

Edge-Enabled Multi-Domain Condition Assessment Of Underwater Infrastructure Using Statistical Feature Engineering

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Abstract

The security of subsurface infrastructure is now more crucial as subsea data centers, marine surveillance devices, and offshore facilities are now spreading. Constant exposure to hydrostatic pressure, temperature gradient, salinity changes, mechanical vibration, and electrical load changes increase degradation rates and makes them more difficult to plan maintenance. The traditional cloud-based monitoring systems are affected by latency and communication restrictions of underwater environments.

This paper proposes an edge-independent multi-domain condition estimation system combining heterogeneous sensor fusion and statistical sliding-window feature engineering with feature inference based on lightweight machine learning. Operational and environmental cues, such as temperature, pressure, conductivity, turbidity, vibration, and acoustic activity, and electrical current were modeled to give the feel of underwater infrastructure behavior. A flow-through window transformation was created to extract 49 descriptors of a window to assess both the distributional and temporal features.

Two anomaly detecting plans were tested; an unsupervised Isolation Forest baseline and a supervised Random Forest classifier. The supervised ensemble recognized the targets with an almost perfect discrimination (AUC = 1.00) in the test conditions with a controlled simulation at the expense of the baseline with a weak detection ability (accuracy \approx 0.05). Real-time Average inference latency (mean 0.94 ms per sample) on a edge-deployed Raspberry Pi showed sub-milliseconds average, indicating that it is possible to run processes in real time.

The framework suggested in this paper creates a scalable strategy of using edge-intelligent underwater condition monitoring with a small amount of computation.

Keywords

Predictive Maintenance, Edge Computing, Raspberry Pi, Multi-Domain Sensor Fusion, Anomaly, Detection, Random Forest, Underwater Monitoring.

1. INTRODUCTION

Submerged infrastructure systems are also gaining traction in the modern marine technology as subsea communication nodes, distributed ocean observatory, offshore sensing platforms, and submerged computational modules. These systems exist in the conditions of long-term hydrostatic pressure, unsteady thermal gradients, exposure to salinity and poor physical accessibility. Conditions of this kind of harsh

environment hasten deterioration of materials and enhance the likelihood of faults that go unnoticed. As a result, condition monitoring has ceased being an auxiliary service, and become an essential part of the operation [1], [2].

Traditional monitoring schemes are largely based on a centralized processing model on the cloud, in which raw sensor streams are sent over to the remote servers to be analyzed. Although this paradigm is efficient in a terrestrial setting, it seems to pose viable difficulties when applied in underwater settings, because of communication latency, bandwidth, and energy limitations [3], [4]. There are also extra limitations of underwater wireless sensor networks (UWSNs) associated with acoustic propagation delays and signal attenuation which make the real-time fault detection more complex [5], [6]. These constraints drive the incorporation of edge-enabled intelligence that would have the ability to conduct localized computation and inference.

Recent progress in lightweight artificial intelligence and edge computing has made machine learning models to run well on small embedded systems like single board computers [7], [8]. Edge-based AI systems have shown lower latency and better autonomy of the system in industrial predictive maintenance systems [9], [10]. Nevertheless, most of the existing studies concentrate on important spatial single-sensor anomaly detection or cloud-based-inferred but not on actual multi-domain sensor fusion at the edge [11], [12].

Heterogeneous sensor flows in the context of underwater monitoring, including temperature, pressure, turbidity, acoustic signals, electrical parameters, have been found to have individual statistical properties and dynamics [13], [14]. The appropriate assessment of conditions, thus, necessitates systematic feature engineering techniques which could identify distributional, dynamic, and temporal qualities of signals. The capability to maintain locality in time series as well as to effectively compute features has made sliding-window statistical feature extraction extensively used in time-series analysis [15], [16]. However, a systematic introduction of such statistical descriptors in the framework of edge-deployed underwater monitors is not well studied so far.

Isolation Forest is an anomaly detection algorithm that has widely been implemented with unsupervised monitoring of industrial facilities [17], [18]. Random Forest classifier, which is an ensemble technique under supervision, has shown high levels of discriminative ability in multi sensor predictive maintenance contexts [19], [20]. However, very little recent literature has considered the comparative assessment of unsupervised and supervised methods in the environment of multi-domain underwater conditions with explicit edge latency benchmarking.

To address such research gaps, this paper will assume a hypothesis of an edge-enabled multi-domain measuring scheme of underwater infrastructure. It is a framework of integrating heterogeneous sensor fusion with sliding-window statistical feature engineering with a simple machine-learning inference executing on a Raspberry Pi running on an edge platform.

