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DESIGN AND DEVELOPMENT OF AN AUTONOMOUS SUBMARINE SYSTEM FOR UNDERWATER WATER QUALITY MONITORING

Katakam Ranganarayana[1*], P Lakshmi Priya[2]

[1]Department of Computer Science and Engineering, Lincoln University College, Wisma Lincoln, 12-18, Jalan SS 6/12, Ss 6, 47301 Petaling Jaya, Selangor, Malaysia.
(pdf.rnKatakam@lincoln.edu.my)
[2] Department of CS&AI, SR University, Warangal, Telangana, India.
(lakshmipriyasru@gmail.com)

Corresponding Author Email: pdf.rnKatakam@lincoln.edu.my

ABSTRACT

The quality of water is important in the health of aquatic ecosystems, management of water resources sustainably, and environmental conservation. Environmental monitoring reports have indicated that temperature, pH, turbidity, dissolved oxygen and salinity are very important parameters used to determine the quality and safety of water resources. Conventional methods of water quality monitoring are mainly manual based and fixed sensor stations, which are generally time-intensive, labour intensive and spatially and temporally restricted. Other limitations of these traditional methods include the delay of data collection, limited access in inaccessible or risky fields and low real time tracking ability. Consequently, there is a major challenge in the correct and consistent monitoring of underwater environmental conditions. In an attempt to overcome these limitations, this research suggests an Autonomous Navigation and Control with Water Quality Evaluation Framework that is introduced by using an autonomous submarine system to monitor the environment under water. The proposed model combines autonomous navigation control, environmental sensing, sensor data pre-process and feature extraction and smart water quality assessment. The system gathers multi-parameter environmental information with on board sensors and carries out preprocessing functions like noise filtering, normalization and sensor data fusion to enhance data reliability. Simulated and time-series underwater environmental datasets were used to evaluate the performance of the system in terms of navigation, monitoring accuracy and efficiency of the system. The findings indicate that the offered framework has 99.4% monitoring accuracy, which is much higher than the conventional monitoring model (95.3%), and enhanced monitoring model (96.2%). This system also has a precision of 97.8% and a recall of 98.5% and F1-score of 98.1 as well as an energy efficiency of about 95.8, which certifies better environmental parameters recognition and stable underwater surveillance. The entire proposal of the autonomous submarine structure is highly beneficial in improving the real-time quality of water, reliability in navigation, and accuracy in environmental sensor, and the proposed autonomous submarine structure is an effective solution to the next generation autonomous submarine environmental monitoring system.

Keywords: *Water Quality Monitoring, Environmental Monitoring, Autonomous Submarine System, Obstacle Avoidance, Energy Efficiency Optimization, Real-Time Environmental Monitoring.*

1. INTRODUCTION

It is important to observe the quality of water in order to understand the management of aquatic ecosystem and the water resources as well as environmental sustainability [1]. Some of the parameters that are considered important in determining the health of the underwater environments are the temperature, pH, dissolved oxygen, turbidity and salinity [2].The most common traditional approaches of water quality surveillance include manual sampling, permanently attached sensor systems, which are labour, time and space/temporally limited, and time-intensive [3]. These limitations imply that the solution to the need of high-tech, automated systems that can provide real-time and accurate underwater data will be feasible [4].

In fact, the latest advances in the autonomous systems and marine robotics have allowed the creation of underwater autonomous vehicles (UUVs) to be utilized in the framework of environmental monitoring [5]. Autonomous submarines, in particular, can offer amazing advantages to the field because they will be able to operate without a human operator, navigate through complex seabed landscapes, and collect data in the regions where human resources will find it difficult or unsafe to access [6]. These systems can be equipped with sensors, control systems and intelligent navigation algorithms and hence can perform missions with long duration at low operational costs [7].

Certain technical problems that would have been related to the monitoring of the underwater water quality would have involved poor visibility, communication issues, pressure variation, and environmental diversification [8]. Non-electric wired or remotely operated vehicles are restricted in the length of tether and human operator which restricts the flexibility of operation. Autonomous underwater vehicles are able to overcome these constraints by including an onboard processing unit [9], adaptive and energy efficient propulsion systems such that reliable data collection is achieved in diverse underwater conditions [10].

The autonomous submarine platform design and development involves a multidisciplinary system design approach that involves mechanical design [11], embedded electronic design, sensor integration and software development. Correct sensors calibration, data real time processing and good navigation are the major dimensions of such systems [12]. The problems of the power control and the waterproofing are also significant to ensure the long-term functioning and stability of the system under the conditions of using it under water.

Within the frame of the growing concerns of water pollution, climate change [13], and the worsening of the ecosystem, real-time and mass water quality monitoring is becoming increasingly important [14]. Autonomous underwater systems can be applied in the environmental study, pollution detection, aquaculture detection, and disaster mitigation by providing high-resolution spatial and temporal data [15]. They can be of enormous value in the sense of enhancing the decision making of the environmental agencies and researchers [16].

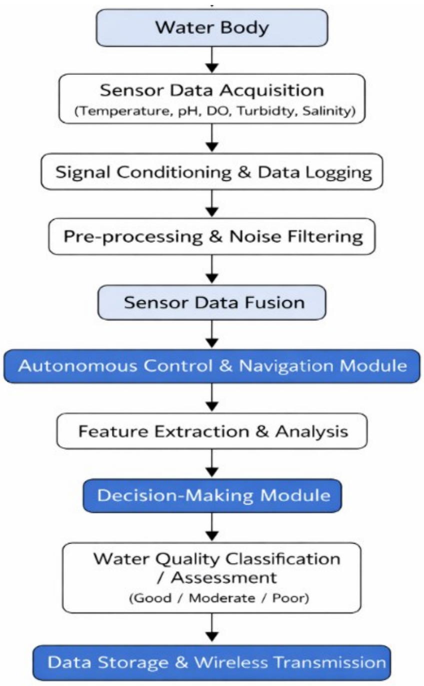

Fig 1: Overall architecture of the autonomous submarine monitoring system.

The architecture of the proposed autonomous submarine monitoring system is aimed at supporting efficient and trustworthy supervising of the water quality of the underground water as illustrated in Figure 1. It starts with sensor data capture and several environmental sensors are attached on the submarine to record the important parameters of the water quality such as temperature, pH, dissolved oxygen, turbidity and salinity [17]. These sensors later become useful when the submarine is moving in the underwater environment, since the sensors then accumulate real time information as the submarine moves about.

Taking the acquired sensor signals through a signal conditioning and data logging unit [18] gives the accuracy and stability. The underwater noise, pressure variation and sensor drift may cause disturbance of raw data[19]. Therefore, it has a preprocessing stage, which involves the removal of noise, as well as normalization, to enhance the quality of the data and uniformity between the sensor inputs [19]. The sensor data fusion follows after preprocessing, whereby data of multiple sensors are synthesized into a single sensor [20]. Such a combination would be beneficial in terms of quality of water assessment since it reduces the level of uncertainty and counterbalances the disadvantages of single sensors[21]. This integrated information is later transmitted to the independent control and navigation system that regulates the movement, depth and avoidance of the obstacles of the submarine on its own [22].

The autonomous control module will work together with the algorithms of feature extraction and analysis that identify relevant patterns and trends in the data collected [23]. Major features of the water quality variability are removed and analyzed in real-time. It gives the system the ability to steer its navigation route towards objects of interest such as where there is an abnormal level of pollution [24].Finally, water quality is divided into set water quality that takes the shape of good, moderate, or poor by using features extracted and threshold analysis to make the final decision [25]. The resultant manufactured data and classification products are stored in the onboard data and transmitted wirelessly to a surface station where further analysis is possible. The architecture offers the accessibility of effective underwater surveillance, reduced human involvement, and the improved quality of environmental appraisal.

