

Article

Underwater Digital Twin Sensor Network-Based Maritime Communication and Monitoring Using Exponential Hyperbolic Crisp Adaptive Network-Based Fuzzy Inference System

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Abstract: The underwater conditions of the coastal ecosystem require careful monitoring to anticipate potential environmental hazards. Moreover, the unique characteristics of the marine underwater environment have presented numerous challenges for the advancement of underwater sensor networks. Current studies have not extensively integrated Digital Twins with underwater sensor networks aimed at monitoring the marine ecosystem. Consequently, this study proposes a decision-making framework based on Underwater Digital Twins (UDTs) utilizing the Exponential Hyperbolic Crisp Adaptive Network-based Fuzzy Inference System (EHC-ANFIS). The process begins with the initialization and registration of an Underwater Autonomous Vehicle (UAV). Subsequently, data are collected from the sensor network and relayed to the UDT model. The optimal path is determined using Adaptive Pheromone Ant Colony Optimization (AP-ACO) to ensure efficient data transmission. Following this, data compression is achieved through the Sliding–Huffman Coding (SHC) algorithm. The Twisted Koblitz Curve Cryptography (TKCC) method is employed to enhance data security. Additionally, an Anomaly Detection System (ADS) is trained, which involves collecting and pre-processing sensor network data. A Radial Chart is then utilized for effective visualization. Anomalies are detected using the CosLU-Variational Shake-Long Short-Term Memory (CosLU-VS-LSTM) approach. For standard data, decision-making based on the UDT model is conducted using EHC-ANFIS, with a fuzzification duration of 21,045 milliseconds. Finally, alerts are dispatched to the Maritime Alert Command Centre (MACC). This approach enhances maritime communication and monitoring along coastal areas, with specific reference to the Coromandel Coast, thereby contributing to the protection of the coastal ecosystem.

Keywords: underwater digital twins (UDTs); maritime communication and monitoring; sensor network; monitoring coromandel coast; artificial intelligence; data security; dynamic coastal environment

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1. Introduction

Digital Twin (DT) technology has been increasingly utilized across various sectors to create virtual models of physical systems for monitoring, simulation, and optimization. In the context of maritime communication and environmental monitoring, Digital Twins, particularly Underwater Digital Twins (UDTs), offer a powerful tool to enhance the management and protection of coastal ecosystems.

Virtual representations of real-world habitats, such as undersea ecosystems, are produced in marine surveillance through Digital Twins. The data from sensors installed in Autonomous Underwater Vehicles (AUVs) is used to create these virtual models, which aid in real-time monitoring and simulation of changes. This real-time virtual model may enhance decision-making, and environmental hazards like pollution or tsunamis can be addressed more quickly. Digital Twins combine information from several sensors into a single model that is updated continuously in response to new sensor data, giving an accurate and dynamic depiction of the surroundings. At the core of Digital Twin systems, especially underwater, sensors gather essential data regarding environmental factors such as water temperature, salinity, current velocity, tide heights, and atmospheric conditions. This information is sent to the Digital Twin, where it is analyzed and utilized to refresh the virtual representation of the marine surroundings. The combination of sensors and Digital Twins offers significant advantages, such as real-time monitoring, for observing swiftly evolving situations in dynamic coastal regions. Moreover, by gathering extensive data, Digital Twins provide improved precision in comprehending environmental conditions, while machine learning techniques, such as CosLU-VS-LSTM, aid in identifying anomalies and producing predictive insights regarding possible risks. To manage large volumes of sensor data and maintain security, methods like Sliding-Huffman Coding (SHC) for compressing data and Twisted Koblitz Curve Cryptography (TKCC) for safeguarding data are used, guaranteeing effective transmission while preserving data integrity. In conclusion, sensors are essential for collecting real-time environmental data for Digital Twin systems. These utilize these data to develop comprehensive virtual models supporting informed maritime surveillance and conservation decision-making. The collaboration between sensors and Digital Twins improves maritime activities, leading to improved risk management and faster responses to irregularities, and aiding in the sustainability of coastal ecosystems. The Coromandel Coast represents the southeastern coastal area of the Indian subcontinent, functioning as a vital corridor for maritime activities [1]. These activities encompass naval operations, environmental protection, maritime surveillance, fishing, and more [2,3]. To ensure both safety and sustainability, there is a pressing need for an advanced maritime communication and monitoring system [4].

Nevertheless, the intricate underwater environment presents significant challenges for monitoring maritime conditions [5]. To assess the risks beneath the surface, Digital Twins—a virtual representation—facilitate an information exchange process that supports effective decision-making [6,7]. By merging the underwater sensor network with Digital Twins [8], real-time environmental changes can be accurately detected [9], and timely risk alerts can be issued, particularly in ecologically sensitive areas such as the Coromandel Coast.

Artificial Intelligence (AI) significantly enhances the functionality of Digital Twins [10]. Deep Learning models effectively identify and analyze patterns within sensor data [11]. Furthermore, AI facilitates improved maritime communication by transmitting acoustic signals to the Maritime Alert Command Centre (MACC) [12].

Syed et al. [13] reviewed AI techniques in water resource management, identifying gaps in their integration for better prediction and management. They covered methods like ANN, DL, LSTM, ML models, and RF. The authors proposed a novel framework that combines these approaches with a Digital Twin and multi-modal transformer to improve prediction accuracy and efficiency. This sets the foundation for a future detailed model that could enhance water demand forecasting and support global sustainability in water use. Moreover, this work supports our research by proposing a unified AI framework that integrates various techniques to enhance prediction accuracy and operational efficiency in water resource management. This aligns with our goal of improving forecasting methods.

The popularity of Artificial Intelligence and Digital Twins has surged in recent years, leading to their application across various domains for numerous scenarios.

Epiphaniou et al. [14] assessed the enhancement of cyber resilience in Internet of Things (IoT) applications by implementing Digital Twins within underwater ecosystems. The underwater parameters were optimized using a Genetic Algorithm (GA). Subsequently, anomalies in the sensor data were predicted by employing a Support Vector Machine (SVM). This approach improved cyber security resilience for underwater coastal monitoring; however, the subpar quality of the data resulted in an ineffective resilience strategy.

Bi et al. [15] focused on the development of Digital Twins to monitor intricate coastal terrains. This study integrated IoT sensor data collected from underwater environments into the Digital Twin framework. The monitoring and early warning systems were established by transmitting these data to a neural network algorithm. This facilitated timely interventions based on the alerts generated. Nonetheless, the integration of multiple sensors introduced complexities to the model. The proposed Underwater Digital Twin (UDT) sensor network offers an innovative maritime communication and monitoring system, distinguishing itself from existing networks and AI frameworks. Its key advantage lies in the advanced AI integration, specifically the Exponential Hyperbolic Crisp Adaptive Network-based Fuzzy Inference System (EHC-ANFIS), which excels in decision-making processes. The system utilizes the CosLU-VS-LSTM method for anomaly detection, surpassing traditional models in precision and accuracy. Epiphaniou et al. [14] and Bi et al. [15] struggle with complexity and data handling; this model addresses these challenges through efficient data compression, optimized communication paths, and enhanced security. This ensures reliable and secure communication in the demanding underwater environments of the Coromandel Coast, improving ecosystem monitoring.

Zhou et al. [16] implemented a tsunami monitoring system in coastal areas utilizing Digital Twins. This system was designed to detect variations in the underwater marine ecosystem. The Wavelet Transform technique was employed to identify waveforms specific to tsunamis. Anomalies in the sensor data were subsequently detected using a threshold-based method. This buoy-based system enabled a quicker response; however, the prevalence of false positives increased due to background marine noise, leading to inaccurate alerts.

Wang et al. [17] introduced a model for safety management and decision support in port operations and logistics, utilizing a Digital Twin framework. This model integrates a hybrid approach combining Convolutional Neural Networks (CNNs) and Long Short Term Memory (LSTM) networks to facilitate decision-making within the Digital Twin paradigm. The framework enhances safety measures, thereby decreasing the probability of accidents. Nonetheless, it faced limitations in managing large datasets.

Zhou et al. [18] proposed a Digital Twin-based smart maritime logistics maintenance system aligned with Industry 5.0. The initial phase involved the deployment of sensors to collect real-time data. Subsequently, features were extracted from these data and input into neural networks. The deep learning models generated optimal decisions to enhance the reliability of the Digital Twin systems. However, this approach exhibited significant computational complexity.

Charpentier et al. [19] focused on creating a safer and more efficient maritime industry by implementing 5G and advanced edge computing systems. Their research utilized edge network softwarization and intelligence to develop applications that improve the safety and efficiency of maritime operations. This model streamlined the creation of intricate 5G vertical services and beyond and encouraged collaboration among industry stakeholders, network specialists, and EdgeApp developers. However, deploying this model

in challenging maritime environments characterized by saltwater and high humidity proved difficult.

Adityawan et al. [20] investigated a tsunami early warning system along the coast that utilizes maritime wireless communication. This system integrated communication between vessels at sea and coastal radio stations. The ships involved in this framework were outfitted with Very High Frequency (VHF) radio communication technology. The model effectively transmitted warning messages promptly and did not necessitate ongoing maintenance or monitoring. However, the study identified a restricted communication range, especially in isolated or challenging coastal areas, which resulted in connectivity challenges.

Current research on environmental monitoring in maritime settings has largely neglected data security, impacting coastal area monitoring efficacy. To enhance cybersecurity, data encryption from sensors is vital. Furthermore, existing studies inadequately address the dynamic environmental conditions necessary for risk prediction in coastal systems. Noteworthy shortcomings include the lack of inquiry into coastal ecosystem monitoring in light of variable conditions influenced by Digital Twins, the vulnerability of underwater sensor networks to cyber threats, insufficient analysis of unusual data spikes and unauthorized requests that impede monitoring, bandwidth limitations in underwater communication affecting data processing, and excessive energy use by traditional communication protocols.

