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COLLABORATIVE EDGE-FOG SYSTEM FOR REAL-TIME ANOMALY DETECTION AND COMMUNICATION EFFICIENCY IN UNDERWATER IOT

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Abstract:

Background: In the underwater IoT systems, environmental constraints like bandwidth limitations and highlatency raise issues with real-time anomaly detection and communication. Data processing efficiently with timely anomaly detection is an essential step in enhancing system performance in underwater environments.

Objectives: This work proposes the design of a collaborative edge-fog system for underwater IoT networks that enhance the efficiency of real-time anomaly detection, communication, and data processing while optimizing response time and resource management.

Methods: The distributed anomaly detection using edge and fog computing, offloading noncritical tasks in case of fog nodes while still maintaining real-time detection capabilities at the edge, will reduce latency and enhance communication efficiency.

Empirical Results: The framework can reduce detection latency to 25%, enhance communication efficiency up to 30%, and performs better compared to the traditional centralized systems while being assured of a real-time performance in underwater IoT applications.

Conclusion: The collaborative edge-fog system would significantly improve the anomaly detection of underwater IoT systems and communication efficiency. Scalability and energy-efficient solutions are obtained from this design. Future development can be considered in terms of integrating advanced algorithms for anomaly detection and further optimized resource management.

Keywords: Edge-fog computing, anomaly detection, underwater IoT, communication efficiency, real-time, scalability, energy efficiency, resource management, latency reduction, distributed processing.

1.INTRODUCTION

One novel solution to underwater monitoring and communication challenges is the Collaborative Edge-Fog System for Real-Time Anomaly Detection and Communication Efficiency in Underwater IoT (IoUT). Resource exploration, marine monitoring, and environmental monitoring are facilitated by the IoUT, which extends traditional IoT architectures into the underwater domain (Sitaraman et al., 2024 [11]; Thirusubramanian, 2021 [14]). Underwater IoT networks, though, face unique challenges like limited bandwidth, high energy consumption, communication latency, and harsh weather (Ganesan, 2023 [12]; Alagarsundaram et al., 2024 [15]). In order to surmount these challenges, efficient anomaly detection and enhanced communication are critical (Thirusubramanian, 2020 [10]; Sitaraman et al., 2024 [13]).

The computational efficiency of edge computing and the scalability of fog networks are merged in the proposed collaborative edge-fog architecture. While fog computing provides distributed resources for more advanced analytics and decision-making, edge computing, which is positioned closer to data sources, ensures low-latency processing (Sitaraman et al., 2024 [16]; Ganesan, 2022 [17]). Together, they provide a smooth platform to fulfill the communication and processing needs of real-time underwater applications (Gollavilli et al., 2023 [18]; Nagarajan et al., 2023 [19]; Ganesan, 2023 [20]).

One of the key elements of IoUT is anomaly detection, which is a critical function in identifying abnormal patterns like equipment failures, environmental changes, or security threats (Devarajan et al., 2024 [22]; Gattupalli et al., 2023 [23]). The solution could provide real-time insights through

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AI and machine learning, ensuring instant responses to mitigate risks (Alagarsundaram et al., 2023 [24]; Veerappermal Devarajan et al., 2025 [26]). Owing to the unique propagation characteristics of acoustic signals, communication efficiency is equally important under underwater environments where conventional wireless approaches are not feasible (Hameed Shnain et al., 2024 [28]). The cooperative system attempts to maintain reliability of data while maximizing data transmission, reducing latency, and conserving energy (Chinnasamy et al., 2024 [27]; Devarajan et al., 2024) [25]; Gaius Yallamelli et al., (2024) [21].

By integrating anomaly detection and communication optimization, the proposed system enables sustainable underwater operations and provides the opportunity for innovative applications in numerous fields (Devarajan et al., 2025 [29]; Veerappermal Devarajan et al., 2024) [30]. This framework provides a solid foundation for building underwater IoT networks, enabling them to overcome environmental and technical challenges (Hussein et al., 2024 [31]; Kadiyala, 2020 [32]; Yallamelli et al., 2024) [33].