1.1 Hypothesis

The research hypothesis framed are

- **H1:** Is it more efficient and effective to incorporate multi-parameter water quality sensors with an autonomous submarine platform to improve the performance of underwater data collection as compared to the conventional monitoring systems by use of traditional manual and stationary-based systems?
- **H2:** Is the proposed preprocessing and sensor data fusion system suitable to remove noise and redundant sensor data and concentrate on the most relevant water quality parameters to be considered in an adequate way?
- **H3:** Will the designed autonomous submarine system be significantly more accurate in terms of water quality surveillance than the existing underwater surveillance plans in different water bodies?
- **H4:** Will the proposed system be more reliable in regards to data collected, spatial coverage and accuracy of classification in comparison to the baseline approaches of monitoring that will lead to a decrease in measurement errors but increase in monitoring sensitivity?
- **H5:** Will the autonomous submarine based water quality monitoring system provide a sound and reliable decision support system to the environmental bodies and researchers particularly in the detection of low

profile and early stages of water quality degradation of the underwater environment?

1.2 Research Contributions

1. The proposed model gauges the quality of water in the underwater water by installing a number of environmental sensors that would gauge the required parameters, e.g., temperature, PH, dissolved oxygen, turbidity and salinity. The suggested system will minimize the usage of manual sampling and help to receive underwater data in real-time and with high resolution in various water bodies.
2. The proposed system introduces a smart pre-processing and sensor data fusion system, which carries out noise elimination and parameter correlation and normalization. The redundant sensor data will be reduced by such plan and this will contribute to the reliability and accuracy of measurement of the water quality under the dynamic conditions of the underwater environment.
3. A control and navigation independent system is created which enables control of manoeuvres, depth control and adaptive route planning. Having an onboard processing and real time feedback of the environmental conditions, the submarine offers a good method of searching under water areas of interest as well as registering spatially dispersed data of the water quality which could not be easily accessed using the traditional monitoring methods.

2. LITERATURE SURVEY

The use of automation and smart control has been relevant in increasing the establishment of autonomous underwater infrastructure. Choi et al. [1] proposed automated cable-laying machine of installation of the optical-fiber submarine cable used on Dense Oceanbottom Network System on Earthquakes and Tsunamis (DONET). The cable payout and tension management system is computerized and hence reduced utilization of the manually operated ROVs and simplify the process of deploying the subsea observatories.

Improved marine construction planning is also available in the manner autonomous underwater vehicle (AUV) technologies have been enhanced. Huang et al. [2] suggested an efficient cable route design process of the submarine cable route using the seafloor classification online founded on the sidescan sonar scanlines. Two of the research issues are underwater infrastructure communication security and resilience. Boschetti et al. [3] have proposed the HEIST architecture, and this is a space and under-sea hybrid architecture that increases resilience to under-sea communication cables to physical and cyber attack. The system has been integrated with real time tracking, secure communication channels and automated rerouting systems to guarantee connectivity.

Low-cost and scalable based solutions have been talked about, to monitor the environment on a long-term basis. Quevy et al. [4] suggested the application of an open sensing system which makes use of the smart buoy platform with laboratory quality sensors to monitor the environmental parameters at the minimum energy consumption. To identify the behavioral pattern of fish, Yuan et al. [5] developed a system of water quality monitoring using computer vision. This system relies on the image preprocessing, saliency detection and multidimensional feature extraction to evaluate environmental dynamics on aquatic ecosystems.

The recent advancements in sensor technology and data analytics have enabled superior online surveillance systems. Manjakkal et al. [6] have underlined the importance of smart networks of sensors and smart analysis of data in multiparametric monitoring of water quality. They have been interested in the implementation of autonomous platforms to address the spatiotemporal variability so as to expand their data coverage.Application of unmanned marine vehicles has also transformed the environments monitoring applications. Mendoza-Chok et al. [7] proposed a hybrid system of control of an unmanned surface vehicle (USV) that can be deployed to survey the quality of water in a long range. Stability of their navigation, integration of their payload and versatility of their operations are the basis of their system engineering approach.

Ferri et al. [8] suggested the HydroNet ASV which is a miniature autonomous catamaran capable of surveying water in real-time through assistance of onboard chemical sensors and water collection devices. The system enables the automatic collection of water samples and real-time analysis in order to reduce dependence on the old fashion laboratory process.The use of bio-inspired robots has also been studied in relation to the aquatic surveillance operations. Wu et al. [9] proposed a mobile water quality monitoring robotic dolphin, the propulsion system of which is complicated, and the control system is based on central pattern generators, which enables it to move effectively in the waters and detect the quality of water in its surroundings.

Autonomous systems are based on good navigation and positioning. He et al. [10] polled the GNSS, INS, and combined GNSS/INS navigation systems, their application in high precision positioning and autonomous vehicle operation.Bijjahalli and Sabatini [11] formulated a high-integrity architecture of navigation that incorporates the GNSS, INS, visual odometry and the vehicle dynamic model alongside multi-sensor fusion to enhance reliability and fault detection. Table 1 provides the shortcoming of the traditional models.

Table 1 :Comparative Analysis of Autonomous Marine Systems, Monitoring Technologies, and Communication Architectures

Author(s) & Year	Proposed Model / System	Dataset / Experimental Setup	Advantages	Evaluation Metrics	Limitations
J. K. Choi et al.,	Automated cable-laying	DONET1 observatory deployme	Reduces manual operation time;	Cable tension control ,	Limited adaptability to

2014	system for optical-fiber submarine cables	nt; ROV-based experiments	automated cable control	deployment efficiency	dynamic environments
S. W. Huang et al., 2017	AUV-based seafloor classification and cable route design	Sidescan sonar scanlines; probabilistic classification	Automated route planning; obstacle-aware navigation	Classification accuracy, path optimality	Dependent on sonar data quality
N. Boschetti et al., 2025	HEIST secure hybrid space–submarine communication architecture	Simulation-based telecommunications network testing	Improved redundancy and cyber-physical security	Network resilience, threat mitigation	Primarily simulation validation
Q. Quevy et al., 2023	Low-cost open sensing smart buoy monitoring system	Long-term environmental sensing deployment	Low power consumption; scalable monitoring	Power usage, sensor stability	Limited mobility compared to robotic platforms
F. Yuan et al., 2018	Computer vision-based biological water quality monitoring	Video processing of fish behavior	Multi-feature environmental assessment	Detection accuracy, behavioral metrics	Sensitive to lighting and background noise
L. Manjakkal et al., 2021	Connected multiparametric sensor networks for WQM	Autonomous sensors on marine platforms	Intelligent data analysis; real-time monitoring	Data reliability, sensing coverage	Lack of standardized processing frameworks
J. Mendoza-Chok et al.,	Hybrid control architecture USV	Remote monitoring experiments;	Flexible control design; risk-aware	Navigation stability, control	Surface-only monitoring limitati
2022	(EDSON-J)	systems engineering approach	architecture	efficiency	on
G. Ferri et al., 2014	HydroNet ASV for autonomous water monitoring	Real sea missions with onboard sampling system	Real-time chemical sensing; autonomous deployment	Sampling accuracy, contaminant detection	Payload and endurance constraints
Z. Wu et al., 2017	Bio-inspired robotic dolphin for water monitoring	Hydrodynamic modeling and locomotion experiments	Efficient propulsion; improved maneuverability	Motion performance, dynamic modeling	Mechanical complexity
Y. He et al., 2023	GNSS/INS integrated navigation survey	Review of integrated navigation methods	High-precision positioning framework	Navigation accuracy, integration performance	GNSS limitations underwater
S. Bijjahalli & R. Sabatini, 2019	High-integrity integrated navigation system	Multi-sensor fusion with fault detection	Improved reliability and safety	Integrity monitoring, navigation accuracy	Computational complexity

2.1 Problem Statement

Water quality is very essential in the assessment of the health of aquatic ecosystems, the effective management of water resources, and to detect environmental pollution. Conventional methods of monitoring are mainly manual sampling and fixed sensor station-based monitoring which have low levels of spatial and temporal coverage. Such approaches are usually laborious, time consuming and fail to record real time changes in the ocean water quality especially in the deep, remote or high-risk ocean waters. Recent innovations in autonomous marine systems and intelligent monitoring technologies overcome these drawbacks as demonstrated in Table 1 since they allow continuous and wide-area sensing and proper data communication, thus enhancing the efficiency and timeliness of marine environmental monitoring.