Wang et al. [21] proposed a blind channel estimation method for FBMC/OQAM systems that avoids using preambles, thereby improving spectral efficiency. The technique enhances estimation accuracy by leveraging spatial diversity to introduce data redundancy, especially at high SNRs. Simulation results demonstrate its superior performance over traditional preamble-based methods. However, this work supports our research by offering a highly efficient blind channel estimation approach to enhance the spectral efficiency and accuracy of underwater Digital Twin sensor networks in maritime communication systems using EHC-ANFIS. This reference is relevant to underwater communication channel estimation, offering potential improvements in data transmission for maritime sensor networks. Increasing spectral efficiency and estimation accuracy through blind methods and spatial diversity supports more reliable and efficient communication in challenging underwater environments.

Table 1 presents a comparative analysis of the proposed model against existing studies, highlighting its objectives, benefits, and drawbacks.

Table 1. Comparative analysis of the proposed model with existing studies.

Author's Name	Aim	Advantages	Disadvantages
Proposed Model	Underwater Digital Twin sensor network-based maritime communication and monitoring of the Coromandel Coast.	The proposed model efficiently performed maritime communication and Coromandel Coast monitoring with superior outcomes.	However, the types of coastal ecosystems, such as coral reefs, salt marshes, mangrove forests, kelp forests, etc., were not considered.
Ramírez-Herrera et al. [22]	Hunga Tonga-Hunga Ha'apai volcano eruption-assisted tsunami effects on the coast of Mexico.	This framework proficiently analyzed the tsunami effects and its associated hazards.	But this tsunami warning system had a high false alarm rate.
Pribadi et al. [23]	An effective knowledge management system based on past earthquake disasters.	This framework efficiently enhanced environmental monitoring.	But it incurred considerable initial setup cost.

Suppasri et al. [24]	Disaster risk reduction framework.	This model had higher significance in coastal management.	However, it was less effective due to the complex system.
Epiphaniou et al. [14]	Digital Twins in cyber effects modeling of IoT paradigm.	This framework significantly reduced human intervention, enhancing the model's efficiency.	But it had energy constrained issues.
Zhou et al. [16]	Tsunami monitoring system via submerged mooring.	This model had higher resilience and good security	But it required a massive amount of real-time data.

The proposed model demonstrated remarkable efficiency in maritime communication and monitoring of the Coromandel Coast, yielding superior results. In contrast, the existing model by Ramírez-Herrera et al. [22] exhibited a high false alarm rate, while the approach by Pribadi et al. [23] was burdened with significant initial setup costs. Additionally, the traditional method outlined by Suppasri et al. [24] proved to be less effective due to its complex system. Furthermore, the models presented by Epiphaniou et al. [14] and Zhou et al. [16] achieved only limited performance. Therefore, the proposed framework surpasses the current adopted techniques.

Consequently, a framework is proposed to enhance the Underwater Digital Twins Sensor Network (UDTSN), thereby supporting coastal ecosystems' sustainable management and protection. The proposed framework offers several significant contributions.

- It facilitates the monitoring of the Coromandel Coast through a Digital Twin-based decision-making process that employs the AI-driven EHC-ANFIS technique.
- It safeguards the underwater sensor data within the maritime ecosystem by implementing the TKCC method.
- It enables the analysis of anomalous patterns during data transmission through the Anomaly Detection System (ADS) model, utilizing the CosLU-VS-LSTM deep learning classifier.
- To ensure efficient data transmission within a static bandwidth, data compression is used using the SHC model.
- Lastly, it identifies the optimal path for data transmission to enhance communication efficiency by employing the AP-ACO technique.

The remaining paper is arranged as follows: Section 2 analyzes the existing works, Section 3 explains the proposed coastal monitoring system, Section 4 describes the performance of the proposed model, and Section 3 concludes the research paper with future recommendations.

2. Materials and Methods: Maritime Communication and Monitoring Methodology

This paper addresses the security of underwater sensor data and conducts maritime communication and monitoring in relation to the dynamic environmental conditions of the Coromandel Coast. Figure 1 depicts the block diagram representing the proposed work.

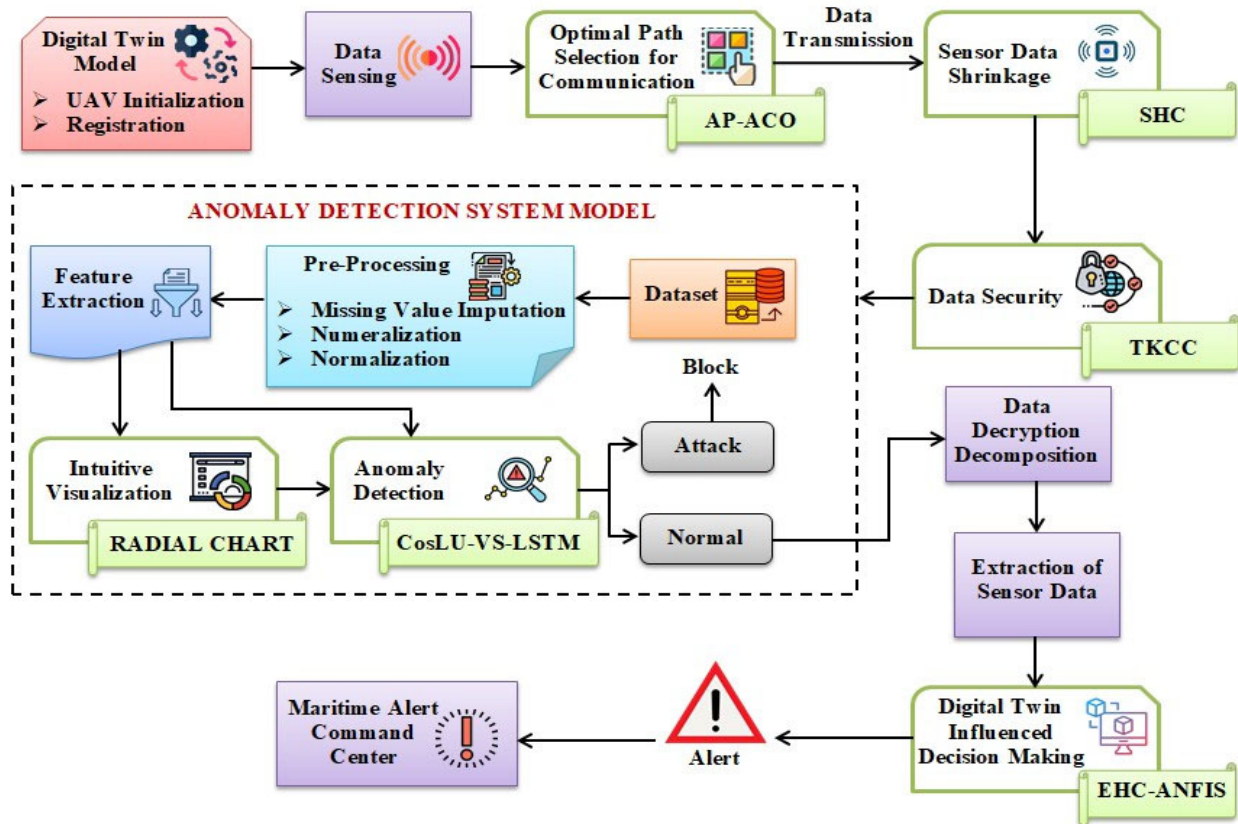


Figure 1. Architecture of the proposed framework.

2.1. UAV Initialization and Registration

The maritime communication and monitoring of the Coromandel Coast starts with the initialization of the AUV (B) and is given by the following:

$$B = \{B_1, B_2, B_3, \dots, B_s\} \tag{1}$$

where (s) is the number of AUVs. Next, AUVs are registered into the UDTSN with the AUV identity number and initial Global Positioning System (GPS) coordinates. After registration, by utilizing Digital Twins, the replica of an AUV is created, which helps in the navigation of AUVs underwater without collision.

2.2. Data Sensing

The underwater sensor data (H), which includes parameters such as tide level, current speed, wind speed, water temperature, and salinity – collectively referred to as Internet of Things (IoT) data – are acquired by the Autonomous Underwater Vehicle (AUV) (B). Wind speed and other environmental factors, including tide levels, current speed, water temperature, and salinity, are measured by the underwater sensor network, which also includes an Autonomous Underwater Vehicle (AUV). These data are gathered by the sensors and sent to a monitoring system for evaluation and decision-making, including possible notifications for ecosystem monitoring and marine communication. This is represented as follows:

$$H = \langle H^1, H^2, H^3, \dots, H^{j-1}, H^j \rangle \tag{2}$$

where (j) is the number of data points sensed using the AUV. The number of data points sensed by the Autonomous Underwater Vehicle (AUV), with “ j ” representing the total

count of these measurements, such as tide levels, wind speed, and other environmental factors.

2.3. Optimal Path Selection for Communication

To enhance the communication of the Autonomous Underwater Vehicle (AUV) via the Underwater Delay Tolerant Sensor Network (UDTSN) to the Maritime Alert Command Centre (MACC), the optimal transmission path for (H) is determined using Adaptive Pheromone Ant Colony Optimization (AP-ACO).

This method leverages Ant Colony Optimization, which adapts to dynamic environments for real-time pathfinding. However, it is noted that ACO exhibits slow convergence in extensive spaces. Consequently, an Adaptive Pheromone (AP) distribution function is employed during the exploration phase. The Adaptive Pheromone Ant Colony Optimization (AP-ACO) technique, derived from the classical Ant Colony Optimization (ACO) algorithm, is adapted in this study to optimize communication paths within an Underwater Digital Twin Sensor Network (UDTSN). Traditional ACO, inspired by the foraging behavior of ants, is known for pathfinding in large and dynamic spaces. However, the AP-ACO method introduces an Adaptive Pheromone distribution function that adjusts pheromone levels more effectively, improving the convergence speed, which is crucial in underwater sensor networks with fluctuating environmental conditions and bandwidth constraints. The algorithm is tailored to address the unique challenges of real-time ecological monitoring by continuously adjusting pheromone levels during the exploration phase, ensuring efficient identification of optimal communication paths between Autonomous Underwater Vehicles (AUVs) and the Maritime Alert Command Centre (MACC). This adaptation enhances the performance of the ACO algorithm by enabling faster convergence, making it more suitable for underwater networks where traditional ACO might struggle with slow convergence in large, dynamic environments. While the AP-ACO technique itself is not novel, its specific application for underwater communication systems in this study represents a novel use of ACO in a complex and dynamic environment, improving communication efficiency for real-time maritime monitoring systems. The AP-ACO process is elaborated as follows.

