohulls [14]. The separated twin hulls increase the metacentric height, reducing roll motions, which is beneficial for keeping sensors and cameras level. The design process evaluated multiple hull concepts via simulation for resistance and stability. Catamaran designs showed low drag at the target speed of 1 m/s and a positive righting moment across heeling angles, indicating good stability (righting moment 17.8 N·m for small heel angles).

A ducted propeller thruster system was selected for propulsion, as it is commonly used for precise low-speed manoeuvring in marine vessels [7]. Thrusters provide efficient thrust in both forward and reverse and improved safety with a shrouded propeller, which is valuable in cluttered waters. Prior work by [7] on automatic ship berthing highlighted the effectiveness of using bow and stern thrusters for fine control in tight spaces. For the USV, a single rear-mounted thruster on each hull was implemented, enabling differential steering for a tight turning radius. The power requirement to reach 1 m/s was estimated via hydrodynamic simulation, approximately 15.7 N total drag, requiring 8 N thrust per thruster. Bench tests confirmed that the chosen brushless DC motors draw about 3.3 A each at 12 V (≈40 W) to produce the needed thrust, which informed battery sizing.

3.2 Vision-based obstacle detection

The field of USV obstacle avoidance has shifted toward computer vision in the past decade, in parallel with advances in autonomous cars and drones. Early USV systems used non-vision sensors; for instance, [6] implemented a radar-based collision avoidance algorithm fused with a velocity-obstacle method to navigate around moving targets. While effective in the open sea, radar setups add cost and weight and may miss low-lying objects. Vision systems offer rich perception; [8] developed an RGB camera method for lake USVs that used horizon detection and multi-frame analysis to infer obstacle location. They segmented the image into sky versus non-sky regions and looked for objects protruding above the waterline. This classic approach worked in calm conditions but could be confused by reflections or waves.

The introduction of deep learning significantly improved robustness. Semantic segmentation networks can classify each pixel into categories like water, sky, or obstacle based on training from many annotated images. [1] developed WODIS, a specialised CNN for water obstacle segmentation, reporting over 91% pixel-wise accuracy. Similarly, [9] incorporated inertial data to stabilise segmentation outputs on a moving USV, achieving reliable obstacle recognition under moderate waves. These works demonstrate that deep CNNs can learn to effectively "see" obstacles on water, filtering out waves and glare better than fixed algorithms.

The computational load of CNNs is non-trivial, but modern single-board computers, such as the Raspberry Pi-4 or NVIDIA Jetson can run optimised models at a few frames per second, sufficient for slow-moving USVs. The approach in this research leverages a pre-trained segmentation model to identify obstacle pixels in real time [1, 9]. By focusing only on the lower half of the camera frame where obstacles on the water would appear and partitioning it into regions, we reduce the processing requirements and derive basic position information of obstacles, for decision making.

3.3 Mechanical design and construction

The USV uses a catamaran hull fabricated from 3D-printed PETG, chosen for durability and water resistance, with aluminium crossbeams providing structural rigidity and corrosion resistance [14]. Each hull is 0.8 m long with a tapered bow to minimise drag. The complete platform weighs 5.5 kg, with a displacement volume of 0.38 m^3 supporting up to 38 kg total mass. Tests confirmed the platform safely carries a 15 kg payload, and 20 kg was determined as the upper safety limit [14].

Two Blue Robotics T200 ducted thrusters are mounted under the aft crossbeam, each delivering 8 N thrust at 40 W and controlled via ESCs for forward/reverse operation [7]. Differential thrust enables zero-radius turns, which is vital for manoeuvring in tight harbour areas. Figure 1 shows the completed prototype during water trials with visible components: the front camera mast and yellow hulls designed for high visibility.

Fig. 1. Physical platform in testing conditions.

The on-board power system includes a 12V 7Ah sealed lead-acid battery and a 30 W solar panel mounted centrally, which charges the battery through a controller. The panel delivers up to 1.8 A in full sun and effectively extending the mission duration during daylight. Power regulation is handled via a 5V buck converter for sensors and Pi, with 12V lines feeding motors and analogue inputs. Dual leak detectors are embedded in each hull to shut down power if water ingress is detected - a key safety feature.