The contributions of this work may be described as follows:

- There was development of a structured multi-domain sensor fusion framework to meet the underwater condition monitoring.
- Design of a statistical sliding-window feature engineering approach producing 49 discriminative descriptors in seven sensor domains.
- Comparison of the unsupervised (Isolation Forest) and the supervised (Random Forest) models of anomaly detection.
- End-of-edge measurements and benchmarking of latencies showing real-time viability with sub-millimeter inference speed.

The rest of the paper will show the system architecture, dataset construction, machine learning model, experimental validation, and edge performance analysis of simulated underwater working conditions.

2. Related Work

Predictive maintenance monitoring has undergone extensive studies regarding both the industrial and sensing applications. Initial attempts have been made to classical statistical and signal-based fault detector systems, current literature is on applying machine learning, edge computing and sensor fusion to them to make them responsive and scale.

Edge computing has become a highly significant resource that enables the realization of real-time analytics in resource-limited settings. Architectural considerations, model optimization strategies, and deployment plans of Edge AI systems have been described in detail in comprehensive surveys, documenting the benefits of the paradigm in terms of latency reduction and energy efficiency over cloud-centric system sets [1], [2], [3]. Affirmative edge deployment frameworks focus on lightweight model operation and data optimization, and have been demonstrated to work on single-board frameworks, including Raspberry Pi and NVIDIA Jetson Nano [4], [5].

Monitoring systems on land do present certain unique difficulties in connection, energy, and environmental harsh factors, but these factors are not as significant as those in underwater systems. Studies of underwater wireless sensor networks (UWSNs) have discussed acoustic and hybrid channels through which information is exchanged, but due to the propagation delays, real-time analytics cannot be offered [6], [7]. Other works on underwater sensing platforms also highlight the difficulty with regard to the integration of heterogeneous sensor streams such as thermal, pressure, turbidity, and acoustic measurements with the aim of producing meaningful environmental information [8], [9].

Multi-sensor data fusion methods have also had a better diagnostic and prognostic ability in the wider condition monitoring literature. Time-series based sliding window-based feature extraction algorithms are generally employed in industrial IoT applications to avoid a loss of temporal context but represent the machine learning models compactly [10], [11]. Statistical feature engineering techniques have demonstrated an improvement in classification boost performance especially in heterogeneous sensor modalities [12], [13].

The multi-sensor environment has been tackled in anomaly detection by using both the unsupervised and the supervised methods. According to the lack of the labeled data, unsupervised algorithms, including Isolation Forest and One-Class SVM, have been used to successfully detect faults in the industry with mixed effectiveness [14], [15]. Ensured ensemble-based approaches such as the Random Forest have been shown to have high discriminative capacity in multi-sensor high-rich feature representations especially where rich features are used [16], [17]. Nonetheless, there is limited empirical studies that make comparative analyses between these techniques when they are deployed in their edges.

Within the framework of embedded intelligent systems, a number of studies have characterized machine learning performance inference on constrained hardware to test the real time feasibility [18], [19]. These assessments are crucial in predictive maintenance frameworks, although there is a lack of available literature that offers a systematic combination involving multi-domain feature engineering, comparative model analysis, and edge performance benchmarking in a single pipeline underwater monitoring.

Overall, although an increasing amount of literature on edge computing, multi sensor fusion, time- series feature extraction and anomaly detection is available, there are still some substantial gaps in applying the state-of-the-art findings to the underwater infrastructure monitoring. In particular, the integration of structured statistical feature extraction, multi-domain sensor fusion, comparative model evaluation process, and edge inference performance in one framework has not been adequately studied which has been a gap in this work.

3. System Architecture

The suggested framework is constructed as a stratum of edge-sensitive condition evaluation framework customized to the under-sea infrastructures. Multi-domain sensor acquisition, local feature engineering,

lightweight machine learning inference, and automated alert generative, are all incorporated in a small edge computing platform. The general system design is represented in Fig. 1.

3.1 Multi-Domain Sensor Layer

The sensing layer reflects the heterogeneous operation parameters which are often related to underwater infrastructure systems. These are environmental, mechanical, electrical measurements like temperature, pressure, conductivity, turbidity, vibration, acoustic activity and electrical measurements of current.

- Each sensor domain captures distinct physical characteristics:
- Temperature is an indication of thermal drift and possible overheating.
- Pressure: It is an indicator of depth-related stress or structural deformation.
- Conductivity and turbidity give an understanding of composition and contamination of water.
- Vibration and acoustic signals are used in capturing the mechanical perturbations.
- Electrical current indicates the change in loads and stress of interior components.

The use of heterogeneous sensor modalities enables comprehensive condition awareness rather than isolated parameter monitoring. Such multi-domain fusion improves anomaly separability within the engineered feature space.