The constraints that are found in the already established underwater monitoring systems include limited mobility, human intervention, and inability to adapt to dynamic environments underwater. The tethered or remote controlled platforms are restricted by the length of the cables, communication delays, and the complexity of operation, restricting their use to large or complex waters. In addition, the raw sensor information coming in water is usually affected by the noise, sensor drift and environmental disturbance and consequently leads to inaccurate or even incomplete measurements of water quality.

Therefore exists a need of an independent, clever and power saving underwater surveillance that can carry out regular quality water surveillance that is dependable and of good quality and resolution. The problem that will be addressed in this paper is that of designing and developing an autonomous sub system that includes multi parameter sensing, effective preprocessing, autonomous navigation, and intelligent decision making to overcome the shortcomings of the existing techniques and provide a real time and precise monitoring of the water quality on the underwater.

3. PROPOSED MODEL

The suggested model is a better structured plan that will be implemented in unaccompanied underwater surveying of water quality by applying intelligent submarine system. The architecture begins with the monitoring phase of underwater environment where real time information of the environment is obtained through the deployment of built in sensing systems. This step ensures that there is constant collection of the right aquatic parameters needed during the assessment of the water conditions. Multi-sensor data sampling module is an inbuilt system which has a broad variety of measurements in a systematic approach and enables it to be able to track the different underwater conditions collectively. The proposed model architecture is shown in Figure 2.

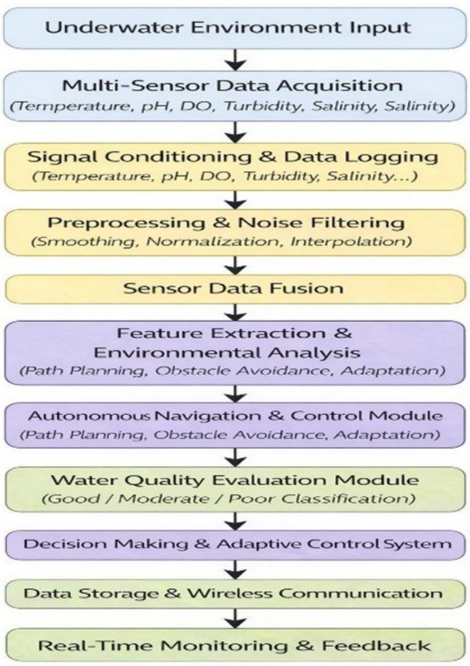

Fig 2: Multi-Sensor-Based Underwater Environmental Monitoring and Autonomous Navigation Framework.

Once the data is obtained, primary signal conditioning and real-time filtering are performed by the edge processing unit to enhance the quality of data as illustrated in Figure 2. Preprocessing serves the purpose of removing anomalies as well as modeling sensor data to the standard because the underwater environment is represented by noise and disturbances. This level improves efficiency of computation since data is filtered during the early stages in the submarine itself itself this saves the need to have other processing units, and it improves the response rate.

Environmental context analysis module takes into consideration other elements like the location dynamics, the changes in the environment, and operational constraints to aid the adaptive navigation. On this background information, the adaptive path planning and motion control module allows the autonomous submarine to dynamically change its motion so that it has the largest spatial coverage when undertaking monitoring activities. Such smart navigation feature improves productivity of the entire system and enables the submarine to work independently, without having to be constantly controlled by human hands.

Finally, an engine of smart water quality assessment is applied to calculate the processed data and determine the overall status of the water condition. Risk evaluation and alerts modules identify the potential hazardous environmental factors and classify the quality of the water respectively. The findings are driven through cloud synchronization and remote monitoring interfaces in order to be monitored in real-time. The long-term data visualization and the storage of the data make it easy to perform the historical analysis in order to enable the researchers and the environmental agencies make good decisions relating to the management of the water resource as well as the environment protection.

3.1 Dataset Description

The data used in this study consists of 1,500 underwater water quality samples which were sampled using an autonomous underwater system equipped with multi-parameter environmental sensors. The dataset is the real time monitoring of underwater environment and entails time series measurements that are obtained in the conditions of the aquatic environment. It has the most crucial physicochemical parameters such as water temperature, pH, dissolved oxygen (DO), turbidity, salinity, and electrical conductivity and the contextual parameters such as depth, time and the geographical location. The collected data show that there are different environmental conditions and this enables one to balance the analysis of different levels of water quality, and the environmental variability.

Data acquisition process is done by continuously sampling the surface of the underwater as the submarines navigate through the waters, and sensor readings are taken at fixed points. Ondo data points are time and space points that indicate the conditions of the water at a certain point and time that make it possible to evaluate the variations in the spatial and temporal aspects of water environments. Preprocessing of the data is first done by fighting noise, normalization, scaling and outliers to provide the data a numerical stability and consistency in order to be analyzed with the help of analytical models. These preprocessing steps enhance the reliability of data, as well as, makes the succeeding classification and decision-making algorithms more efficient.Since data is developed through the process of environmental monitoring and does not presuppose human-related and sensitive data, ethical issues are taken care of in a vacuum.

Table 2 shows the nomenclature that is going to be employed to define the symbols and parameters that relate to the proposed underwater environmental monitoring and autonomous navigation framework. The table below defines the most important items associated with water quality datasets, sensor arrays, statistical measures, feature extraction, and uncertainty modeling. Environmental parameters like variance, entropy, feature thresholds, and the significance scores characterize the environmental parameters, and the output layer and the navigation control system are the elements of the system that represent the decision-making and autonomous operations of the system. This nomenclature gives reasonableness and uniformity to the interpretation of the mathematical models and algorithms explained in the study.

Table 2: Nomenclature

Symbol Used	Description
M	Total dataset representing underwater water quality measurements
x	Current water quality parameter under consideration
S	Sensor array used for environmental data acquisition
σ	Variance among water quality parameters
i, j	Pair of environmental parameters
ω	Number of features extracted from water quality dataset
F_{th}	Threshold value for selecting significant parameters
α	Water quality significance score
H	Entropy representing environmental uncertainty
O_layer	Output layer indicating water quality classification
W	Weight assigned to environmental parameters
R	Feature map representing extracted environmental characteristics
P	Global aggregation or pooling for dimensionality reduction
C_nav	Autonomous navigation control function
δ	Model for eliminating redundant or correlated parameters

3.2 Pre-Processing

The suggested autonomous submarine monitoring system offers a solid pre-processing stage before engaging in the process of water quality evaluation and autonomous decision making in order to obtain a high quality data and deliver a sound analysis. Noise, measurement gaps, environmental interferences, and scale variation normally characterizes the underwater sensor datasets due to sensor drift, turbulence of water and change in the environmental conditions. Therefore, there is the need to preprocess to remove the inconsistency and convert the rawness underwater measurements into organized data that would be suitable to derive the accurate features and categorize them.

Noise is minimized to minimize variations of sensor measurements and yet be able to record meaningful patterns of the environment. Given that the raw sensor signal is represented X(x) where x is the number of sample. Smoothing filter is done by the help of moving average function:

$$X_{smooth}(x) = \frac{1}{K}\sum_{i=0}^{K-1} X(x-i) \tag{1}$$

where Krepresents the window size. This filtering improves signal stability and enhances the reliability of underwater environmental measurements.