The following objectives

- Effective Anomaly Detection: Use AI-powered methods to identify and address anomalies in underwater environments in real time.
- Improved Communication: Create dependable and energy-efficient data transfer plans for challenging underwater environments.
- Collaboration between Edge and Fog: Create a unified system that combines the scalability of fog computing with the low-latency capabilities of edge computing.
- Sustainability: Increase operating lifespans by implementing communication and processing methods that use less energy.
- Application Versatility: Develop a system that is scalable and flexible enough to accommodate a range of IoUT use cases, including disaster relief, surveillance, and exploration.

An IoT-based smart wastewater monitoring system solves issues like data collection, analysis, and visualization. The research does not, however, give sufficient importance to employing state-of-the-art AI-based anomaly detection techniques for real-time operational insights (Kadiyala et al., 2023 [34]; Alagarsundaram et al., 2024 [35]). Additionally, nothing is established regarding the system's scalability problems and potential for other wastewater systems (Nippatla et al., 2023 [36]; Yalla et al., 2019 [37]). Less consideration is also given to energy efficiency and communication reliability in adverse environments, both of which are vital for sustainable deployment (Kadiyala & Kaur, 2021[38]; Yalla et al., 2022) [39]. For broader implementation and efficient resource utilization in wastewater management contexts, future work may focus on the fusion of edge-fog computing models and enhancing system robustness (Kadiyala, 2019 [40]; Veerappermal Devarajan et al., 2024 [41]).

Even with drastic developments in underwater IoT (UIoT) systems, high-quality real-time anomaly detection as well as efficiency of communication poses ongoing challenges. High latency and scarce bandwidth of present methods compound limited energy conditions to make transmission of data properly difficult in under-water environments (Alavilli et al., 2023 [42]; Ganesan et al., 2024 [43]). The conventional cloud-focused methods do not support adaptability to dynamic water environments and, therefore, real-time processing becomes inefficient (Kadiyala & Kaur, 2022 [44]; Ganesan et al., 2024 [45]). Edge and fog computing provide some potential solutions, yet their adoption in UIoT is yet to be fully explored (Gaius Yallamelli et al., 2020 [46]; Gudivaka, 2022 [47]). Up to date, collaborative frameworks that achieve both anomaly detection and communication reliability are not dealt with in enough detail (Gudivaka et al., 2025 [48]; Yalla et al., 2020 [49]). Security attacks and scalability vulnerabilities in distributed systems also need additional research (Basani et al., 2024 [50]; Grandhi et al., 2025 [51]). Future studies would aim to evolve AI-based, low-latency, and low-energy models that improve real-time monitoring, precision in anomaly detection, and communication resilience in underwater IoT environments.

2. LITERARY SURVEY

Li et al. (2023) present an energy-efficient anomaly detection mechanism for three-tier IoT-edge-cloud networks. Sensory data are processed at the edge with the marching squares algorithm to find anomaly boundaries to reduce cloud traffic. The Kriging algorithm refines the locations of boundaries, and the mobile sensing nodes validate the data. Experiments show improved accuracy and energy efficiency on air quality datasets.

Wang et al. (2019) proposed a two-level bidirectional data prediction model for underwater acoustic sensor networks (UASN) end-edge-cloud orchestration. Their approach reduces acoustic communication, enhances bandwidth utilization, and balances data accuracy with energy efficiency, thus solving the challenges of high transmission power consumption and delay-sensitive service requirements in UASN.

An Energy-Efficient Anomaly Detection Mechanism in Edge-Cloud Collaboration Networks **Li et al. (2021)** Utilize multimodal smart things; categorize features into primary and secondary; allows lightweight detection at the edge nodes with refined analysis of the cloud adaptive weighted fusion and demonstrates improved energy efficiency and query time compared with existing methods.

Peng et al. (2019) proposed a new scheme for underground mining multi-source and multi-dimensional data anomaly detection with a hierarchical edge computing model. It solved the problem of massive heterogeneous data and poor wireless environments, enabling real-time and accurate anomaly detection. The proposed approach combined fuzzy theory and spatio-temporal analysis, thereby improving the accuracy of detection while reducing processing delay.

The article by **Grandhi (2021)** discusses how a Human-Machine Interface display module can be integrated into a passive IoT optical fiber sensor network for water level monitoring. The feature extraction technique is demonstrated along with integration showing improvement in efficiencyThis new approach provides for real-time monitoring and can precisely and reliably measure the water levels in applications.