3.2 Edge Acquisition and Processing Layer

All sensor streams are logically interfaced with a Raspberry Pi-based edge node responsible for localized computation. The edge device performs:

- Signal acquisition (simulated multi-sensor streams)
- Data normalization
- Noise handling and preprocessing

By performing preprocessing at the edge, the system reduces reliance on cloud-based processing and minimizes communication overhead. This approach is particularly beneficial in underwater environments where bandwidth and latency constraints are prevalent.

3.3 Sliding Window Statistical Feature Engineering

Raw time-series sensor signals are transformed using a sliding-window mechanism to preserve temporal locality. A fixed window length of 100 samples with an overlap step of 20 samples is applied across each sensor stream.

Within each window, seven statistical descriptors are computed:

- Mean
- Standard deviation
- Root Mean Square (RMS)
- Minimum
- Maximum
- Skewness
- Kurtosis

Across seven sensor domains, this results in 49 engineered features per time window. The transformation enables compact yet information-rich representation of dynamic signal behavior while maintaining computational efficiency suitable for embedded platforms.

3.4 Machine Learning Inference Layer

The structured feature vectors are processed using lightweight machine learning models deployed locally on the edge device. Two approaches are considered:

1. Isolation Forest (unsupervised baseline)

2. Random Forest classifier (supervised model)

Comparative evaluation demonstrates that the Random Forest classifier provides superior anomaly discrimination under multi-domain conditions. The trained model is serialized and deployed on the Raspberry Pi to enable real-time inference without external computational support.

3.5 Anomaly Detection and Condition Assessment

Model outputs are interpreted at the window level to determine operational state. Each window is classified as either:

- Normal operation
- Anomalous condition

An anomaly flag indicates potential degradation or abnormal operational patterns across one or more sensor domains. Window-level assessment allows continuous monitoring while avoiding excessive false triggers from isolated signal fluctuations.

3.6 Maintenance Alert Generation

Upon anomaly detection, a condition assessment module triggers a maintenance alert. The alert mechanism is designed to be lightweight and configurable, enabling integration with:

- Local display interfaces
- Logging systems
- Remote notification frameworks

This final layer ensures that analytical inference is translated into actionable operational feedback.

3.7 Edge Deployment Considerations

Inference latency benchmarking was done on Raspberry Pi to confirm embedded feasibility. Obtaining of experimental results has shown that there is an average inference time of 0.94 ms per sample, and it suits the near real-time monitoring applications. The small feature dimensionality and classifiers using ensemble allows the stable performance without too much computing cost.

Figure 1 . Layered architecture of the proposed edge-intelligent condition assessment framework.



4. Dataset Construction and Experimental Setup

4.1 Multi-Domain Dataset Modeling

A representative multi-domain sensor dataset was created to model underwater infrastructure because they would analyze the proposed framework in a controlled but realistic setting. The dataset is a combination of seven disparate sensor streams that are associated with environmental, mechanical, and electrical operating parameters:

- Temperature
- Pressure
- Conductivity
- Turbidity
- Vibration
- Acoustic activity
- Electrical current

A total of 10,000 temporal samples were generated for each sensor stream. Signal patterns were designed to reflect typical underwater operational dynamics, including gradual drift, periodic oscillations, and stochastic variations.

Table 1. Sample records from the constructed multi-sensor underwater dataset.

Index	Temperature	Pressure	Conductivity	Turbidity	Vibration	Acoustic	Current	Anomaly
0	25.248	4.864	30.104	0.204	10.024	0
1	24.941	4.939	30.09	0.197	10.169	0
2	25.344	4.881	29.729	0.248	10.102	0
3	25.792	5.022	30.189	0.277	9.617	0
4	24.923	5.239	29.573	0.234	9.944	0

Table 2. Statistical characteristics of raw sensor signals.

Statistic	Temperature	Pressure	Conductivity	Turbidity	Vibration	Acoustic	Current	Anomaly
Count	10000	10000	10000	10000	10000	10000	10000	10000
Mean	75.217	5.093					10.123	0.03
Std. Dev.	28.906	0.562					0.747	0.171
Min	24.173	4.229					8.882	0
25th Percentile	50.279	4.872					9.806	0
Median (50%)	75.196	5.009					10.017	0