The initial position (R) of the communication paths (ant) in UDSTN is initialized as follows:

$$R = [ub^R - lb^R] \times \alpha + lb^R \quad (3)$$

where (ub^R !lb^R) are the upper bound and lower bound values of (R), and (α) is the random number. Next, the fitness function (\mathfrak{S}) that determines the best path is evaluated regarding the minimum response time (I) as follows:

$$\mathfrak{S} = \min I \quad (4)$$

Now, the position of the ants regarding the search for food using exploration and exploitation is updated. During the exploration phase, the ants release pheromones, which influence the selection of their paths. In this context, the parameter AP (δ), which determines a more effective starting point and enhances convergence, is defined as follows:

$$\delta = \frac{g(1 - \beta) \times \chi}{\Sigma g * \chi} \quad (5)$$

where (g) is the pheromone level, (β) is the pheromone evaporation rate, and (χ) is the heuristic value. Now, the new position (R') of ants regarding (δ) is updated as follows:

$$R' = [R \times (1 - \beta) \times \delta] + R \quad (6)$$

Next, during the local update (exploitation phase), the ants encourage other ants to choose (δ); thus, the updated position (\ddot{R}) is equated by the following:

$$\vec{R} = \{R' * \delta\} + \sum R'(\delta) \tag{7}$$

Finally, the optimal path for the efficient transmission of maritime sensor data via the UDTSN has been determined based on the fitness (\mathfrak{F}). The route selected is denoted as (R^{best}). This study presents a robust mathematical model integrating Underwater Digital Twins (UDTs) with a sensor network to enhance maritime communication and monitor coastal ecosystems, particularly along the Coromandel Coast. It uses advanced techniques like AP-ACO for optimized data transmission, SHC for data compression, TKCC for encryption, and CosLU-VS-LSTM for anomaly detection. The model, validated using the NSL-KDD dataset, shows superior data accuracy, security, and compression performance. This approach significantly contributes to sustainable marine resource management by improving ecosystem monitoring and hazard detection, although future work could expand to include more coastal ecosystems. Mathematical modeling and validations are important for comprehending marine ecosystems and maintaining ecological balance while enhancing resource management for sustainability. Incorporating technologies such as Underwater Digital Twins, sensor networks, and AI offers creative solutions. The UDT framework generates a digital marine ecosystem model, allowing for real-time observation and knowledgeable decision-making. It employs AI-driven fuzzy logic alongside the EHC-ANFIS for data processing, AP-ACO for enhancing data transmission efficiency, SHC for compressing data, and TKCC for ensuring data security. CosLU-VS-LSTM deep learning detects anomalies for swift environmental threat awareness. Sensor networks gather information on tide levels, salinity, temperature, and currents, transmitting it to the Maritime Alert Command Centre (MACC) for risk management. Metrics like precision, recall, and accuracy assess how effectively the model forecasts. This system improves sustainable resource extraction and risk identification, with future investigations focused on broadening its structure to protect various coastal ecosystems while promoting sustainable management of marine resources.

Table 2 compares underwater sensor networks’ optimization methods, such as AP-ACO, PSO, FMM, Visibility Graph, Potential Fields, and GNN. It highlights each method’s advantages, disadvantages, and relevant recent references (2020–2024). This comparison explains why AP-ACO is preferred for real-time, dynamic underwater environments due to its adaptability and efficiency.

Table 2. Comparative analysis of optimization methods for underwater sensor networks.

Optimization Method	Advantages	Disadvantages
AP-ACO	<ul style="list-style-type: none"> - Adaptability to Dynamic Environments: well suited for underwater settings with changing conditions. - Real-Time Pathfinding: adaptive pheromone distribution ensures optimal real-time data transmission paths. 	<ul style="list-style-type: none"> - Slow Convergence: large, complex networks can be slow despite adaptive pheromone distribution.
PSO, Jiang et al. [25]	<ul style="list-style-type: none"> - Fast Convergence: faster than ACO in finding an optimal path. - Simple Implementation: easy to implement in optimization problems. 	<ul style="list-style-type: none"> - Less Adaptable: struggles with dynamic, real-time changes in the underwater environment. - Premature Convergence: may converge prematurely and find suboptimal paths.
FMM, Sethian [26]	<ul style="list-style-type: none"> - Efficient for Static Environments: works well in predefined or static environments. 	<ul style="list-style-type: none"> - Limited Use in Dynamic Environments: struggles with real-time changes, making it ineffective for underwater networks.

	- Computationally Efficient: less intensive for static pathfinding.	- Requires Predefined Map: only useful if the environment is predefined.
Visibility Graph, Khatib [27]	- Effective for Geometric Pathfinding: works well in structured, grid-based environments. - Deterministic: produces predictable paths.	- Not Suitable for Dynamic Environments: struggles with underwater networks where visibility is often constrained.
Potential Fields, Khatib et al [28]	- Simple and Computationally Inexpensive: quick to implement for basic pathfinding. - Local Minima Avoidance: proper tuning avoids simple pitfalls like local minima.	- Limited for Complex, Dynamic Environments: struggles with unpredictable underwater conditions. - Local Minima Problem: can still get stuck in local minima.
GNN, Zhou et al. [29], Zhang et al. [30]	- Can Handle Complex Relationships: great for networks with complex, interdependent data. - Adaptability: trains on historical data to recognize patterns.	- Computationally Expensive: high resource consumption, unsuitable for real-time applications in underwater networks. - Overfitting: can struggle with overfitting, particularly in sparse datasets.

2.4. Sensor Data Shrinkage

In this stage, the transmission of sensor data (H) with a fixed bandwidth is optimized by applying shrinkage techniques utilizing SHC. In this context, Huffman Coding (HC) is employed to compress the data, allowing its reconstruction into the original format without any loss of information.

On the contrary, input that frequently alters could not be updated in the Huffman tree, as the codes are fixed in the tree. Consequently, the Sliding Window technique is employed in Huffman Coding to incorporate the data into the tree.

To create a Huffman tree (\mathfrak{R}) based on new sensor data, the Sliding Window (q), which discards the old data and includes the latest data as segments, is included into (\mathfrak{R}). It is expressed as follows:

$$\mathfrak{R} = q[H] * d(G) \quad (8)$$

where (d) is the frequency of the symbols (G). Here, shorter codes are assigned for frequent symbols, and longer ones are allotted to less frequent symbols. The frequency (d) is updated for each symbol, which helps in compression of the data. The updated frequency (d^*) is equated by the following:

$$d^* = (d+1)G/(d-1)G \quad (9)$$

The Huffman tree is rebalanced based on (d^*) to give the compressed sensor data (\tilde{H}) as follows:

$$\tilde{H} = H[\mathfrak{R} \otimes d^*] \quad (10)$$

Thus, the compressed sensor data (\tilde{H}) are transmitted effectively through the selected path (R^{best}) of the Underwater Digital Twins Sensor Network.

2.5. Data Security

Here, to ensure that the data received in the MACC matches the transmitted data, the compressed data (\tilde{H}) are protected using TKCC.

The method employed for securing the data is Elliptic Curve Cryptography (ECC), which offers a high level of security with a reduced key size. Nevertheless, the drawbacks associated with the Elliptic Curve lead to increased computational complexity. The

Twisted Koblitz Curve (TKC) is utilized as an alternative to the Elliptic Curve in ECC to address this challenge. The data security process is illustrated below.

The TKC (Z), responsible for managing the coordinates within the finite field and providing a non-zero variable, is expressed as follows:

$$Z \rightarrow M^2 = L^3 + (u * L^2) + v \quad (11)$$

where (L, M) are the horizontal and vertical axes of (Z) , and (u, v) are the coordinate values. Now, the public key (ϕ) and the private key (γ) of the TKCC are calculated for securing the input data.

$$\phi = (u + v) * Z(e) \quad (12)$$

$$\gamma = \phi * Z(e) \quad (13)$$

where (e) is the randomly generated coordinate of the TKC. Finally, (\tilde{H}) is secured using (ϕ) and (γ) to make sure that the data security persists during data transmission in the complex acoustic environment of the Coromandel Coast. The secured data (X) is equated as follows:

$$X = \tilde{H} \oplus \phi \oplus \gamma \quad (13)$$

The pseudo-code of TKCC is explained in Algorithm 1.

Algorithm 1. Pseudo-code for TKCC

Input: Compressed sensor data (\tilde{H})

Output: Secured data (X)

Begin

Initialize coordinate parameters (u, v)

Create TKC

$$$Z \rightarrow M^2 = L^3 + (u * L^2) + v$$$

For (\tilde{H})

While $[(L, M) \in Z]$

Calculate the public key using (u, v)

$$$\phi = (u + v) * Z(e)$$$

Generate private key regarding (ϕ)

$$$\gamma = \phi * Z(e)$$$

Encrypt sensor data

$$$X = \tilde{H} \oplus \phi \oplus \gamma$$$

Continue data transmission

End while

End for

Obtain Secured sensor data (X)

End

Thus, the sensitive sensor data are encrypted and sent for further processing.

2.6. Anomaly Detection System Model

In this stage, the Anomaly Detection System (ADS) model is trained to safeguard the integrity of sensitive maritime data transmitted via the Underwater Digital Twins Sensor Network. The details of the ADS model training are outlined below.

2.6.1. Dataset

Initially, to train the ADS model regarding anomaly detection during sensor data transmission, the NSL-KDD dataset is collected. The data(U) present in the NSL-KDD dataset are given by the following:

$$U = [U_1, U_2, U_3, U_4, \dots, U_f] \quad (14)$$

where (f) represents the number of (U).

2.6.2. Pre-Processing

Next, to structure the data for effective anomaly detection, the pre-processing steps, such as Missing Value Imputation (MVI), numeralization, and normalization are implemented.