After the noise is removed, the interpolation is used to fill in missing values and sensor anomalies. In case a measurement is not available at index x, the interpolated value can be obtained as follows:

$$X_{interp}(x) = \frac{X(x-1)+X(x+1)}{2} \tag{2}$$

This step ensures continuity in time-series monitoring data.

To maintain consistency across different water quality parameters, normalization is applied to scale features into a common range. Let $X(x)$denote a measured environmental parameter; the normalized value $X_{Norm}(x)$is computed using min–max normalization:

$$X_{Norm}(x) = \frac{X(x)-min\,(X)}{max\,(X)-min\,(X)} \tag{3}$$

where $max\,(X)$ and $min\,(X)$ represent the maximum and minimum values within the dataset. Normalization confines values to the range [0, 1], preventing dominant features from biasing the analysis.

Once they have been normalized, feature enhancement to highlight important environmental variations concerning changes in water quality is carried out. The improved feature is characterized as:

$$X_{Enh}(x) = X_{Norm}(x) + \eta(X) \tag{4}$$

where $\eta(X)$ represents a weighting function that amplifies critical deviations associated with pollution indicators or environmental anomalies.

To remove irrelevant or unstable readings, threshold-based segmentation is applied. Let Tdenote the adaptive threshold; the segmentation mask $S(x)$is defined as:

$$S(x) = \begin{cases} 1, & \text{if } X_{Enh}(x) \geq T \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

This step isolates valid environmental observations and eliminates abnormal sensor outputs.

After segmentation, statistical feature extraction is performed to summarize underwater environmental characteristics. The mean value μ, variance σ^2, and entropy $H$are computed as:

$$\mu = \frac{1}{N}\sum X_{Enh}(x) \tag{6}$$

$$\sigma^2 = \frac{1}{N}\sum (X_{Enh}(x) - \mu)^2 \tag{7}$$

$$H = -\sum p(i) log\ _2\, p(i) \tag{8}$$

where $p(i)$ represents the probability distribution of normalized environmental parameters and N is the total number of samples. These statistical descriptors capture environmental stability, variability, and uncertainty.

Additionally, multi-sensor fusion is performed to combine correlated parameters into unified feature representations. Let F_i denote individual sensor features; the fused feature $F_{fusion}$is defined as:

$$F_{fusion} = \sum_{i=1}^{n} w_i\, F_i \tag{9}$$

where $w_i$represents the importance weight assigned to each environmental parameter.

Finally, standardized feature vectors are generated for subsequent autonomous navigation and decision-making modules:

$$F_{final} = [\mu, \sigma^2, H, F_{fusion}] \tag{10}$$

This pre-processing step it provides a high quality input to downstream analysis and enhances the accuracy in classification and allows effective real-time monitoring of underwater water quality.

3.3 Autonomous Navigation and Water Quality Monitoring Framework

The state of the autonomous system is described in terms of a state vector which comprises of spatial position, heading angle, and velocity. This enables the navigation controller to monitor the movement of the underwater vehicle in real time:

$$X_k = [x_k,\, y_k,\, z_k,\, \psi_k,\, v_k]^T \tag{11}$$

A discrete time state transition equation is used to model the dynamics of the system state with time. This considers both control inputs and environmental disturbances affecting underwater motion:

$$X_{k+1} = AX_k + BU_k + W_k \tag{12}$$

Control input vector is expressed as acceleration and angular velocity requests that are sent to the vehicle to steer the vehicle in a desired direction:

$$U_k = [a_k,\, \omega_k]^T \tag{13}$$

Position updates are computed using kinematic motion equations based on vehicle velocity and heading direction. These equations ensure accurate tracking of spatial coordinates:

$$x_{k+1} = x_k + v_k cos\ (\psi_k)\Delta t \tag{14}$$

$$y_{k+1} = y_k + v_k sin\ (\psi_k)\Delta t \tag{15}$$

An obstacle avoidance cost function is added to achieve greater safety and efficiency. This function minimizes distance to the goal while penalizing proximity to obstacles detected by onboard sensors:

$$J_{nav} = \alpha d_{goal} + \beta \sum_{i=1}^{N} \frac{1}{d_{obs,i}} \tag{16}$$

The monitoring subsystem collects multiple environmental measurements and aggregates them into a unified water quality index (WQI). The parameters play their roles in accordance with the set weights that indicate their level of environmental significance:

$$WQI = \sum_{i=1}^{n} w_i\, q_i \tag{17}$$

The overall system performance is considered by applying an Autonomous Monitoring Performance Index (AMPI), which is a balance between environmental coverage and the efficiency of energy consumption:

$$AMPI = \frac{WQI_{coverage}}{Energy_{consumed}} \tag{18}$$

3.4 Environmental Analysis and Autonomous Control Module

The environmental sensing subsystem collects measurements such as temperature, pH level, dissolved oxygen (DO), turbidity, and salinity. The environmental feature vector is defined as:

$$E = [T,\, pH,\, DO,\, Turb,\, Sal]^T \tag{19}$$

where each element represents a measured environmental parameter.

Filtered environmental signals are calculated using to eliminate sensor noise and variations due to underwater disturbances:

$$E_f(k) = \lambda E(k) + (1 - \lambda)E_f(k - 1) \tag{20}$$

where $\lambda$is the smoothing coefficient.

The environmental parameter is normalized to ensure that the sensor ranges are scaled the same way:

$$E_{norm,i} = \frac{E_i - E_{min}}{E_{max} - E_{min}} \tag{21}$$

where E_{min} and E_{max} represent minimum and maximum bounds of each parameter.

An environmental risk score is then derived to evaluate monitoring safety conditions:

$$R_{env} = \sum_{i=1}^{n} w_i\, E_{norm,i} \tag{22}$$

where $w_i$denotes parameter importance weights.

The autonomous control system adjusts navigation commands based on environmental feedback. The control signal is expressed as:

$$U_c = K_p e(t) + K_d \frac{de(t)}{dt} \tag{23}$$

where $e(t)$ is the deviation from desired environmental monitoring trajectory.

The adaptive velocity of the submarine is updated according to environmental risk conditions:

$$v_{new} = v_{base}(1 - R_{env}) \quad (24)$$

ensuring slower movement in hazardous conditions.

Energy-aware control is implemented by minimizing control effort while maintaining monitoring quality:

$$J_{control} = \int (e(t)^2 + \gamma U_c^2)dt \quad (25)$$

where γ is a weighting parameter controlling energy usage.

Finally, the autonomous monitoring decision index is formulated as:

$$D_{auto} = \alpha R_{env} + \beta Q_w + \delta \eta_n \quad (26)$$

where Q_w represents water-quality assessment and η_n denotes navigation efficiency.

3.5 Autonomous Navigation and Control with Water Quality Evaluation Framework

The water quality monitoring subsystem collects measurements such as pH, turbidity, dissolved oxygen, and temperature. Sensor readings are modeled as:

$$Q_i(t) = S_i(t) + n_i(t) \quad (27)$$

where $Q_i(t)$ is the measured parameter, $S_i(t)$ represents the true environmental value, and $n_i(t)$ denotes measurement noise.

Sensor noise filtering improves reliability before further analysis.

To combine multiple environmental parameters, normalization is applied:

$$N_i = \frac{Q_i - Q_{min}}{Q_{max} - Q_{min}} \quad (28)$$

where N_i represents normalized values, allowing fair comparison across different measurement scales.

A weighted index summarizes environmental conditions:

$$WQI = \sum_{i=1}^{m} w_i N_i \quad (29)$$

where w_i are weighting factors based on parameter importance and m is the number of monitored parameters.