3.4 Sensing and electronics integration

To monitor water quality, the USV integrates four key sensors: temperature, pH, turbidity, and total dissolved solids (TDS). These parameters were selected due to their relevance to environmental health, for instance, turbidity reflects sediment levels and TDS indicates pollutant concentration. The temperature sensor uses a digital 1-wire interface, while the pH, turbidity, and TDS sensors provide analogue outputs. A 16-bit ADS1115 ADC (Texas Instruments) interfaces with these analogue signals to the Raspberry Pi, enabling high-resolution (0.1% variation) measurement accuracy for fine anomaly detection [14].

Sensors are mounted through the bottom of one hull section so they remain submerged during operation. Due to the USV's natural motion, water flows over the probes without the need for a pump. Sensor readings are taken every 30 seconds using a Python acquisition script on the Raspberry Pi. This interval meets the system's real-time monitoring goals while avoiding data redundancy. Tests confirmed the reliable operation, with typical pool values recorded: 7.3 pH, 500 ppm TDS, 0 NTU turbidity, and 25 °C temperature, all logged with timestamps and stored locally on the Pi's SD card.

Simultaneously, data is transmitted via a 4G modem to remote dashboards. All electronics, including the Pi, ADC, modem, ESCs, and safety circuits, are enclosed in a waterproof box mounted topside, with cable glands ensuring sealed entry points. A system schematic (Figure 2) shows the power flow from the 12 V battery (charged by the solar panel), with a 5V regulator for digital components. Safety features include leak sensors in each hull that cut power and trigger alerts if water is detected.

This integrated electronics design ensures reliable autonomous sensing in marine environments, with redundancy, waterproofing, and built-in real-time data handling.

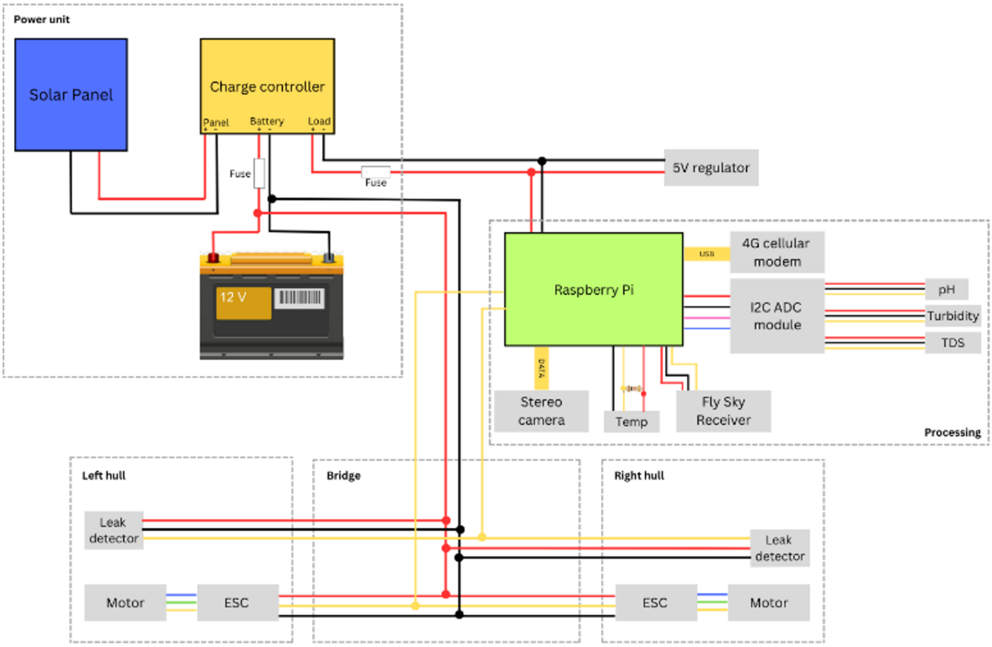

Fig. 2. Electrical system overview.