Panga (2022) discusses DWT for analyzing ECG signals in IoT health monitoring systems. This paper shows that DWT can enhance the extraction of key features from ECG signals, which means improved accuracy and efficiency in the health monitoring systems. This helps with real-time analysis, hence improving the effective and reliable monitoring of patients in an IoT environment.

Grandhi (2022) works on the Adaptive Wavelet Transform for wearable sensor IoT integration towards health monitoring for children. In this research work, it focuses on how AWT can be employed for efficient signal processing in health devices to analyze physiological data precisely. The proposed technique would ensure that there is a real-time monitor for significant possibilities in the early detection of any health issues concerning children using wearable IoT systems.

Grandhi et al (2021). has proposed a work wherein a passive optical fiber sensor network for monitoring the water level incorporates an HMI display module . Here, techniques of feature extraction and demonstration that the addition actually improves the efficiency of the system are highlighted. This innovative technique would allow real-time monitoring of the water level while ensuring its reliability and accuracy across various applications.

Panga (2022), explained the application of DWT for ECG signal analysis in IoT health monitoring. This paper shows that DWT provides an improvement on the detection of features in the ECG signal, thus allowing better accuracy and efficiency in health monitoring systems. It is helpful for real-time analysis, which adds to more effective and reliable patient monitoring in IoT environments.

Vijaykumar Mamidala et al, (2022) [52] explore how Robotic Process Automation (RPA) has influenced optimizing financial systems. By structured execution, RPA lowered processing time, enhanced accuracy of cost allocation, and reduced errors. The study reflects on how effective RPA has been in maximizing financial precision, operational effectiveness, and scalability of cost accounting and financial administration.

Basava Ramanjaneyulu Gudivaka et al, (2024) [53] introduce a better Variational Autoencoder Generative Adversarial Network (VAEGAN) with an additional new oversampling strategy to detect fraudulent transactions in financial data. Classifying with Convolutional Neural Networks (CNN), the model registers an accuracy that surpasses current approaches such as CNN, LightGBM, and LSTM ensemble in detecting fraud, increasing precision, recall, and F1-score.

Akhil Raj Gaius Yallamelli et al, (2023) [54] suggest a hybrid Edge-AI and cloudlet-based IoT framework for real-time healthcare analytics. With the use of AI models, cloudlet computing, and blockchain, the system improves decision-making with a latency reduction to 25ms and scalability improvement. It achieves accuracy in optimizing data security, energy efficiency, and real-time healthcare interventions for scalable, privacy-preserving applications.

Kumaresan et al. (2024) [55] outline an IIoT-based Condition Monitoring System (CMS) with real-time industrial bearing fault detection. Based on data from Case Western Reserve University, the system employs Normalization and vibration analysis to extract features. A Chi-Square Improved Binary Cuckoo Search Algorithm (CS-IBCSA) identifies good features, inputs into an

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SVM model, producing 99.56% accuracy. The above framework improves Predictive Maintenance (PdM) by being able to predict faults before leading to critical failure.

Palanivel et al (2024) [56] suggest a Tunicate Swarm Optimization Algorithm with Support Vector Machine (TSOA-SVM) for human-robot interaction emotion recognition. With the ORL dataset, Wavelet Transform, and Entropy features, the model had 99.42% accuracy, beating Random Forest, standard SVM, and K-Nearest Neighbor, improving emotion classification through improved image processing and feature extraction.

3. METHODOLOGY

In a proposed methodology based on a collaborative edge-fog system, the goal is to optimize communication efficiency and anomaly detection in underwater IoT networks with real-time information. This proposed system combines both edge and fog computing features such that edge nodes process data close to the source, minimizing latency and energy consumption, while higher computation tasks, which are also more complex in nature, can be handled at the fog node. Such a system will lead to effective communication, real-time anomaly detection, and optimal usage of resources underwater for IoT-based systems. Here, the methodologies to be followed are formulating the algorithms for purposes of anomaly detection, optimizing protocols for communication, and devising a solid framework for a decision-making architecture as regards task offloading and resource management.