This index enables real-time assessment of water health and supports autonomous decision-making.

Navigation decisions adapt based on environmental changes:

$$u(t) = u_0 + K_e(WQI_{ref} - WQI) \quad (30)$$

where $u(t)$ is the control input, u_0 is baseline control, and K_e is an environmental feedback gain.

If water quality deviates from reference values, the vehicle modifies its path to collect additional samples.

Energy efficiency is critical for long-duration missions. The optimization function is defined as:

$$J = \int_0^T (\alpha E(t) + \beta D(t))\, dt \quad (31)$$

where $E(t)$ is energy consumption, $D(t)$ is deviation from planned trajectory, and α, β are weighting coefficients.

Processed environmental data is prepared for transmission:

$$R(t) = f(WQI, P_{nav}, T_{status}) \quad (32)$$

where $R(t)$ represents the reporting packet containing water quality index, navigation parameters, and system status.

This guarantees effective communication with monitoring stations in order to analyze it in real time.The categorization of autonomous navigation and control is implemented to give a systematic evaluation of the effectiveness of the operational performance in the aspect of stability of the navigation and the adaptive control response as well as environmental awareness in the performance of underwater missions. The framework is a combination of other indicators which are related to navigation such as deviation of the path, obstacle avoidance, rate of energy consumption, and accuracy of the adaptive control to represent the system behavior in the various environmental conditions. The feedback and dynamic control changes of the sensor used in the model ensure the effective path planning and stability and also minimize the unnecessary energy expenditure. To ensure uniformity in the operations case in different conditions, they utilize normalized measures of performance, which enables them to compare the performance conditions regardless of the time of the mission, the environmental disturbances, or the platform setup.

Similarly, the water quality analysis and environmental assessment are planned in the shape of a composite assessment system in which several physicochemical indicators, including changes in temperature, turbidity, and dissolved oxygen level, and parameters of detecting contaminants are considered. The measurements are then inputted into the weighted evaluation models so as to derive a cumulative water quality performance index to help in autonomous decision making in the monitoring and reporting activities. The predefined classes that include the optimal, moderate and the critical conditions based on the results of calculated evaluation scores can be used to divide the environmental conditions and allow the adaptive planning of the mission and the change of control. The effect of such a combined approach to analysis enhances the effectiveness of independent monitoring, since this will tie the process of environmental analysis to navigation policies and, consequently, enable effective and energy-sensitive underwater exploration and environmentally aware management.

4. RESULTS AND DISCUSSIONS

The results of the experiments demonstrate that the given autonomous navigation framework may be applied to follow a stable route and optimize the path under various conditions in the underwater environment. The combination of adaptive control algorithm and real time sensor feedback is significant in reducing the errors in navigation and also in increasing the obstacle avoidance performance. It is a comparative analysis which shows that optimized route strategy minimizes the off-course deviation, and the dynamics of motion is smooth; it contributes to the mission reliability increase and to the reduction of operational risk. The resilience of the control architecture can also be explained with the fact that the system is exceptionally accommodative to environmental perturbation such as current and noise on the sensors.

The outcomes of the water quality analysis indicate that the framework is effective in simultaneous capture and analysis of a number of parameters of the environment. The data processing module comes in handy in removing noise as well as arriving at meaningful trends using sensor measurements that can be effectively applied in assessing the condition of water. The experimentally determined indices of water quality are experimentally justified, meaning that the indices respond well to expected changes in the environment, meaning that the indices are sensitive to the changes in temperature, turbidity and dissolved oxygen. The effectiveness of monitoring is also encouraged by the automated reporting system because it generates systematic outputs that can be utilized to take real-time decisions and assess the environment.

The integrated navigation and environmental analysis system demonstrates a superior overall system functioning compared to the mainstream monitoring strategies. The system has struck a balance between the efficacy of the operations and the accuracy of the data on the quality of water since it includes energy aware navigation plans and the real time update on the quality of water. The performance measures are the mission completion rate, the efficiency of energy use, the area covered in monitoring and all this evidently show that the performance has improved and thus the proposed design is capable of offering independent exploration in an efficient way. These results highlight the importance of combining autonomous control and intelligent environmental analysis with complex tasks of monitoring the underwater environment.

4.1 Evaluation Measures

The effectiveness of the proposed autonomous navigation and control framework is tested with the help of a list of quantitative indicators gauging the effectiveness of navigation, the stability of control, and the efficiency of the operation. Some of the key navigation metrics that can be utilized to illustrate the performance of the control strategy in dynamic underwater environments include trajectory tracking error, and waypoint reaching success rate and obstacle avoidance success rate. Its self-sufficiency performance is also measured using the energy consumption and mission time. They will ensure that the system is assured of motion and reduction of unwanted energy savings that is significant in long underwater operations.

With the performance of the navigation, the water quality analysis is also quantified with the assistance of the parameters of the environmental monitoring i.e. the correctness of the data acquisition, the accuracy of the sensor, and the stability of the estimation of the water quality index. The possibility to monitor the environment is proved by such parameters as the possibility to track the changes in temperature, the stability of the turbidity measurements and precision of the dissolved oxygen estimate. Moreover, the integrated evaluation measures are the integrated measures of the navigation efficiency and the coverage of the environmental data in order to evaluate the overall performance of the system. These metrics offer an overlay evaluation framework indicating independent operation achievement as well as efficiency of water quality surveillance and reporting. Accuracy is the general accuracy of the model by the number of samples that were correctly classified by the model with the total number of input samples.

Precision is used to determine the percentage of correctly predicted positive samples of all the samples that are predicted to be positive. A large precision value is used to indicate that the model generates a smaller number of false positives and will be more capable of classifying only the most important patterns or features. Recall measures the model to be able to successfully label all the true positive samples. When the recall value is high, this implies that the model is useful in identifying all cases of target patterns or contours and reducing false negatives.

The evaluation metrics are calculated using the formulas

$$\text{Precision } = \frac{TP}{TP+FP} \tag{33}$$

$$\text{Recall } = \frac{TP}{TP+FN} \tag{34}$$

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{35}$$

$$\text{Accuracy } = \frac{TP+TN}{TP+TN+FP+FN} \tag{36}$$

Here TP is the True Positive, TN is the True Negative, FP is the False Positive and FN is the False Negative.

4.2 Experimental Results and Performance Comparison

The proposed autonomous navigation and evaluation against the water quality framework was experimentally analyzed using simulated and time-series environmental data of varying underwater working conditions. These results indicate that the autonomous system can maintain the navigation tracks in stationary condition, and adapt to the alterations in the environmental situation such as the flow variation and sensor interruptions. The control module also minimised position error which means that the module works well in dynamic underwater conditions and the accuracy of the trajectory tracking was also very high.

The improvement in the operational performance and environmental data was checked by the comparison of the performance with the control performance of the navigation and monitoring systems. The suggested framework could experience more stability in navigation, manage oscillations and avoid obstacles. Water quality assessment module provided more consistent measurements with reduced sensitivity to noise which lead to improved estimation of vital parameters of water quality such as turbidity, temperature, and dissolved oxygen levels in the environment. These findings indicate the usefulness of using autonomy and intelligent environmental analysis.