3.5 On-board computing and communication

The USV's core computing platform is a Raspberry Pi 4 Model B (4 GB RAM), chosen for its balance of processing capability (quad-core 1.5 GHz CPU with GPU acceleration) and low power consumption. The Pi handles sensor acquisition, deep learning-based obstacle detection, and wireless communication tasks [1]. It processes RGB+depth video from a front-mounted Luxonis OAK-D Lite stereo camera via USB This camera was originally intended for direct depth mapping, however, water surface noise rendered the raw depth data unreliable, prompting the use of a CNN-based semantic segmentation strategy instead [1].

For long-range communication, the Pi is connected to a SIMCom SIM7600 4G LTE modem, enabling cellular data access in the field. A VPN provides secure, persistent connectivity to the Pi, which runs a Flask web server offering RESTful API endpoints for live sensor data. Clients such as the mobile app request JSON-formatted data at 30-second intervals. In practice, latency from sampling to cloud update was around 1–2 seconds, enabling near-real-time monitoring.

A FlySky FS-iA6 RC receiver is also connected to the Pi for manual override via a handheld transmitter. If needed, the Pi can switch from autonomous mode to direct RC control, a critical safety mechanism during early testing or failure scenarios. This communication stack supports robust, real-time, remote monitoring and control while preserving redundancy and local fallback options.

4 Experimental results

4.1 Obstacle avoidance strategy

Obstacle avoidance on water requires accounting for dynamic environments and visual noise from reflections. The USV uses a CNN-based semantic segmentation model to classify each camera frame into “obstacle”, “water”, and “sky” regions. A confidence threshold of 0.9 is applied to filter out misclassifications [1], following practices in [8, 9]. Figure 3 illustrates the vision system output in a scenario with no obstacles detected.

Fig. 3. Vision system view unobstructed.

For decision-making, the camera view is divided into three vertical zones: left, centre, and right. If any region has more than 15% of its pixels classified as obstacle, the system flags a threat in that direction [1]. Figures 4 and 5 show examples of multi-zone obstacle detections. The obstacle's vertical position within the image frame provides a coarse distance estimate; objects lower in the frame are closer to the USV.

Fig. 4. Vision system view partially obstructed.

Fig. 5. Vision system view fully obstructed.

Avoidance behaviour is reactive. In “Cruise” mode, the USV continuously moved forward at 1m/s and samples water quality every 30 seconds. Upon detecting an obstacle, it enters “Avoidance” mode. If the left sector triggers, the USV turns right (and vice versa for the right sector). A centre-only detection results in a pre-programmed turn (defaulting left). Multi-sector obstacles flags sharper manoeuvres (for example, 90° turns if all three zones are blocked). If the path ahead remains blocked after a turn, the USV comes to a full stop and re-evaluates. (Note: The OAK-D's stereo depth output was initially tested measure obstacle range but was abandoned due to unreliable readings in marine conditions.)

This simple reactive strategy proved effective for real-time avoidance in structured environments like harbours. All avoidance actions and frame segmented camera frames were logged for later analysis.

4.2 Software and user interface

In addition to the on-board control code written in Python and C++, a custom mobile application was developed using Flutter for Android/iOS. The app provides operators with a live dashboard showing real-time sensor readings, USV status (GPS, battery, connectivity), and basic commands like switching between autonomous and manual modes. It connects via VPN to the on-board Raspberry Pi and pulls data through the Flask-based REST API every 30 seconds [5].

The user interface features a static launch screen (Figure 6) and a main dashboard with individual sensor cards for pH, turbidity, temperature, and TDS. The dashboard also includes a map view if GPS is available, although during harbour testing the GPS was non-critical due to the confined area of operation.

The app connects through the VPN tunnel and retrieves water quality data and status updates from the USV, enabling fully remote monitoring during missions beyond the visual line of sight.