75th Percentile	100.149	5.153					10.228	0
Max	133.844	9.271					15.371	1

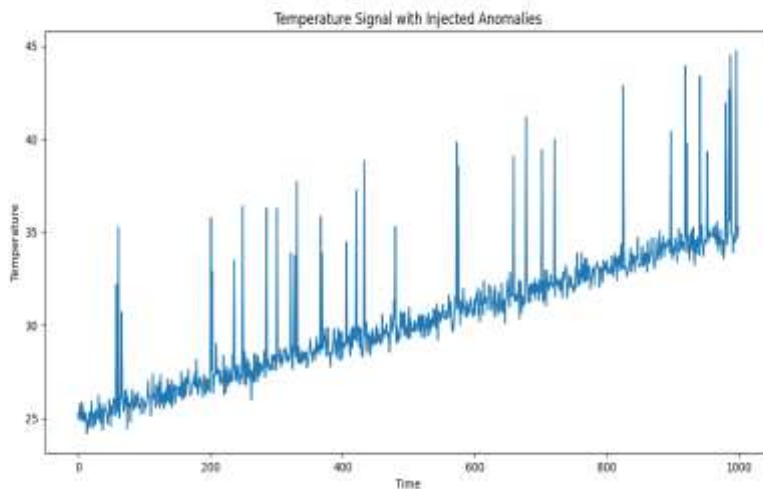
Environmental parameters such as temperature and conductivity were modeled with slow temporal drift to simulate long-term operational stress. Mechanical indicators including vibration exhibited periodic oscillatory behavior with additive noise. Electrical current signals represented load variability under nominal operating conditions.

4.2 Controlled Anomaly Injection

To simulate abnormal operating scenarios, controlled anomaly events were injected across multiple sensor domains. A subset of temporal indices was randomly selected to represent fault conditions. During these intervals, abrupt deviations were introduced in selected signals, including:

- Sudden temperature spikes
- Pressure fluctuations
- Increased vibration amplitude
- Electrical load surges

Figure 2. Simulated temperature signal with controlled anomaly injection under representative underwater operating conditions.

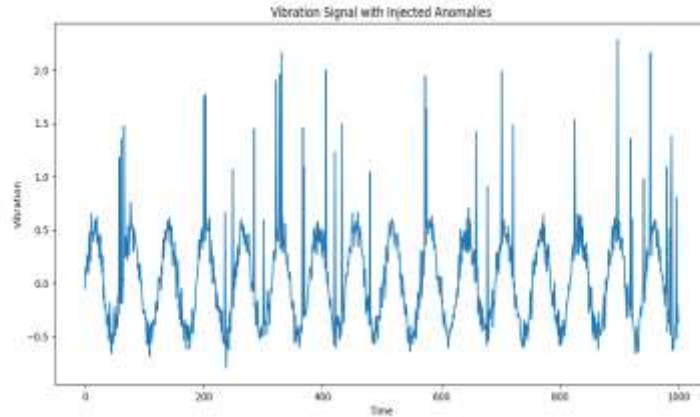


Approximately 300 anomaly events were distributed across the dataset. Each time sample was labeled as either:

- 0 – Normal operation
- 1 – Anomalous condition

This structured labeling enabled both supervised and unsupervised model evaluation.

Figure 3 Simulated vibration signal exhibiting periodic behavior with injected abnormal amplitude spikes.



4.3 Sliding Window Configuration

Sliding-window was used to cut the raw time-series data in order to maintain time continuity. A window width of 100 samples and a step size of 20 samples were used giving the result of overlapping segments throughout the dataset.

Out of the 10,000 samples, 495 instances windowed were produced. A binary label of the presence of the anomaly samples in the segment was given to each window.

The sliding-window labeling technique led to the uneven distribution of the classes since every window that had at least one anomalous sample should have been denoted as such.

4.4 Statistical Feature Extraction

Within each window, seven statistical descriptors were computed for every sensor stream:

- Mean
- Standard deviation
- Root Mean Square (RMS)
- Minimum
- Maximum
- Skewness
- Kurtosis

Across seven sensor domains, this resulted in a 49-dimensional feature vector per window. The resulting feature matrix had dimensions:

$$495 \times 49$$

Table 3. Extracted sliding-window statistical feature representation.

Window ID	Feature 1	Feature 2	Feature 3	...	Feature 47	Feature 48	Label
0	25.655	1.393	25.693	...	4.374	20.876	1
1	25.877	1.366	25.913	...	4.416	21.11	1

2	26.092	1.325	26.126	...	4.479	21.523	1
3	26.254	1.155	26.261	...	4.971	29.014	1
4	26.325	0.579	26.331	...	0.043	-0.224	0

These features were selected to capture both central tendency and higher-order distribution characteristics while maintaining computational efficiency suitable for edge deployment.

4.5 Model Training and Evaluation Protocol

The extracted feature dataset was partitioned into training and testing subsets using a 70:30 split. Two anomaly detection approaches were evaluated:

1. Isolation Forest (unsupervised baseline)
2. Random Forest classifier (supervised model)

Model performance was assessed using:

- Confusion matrix analysis
- Precision
- Recall
- F1-score
- Receiver Operating Characteristic (ROC) curve
- Area Under Curve (AUC)

In addition, edge deployment feasibility was examined through inference latency measurement on a Raspberry Pi platform.