✓ Missing Value Imputation

Here, the missing values in (U) are added based on the median of the neighboring data. The imputation of the values is evaluated as follows:

$$U''' = \left[\frac{\sum_f U}{f} \right] \oplus U \quad (15)$$

where (U''') represents the imputed data for the missing value of (f).

✓ Numeralization

Following MVI, the string data in (U''') are transformed in numerical values, facilitating the processing of Artificial Intelligence (AI). The numeralization of (U''') is given below.

$$\ddot{U} \rightarrow (U) * k \quad (16)$$

where (\ddot{U}) is the numeralized data, and (k) is the binary vector.

❖ Normalization

Finally, (\ddot{U}) is normalized using the min-max technique. Here, the data are scaled to fall in the range of (0 to 1). Consequently, all data points that exist on varying scales undergo scalar transformation. The normalization process is represented as follows:

$$\hat{U} = \frac{[\ddot{U} - \ddot{U}^{min}]}{[\ddot{U}^{max} - \ddot{U}^{min}]} \quad (17)$$

where (\hat{U}) is the normalized data, which are the final pre-processed output, and ($\ddot{U}^{min}, \ddot{U}^{max}$) are the minimum and maximum values of (\ddot{U}).

2.6.3. Feature Extraction

Here, from (\hat{U}), various features are extracted, including duration, protocol_type, service, flag, src_bytes, dst_bytes, wrong_fragment, urgent, dst_host_srv_count, count, num_compromised, num_access_files, serror_rate, dst_host_count, dst_host_srv_rerror_rate, and are represented as follows:

$$T = (T_1, T_2, T_3, T_4, \dots, T_y) \quad (18)$$

where (T) is the feature extracted, and (y) is the number of (T).

2.6.4. Intuitive Visualization

To analyze the differences and similarities in (T), the Radial Chart is employed, as it effectively captures patterns in the input, particularly when examining the features over time. It is expressed as

$$F = (\lambda \times c) * T \tag{20}$$

where (F) is the intuitive visualization of (T), (λ) is the axes of the Radial Chart, and (c) is the circular format of the chart.

2.6.5. Anomaly Detection

In this stage, identification of anomalies within the data packets is conducted through the application of the CosLU-VS-LSTM Artificial Intelligence methodology. This approach employs Long Short-Term Memory (LSTM) networks, which address the vanishing gradient issue and facilitate more efficient training on extensive sequences of IoT sensor data for the purpose of anomaly detection. However, LSTM networks are susceptible to overfitting, and using the sigmoid activation function can hinder the classification speed. Variational Shake-drop (VS) regularization is implemented to mitigate the overfitting concern. At the same time, the Cosinu-sigmoidal Linear Unit (CosLU) function is adopted in place of the sigmoid activation function to enhance the speed of the anomaly detection process. The architecture of the proposed classifier is illustrated in Figure 2.

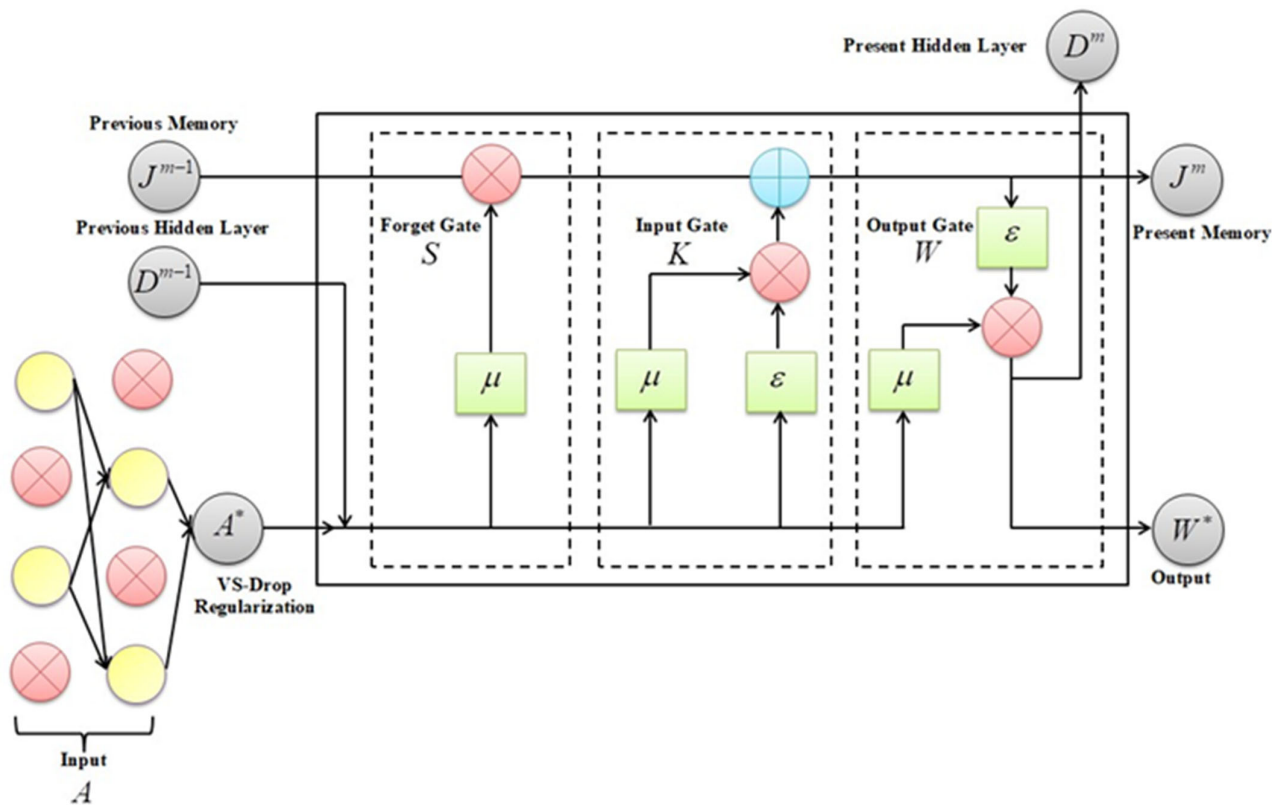


Figure 2. CosLU-VS-LSTM classifier diagram.

The following sections detail the method of CosLU-VS-LSTM, which incorporates elements such as forget date, input gate, output gate, cell state, and memory.

⚡ Regularization

The proposed classifier’s input is denoted as (T), and (F) is represented together as (A).

To address the overfitting issue, the vs. regularization technique is employed, which facilitates the learning of a robust representation within the data and appropriately scales the data. This technique is indicated by the following:

$$A^* = (A \times p) + [(1 - p)A * \kappa] \tag{21}$$

where (A^*) is the regularized data, (p) is the weight value, and (κ) is the skip connection factor.

⇨ Activation Function

Next, the CosLU function (μ) , which combines linear and cosine components to capture complex patterns, and the hyperbolic tangent (tanh) activation function (ϵ) that maps the patterns effectively, are calculated as follows:

$$\mu = A^* + \{\theta * [1 - \cos(A^*)]\} \tag{22}$$

$$\epsilon = [\exp^A - \exp^{-A}] / [\exp^A + \exp^{-A}] \tag{23}$$

where (θ) is the scaling hyperparameter, and (\exp) is the exponential factor.

⇨ Forget Gate

Here, the data that are not necessary for detecting anomaly are removed. The previous hidden layer (D^{m-1}) , with time (m) , previous memory (J^{m-1}) , and the input (A^*) , is added and activated using (μ) . This is expressed as follows:

$$S = [\{ [A^*, D^{m-1}, J^{m-1}] * p \} + n] \otimes \mu \tag{24}$$

where (S) is the output of the forget gate, and (n) the bias value.

⇨ Input gate

Here, the information is added to the present memory (J^m) . Here, the inputs are activated using (μ) and (ϵ) simultaneously as follows:

$$K = S \otimes [\{ [A^*, D^{m-1}] * p \} + n] * \epsilon \tag{25}$$

where (K) is the output of the input gate.

⇨ Memory

The output of the forget gate (S) and the input gate (K) are added to update the present memory (J^m) as follows:

$$J^m = S \oplus K \tag{26}$$

⇨ Output gate

Finally, depending on (J^m) , and (A^*) , the output gate value (W) , which extracts the most important information and helps in identifying the anomaly, is calculated as follows:

$$W = [J^m * \epsilon] \otimes \{ \mu * [A^*, D^{m-1}] \} \tag{27}$$

$$W^* = \begin{cases} W(z) \vee (W = 1) \\ W(w) \vee (W = 0) \end{cases} \tag{28}$$

where (W^*) is the overall anomaly detected output, $W(z)$ shows the presence of anomaly when $(W=1)$, and $W(w)$ is the normal class when $(W=0)$. The pseudo-code for CosLU-VS-LSTM is explained in Algorithm 2.

Algorithm 2. Pseudo-code for CosLU-VS-LSTM

Input: Features (T) , Intuitive representation (F)

Output: Anomaly detected output (W^*)

Begin

Initialize $(p), (n)$

Regularize input

$$A^* = (A * p) + [(1 - p)A * \kappa]$$

```

For ( $A^*$ )
  Calculate activation function
   $\mu = A^* + \{\theta * 1 - \cos(A^*)\}$ 
   $\varepsilon = [\exp^A - \exp^{-A}] / [\exp^A + \exp^{-A}]$ 
  While ( $\mu, \varepsilon$ )
    For ( $time = m$ )
      Evaluate forget gate
       $S = \{[A^*, D^{m-1}, J^{m-1} * p] + n\} \otimes \mu$ 
      Determine input gate
       $K = S \otimes \{[(A^*, D^{m-1}) * p] + n\} * \varepsilon$ 
      Update memory
       $J^m = S \oplus K$ 
      Calculate output gate
       $W = J^m * \varepsilon \otimes \{\mu * [A^*, D^m]^{-1}\}$ 
      Attain classified output
    End if
  End for
Return ( $W^*$ )
End

```

The proposed framework enhances underwater communication and monitoring for the Coromandel Coast by integrating advanced technologies. It uses Underwater Digital Twin (UDT) technology for real-time environmental monitoring, with decision-making powered by an AI-driven Exponential Hyperbolic Crisp Adaptive Network-based Fuzzy Inference System (EHC-ANFIS). Data security is ensured through Twisted Koblitz Curve Cryptography (TKCC), while an Anomaly Detection System (ADS) with CosLU-VS-LSTM identifies irregularities in sensor data. To optimize bandwidth, Sliding-Huffman Coding (SHC) compresses the data, and Adaptive Pheromone Ant Colony Optimization (AP-ACO) selects the optimal communication path. These innovations collectively improve the efficiency of maritime communication and monitoring, contributing to the sustainable management of coastal ecosystems.