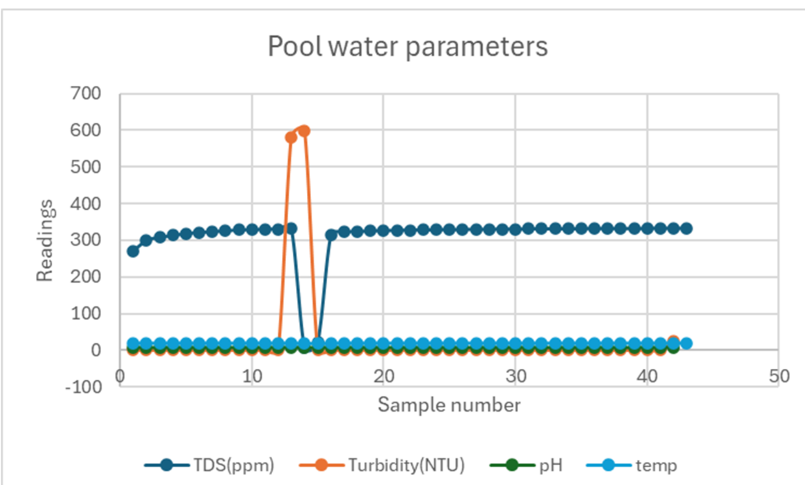

Fig. 6. Data captures during testing conditions.

Data collected through the app is also stored locally on the USV for redundancy and post-mission review. During field trials, this setup allowed operators to monitor the system in real-time from shore, verifying functionality and adjusting parameters as needed. The app's integration provides a complete HMI solution, linking on-board sensing, control logic, and remote access for the operators.

4.3 Water monitoring performance

4.3.1 Station-keeping and sampling

The USV was tested in a controlled pool environment at the Nelson Mandela University to evaluate its ability to take measurements at the required interval without significant drift. When the USV stops every 30 seconds to sample, it remains mostly in place due to inertia and low wind resistance. The slight drift did not noticeably affect the sensor readings in the homogeneous pool environment. Over a 5-minute run, 10 sets of readings were successfully collected and transmitted.

The system consistently met the 30-s sampling period. For example, a segment of logged data showed pH values of 7.30, 7.32, and 7.30 at 30-s intervals, confirming the timing accuracy. As expected in a pool, turbidity was 0 NTU (clear water) with minimal variation, and TDS was steady (500 ppm) as the pool water's salinity was constant [14]. This baseline test validated that the sensor integration and logging pipeline functioned correctly. It also gave confidence that the vehicle's motion does not introduce significant noise: the pH and conductivity readings stabilised within 1–2 s after stopping, suggesting that any water disturbance from the boat's movement dissipates quickly enough for accurate measurement. Due to an equipment failure during the river trials (the on-board Raspberry Pi was lost after being accidentally damaged), no water-quality measurements were recorded in the river environment; therefore, we do not report quantitative river water-quality analysis in this paper.

4.3.2 Data transmission and UI:

Throughout the tests, the 4G connection remained robust. In the harbour area, the available cellular bandwidth easily accommodated the low data rate (only a few bytes every 30 seconds plus periodic status messages). The mobile app was updated promptly and effectively in real time from a user perspective. This confirms that using existing cellular infrastructure is a viable solution for USV communication in populated coastal areas. It also means multiple USVs could potentially be monitored from a central web dashboard anywhere in the world, opening opportunities for scaling up such monitoring networks.

4.4 Autonomous navigation and obstacle avoidance

4.4.1 Stability and manoeuvrability

During the water trials in the Swartkops River, the USV exhibited excellent stability. Even when crossing boat wakes of 5–10 cm wave height, the catamaran hulls kept the platform steady – roll was limited to a few degrees. The pitch and roll angles over time were measured with the on-board IMU while the USV made a circuit in choppy water with abrupt stops and turns. Pitch oscillated between approximately +28° and –20° at its extremes during a sudden acceleration or deceleration, which cause the bow to rise or dip. Roll stayed within ±3° during straight cruising and reached a maximum of approximately 20° during a sharp turn. These angles are well within safe bounds – at no point did the hulls approach submersion of one side. The positive righting moment, measured at 17.8 N·m at 5° heel was clearly sufficient as the boat self-corrected quickly after tilting.