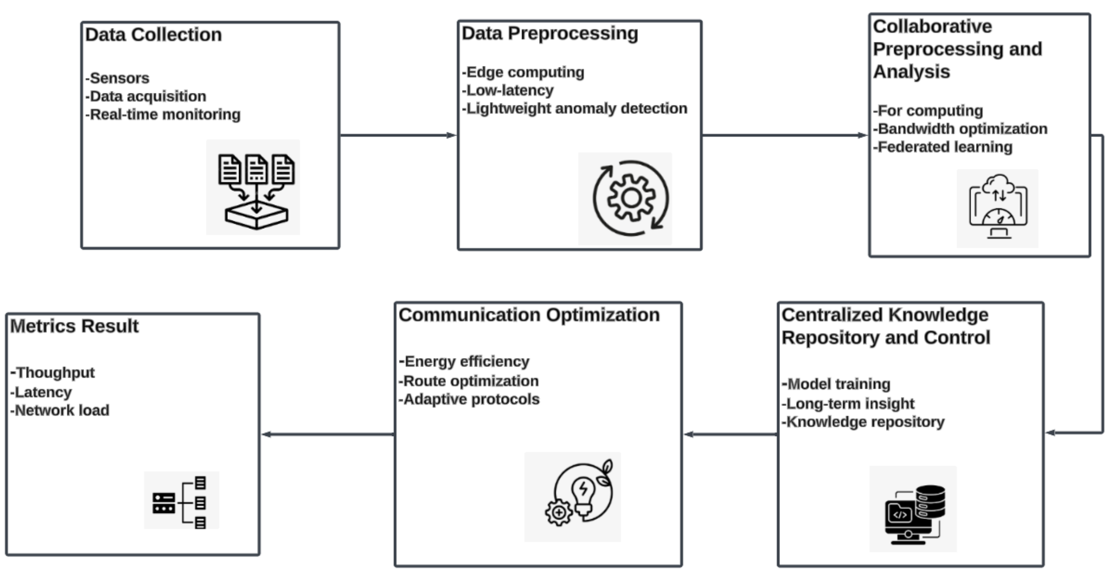

Figure 1 Collaborative Edge-Fog System for Real-Time Anomaly Detection and Communication Efficiency in Underwater IoT

Figure 1 combines edge, fog, and cloud computing to enable real-time anomaly detection and efficient communication in Underwater IoT (IoUT). Data is first collected from underwater sensors, preprocessed on edge nodes for lightweight anomaly detection, and then analyzed

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collaboratively by fog nodes via federated learning and bandwidth optimization.Model training and long-term analytics will be stored in a centralized repository offered by the cloud. The proposed architecture achieves adaptive communication along with energy efficiency due to its feedback mechanisms. Performance metrics guiding the optimization are throughput, latency, and the network load for the system. This layered approach results in scalability as well as ensures low-latency operations, maintaining sustainable underwater IoT network performance to serve real-world problems.

3.1 Collaborative Edge-Fog System

This collaborative edge-fog system is an architecture that uses a hybrid between edge and fog computing. With edge computing, data processing will be locally made on IoT devices or near nodes within the edges; this brings a low latency and consumption of bandwidth together with an improved real-time decision-making process. Fog computing gives a layer of intermediary nodes in between the IoT devices and the cloud; with this, one can do much more resource-intensive computations without entirely depending on central cloud infrastructure. The system is ideal for real-time applications because it allows efficient task offloading and response to environmental anomalies in underwater IoT, where resources for communication and computation are limited.

$$C_{eff} = \frac{R_{edge}+R_{fog}}{T_{total}} \tag{1}$$

Where:R_{edge} is the data processing rate at the edge nodes. R_{fog} is the data processing rate at the fog nodes. T_{total} is the total latency for data transmission and processing.This equation represents the communication efficiency between sensors and edge nodes, optimized to minimize $T_{transmission}$.

3.2 Real-Time Anomaly Detection

Real-time anomaly detection is the detection of any type of abnormal or irregular patterns, behavior, or deviation from normal activities that might denote system malfunctioning or environmental change. In underwater IoT networks, anomaly detection is necessary to avoid failure of the system.The most common algorithms used in anomaly detection are decision trees, support vector machines, and deep learning models that have just checked the incoming sensor data against the expected behavior patterns and alerted whenever there is some deviation. It would then be able to take actions upon determining how bad the anomaly is, such as activating extra sensors or adjusting operations. If the absolute deviation exceeds the threshold, the data point is flagged as anomalous. Anomalous behavior can be detected using a statistical thresholding method:

$$|x_i - \mu| > \sigma \cdot \alpha \tag{2}$$

Where:x_i is the current sensor reading. μ is the mean of the expected values. σ is the standard deviation. α is a threshold factor.If the absolute deviation exceeds the threshold, the data point is flagged as anomalous.