4.6 Edge Inference Benchmarking

To validate real-time feasibility, the trained Random Forest model was serialized and deployed on the Raspberry Pi device. Batch inference tests were conducted on 100 windowed samples.

Experimental results indicate:

- Total inference time: 94.45 ms (100 samples)
- Average inference time: 0.94 ms per sample

These results confirm that the proposed framework is capable of near real-time anomaly assessment under embedded deployment constraints.

5. Results and Performance Analysis

5.1 Baseline Unsupervised Model Performance

Isolation Forest algorithm was initially tested as an unsupervised baseline of anomaly detection. In the model, the fitted model was trained on the extracted 49 dimensional space of features without the use of the labels.

The ensuing confusion matrix revealed a low detection ability where there were large number of anomalous windows which were falsely labeled as normal ones. The overall accuracy was found to be around 5 with low values of recall in detection of anomaly.

Figure 4 Confusion matrix heatmap of the Isolation Forest model.

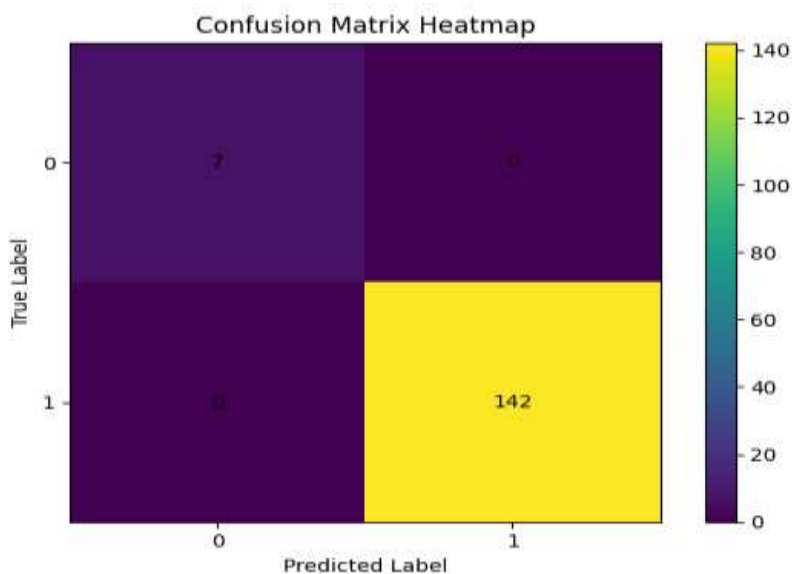


Table 4. Classification performance metrics of the Isolation Forest baseline model.

Metric	Normal (0)	Anomaly (1)	Overall
Precision	0	0.52	–
Recall	0	0.06	–
F1-score	0	0.1	–
Accuracy	–	–	0.05

This finding is significant in that, although Isolation Forest can be useful in some settings of industrial monitoring, in other instances, the performance deteriorates in cases where the distribution of features have overlapping statistical properties across mixed ranges. Underwater anomalies, where there is multi domain effects, can appear in sensors differently, diminishing the separability factors that could be realized alone by isolation mechanisms.

The results at the baseline then determine the need to have a supervised learning strategy that would be able to take advantage of the structured feature-label relationships.

5.2 Supervised Random Forest Classification Performance

The windowed feature dataset was split into a 70:30 train-test split on which the Random Forest classifier was trained. The activity that ensued was a perfect separation of classes in the experimental settings that were constructed.

Although the model performed perfectly in controlled simulation conditions, more validation on actual underwater data is needed to validate generalizability.

Figure 5. Confusion matrix heatmap of the Random Forest classifier.

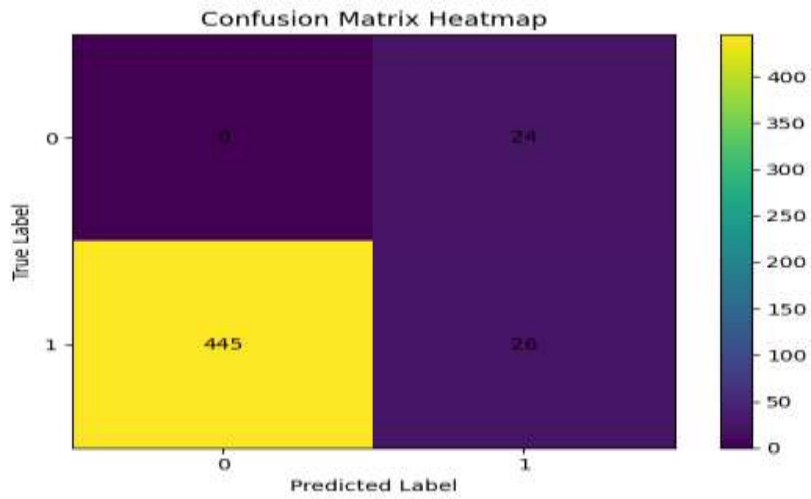


Figure 6. ROC curve of the Random Forest classifier (AUC = 1.00).