Such stability is crucial for the vision system since excessive rocking could misalign the camera view. The gentle motions observed meant the camera horizon stayed roughly level, which likely aided the segmentation algorithm.

The thruster-based propulsion also proved effective. The USV could execute a 360° turn in place in roughly 5 seconds by counter-rotating the thrusters. This agility is advantageous for avoidance, if boxed in, the craft can essentially pivot and escape. Straight line tracking was decent; due to minor asymmetries between the two hulls and thrusters, which caused slightly more drag, the boat tended to drift 5° to port when both thrusters ran equally. This was compensated in software by applying a slight bias or differential thrust to maintain a straight heading. The top speed achieved was 1.2 m/s, which is sufficient for harbour patrol. The system was generally operated at 1 m/s or less during autonomous mode to allow the vision system ample time to react to obstacles.

4.4.2 Obstacle detection accuracy

The core of the obstacle avoidance system is vision-based obstacle detection. The system's performance was systematically evaluated under different lighting conditions, as lighting was expected to be a major factor, considering harbours can have bright glare in the morning/evening and low contrast under overcast skies. The USV was set up in the Swartkops River to approach a known obstacle (a pier piling) at various times of day, and the detection behaviour was recorded. These trials were conducted at approximately 07:00, 11:00, and 15:00 (early morning, midday, and late afternoon) on days with similar moderate cloud cover. This approach ensured that a range of low-angle and high-angle sunlight conditions was tested while keeping other environmental factors relatively constant. The detection range, defined as the distance at which the system first recognised the obstacle and stopped, and flagged it, and stopped - was measured by marking the water and using a laser rangefinder from the boat to the piling after the USV halted[14].

Under the bright midday sun, the obstacle detection system demonstrated its best performance, achieving the longest detection range (approximately 3.4 m) with very consistent obstacle recognition. In these optimal conditions, the segmentation model reliably distinguished obstacles from water and sky . In contrast, early morning conditions with low-angle sunlight introduced challenges. Detection effectiveness appeared reduced, and the system exhibited more false positives due to intense glare and specular reflections on the water surface. The segmentation model occasionally misclassified these reflections, triggering premature or unnecessary avoidance manoeuvres. During late afternoon testing under diffuse lighting and lower sun angles, the system showed moderate performance. Detection was more stable than in the morning but not as robust as under midday lighting. Variability during this period was likely caused by water surface reflections and long shadows, which at times disrupted the segmentation process. Figure 7 illustrates the relative detection effectiveness at different times of day.

4.4.3 Avoidance behaviour

The reactive avoidance logic triggered appropriate turns in most scenarios. Obstacles detected in left, centre, or right regions caused the USV to initiate the corresponding pre-programmed turn away from the threat. When multiple regions were simultaneously flagged, the USV performed sharper or full-stop manoeuvres. However, in narrow passages such as with a pier and buoy, the USV occasionally entered oscillating loops, bouncing between conflicting avoidance directions. Manual override resolved these. This reactive-only method handled most hazards, incorporating a higher-level path-planning algorithm could prevent such inefficient oscillations.

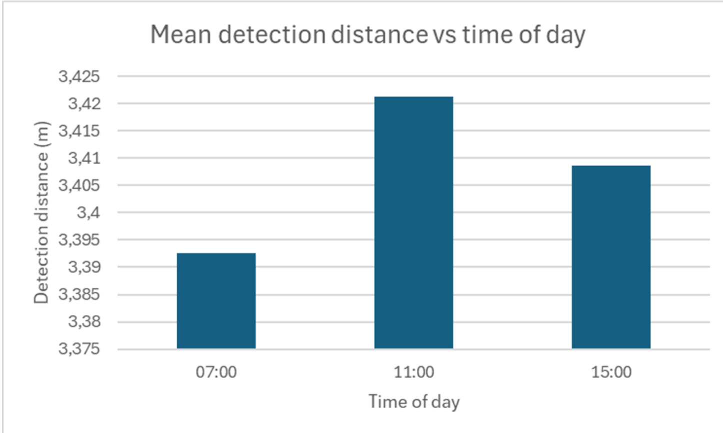

Fig. 7. Testing results at various times of the day.