Upon completion of the ADS model training, any detected anomalies during the real-time transmission of data (X) will result in the blocking of that transmission, while data transmission for the normal class will proceed uninterrupted within the UDTSN.

2.7. Data Decryption and Decomposition

For $W(z)$, the data (X) are transmitted along the Underwater Digital Twins Sensor Network. To further process the data for the monitoring purpose of the Coromandel Coast, decryption is performed using the keys (ϕ) and (γ) generated by the TKCC method as explained in the following sections.

$$Y = X - \phi - \gamma \quad (29)$$

where (Y) is the decrypted data. Next, (Y) is decomposed using (\mathfrak{R}) to obtain the exact file and is given by the following:

$$Q = \frac{Y}{\mathfrak{R}} \quad (30)$$

where (Q) is the decomposed data.

2.8. Extraction of Sensor Data

Here, the original sensor data (H) passing through the UDTSN are extracted from (Q). These data are further used to monitor the Coromandel Coast for varying complex environmental changes and conditions.

2.9. Digital Twin-Influenced Decision-Making

The final decision-making process concerning the monitoring level of the Coromandel Coast is conducted through the EHC-ANFIS (AI-IoT) hybrid approach. The data (H), collected via the Underwater Digital Twins Sensor Network, serve as the input for the EHC-ANFIS system. This system employs the Adaptive Network-based Fuzzy Inference System, which evaluates the IoT sensor data obtained from Autonomous Underwater Vehicles (AUVs) and modifies parameters in response to updated climatic information, thereby facilitating decisions related to the monitoring of the Coromandel Coast. Optimizing fuzzy rules and threshold settings in a maritime monitoring system based on Underwater Digital Twins (UDTs) using the Exponential Hyperbolic Crisp Adaptive Network-based Fuzzy Inference System (EHC-ANFIS). It starts with defining fuzzy rules based on environmental parameters like tide level, current speed, wind speed, water temperature, and salinity, with an “if-then” structure, such as “If tide level = low, then risk = low”. The data collected from the sensors are fuzzified using the EHC membership function, which improves the handling of crisp inputs, making it easier for the system to manage uncertainty. These fuzzified inputs are then evaluated by the ANFIS, which applies fuzzy logic to assess relationships between input variables and determines the appropriate risk level, such as issuing a “green”, “yellow”, or “red” alert. Threshold values, such as “high tide > 5 m”, are optimized to maximize detection accuracy and minimize false alerts by adjusting boundaries based on historical or real-time data. After the fuzzy rules and thresholds are applied, the output is defuzzified to generate a crisp decision, such as a specific alert level. The EHC-ANFIS hybrid model refines the system by dynamically adjusting fuzzy rules and thresholds based on incoming sensor data, ensuring optimal decision-making efficiency. This continuous optimization enhances the system’s performance, providing accurate and timely alerts and responses based on varying environmental conditions. It is important to note that the ANFIS framework necessitates specialized knowledge and expertise to accurately define fuzzy sets, membership functions, and rule bases. The Exponential Hyperbolic Crisp (EHC) membership function is implemented to improve the decision-making process. The subsequent steps involved in the decision-making process are outlined below.

✓ Rule

The fuzzy rule (C) based on the if-then condition is initially set for making adequate decisions to monitor the coastal ecosystem. It is equated as follows:

$$C = \begin{cases} \text{if } (a = 1), (b = 1.5), (i < 20), (t = 24), (r = 35) & \text{then } E^1 \\ \text{if } (a = 2), (b = 2.5), (i = 35), (t = 27), (r = 38) & \text{then } E^2 \\ \text{if } (a = 2.8), (b = 3.5), (i = 50), (t = 29), (r = 40) & \text{then } E^3 \\ \text{if } (a = 2.9), (b = 4), (i = 70), (t = 31), (r = 42) & \text{then } E^4 \\ \text{if } (l = 1400), (b = 3), (i = \text{calm}) & \text{then } E^5 \\ \text{if } (i = 65), (b = 3.5), (a = 2.5) & \text{then } E^6 \\ \text{if } (a = 3), (b = 3.8), (i = 70), (x = \text{low}) & \text{then } E^7 \end{cases} \quad (31)$$

where the tide level (a) is recorded in meters, the current speed (b) is expressed in meters per second, the wind speed (i) is indicated in kilometers per hour, the water temperature (t) is measured in Celsius degrees, and salinity (r) is quantified using the Practical Salinity Unit (PSU). Additionally, (l) denotes the sound velocity, influencing the acoustic sensor performance, while (x) represents the sensor battery level. In this context, the

decision-making (E) related to the monitoring of the coast is categorized as follows: (E^1) signifies a green alert indicating low risk, (E^2) denotes a yellow alert representing moderate risk, (E^3) indicates a red alert for high risk, (E^4) refers to a red alert for critical hazards, (E^5) is a special alert for disruption in acoustic propagation, (E^6) represents the yellow alert with pre-emptive early warning for incoming storms, and (E^7) is a multi-factor red alert that combines risks from environmental factors and system failures. In order to monitor the coastal ecology, the Autonomous Underwater Vehicle (AUV)'s sensors gather various environmental data. Water temperature (in Celsius degrees), salinity (measured in Practical Salinity Units, PSUs), wind speed (in kilometers per hour), tide level (in meters), and current speed (in meters per second) are among the particular characteristics. The AUV gathers these characteristics, Internet of Things (IoT) data, for subsequent processing in the underwater sensor network.

✓ Membership Function

Now, the EHC membership function (ψ) that identifies the parameters effectively, is used. It is equated as

$$\psi = \begin{cases} 1 & \forall [H \leq o^1] \\ \exp^{-\frac{(H-o^1)}{o^2}} & \forall [o^1 < H < o^2] \\ 0 & \forall [H \geq o^2] \end{cases} \quad (32)$$

where (o^1, o^2) are the scaling parameters of the input (H). Regression analysis models the relationship between a dependent variable (ground truth) and independent variables (predictions from various models). Techniques like Linear Regression are useful for simple, linear relationships, while Polynomial Regression captures non-linear patterns. Ridge and Lasso Regression add regularization to prevent overfitting, with Lasso also performing feature selection. Support Vector Regression (SVR) handles non-linear data, and Random Forest Regression uses multiple decision trees to reduce overfitting. Neural Networks and Gradient Boosting Machines (GBMs) like XGBoost are used for complex, high-performance models, with GBMs improving weak models through sequential decision trees. The choice of method depends on data complexity and model performance needs.

✓ Fuzzification

Here, the input (H) is converted into fuzzy data (\hat{H}) so that the AI method can learn the input data precisely. It is given by

$$\hat{H} = H * \psi \quad (33)$$

The input is multiplied by the membership function to assess the extent of the relationship between the data.

✓ Defuzzification

The fuzzy data (\hat{H}) are derived using the rule (C) and subsequently defuzzified to obtain the final output as shown below.

$$E = \frac{\sum \hat{H} \times C}{\sum \hat{H}} \quad (34)$$

Thus, (E) represents the decision-making in monitoring the Coromandel Coast.

2.10. Alert to Maritime Alert Command Centre

According to the obtained (E), an alert is sent to the MACC. Consequently, the proposed framework's implementation enhances maritime communication and surveillance of the Coromandel Coast. The effectiveness of the proposed initiative is detailed below.

3. Results and Discussions

This section presents the performance evaluation and comparative analysis of the proposed model alongside existing techniques to demonstrate the reliability of the proposed model. Additionally, the implementation of the proposed model is carried out on the PYTHON working platform.

3.1. Dataset Description

The framework presented utilizes the "NSL-KDD" dataset to evaluate the proposed model. The NSL-KDD dataset is an improved version of the KDD Cup 1999 dataset for evaluating intrusion detection systems. It contains labeled network traffic data, categorized into normal and attack types, and is commonly used in research. The dataset includes features like connection statistics and service types, which are essential for detecting malicious network activities. It is available publicly on platforms like Kaggle. This dataset has been sourced from publicly accessible materials, with the corresponding link provided in the References section. It comprises a total of 125,973 data entries. Of this total, 80%, equating to 100,778 entries, is allocated for training, while the remaining 20%, amounting to 25,195 entries, is designated for testing purposes.

3.2. Performance Assessment

The evaluation of the proposed method alongside existing techniques is conducted to demonstrate the effectiveness of the proposed model.

Figure 3 illustrates the graphical comparison between the proposed EHC-ANFIS and existing methodologies regarding fuzzification, defuzzification, and rule generation times. The EHC-ANFIS model exhibited significantly lower times of 21,045 ms for fuzzification, 45,012 ms for defuzzification, and 51,452 ms for rule generation, attributed to implementing the Exponential Hyperbolic Crisp Membership Function. In contrast, the conventional techniques, including ANFIS, Fuzzy, Rule-Based Prediction (RBP), and Trapezoidal Fuzzy Logic System (Trapezoidal FLS), recorded higher average times of 71,422.25 ms, 80,329.5 ms, and 89,144.75 ms for fuzzification, defuzzification, and rule generation, respectively. This highlights the superior performance of the proposed model.