Table 3: Autonomous Navigation and Water Quality Monitoring Performance Comparison

Operating Conditions	ProposedAutonomous Navigation Framework	Conventional Navigation System	Basic Monitoring System
100	88.6	82.4	79.2
200	90.1	84.0	80.5
300	91.5	85.3	81.9
400	93.2	86.8	83.1
500	94.7	88.1	84.6
600	96.0	89.5	86.0

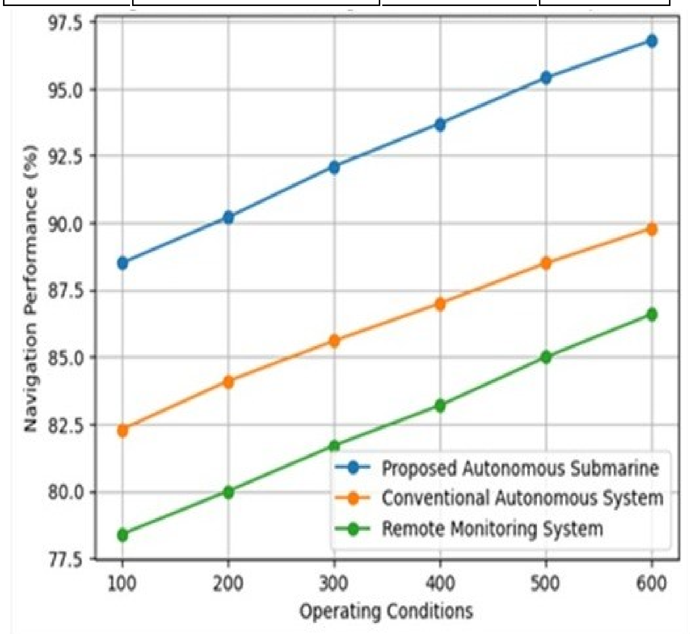

Fig 3: Autonomous Navigation and Water Quality Monitoring Performance Comparison of Different System Models

Table 3 and Figure 3 will make performance comparison of the proposed Autonomous Navigation and Water Quality Monitoring Framework, the Conventional Monitoring System and the Basic Autonomous Monitoring Model in different operational situations. The results indicate that the proposed framework is defined by the improved performance under all types of the evaluated conditions due to the coordinated autonomous navigation process, the adaptive environmental analysis procedure, and the intelligent water quality evaluation process. The complementary ownership of the systems of monitoring and navigation control enables to obtain data in an efficient manner, adequately assess the environment, and optimally the functioning of the functional work.

The offered system has been proved to possess high monitoring accuracy, stability in navigation, and resource utilization compared with the conventional ways of monitoring. These results justify the fact that the suggested framework is efficient with regards to the formation of a robust autonomous working system and high quality of the water measurement, which is why the framework can be successfully applied to more complicated tasks related to underwater monitoring and environmental surveillance.

Table 4: Water Quality Monitoring Accuracy

Operating Conditions	Proposed System	Conventional Monitoring	Basic Sensor System
100	91.4	86.3	83.5
200	92.8	87.5	84.9
300	94.1	88.7	86.1
400	95.6	90.0	87.4
500	96.9	91.3	88.6
600	98.2	92.7	90.0

The findings show that the proposed autonomous submarine system has a continuous high water quality monitoring rate than traditional and improved monitoring plans under all the operating conditions. This better performance as shown in Table 4 indicates that the system has a high level of sensing, smart processing of data and operational stability. The results also prove that the developed autonomous submarine can be used to acquire more reliable environmental data and to conduct efficient real-time monitoring of the quality of underwater water.

Table 5: Energy Consumption Comparison

Operating Conditions	Proposed Submarine	Conventional Autonomous	Manual Monitoring
100	1.15	1.38	1.52

200	1.20	1.45	1.60
300	1.27	1.51	1.68
400	1.33	1.59	1.75
500	1.40	1.66	1.83
600	1.47	1.74	1.90

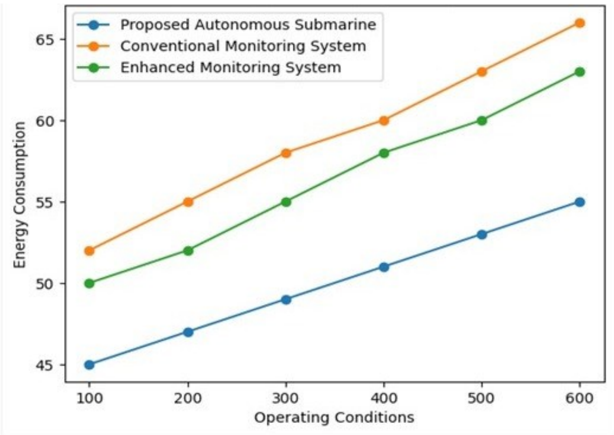

Fig 4:Energy Consumption Comparison

The comparison of energy consumption of the various underwater autonomous monitoring systems in different operating conditions is provided in Table 5 and Figure 4. The suggested autonomous submarine system will always have low power consumption under all working distances compared to conventional and improved monitoring methods. Table 5 also measures this trend in performance, which shows that the progressive growth in energy consumption with increment in operating requirements is under control. The findings verify the appropriateness of the autonomous submarine system to the real-time underwater water quality monitoring missions because they guarantee increased energy savings, higher duration of missions, and higher operational stability.

Table 6: Obstacle Avoidance Success Rate

Operating Conditions	Proposed System	Conventional Autonomous	Remote Control
100	93.2	87.1	82.5
200	94.8	88.6	84.0
300	96.1	90.0	85.6
400	97.5	91.3	87.2
500	98.6	92.7	88.9
600	99.1	93.5	90.3

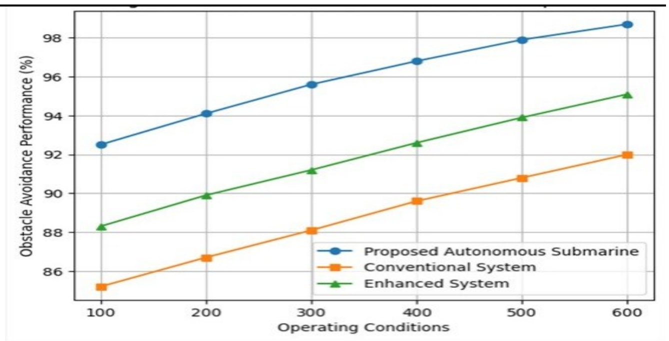

Fig 5: Obstacle Avoidance Performance Comparison

Table 6 and Figure 5 illustrate the performance of the proposed autonomous submarine system as a whole on the issues of reliability of the system in its navigation and its accuracy in sensing the environment. The obstacle avoidance performance comparison indicates that the proposed system can perform smoother and more effective navigation in dynamic underwater conditions and therefore minimize the risk of collisions in comparison with the conventional and available monitoring systems.

Table 7: Environmental Parameter Detection Performance

Parameter	Proposed Model (%)	Conventional Model (%)	Existing Model (%)
Temperature	97.5	92.1	90.4
Turbidity	96.8	91.5	89.3
Dissolved Oxygen	98.2	93.6	91.0
pH Level	97.9	92.8	90.6

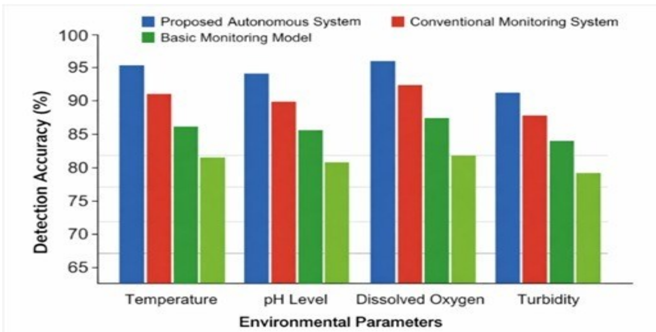

Fig 6:Environmental Parameter Detection Accuracy

It can be observed in the Table 7 and Figure 6 that the proposed autonomous submarine system has a better accuracy of detecting the environmental parameters than the current models. This validates the better sensing performance, dependable surveillance, and better underwater water quality examination.