4.4.4 Autonomy and reliability

Minor operational issues, such as clock drift on the Raspberry Pi, were effectively mitigated through NTP synchronisation. However, incorporating a hardware-based real-time clock (RTC) would enhance timestamp reliability during offline missions or extended deployments.

Overall, the platform achieved its primary objectives for water quality monitoring and obstacle avoidance across a range of environmental conditions. Although detection performance diminished under suboptimal lighting, the system consistently avoided collisions and maintained functional obstacle recognition. Proposed enhancements to address these limitations are detailed in later discussions.

5 Critical evaluation

5.1 Theoretical foundations

The research project builds on strong foundational concepts in environmental sensing, autonomous robotics, and deep learning. It applies well-established water quality metrics such as pH, TDS, and turbidity, well-established pollution and environmental health indicators, combined with recent advancements in CNN-based semantic segmentation for obstacle detection. The choice to use a vision-based segmentation network rather than classical depth sensing is well-justified by prior work showing improved robustness in marine scenes [8].

5.2 Methodological strengths and limitations

The test environments, pool and a river, offered practical contrasts, verifying both sensor accuracy and system robustness in real conditions. The 30 s sampling period is methodologically sound, but longer-term deployments were not tested. Notably, a controlled pool provides stable and homogeneous conditions, while natural water bodies like the Swartkops River have variable flows and heterogeneous water quality distributions [10]. Thus, results from the pool tests may not directly translate to more complex field environments, underscoring the importance of comprehensive in-situ testing. Unfortunately, due to an unforeseen hardware malfunction (the loss of the on-board Raspberry Pi during the river trial), water quality data could not be collected in the river environment. This prevented a direct performance comparison between the pool and river tests, and it highlights the need for robust equipment protection and data backup strategies in future field deployments.

5.3 Statistical and mathematical accuracy

Sensor readings and sampling intervals aligned closely with expectations. For example, pH values of approximately 7.3 in the controlled pool environment, consistent with established literature benchmarks. The obstacle detection range of 3.4m and the CNN met the system's design target, indicating that the vision-based approach performed as intended under ideal conditions.

6 Recommendations

Improving the USV's vision system is a priority, as obstacle detection was inconsistent in glare and low-light conditions. One approach is to fine-tune the convolutional neural network (CNN) using additional image data captured during morning, dusk, and varying weather scenarios. This could help the model generalise better and reduce errors. Integrating an infrared or thermal camera would provide consistent detection even in darkness or high-glare scenes to further mitigate poor visibility. A simple hardware solution, like adding a polarising filter to the camera, could also help minimise surface reflections. Implementing temporal filtering strategies such as multi-frame confirmation or Kalman tracking would reduce false positives from transient reflections.

The current reactive avoidance method is functional but limited. Introducing obstacle distance estimation from stereo depth could improve avoidance accuracy. Incorporating planning algorithms such as the Dynamic Window Approach (DWA) or Rapidly-exploring Random Trees (RRT*) would enable more efficient navigation, particularly when obstacles are densely spaced. These algorithms could convert the segmentation mask into a spatial map for short-term path optimisation. Overlaying this local planning on a GPS-based waypoint system would allow the USV to follow a planned route while dynamically adjusting for hazards.

In terms of environmental monitoring, expanding the sensor suite to include dissolved oxygen (DO) would enhance ecological insights. Using more accurate turbidity or chlorophyll sensors and introducing basic calibration mechanisms, like on-board reference fluids or dual-sensor validation, would improve data quality during longer missions. Additionally, real-time anomaly detection using on-board analytics could notify users of significant environmental changes immediately via the interface if significant water quality changes are detected..

To address endurance limitations, upgrading the power system is recommended. Replacing the sealed lead-acid battery with a lithium-iron-phosphate pack would significantly extend runtime. Solar harvesting could be improved with larger or additional panels, space permitting. Software strategies such as idling the Raspberry Pi between sampling events and dynamically adjusting the vision system frame rate can further conserve power. These measures collectively would allow longer missions and improved area coverage.