The figure compares the processing times (in milliseconds) for fuzzification, defuzzification, and rule generation across different fuzzy inference systems: the proposed EHC-ANFIS, ANFIS, Fuzzy, RBP, and Trapezoidal FLS. It shows that the proposed EHC-ANFIS model has significantly lower processing times for each of the three phases compared to the other systems, indicating better efficiency. This chart does not represent convergence time but illustrates the performance of each system in completing these specific tasks. Convergence time alone does not reflect a model's total quality because it simply counts how quickly it achieves a solution and ignores characteristics such as solution correctness, generalization ability, resilience, and interpretability. A model may converge rapidly yet generate inferior results, be sensitive to hyperparameters, or consume too many resources. To assess a model's performance, it is critical to examine not just convergence time but also accuracy, generalization, efficiency, and stability.

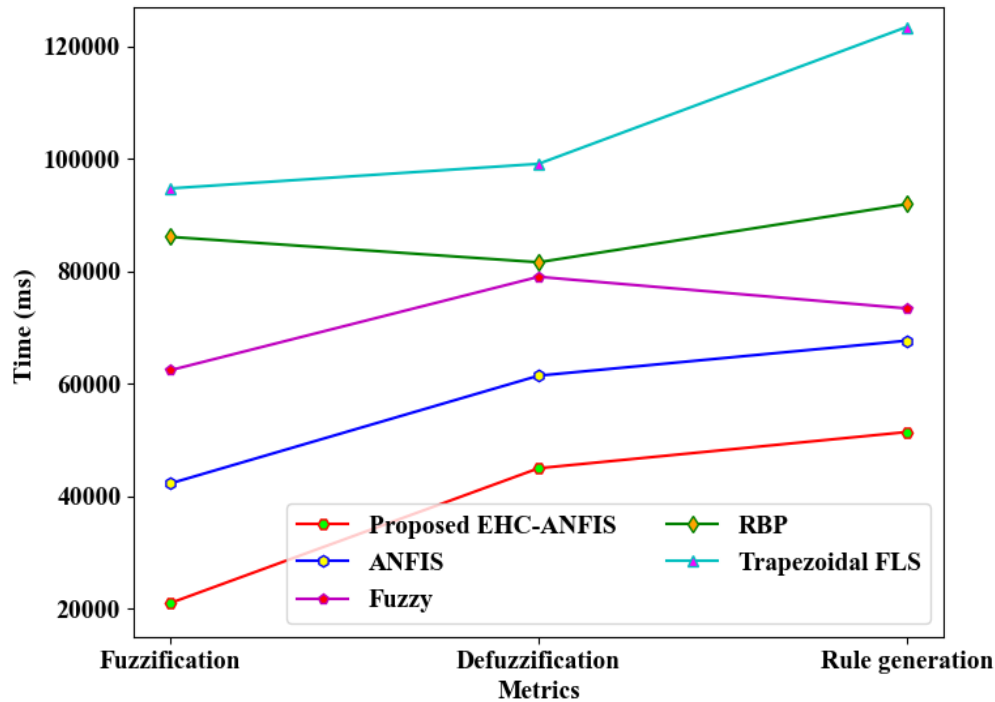


Figure 3. Graphical representation concerning fuzzification, defuzzification, and rule generation time.

The performance validation of the proposed CosLU-VS-LSTM model, along with existing techniques such as LSTM, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Deep Neural Networks (DNNs), is illustrated in Figure 4a,b. The proposed CosLU-VS-LSTM demonstrated impressive metrics, achieving precision, recall, F-Measure, accuracy, sensitivity, and specificity values of 98.35%, 99.15%, 99.00%, 98.62%, 99.15%, and 98.31%, respectively. Additionally, it recorded a low False Positive Rate (FPR) of 0.0268776 and a False Negative Rate (FNR) of 0.008653. In contrast, the existing models—LSTM, CNN, RNN, and DNN—exhibited lower precision rates of 95.13%, 93.75%, 90.87%, and 88.15%, respectively. These established techniques also showed diminished accuracy, recall, F-measure, sensitivity, and specificity. Notably, the existing DNN model had a significantly high FPR of 0.1786746 and an FNR of 0.119243. To address the overfitting problem, the Variational Shake Drop Regularization technique was adapted within the CosLU-VS-LSTM framework. Consequently, the results indicate that the proposed model outperformed the existing methodologies.

Table 3 displays the UDT-EHC-ANFIS model outperforming existing maritime surveillance systems in several areas. It is faster in computational complexity, with processing times of 21,045 ms for fuzzification and 45,012 ms for defuzzification, compared to ANFIS (71,422 ms) and RBP (80,329.5 ms). In security, it achieves 98.01% protection with TKCC, using less memory than traditional methods like ECC. The model excels in anomaly detection, with 98.35% precision and 99.15% recall, surpassing LSTM and DNN. It also compresses data efficiently with SHC in 140,758 ms, outperforming Huffman Coding. Lastly, it achieves superior compression quality with an MSE of 0.00954 and entropy of 32.56, beating traditional methods. This study detects false predictions through the Anomaly Detection System (ADS), which warrants the integrity of maritime sensor data transmitted via the Underwater Digital Twins Sensor Network (UDTSN). The process begins with data preprocessing, which includes Missing Value Imputation (MVI) to fill in

missing values, numeralization to convert string data into numerical values, and normalization to scale the data consistently. Next, relevant features are extracted to help in identifying anomalies. The core of anomaly detection uses the CosLU-VS-LSTM model. This deep learning approach combines a Cosine-sigmoidal Linear Unit (CosLU) activation function with Variational Shake-drop Regularization to prevent overfitting. At the same time, the Long Short-Term Memory (LSTM) network effectively handles time-series data. The model then monitors incoming data, flagging any significant deviations as anomalies (false predictions). The output gate of the LSTM model classifies the data as either normal (0) or anomalous (1). If an abnormality is noticed, the exaggerated data are blocked from transmission to the Maritime Alert Command Centre (MACC), confirming that only valid data are sent. This method has been authenticated with impressive accuracy, precision, and recall metrics, demonstrating its effectiveness in minimizing false predictions and improving the system’s reliability.

Table 3. Comparative analysis of UDT-EHC-ANFIS model vs. existing maritime surveillance models.

Criteria	Proposed UDT-EHC-ANFIS Model	Existing Models
Computational Complexity	Fuzzification time: 21045 ms	
	Defuzzification time: 45012 ms	ANFIS: 71422 ms, RBP: 80329.5 ms, Trapezoidal FLS: 89144.75 ms
	Rule Generation time: 51452 ms	
Security	TKCC: 98.01% security, 1.99% attack level	
	Memory for encryption: 147,245,452 KB	ECC, RSA, DES, ElGamal: Higher memory usage and weaker security
	Memory for decryption: 149,456,981 KB	
Anomaly Detection Accuracy	CosLU-VS-LSTM model: 98.35% precision, 99.15% recall, 98.62% accuracy	LSTM: 95.13% precision, CNN: 93.75%, RNN: 90.87%, DNN: 88.15%

Table 4 illustrates the evaluation of the True Positive Rate (TPR) and True Negative Rate (TNR) for the proposed CosLU-VS-LSTM model compared to existing methodologies. The CosLU-VS-LSTM model utilizes the Variational Shake Drop Regularization technique and the CosLU function to identify anomalies effectively. This model achieved impressive TPR and TNR values of 98.72% and 98.31%, respectively. In contrast, traditional techniques such as LSTM, CNN, RNN, and DNN demonstrated a lower average TPR and TNR, recorded at 93.11% and 89.93%, respectively. Therefore, the reliability of the proposed model is substantiated.

Table 4. TPR and TNR evaluation.

Method	TPR (%)	TNR (%)
Proposed CosLU-VS-LSTM	98.72	98.31
LSTM	95.14	94.37
CNN	93.43	92.75
RNN	94.25	89.22
DNN	89.63	83.37