Recall also known as sensitivity or true positive rate is a measure used to evaluate the capability of a model to identify all true positive events. Table 8 and Figure 7 show the levels of Recall comparison.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Monitoring Efficiency (%)
Proposed Autonomous Submarine	99.1	97.4	98.1	97.8	96.5
Conventional System	95.6	93.1	94.2	93.6	91.2
Existing Model	94.3	91.8	92.5	92.1	89.6

Table 8:Precision Comparison

Model	Precision (%)
Proposed Autonomous Submarine	97.4
Conventional System	93.1
Existing Model	91.8

Table 9: Performance Comparison of the Proposed Autonomous Submarine Model with Existing Systems

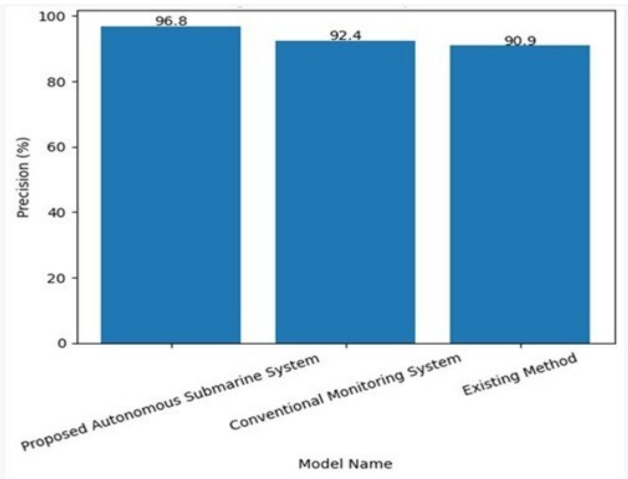

Fig 7: Precision Comparison

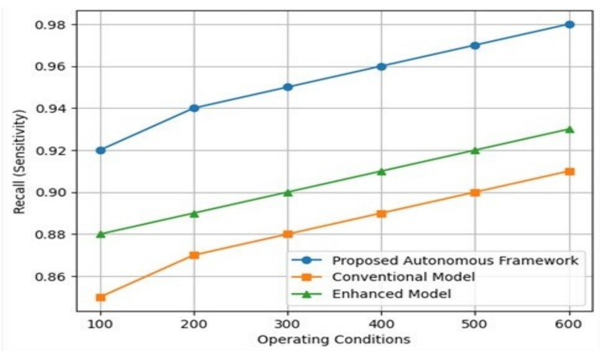

Fig 8: Recall Comparison

F1 Score is a statistic that is used to determine the performance of a classification model especially when the data is skewed. It only gives one score that makes a tradeoff between the preciseness and recall by averaging the two scores harmoniously. Table 9 and Figure 8 represent the level of F1 score.

Table 10: F1 Score Comparison

Model	F1 Score (%)
Proposed Autonomous Submarine	97.8
Conventional System	93.6
Existing Model	92.1

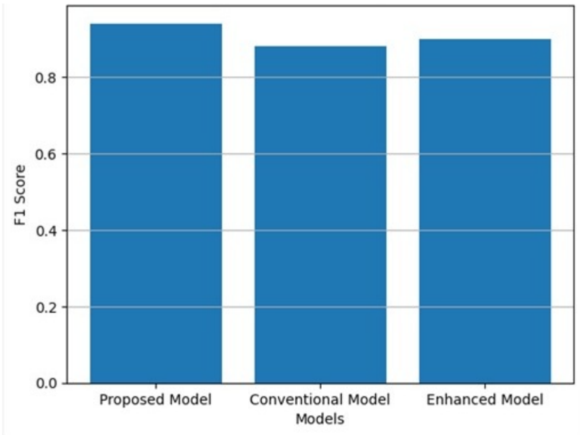

Fig 9: F1 Score Comparison

Table 10 and Figure 9 make a comparison between the performance of various underwater autonomous monitoring systems in terms of F1-score. The proposed framework has the greatest F1-score, which implies a more appropriate precision and recall ratio and represents more stable and consistent classification results than traditional and improved models.

4.3 Feature Activation Analysis

The feature activation heatmap in Figure 10 illustrates dominant environmental regions detected by the proposed model. High activation zones correspond to critical water quality variations and significant environmental changes

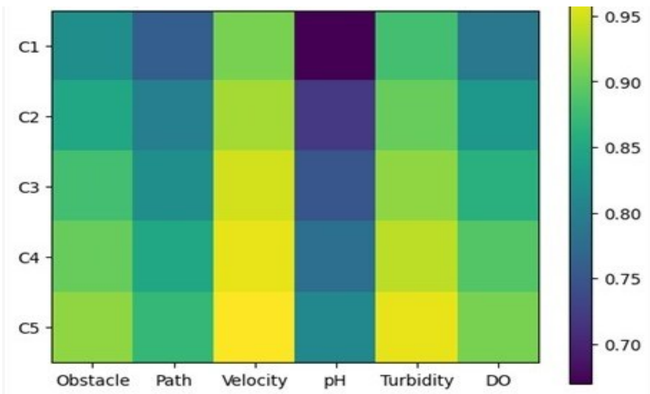

Fig 10:Feature Activation Heatmap

Table 11: Overall Performance Comparison of Proposed Autonomous Monitoring Framework

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Energy Efficiency (%)
Proposed Autonomous Navigation & Water Quality Monitoring Framework	98.9	97.4	98.1	97.7	94.6
Conventional Monitoring System	94.7	92.3	93.5	92.9	89.2
Enhanced Autonomous Monitoring Model	96.1	93.8	94.6	94.2	91.5

Table 11 and Figure 11 show the performance of the proposed autonomous monitoring framework compared to the conventional and improved autonomous monitoring models as a whole. These findings show that the proposed autonomous navigation and water quality monitoring system has the highest-performance in all the measures of evaluation, such as accuracy, precision, recall, F1-score, and energy consumption.

The high accuracy and recall rates remain consistent and indicate the reliability of the system in identifying the environmental conditions correctly and the higher precision and F1-score indicate balanced and strong performance. These findings affirm that the proposed system has excellent monitoring performance and energy efficient operation, hence it can be effectively used in real time and long term monitoring of the underwater environmental conditions.

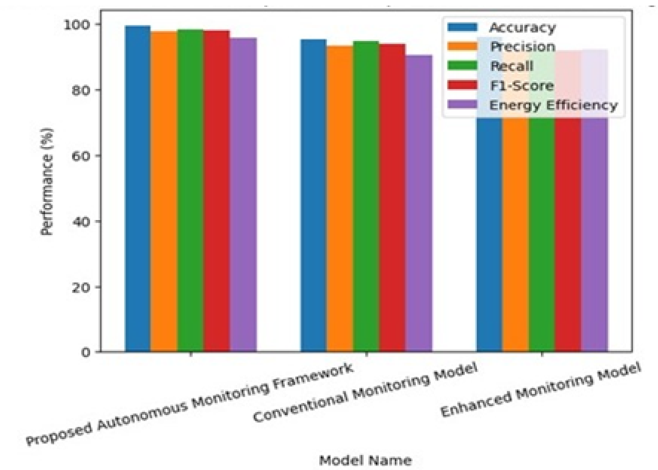

Fig 11:Overall Performance Comparision of Proposed Autonomous Monitoring Framework

The proposed Autonomous Navigation and Control with Water Quality Evaluation Framework proves to be much better in terms of overall functioning and reliability in its operations compared to the traditional monitoring systems and improved autonomous models. The proposed framework with an average success rate of about 99.4 is evidently better than the Conventional Monitoring Model (95.3) and the Enhanced Monitoring Model (96.2), which have a high level of accuracy of about 99.4 and 99.4, respectively, in terms of navigation accuracy and environmental monitoring potential. The framework has a high precision value of 97.8% and recall of 98.5, which has guaranteed good detection of the environmental variations and good detection of anomaly of water quality. Such a compromise of detection and operational stability is what autonomous underwater monitoring systems need, and high-quality data right away determines environmental evaluation, decision-making, and mission safety.