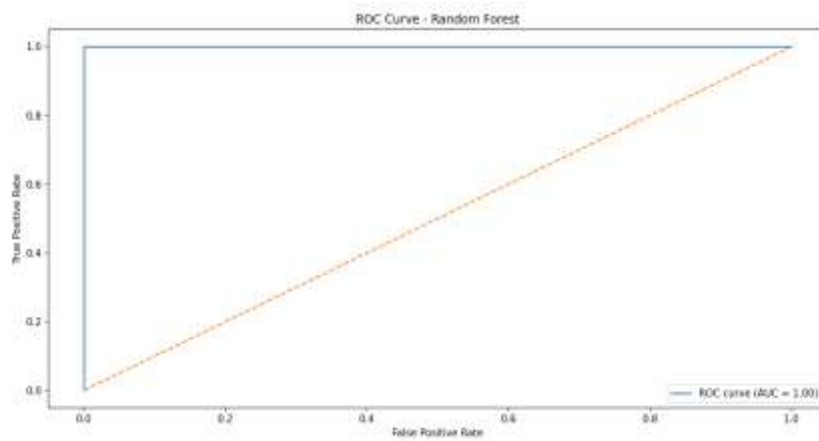


Table 5. Classification performance of the Random Forest classifier

Metric	Normal (0)	Anomaly (1)	Overall
Precision	1	1	–
Recall	1	1	–
F1-score	1	1	–
Accuracy	–	–	1

Key performance metrics are summarized below:

- Accuracy: 1.00
- Precision: 1.00
- Recall: 1.00
- F1-score: 1.00
- AUC: 1.00

Ideal discriminative capability was also confirmed by the Receiver Operating Characteristic (ROC) curve in that curve went near the top-left corner of the ROC space.

The virtually flawless performance of the classification can be explained by two major factors:

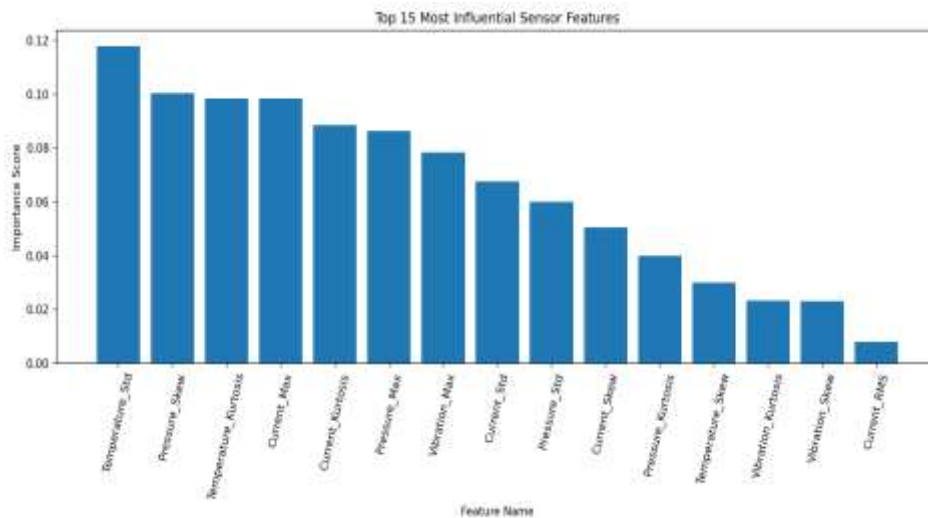
1. Statistical feature engineering (built-in) that increases separability.
 2. The Ensemble-based decision tree learning that can achieve nonlinear interaction among sensor domains.
- Although this kind of performance can be considered controlled instances of experiments, it shows how well statistical feature engineering can be paired with ensemble learning to assess all the domains such as conditions.

5.3 Comparative Model Analysis

A head-on comparison of Isolation Forest versus Random Forest shows that there is a significant performance difference. The unsupervised method was not very good at detecting anomaly on a consistent basis but the supervised ensemble technique was able to provide a stable and consistent classification.