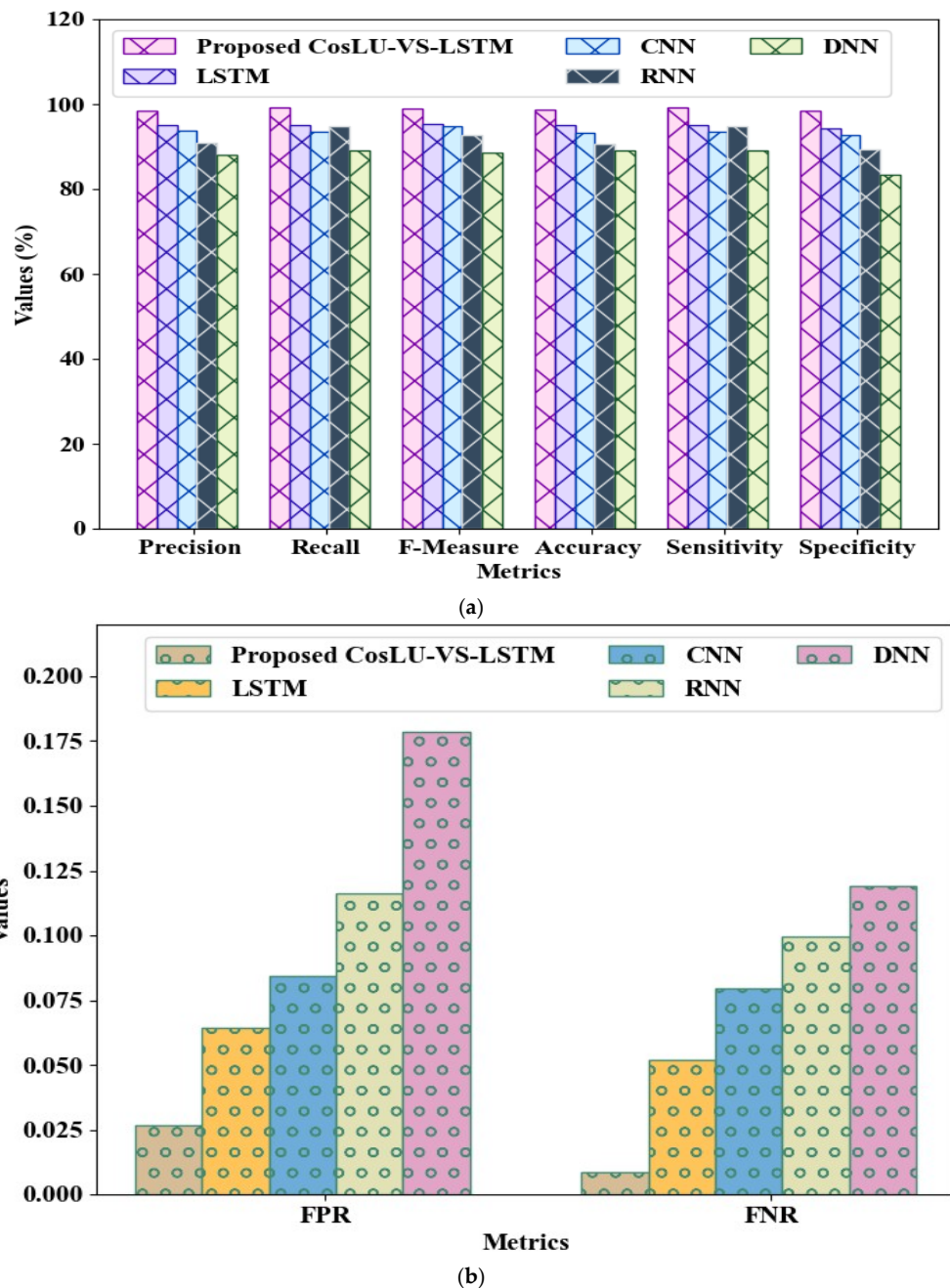
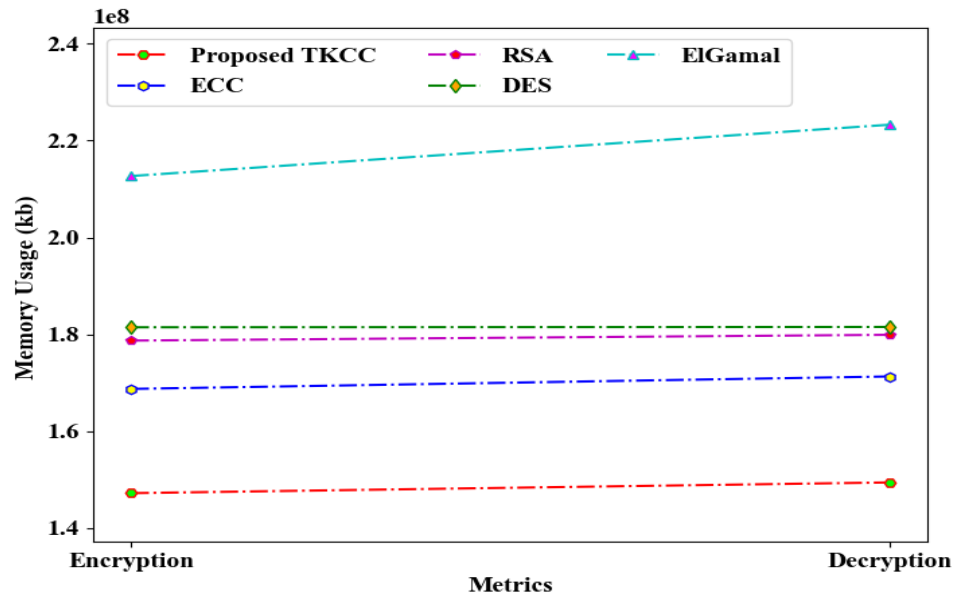


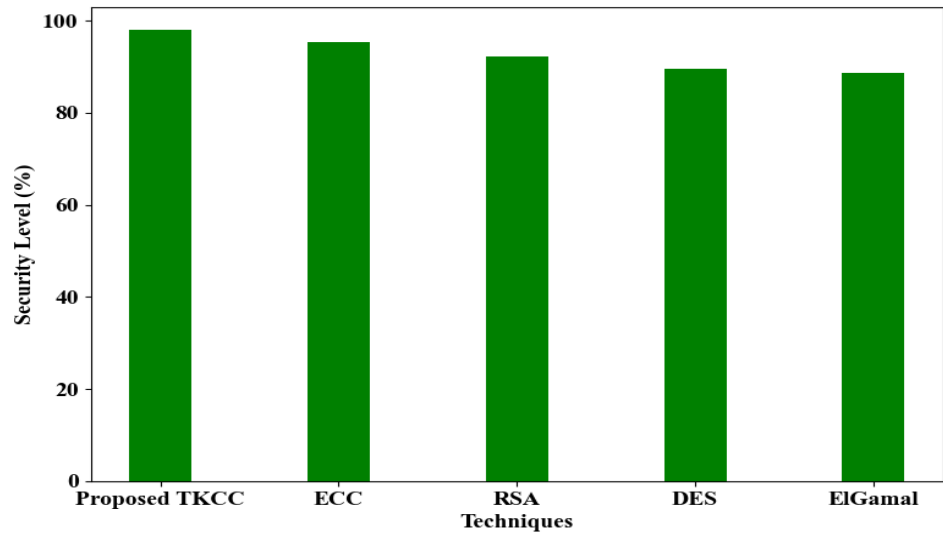
Figure 4. Performance validation regarding (a) precision, recall, F-Measure, accuracy, sensitivity, and specificity; (b) FPR and FNR.

Figure 5a–c illustrate the comparative graphical analysis of the proposed model against traditional methods regarding memory consumption during encryption and decryption processes, as well as their respective security and attack levels. The proposed Twisted Koblitz Curve Cryptography (TKCC) utilized 147,245,452 KB of memory for encryption and 149,456,981 KB for decryption. In addition, the TKCC demonstrated a commendable security level of 98.01% and a minimal attack level of 1.99%, outperforming conventional methods. In contrast, traditional techniques such as Elliptic Curve Cryptography (ECC), Rivest–Shamir–Adleman (RSA), Data Encryption Standard (DES), and El-

Gamal required significantly more memory for both encryption and decryption. Furthermore, these existing methods exhibited inferior security and attack levels. The implementation of the Twisted Koblitz Curve serves to enhance data security.



(a)



(b)

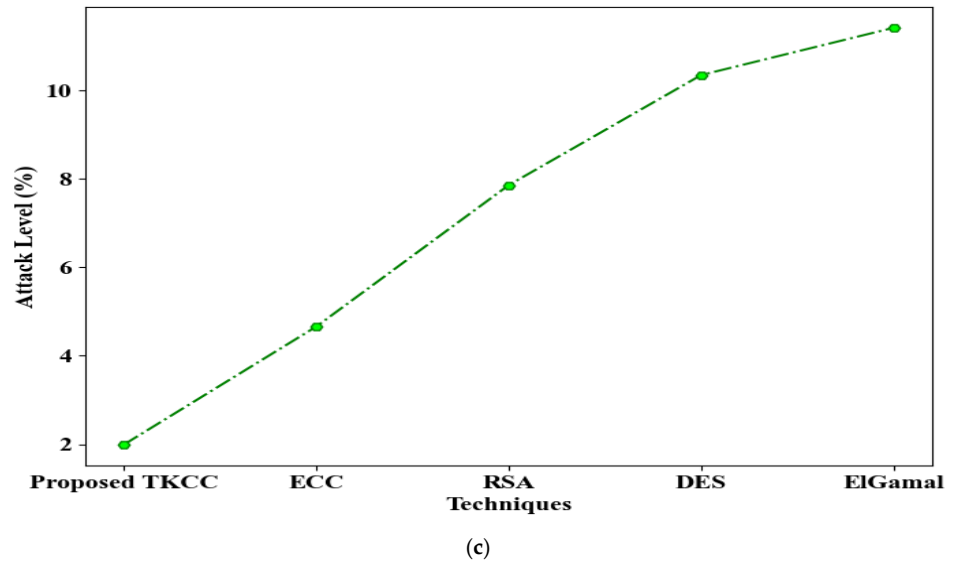


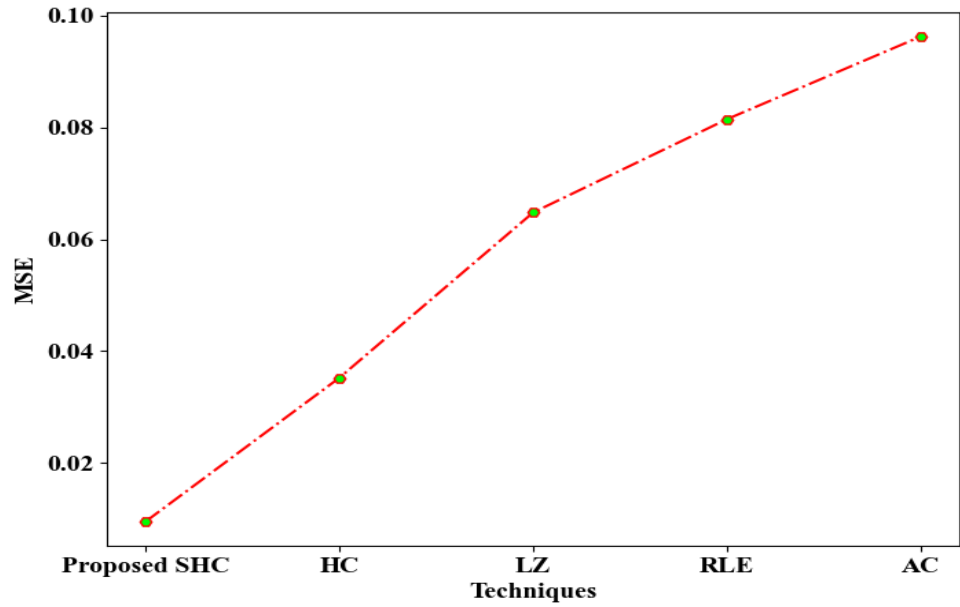
Figure 5. Graphical analysis in terms of (a) memory usage on encryption and decryption, (b) security level, and (c) attack level.

Table 5 presents the analysis of compression times for the proposed SHC and existing techniques. The proposed SHC achieved a notably low compression time of 140,758 ms, in contrast to the conventional methods: Huffman Coding (HC) at 198,563ms, Lempel-Ziv (LZ) at 253,564 ms, Run-Length Encoding (RLE) at 314,748 ms, and Arithmetic Coding (AC) at 398,756 ms. Consequently, the proposed SHC demonstrates superior efficiency in sensor data compression.