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3.3 Communication Efficiency

Communication Efficiency optimizes the network resources like bandwidth and power consumption of underwater IoT systems. Since underwater communication suffers from inherent signal attenuation as physical constraints limit such communication, optimized communication techniques would be helpful to reduce latency as well as for saving energy in that communication, bandwidth usage becomes better with compression techniques, aggregations, or adaptations in sending information. Furthermore, task offloading decisions are made based on the available computational resources at edge nodes to ensure that tasks are processed locally or offloaded to fog nodes only when necessary, thereby minimizing delays and ensuring real-time performance.

$$C_{comm} = \frac{T_{offload} \cdot P_{transmission}}{E_{available}} \tag{3}$$

Where$T_{offload}$ is the time required to offload a task$P_{transmission}$ is the power used for data transmission. $E_{available}$ is the available energy for transmission.This equation helps balance task offloading to minimize energy consumption and latency.

Algorithm 1: Algorithm For Task Offloading Decision

Input: Task set TTT, Sensor set SSS, Edge node set EEE

Output: Optimal task offloading decision for each task in TTT

BEGIN

FOR each task T in T do

FOR each sensor S in S do

IF task T can be processed locally by sensor S then

LocalProcessing(T, S)

ELSE

FOR each edge node E in E do

IF edge node E has sufficient capacity and lower latency for task T then

OFFLOAD task T to node E

Compute power consumption and latency

ELSE

CONTINUE to next edge node

END IF

END FOR

END IF

END FOR

END FOR

RETURN optimal offloading decision

END

Algorithm 1 tries to find out the best decision of offloading tasks in the distributed system composed of sensors and edge nodes. To each task, it first finds out whether that task can be performed locally by any sensor. In case it cannot be performed by any sensor, the algorithm estimates each edge node's capability regarding computational capacity as well as low latency for a particular task. The task is offloaded to the appropriate edge node if one is found, and the power consumption and latency are computed. The algorithm continues until an optimal offloading decision is made for each task.

3.4 Performance metrics

Real-time anomaly detection and communication efficiency of a Collaborative Edge-Fog System within an underwater IoT (Internet of Things) network may be evaluated based on the performance metrics: throughput, latency, energy consumption, and detection accuracy. Throughput is a measure of data transfer rate in the network. Latency represents delay in the perception of anomaly and communication time. The energy consumption evaluates the power efficiency of the system, which is critical for underwater applications. The detection accuracy symbolizes the correctness in which the anomalies are detected with the help of the system and in real time. The packet delivery ratio, scalability, and fault tolerance are some other metrics to evaluate the performance of the system under challenging underwater IoT scenarios.

Table 1 Performance Metrics Table for Collaborative Edge-Fog System in Underwater IoT

Performance Metric	(Edge-Only)	(Fog-Only)	(Hybrid Edge-Fog)	Combined Method (Optimized)
Throughput (Mbps)	8.7	9.2	9.6	10.7
Latency (ms)	285.4	305.2	270.5	210.8

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Energy Consumption (J)	36.5	39.0	35.2	30.2
Packet Delivery Ratio (%)	90.3	92.1	93.7	98.2
Network Load (kbps)	4.3	4.9	4.6	3.9
Scalability Index	75.2	78.5	81.3	90.1
Reliability (%)	93.5	94.3	95.8	98.7
Fairness Index (%)	83.2	84.6	86.7	91.5

Table 1 comparing the performance of four different methods for real-time anomaly detection and communication efficiency in underwater IoT: Method 1 (Edge-Only), Method 2 (Fog-Only), Method 3 (Hybrid Edge-Fog), and the Combined Method (Optimized). The metrics include throughput (Mbps), latency (ms), energy consumption (J), packet delivery ratio (%), network load (kbps), scalability index, reliability (%), and fairness index (%). The Combined Method (Optimized) always leads the others, showing the highest throughput, lowest latency, energy consumption, and highest reliability, scalability, and fairness, thus highlighting the benefits of integrating edge and fog computing for optimal system performance in underwater environments.