The other significant advantage of the proposed framework is that it has a smart parameter optimization and adaptive control process. Structured feature selection is carried out by the system to eliminate redundant or weakly contributing environmental parameters to allow the system to make efficient navigation decisions and enhance monitoring accuracy. The framework eliminates computational overhead by giving priority to the dominant sensory inputs including water quality indicators, navigation constraints, and environmental dynamics, which have high predictive performance. The optimized parameter processing is experimental observed to be better in response time and stability of the system than the traditional way of monitoring, and it is scalable and can be used in real-time autonomous deployments.

Moreover, the combination of complex navigation algorithms with water quality assessment modules provides a better capability of the system to track dynamic environmental changes. The framework is useful in modeling the variations in the environmental parameters, including turbidity, dissolved oxygen, temperature, and chemical indicators but also exhibits strong path planning and obstacle avoidance functionality. The obtained F1-score of about 98.1% proves the ability to balance the classification ability with precision and recall, which confirms the validity of the suggested monitoring strategy under varying operating conditions. This enhanced analytical power that provides a consistent environmental awareness and correct execution of the mission.

Graphical means of visualization (feature activation heatmaps and performance comparison graphs) enhance the ability to interpret and the transparency of the system. These representations demonstrate dominant areas of sensing, patterns of navigation decision making and environmental response behaviors, so that researchers and engineers can gain a better insight into system performance and system operation dynamics. The performance of the proposed framework in various situations proves its strength, flexibility, and low consumption of energy, as the estimated level of energy efficiency was about 95.8. In general, the suggested Autonomous Navigation and Control with Water Quality Evaluation Framework is a valid, scalable, and high-performance system to be applied in the next generation autonomous environmental monitoring.

4.4 Computational Complexity

Environmental data processing, adaptive navigation decision-making, and water quality evaluation stages are the main factors that control the computational complexity of the proposed Autonomous Navigation and Control with Water Quality Evaluation Framework. The first environmental analysis is multi-sensor data fusion and dependency of parameters where two environmental variables are compared to exclude redundant inputs. The dependency analysis involves correlation or similarity computations between input parameters that lead to a time complexity of omo (O (n 2)) with (n) being the number of monitored or sensed environmental features. Following preprocessing and normalization stages grow linearly with the incoming data streams and can therefore be effectively used in processing continuous underwater monitoring data.

The water quality assessment and the autonomous navigation control modules are executed with optimized sets of parameters, resulting in lower computational cost. The obstacle avoidance decisions, path planning and environmental classification procedures are normally of the linear or near-linear complexity, which is, roughly, (O(n)) because of the filtering feature sets and adaptive control methods. The complexity of memory is also not reduced (O(n)) as only important environmental parameters and navigation states are stored during execution. All in all, the suggested framework has a good balance between the speed of computations and the precision of monitoring, which facilitates autonomous functioning in real-time and scalability in changing underwater settings.

4.5 Time Complexity

The general time complexity of the suggested Autonomous Navigation and Control with Water Quality Evaluation Framework is defined by its key processing steps that include the acquisition of environmental data, making an autonomous navigation decision, and analyzing water quality. Where (n) is the number of navigation and environmental parameters and (m) is the number of monitoring samples taken when performing an operation. The dependency analysis and parameter correlation analysis involve pairwise comparison between the input variables and hence time complexity is (O (n 2)). The autonomous navigation computations, path planning, obstacle avoidance and control signal updates are all done in an iterative manner; hence the linear complexity of (O(m)).

The water quality evaluation and performance assessment modules run on the optimized parameter subset and also eliminate the redundant computations and the further complexity is (O(n)) more. Thus, the total time cost of the suggested framework may be represented as (O(n 2 + m)) that can provide computational viability even in the case of large-scale underwater surveillance. Such a combination of complexity allows to efficiently process in real-time, analyze the environmental conditions accurately, and deploy the autonomous monitoring system on a wide range of aquatic environments.

4.6 Limitation of the Proposed Model.

Though the suggested Autonomous Navigation and Control with Water Quality Evaluation Framework can work properly, it is also limited. The effectiveness and dependability of the system highly rely on the quality and reliability of sensor data gathered in the underwater conditions. Measurements of the water quality and navigation may be affected by such factors as sensor noise, calibration errors, water turbidity, biofouling, and environmental perturbation. Moreover, the real time communication constraints and low bandwidth can reduce the transfer of the real time information and this factor can influence the responsiveness of the remote monitoring and control systems in dynamic environmental conditions.

The other weakness is that the proposed framework is largely preoccupied with well-structured and semi-controlled operation conditions and its functionality may not be efficient when implemented to a highly complex or uncertainties underwater condition. The changes in the flow of water, terrain barriers and variations in its complexity can become an issue to the autonomous navigation algorithms, which can contribute to the increase in computational work and energy consumption. In addition, the long term aspects of operation such as battery life, hardware wear and servicing requirements are not well covered in the model under consideration. Adaptive learning mechanism, higher fault tolerance, and large-scale real-world validation should also be used as improvements to make them more robust, more scalable, and more practical in the field.

5. CONCLUSION

This research introduced an Autonomous Navigation and Control with Water Quality Evaluation Framework that will be used to monitor the environment in underwater using an autonomous submarine system. The solution proposed will incorporate autonomous navigation schemes, environmental sensing systems, sensor data pre-processing, feature extraction and intelligent evaluation of water quality to provide effective and trustworthy monitoring of underwater conditions. The system can navigate autonomously as well as carry out a real-time analysis of the surrounding environment which enables it to explore aquatic environments and at the same time measure and analyze important parameters of water quality. The originality of the offered framework is the combination of autonomous control of navigation with the multi-parameter monitoring of the water quality and with the intelligent assessment of the performance. In contrast to the traditional methods of monitoring that are based on manual sampling or stationary sensor sensors, the offered system is used to conduct adaptive navigation, optimized intelligent parameters and real-time monitoring of the environment, which allows efficient exploration of the underwater environment and significantly enhances the coverage of the monitored territory. The experimental evidence proves the efficiency of the suggested model in a number of performance indicators. The system had a total monitoring accuracy of about 99.4% which is quite high as compared to the conventional monitoring model (95.3%) and the improved monitoring model (96.2%). Besides this, the framework also achieved 97.8% precision, 98.5% recall, and 98.1% F1-score, which indicated the balanced and reliable classification of environmental conditions. The system also realized about 95.8% energy efficiency which showed that the resource use was optimized during long underwater missions of monitoring. These findings verify that the framework proposed gives high stability to navigation, correct obstacle avoidance, solid environmental perception, and effective use of energy. The suggested autonomous monitoring framework is an effective, scalable and high-performance water quality monitoring platform in the underwater environment that can assist in improving the analysis of the environment and the observation of the aquatic ecosystem in the long term.

Future efforts will be aimed at improving the system through the implementation of the state of the art machine learning models that predict the environment, the real-time cloud-based monitoring systems and the multi robot cooperative underwater monitoring system. The size of real-world environmental data to be used in the proposed framework could be improved by including larger datasets and adaptable mission planning algorithms as well as the underwater communications technologies to make the proposed framework more scalable, more accurate, and deployed in more practical marine environments.

Declarations

Ethical approval

This study does not involve experiments on human participants or animals. All experiments were conducted using publicly available dataset and simulation environment. Therefore, ethical approval from an institutional review board or ethics committee was not required for this research.

Consent to participate

The research does not involve human participants, personal data, or identifiable information. Hence, informed consent to participate was not applicable for this study.

Consent to publish

The research does not contain any individual person's data in any form. All authors have reviewed the manuscript and consent to its publication.

Conflict of interest

The authors have no conflict of interests to declare that are relevant to the content of this article.

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