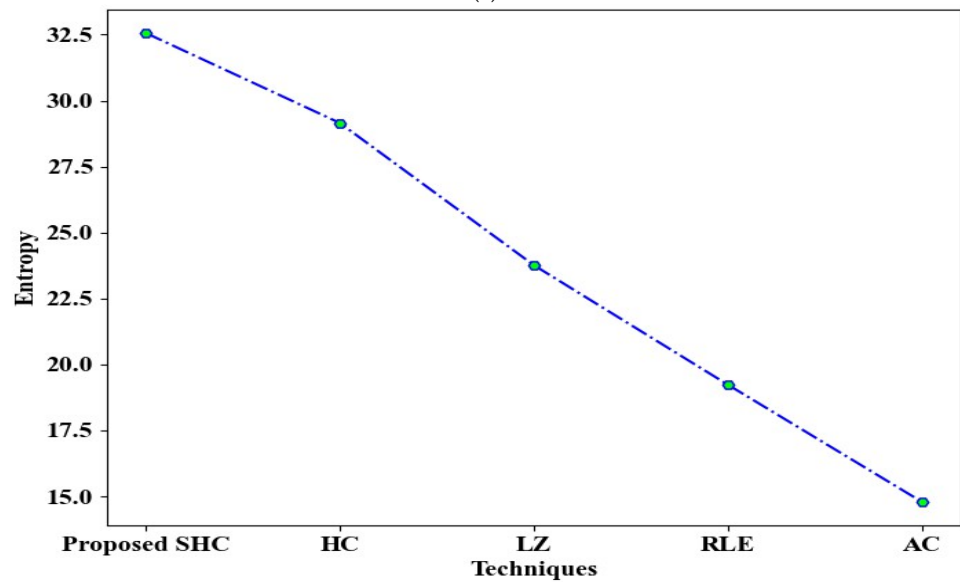
Table 5. Compression time analysis.

Techniques	Compression Time (ms)
Proposed SHC	140,758
HC	198,563
LZ	253,564
RLE	314,748
AC	398,756

Figure 6 illustrates the comparative evaluation of the proposed SHC against established methods, including HC, LZ, RLE, and AC. This analysis has enhanced the sliding window with SHC to mitigate inefficiencies. The proposed SHC demonstrated a low Mean Squared Error (MSE) of 0.00954 and a high entropy value of 32.56. In contrast, the existing techniques, such as HC, LZ, RLE, and AC, recorded a higher average MSE of 0.06942 and a lower average entropy of 21.73. Therefore, the proposed model outperforms the current techniques.



(a)



(b)

Figure 6. Comparative assessment regarding (a) MSE and (b) entropy.

The performance validation of the proposed AP-ACO compared to existing techniques concerning response time and process time is illustrated in Figure 7. The proposed AP-ACO demonstrated a significantly reduced response time of 8701 ms and a processing time of 5117 ms, attributed to its ability to identify optimal solutions adaptively. In contrast, the existing algorithms, including ACO, Dingo Optimization Algorithm (DOA), Osprey Optimization Algorithm (OOA), and Particle Swarm Optimization (PSO), exhibited higher response and process times. Consequently, the findings confirm that the proposed model exhibits lower time complexities.

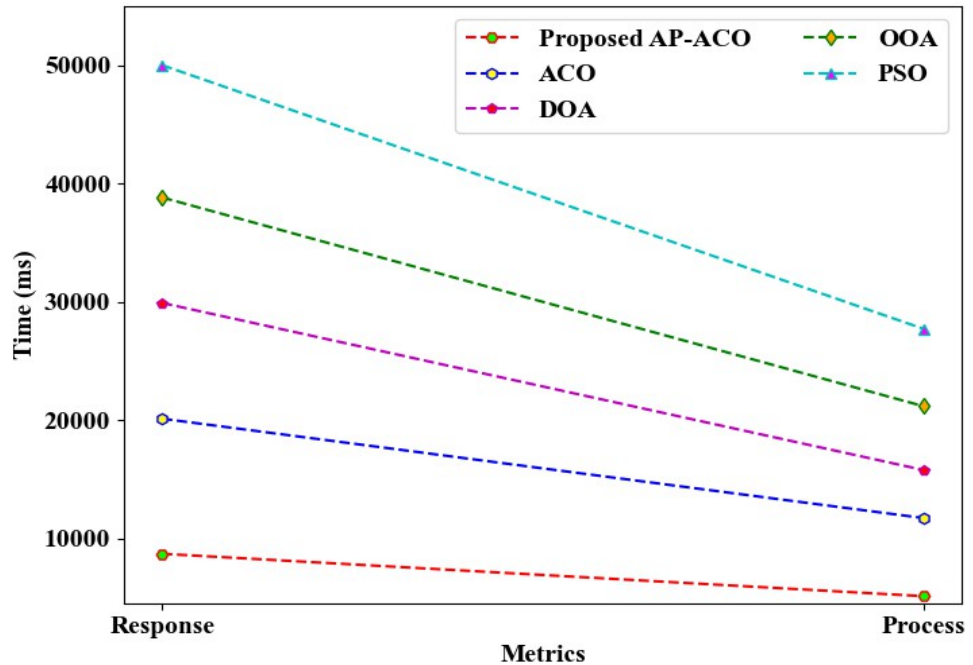


Figure 7. Performance validation of the proposed model and existing techniques.

Table 6 compares Twisted Koblitz Curve Cryptography (TKCC) with traditional security models like ECC, RSA, DES, and ElGamal. TKCC excels in security, efficiency, and low resource usage, making it ideal for real-time maritime applications with low bandwidth and memory constraints. It offers better security (98.01%) and lower attack levels (1.99%) than other models. TKCC is computationally efficient and integrates well with anomaly detection systems, making it the best choice for underwater sensor networks and real-time communication. In contrast, models like ECC and RSA are more computationally expensive and less suitable for resource-constrained environments.

Table 6. Comparative security analysis of Twisted Koblitz Curve Cryptography (TKCC) and alternative maritime data security models.

Criteria	TKCC (Twisted Koblitz Curve Cryptography)	Elliptic Curve Cryptography (ECC)	Rivest-Shamir-Adleman (RSA)	Data Encryption Standard (DES)	ElGamal
Security Level	98.01%	High (but computationally expensive)	High (but slower and more resource-intensive)	Low (outdated, short key sizes)	Moderate (computationally expensive)
Attack Level	1.99%	Moderate (vulnerable to modern attacks with weak keys)	Vulnerable to quantum attacks, high computational overhead	Vulnerable to modern cryptographic attacks	Susceptible to chosen ciphertext attacks
Encryption/Decryption Efficiency	Highly efficient with lower memory usage (Encryption: 147,245,452 KB, Decryption: 149,456,981 KB)	Less efficient due to larger key sizes and computational complexity	Very inefficient due to large key sizes and slower processing	Insecure and slow for modern systems	Slower than TKCC, large key sizes

Memory Consumption	Low (optimized for real-time use)	High (requires more memory for key management)	Very high (needs significant memory for large keys)	Very high for modern systems	High memory requirement for large key sizes
Bandwidth Usage	Optimized for low-bandwidth environments (e.g., underwater sensor networks)	Requires higher bandwidth and processing power	Requires significant bandwidth and memory for key exchange	Outdated, inefficient for modern usage	High bandwidth usage for key exchange
Computational Complexity	Low (designed for resource-constrained environments)	High (complex math, slower processing times)	Very high (complex modular exponentiation)	High (insecure and inefficient for modern applications)	High (complex computations for key generation and encryption)
Real-Time Applicability	Excellent for real-time maritime communication systems due to low overhead	Not ideal for real-time due to high computational overhead	Very inefficient due to high computational cost	Poor for real-time systems due to slow processing	Poor for real-time due to computational complexity
Suitability for Underwater Systems	Optimal (efficiency and security combined for underwater sensor networks)	Less suited for underwater systems due to high memory and computation needs	Poor for real-time applications due to high computational cost	Poor suitability for modern underwater systems	Poor suitability due to computational complexity
Integration with Anomaly Detection Systems	Compatible (can be paired with deep learning-based anomaly detection systems like CosLU-VS-LSTM)	Compatible but less efficient with anomaly detection	Compatible but less efficient with anomaly detection	Not recommended for integration due to inefficiency	Compatible but not ideal for real-time anomaly detection due to inefficiency
Advantages	High security with minimal resource consumption, ideal for real-time use, lower memory usage	High security, well-established cryptographic standard	Strong security, well-established for general use	Simple and fast for small data, historically important	Strong security, widely used but computationally expensive
Disadvantages	Relatively newer may not be as commonly accepted in legacy systems	High computational overhead, inefficient for real-time applications	High computational cost, not efficient for modern systems	Outdated, not secure by today's standards	High computational cost, susceptible to chosen ciphertext attacks

4. Conclusions

This study introduced a robust Underwater Digital Twin-Based Sensor Network designed for maritime communication and monitoring along the Coromandel Coast, utilizing EHC-ANFIS. The proposed model was evaluated using the “NSL-KDD” dataset. The CosLU-VS-LSTM model demonstrated exceptional capability in anomaly detection, achieving impressive accuracy and recall rates of 98.62% and 99.15%, respectively, thereby underscoring the model’s effectiveness. Furthermore, the EHC-ANFIS model excelled in facilitating decision-making influenced by Digital Twins, achieving a minimal rule generation time of 51452ms, which indicates the model’s low time complexity. In addition, the TKCC model effectively secured data, attaining a high-security level of 98.01% and a low attack level of 1.99%, thereby affirming the model’s reliability. The AP-ACO model also successfully identified the optimal communication path, achieving a response time of 8701ms. Consequently, the proposed framework demonstrated efficient maritime communication and monitoring

capabilities for the Coromandel Coast. While the current research effectively applied Digital Twin-based decision-making for disaster management in this region, it did not account for various coastal ecosystems, such as coral reefs, salt marshes, mangrove forests, and kelp forests, which are vital for disaster management. Future work will incorporate these coastal ecosystems to enhance the framework's performance.

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