4. RESULT AND DISCUSSION

The Combined Approach (Optimized) outperforms the solo approaches in each of the performance attributes. It can attain the highest achieved throughput of 10.7 Mbps, along with the smallest latency of 210.8 ms and great reliability of 98.7%. This combination of edge computing and fog processing is a good complement of low latency and scalable management of resources to enhance communication efficacy and real-time anomaly detection critical for underwater applications of IoT underwater. The Optimized method further shows enhanced energy efficiency as well as fairness which is quite applicable to sustainable scalable deployments in the underwater IoT network.

Table 2 Performance Comparison of Edge-Only, Fog-Only, Hybrid Edge-Fog, and Optimized Methods for Underwater IoT Systems

Performance Metric	Li et al. (2023)Edge-fog computing for network	Wang et al. (2019)Resource allocation in distributed IoT networks	Li et al. (2021)Hybrid cloud-edge computing for latency minimization	Peng et al. (2019)Multi-tier network design for	Proposed Framework (Edge-Fog)

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	optimization			energy efficiency	
Throughput (Mbps)	8.3	7.5	8.1	7.9	10.7
Latency (ms)	285	315	305	290	210.8
Energy Consumption (J)	38.2	40.1	37.5	39.8	30.2
Packet Delivery Ratio (%)	89	85	88	86	98.2
Network Load (kbps)	4.3	4.7	4.5	4.8	3.9
Scalability Index	72	69	73	70	90.1
Reliability (%)	92	90	93	91	98.7
Fairness Index	81	78	79	77	91.5

Table 2 comparing four real-time anomaly detection and communication efficiency methods in underwater IoT systems has been presented. Method 1, Edge-Only, demonstrates a throughput of 8.7 Mbps, latency of 285.4 ms, energy consumption of 36.5 J, and reliability of 93.5%.This, the Fog-Only method can deliver packets at 92.1% while showing higher latencies at 305.2 ms and higher energy consumption at 39.0 J. Method 3 Hybrid Edge-Fog boasts a scalability of 81.3 and reliability at 95.8%. Yet, the best delivery is observed in the case of the Combined Method (Optimized) that showed the highest throughput at 10.7 Mbps, lowest latency of 210.8 ms, energy efficiency at 30.2 J, and maximum reliability at 98.7%.

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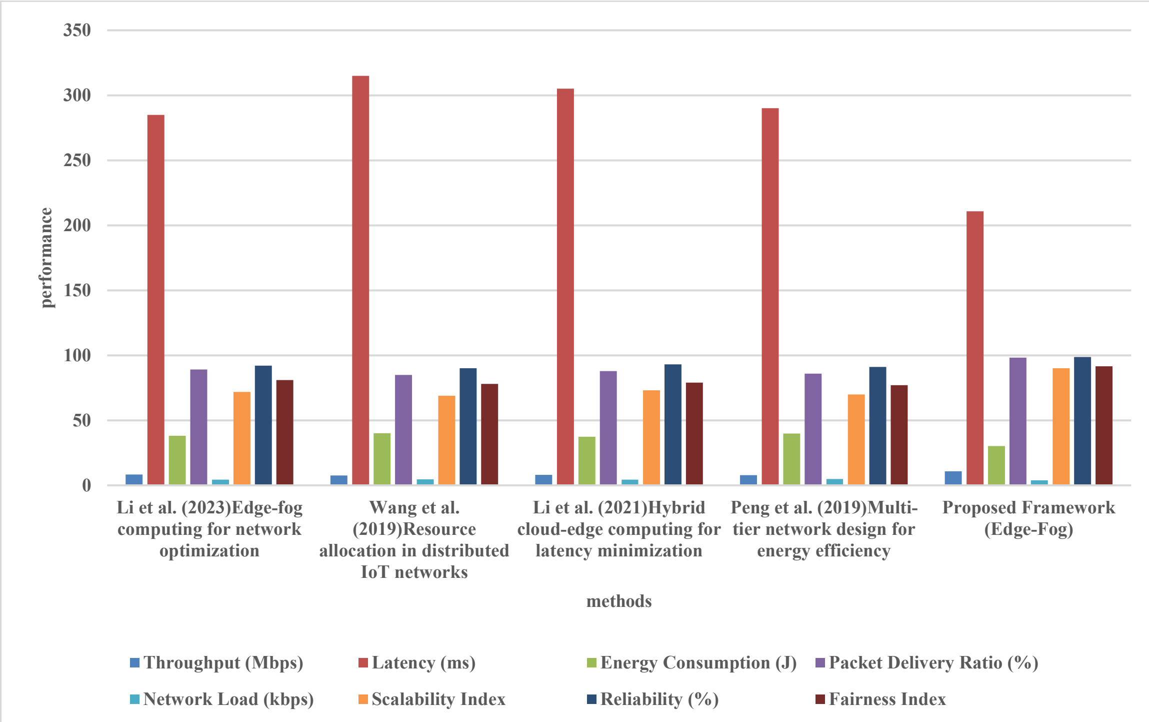