Finally, integrating cloud-based data streaming and visualisation would support multiple USVs operating concurrently for large-scale deployment. A centralised dashboard would help visualise sensor trends across a harbour in real-time. Enhancing the mobile app with remote control capabilities, GPS-based mission planning, and interactive data plots would transform the system into a full-fledged user tool. Operational reliability should be strengthened by conducting extended field trials under varying real-world conditions to develop standard protocols for launch, failure response, and maritime compliance, including integration with AIS systems to signal presence to nearby vessels. These enhancements would make the system viable for long-term autonomous water quality monitoring.

7 Conclusion

This work presented a comprehensive design and evaluation of an autonomous unmanned surface vehicle tailored for water quality monitoring in harbour environments. The USV successfully demonstrated the integration of environmental sensors with an AI-based vision system for navigation, essentially combining the roles of a water sampling buoy and a surveillance vessel into one platform. The vehicle maintained excellent stability and exceeded its payload requirements through a stable catamaran design and careful weight distribution, validating the mechanical design approach. The on-board sensors provided reliable measurements of key water parameters at the desired 30 s interval, and the cellular communication link enabled real-time data access – a marked improvement over traditional manual sampling that can take hours or days to report results [1].

Crucially, the deep learning-driven obstacle detection system enabled the USV to identify obstacles in real time and initiate avoidance responses. However, fully autonomous collision avoidance was not 100% reliable in field tests. Although the CNN-based vision model successfully detected obstacles, the turning manoeuvres were occasionally inconsistent due to unstable PWM signals from the onboard motor controller, which caused the thruster outputs to oscillate. As a result, while the system demonstrated reliable obstacle detection, the avoidance execution was only partially functional. This highlights the need for improved motor control tuning and perhaps more advanced navigation logic in future iterations to achieve truly robust autonomous navigation.

In summary, the research provided a proof-of-concept that a relatively low-cost USV built with open-source hardware and AI models can autonomously navigate a harbour while collecting scientific water quality data. At the same time, the work highlighted several challenges that remain. The sensitivity of the vision system to lighting extremes was evident; additional sensor modalities or improved algorithms will be needed for robust all-weather, all-time operation. The reactive navigation strategy, while effective in preventing collisions, was simplistic and sometimes inefficient, suggesting that more advanced path planning should be explored to handle complex obstacle configurations and to optimize area coverage.

Nonetheless, the successful field trials validate the overall concept of a deep-learning-enabled USV for harbour monitoring, as the vehicle provided data that would be difficult to obtain otherwise – such as spatially distributed, real-time water measurements – and it navigated safely in an environment with common obstacles (piers, buoys). This demonstrates that a low-cost USV can autonomously monitor water quality in real time and safely navigate using advanced vision-based control. By combining deep learning semantic segmentation for perception with a stable catamaran platform and reliable communication, a foundation for autonomous harbour monitoring has been established. The USV collected environmental data with spatiotemporal continuity (impractical to achieve with manned sampling), and its AI-driven obstacle avoidance achieved reliable operation in a controlled harbour scenario.

Challenges remain in extending performance to extreme conditions (especially under low light or heavy glare) and in enhancing the avoidance strategy for more dynamic environments. However, the results strongly suggest that integrating deep learning vision techniques is a promising approach to maritime autonomy – enabling unmanned vessels to "see" and react to obstacles in real time. With the recommended improvements in perception, planning, and power, such USVs could be deployed for continuous environmental surveillance of harbours, providing early warning of pollution events and a comprehensive assessment of water quality. In conclusion, the successful implementation and testing of this USV underscore the viability of AI-powered autonomous surface vehicles for environmental monitoring, while also highlighting the refinements needed to achieve fully robust, all-condition operation in the future.

The financial assistance of the National Research Foundation (NRF), Automotive Industry Development Agency (AIDC), the Advanced Mechatronics Technology Centre (AMTC), and eNtsa at Nelson Mandela University towards this research is hereby acknowledged. The opinions expressed and conclusions drawn are those of the authors and do not necessarily reflect the views of the NRF, AIDC, AMTC or eNtsa

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