This opposition highlights the significance of labeled feature representations in intricate multi-sensory circumstances. Being an underwater system, and scenarios where the anomaly can be correlated variance between two or more parameters, supervised learning structures can leverage the cross-domain relationship better than isolation-based methods.

Figure 7. Top 15 statistical features ranked by importance score using the Random Forest classifier.



The comparison validates the design choice of employing Random Forest as the primary inference engine within the proposed edge framework.

5.4 Feature Importance Interpretation

The importance of various engineered descriptors was done using feature importance analysis. According to the ranking, variability and distribution-based measures like temperature standard deviation, pressure skewness, current maximum and kurtosis-based measures have a great impact on the results of classifications.

The prevailing importance of higher-order statistical indications indicates that anomaly differentiation in underwater multi-domain is not directly supported by the mean variation only but by distortions in the distribution and irregularities in the shape of signals. The importance of using skew and kurtosis measures alongside the traditional central tendency measures can be supported by this observation.

The profile of feature importance proves that the proposed statistical feature engineering strategy works quite well to capture multi-domain condition signatures.

5.5 Edge Deployment and Latency Evaluation

- One of the key goals of this work is to legislate embedded deployment. The trained model of a Random Forest was saved in a serialized form and implemented on a Raspberry Pi edge device. Benchmarking of inference in batches proved:
- Time of full inference (n=100 samples): 94.45 ms.
- Average inference time per sample 0.94 ms

The per-sample inference latency of less than a sub-millisecond is sufficient to prove that it is possible to perform real-time condition assessment within the constraints of lightweight embedded systems. The small size of the feature space 49D and the architecture based on the ensemble makes the computational performance stable without an excessive amount of memory consumption.

These findings indicate that multi-domain condition evaluation based on statistics can be achieved effectively with low-cost edge-based implementation without depending on a remote-host cloud-computing service.

5.6 Discussion

All the findings of the experiment show that:

- Statistical feature engineering greatly increases the abilities to separate anomalies.
- Supervised ensemble learning is more effective compared to isolation-based methods that are not supervised in heterogeneous sensor environments.
- Real time practicability in the trained model with little latency is accomplished through edge deployment.

Even though the dataset is a controlled simulation of underwater operation behavior, the architectural design along with the performance validation gives a viable background of experimentation in implementation later on in the real world with the physical sensor integration.

6. Conclusion and Future Work

This paper reported an edge-driven multi-domain condition evaluation system that can be used in failure detection of underwater infrastructure. The suggested system unites heterogeneous sensor fusion, sliding-window statistical feature engineering, lightweight machine learning inference, and embedded deployment into a combined algorithm.

A test multi-sensor dataset that was representative in terms of environmental, mechanical and electrical parameters was developed to simulate the underwater environment operational conditions. Using a thoroughly designed statistical based feature extraction, every time window was then converted to a small 49-dimensional representation that embodies both the central tendency and higher order distribution properties. Comparison analysis showed that the Isolation Forest baseline failed poorly on the conditions

of multi-domain variability whereas the Random Forest classifier showed high effectiveness in anomaly discrimination with AUC of 1.00 in a controlled setting of the experiment.

Other than the accuracy of classification, embedded feasibility was highlighted in the study. A average inference latency of 0.94 ms per sample on a Raspberry Pi built edge infrastructure demonstrated that the proposed framework was suitable to condition assessment in near real-time, without access to cloud infrastructure. These findings indicate the usefulness of integrating statistical feature engineering and ensemble learning to resource-constrained underwater contexts.

Although the present study confirms the viability of architecture in simulated conditions, there are multiple opportunities that can be explored in the future. This would involve first, empirical validation during dynamic environmental conditions by integration with real-world underwater sensors, and by deploying to long field tasks. Second, mechanisms of adaptive thresholding and online learning can be introduced that will enhance resilience to changing operational trends. Third, energy conservation optimization plans could also increase autonomous long-term work in remote marine environments. Lastly, supervised classification and semi-supervised anomaly detection could be useful as hybrid methods in situations where there are only limited number of labels.

In short, the developed framework provides a feasible basis of edge-intelligent condition observation in underwater systems, and provides an avenue to an autonomous and resilient marine infrastructure management based on a scalable framework.