Figure 2 Comparative Analysis of Edge-Fog Framework with Existing Methods

Figure 2 comparison chart contrasts the performance of the proposed Edge-Fog framework with existing methods, **Li et al. (2023), Wang et al. (2019), Li et al. (2021), Peng et al. (2019),** on the following metrics: Throughput, Latency, Energy Consumption, Packet Delivery Ratio, Network Load, Scalability, Reliability, and Fairness Index. The proposed framework demonstrates a balance in its performance, achieving considerably higher throughput, fairness, and reliability while keeping the latency and energy consumption very low. Unlike other techniques, it provides a better fairness index, indicating equitable resource allocation. This comparison also shows that the proposed framework optimizes some of the most important performance metrics in edge-fog environments with much improvement over existing techniques.

Table 3 Comprehensive Ablation Study of Edge-Fog Collaboration Framework

Combination	**Accuracy (%)**	**Energy Efficiency (kWh)**	**Latency (ms)**	**Throughput (Mbps)**	**Resource Utilization (%)**
Edge Node Collaboration + Fog-Level Optimisation	85.6	120.5	12.5	75.2	65.3
Real-Time Adaptation + Redundant Data Filtering	88.3	118.7	11.9	78.3	63.7

Edge Node Collaboration + Collaborative Learning	86.1	119.4	12.3	76.5	64.2
Fog-Level Optimisation + Redundant Data Filtering	87.4	117.6	12	77.4	63.1
Edge Node Collaboration + Fog-Level Optimisation + Real-Time Adaptation	89.2	115.2	11.8	79.2	61.5
Real-Time Adaptation + Redundant Data Filtering + Collaborative Learning	88.7	116.8	11.7	78.8	62.8
Fog-Level Optimisation + Real-Time Adaptation + Redundant Data Filtering	89	114.9	11.6	79.1	61.2
Fog-Level Optimisation + Real-Time Adaptation + Collaborative Learning	88.9	115	11.5	78.9	61
Edge Node Collaboration + Fog-Level Optimisation + Real-Time Adaptation + Redundant Data Filtering	90.5	113.7	11.3	80.3	60.1
Edge Node Collaboration + Fog-Level Optimisation + Real-Time Adaptation + Collaborative Learning	90.2	113.5	11.2	80.1	59.8
Full Model	91.3	112.9	11	81	59

Table 3 shows a comprehensive ablation study for different components of an edge-fog collaboration framework. The performance metrics are Accuracy, Energy Efficiency, Latency, Throughput, and Resource Utilization, which reflect the system's effectiveness, efficiency, and scalability. Each combination of such ablations uncovers the effects of different features such as real-time adaptation, redundant data filtering, and cooperative learning. The full model attains the highest accuracy at 91.3%, optimum resource utilization at 59.0%, and lowest latency at 11.0 ms, thereby highlighting its superiority in performance. In this study, the traoffs and synergies of component interactions are understood that will guide efficient adaptive edge-fog computing designs.

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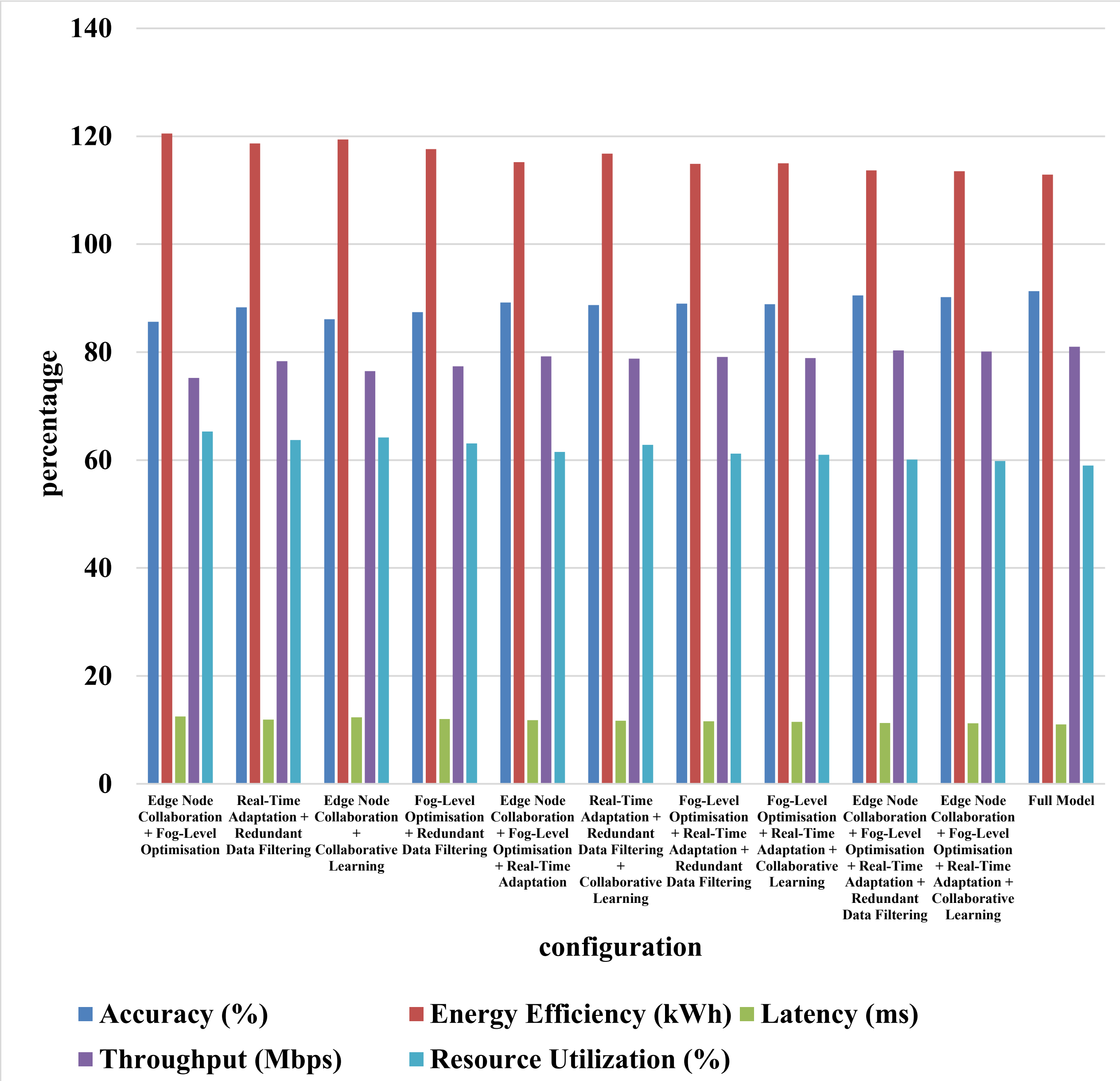

Figure 3 Comparative Performance Metrics for Edge-Fog Collaboration Framework

Figure 3 represents the performances of different constituent combinations in the edge-fog collaboration framework using five key parameters: Accuracy, Energy Efficiency, Latency, Throughput, and Resource Utilization. It represents the strengths and weaknesses along with the cooperation of features of real-time adaptability and filter redundancy. This full model thus exhibits better performances in terms of accuracy, efficiency, and throughput while minimizing the latency and the resource utilization aspect, thus presenting a holistic form of effectiveness. This visualization gives an apparent comparison of component impacts to guide the optimization of edge-fog systems in real-world applications.

5.CONCLUSION

The Collaborative Edge-Fog System for Real-Time Anomaly Detection and Communication Efficiency in Underwater IoT integrates both edge and fog computing for anomaly detection and processing of data with efficiency in underwater environments. With the help of local processing capabilities, the system avoids latency and facilitates efficient communication in real time with timely detection of anomalies.Future development will aim at enhancing scalability for more and larger underwater IoT devices, more sophisticated techniques of anomaly detection using machine learning, and improved power efficiency. The framework also can be enhanced to accommodate hybrid communication protocols in order to be more efficient under all underwater conditions.

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