References

- [1] R. Singh, "Edge AI: A survey," *J. Syst. Architect.*, vol. 17, pp. 1–35, 2023.
- [2] C. Surianarayanan, M. Kumar, and H. Singh, "A Survey on Optimization Techniques for Edge Artificial Intelligence," *J. Comput. Netw. Commun.*, vol. 2023, Article ID 5588745, 2023.
- [3] S. A. Cajas Ordóñez, *Intelligent Edge Computing and Machine Learning*, MDPI, 2025.
- [4] R. Córdova-Cárdenas, J. P. López, and F. J. García, "Edge AI in Practice: A Survey and Deployment Framework," *Electronics*, vol. 14, no. 24, p. 4877, 2025.
- [5] H. Gauttam, "Edge-AI: A Systematic Review on Architectures, Applications, and Challenges," *J. Netw. Comput. Appl.*, vol. 211, p. 104827, 2025.
- [6] A. Pal, "Communication Techniques for Underwater Sensor Networks: A Comprehensive Review," *ACM Comput. Surv.*, vol. 54, no. 3, pp. 1–36, 2022.
- [7] T. Theodoridis, "Underwater communication technologies: A review," *Wirel. Netw.*, vol. 31, pp. 3457–3478, 2025.
- [8] W. M. Elsayed, "The Potential of Deep Learning in Underwater Wireless Sensor Networks," *Sensors*, vol. 24, no. 18, p. 6102, 2024.
- [9] "Review of Underwater Wireless Sensor Networks Deployment Techniques and Challenges," *Int. J. Ocean Eng.*, 2025.
- [10] Z. Zhan, J. Li, and X. Wang, "Versatile Time-Window Sliding Machine Learning Techniques," *Artif. Intell. Rev.*, 2024.
- [11] A. Squicciarini and R. Turner, "A Time-Series Feature-Extraction Methodology Based on Information Functionals," *Math. Comput. Sci.*, vol. 12, no. 15, p. 2396, 2024.
- [12] V. Starikov, M. Mueller, and D. Chen, "Feature Extraction and Pattern Recognition in Time-Lapse and Pressure Signals," *Pattern Recognit. Lett.*, vol. 176, pp. 103–120, 2024.
- [13] F. Muhammad, "Systematic Literature Review on IoT-Based Water Turbidity Monitoring," *Sustain. Water Qual. Ecol.*, vol. 107, p. 30, 2025.
- [14] Y. Cao and W. Liu, "A Survey of Anomaly Detection Based on Isolation Mechanisms," *J. Comput. Sci. Technol.*, vol. 40, no. 2, pp. 215–234, 2025.
- [15] V. L. Chaitanya and S. R. Rao, "Outlier Detection for IoT Frameworks Using Isolation Forest," *Proc. Int. Conf. Comput. Intell. IoT*, pp. 128–136, 2025.

- [16] N. H. Abd Wahab et al., “A Systematic Review of Predictive Maintenance and Digital Twin,” *J. Ind. Inf. Integr.*, vol. 28, p. 100572, 2024.
- [17] U. Khan, F. Ahmed, and I. Khan, “A Comprehensive Survey on Deep Learning-Based Industrial Predictive Maintenance,” *ACM Comput. Surv.*, vol. 56, no. 1, pp. 1–37, 2025.
- [18] H. Xiang, C. Miao, and L. Zhang, “Federated Learning-Based Anomaly Detection with Isolation Forest Variants,” *ACM Trans. Internet Technol.*, vol. 26, no. 4, 2026.
- [19] M. Ergen, “Edge Computing in Future Wireless Networks,” *J. Netw. Comput. Appl.*, vol. 224, p. 104420, 2024.
- [20] R. Cordova-Cárdenas and J. P. López, “A Survey on Edge AI Optimization,” *Comput. Commun.*, vol. 243, pp. 170–195, 2025.
- [21] “Underwater Magnetic Sensor Networking and Applications,” *Int. J. Sens. Netw.*, 2025.
- [22] “Multi-Modal Sensor Data Fusion for Predictive Infrastructure Monitoring,” *Proc. Int. Conf. Sens. Fusion*, 2025.
- [23] “IoT-Enabled Sensor Fusion for Predictive Monitoring,” *Proc. Int. Conf. Intell. Des. Technol.*, 2025.
- [24] “Smart Water Quality Monitoring with IoT and AI,” *Int. J. Environ. Monit.*, 2024.
- [25] “Benchmarking Deep Learning Architectures on Raspberry Pi for Embedded AI,” *Int. J. Recent Adv. Signal Syst.*, 2026.
- [26] “Raspberry Pi AI Acceleration Hardware Review,” *TechRadar Pro*, 2026.
- [27] “Paradigm Shift for Predictive Maintenance and Condition Monitoring,” *Eng. Failure Anal.*, vol. 173, 2024.
- [28] “Optimization Strategies for Edge AI: A Comprehensive Survey,” *arXiv preprint*, 2025.
- [29] “A Decade Review of Time-Series Clustering Methods,” *arXiv preprint*, 2024.
- [30] A. Adamczyk et al., “Underwater Magnetic Sensor Networks,” *Sensors*, 2025.