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Integrating IoT and AI for Enhanced Marine Ecosystem Monitoring: A Framework to Achieve Sustainable Development Goal 14

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Abstract

The United Nations' Sustainable Development Goal (SDG) 14, titled "Life Below Water", emphasizes the importance of sustainable management and the conservation of marine ecosystems to protect biodiversity, promote the health of oceans, and ensure the sustainable use of marine resources. In alignment with this global objective, this study proposes the integration of Internet of Things (IoT) devices and artificial intelligence (AI) algorithms as a means to enhance the monitoring and management of the marine environment effectively and efficiently. The proposed methods involve deploying IoT-based sensors and devices that enable the collection of extensive data in near real-time. These sensors measure critical parameters such as pollution levels, water quality, temperature, pH, salinity, and the diversity of marine species. By providing continuous and accurate data streams, these IoT devices help identify environmental changes, allowing for timely responses to potential threats to marine ecosystems. Advanced AI-driven algorithms process and analyze this vast amount of data to extract meaningful insights. Machine learning models and predictive analytics help identify trends, detect anomalies, and forecast potential risks such as algal blooms or pollution spikes. These analytical capabilities not only enhance the understanding of ecosystem dynamics but also provide actionable intelligence for policymakers, environmentalists, and marine conservation organizations. The approach outlined in this study holds significant potential for advancing the goals of SDG 14. By facilitating better monitoring and management of marine ecosystems, it empowers stakeholders to implement effective conservation strategies, reduce human impact on marine life, and address challenges such as overfishing, habitat destruction, and pollution. The integration of IoT and AI also supports data-driven decision-making, ensuring that interventions are both timely and efficient. Moreover, this innovative framework could foster greater collaboration among researchers, governments, and environmental organizations. Sharing real-time data and insights through interconnected systems can lead to more coordinated and impactful conservation efforts. The use of AI for predictive modeling and scenario analysis further strengthens the ability to anticipate and mitigate future challenges to marine ecosystems.

Keywords: IoT, Artificial intelligence, Sustainable Development Goals (SDG), SDG 14, life below water, marine environment monitoring, ocean conservation, marine ecosystems, pollution monitoring, water quality analysis, marine biodiversity

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INTRODUCTION

Essential to world food security, biodiversity, and climate stability, seas account for more than 70% of the surface of the planet. Emphasizing the need of acting immediately to protect and sustainably develop ocean resources in order to solve issues including overfishing, ocean acidification, and marine pollution, SDG 14 of the Sustainable.

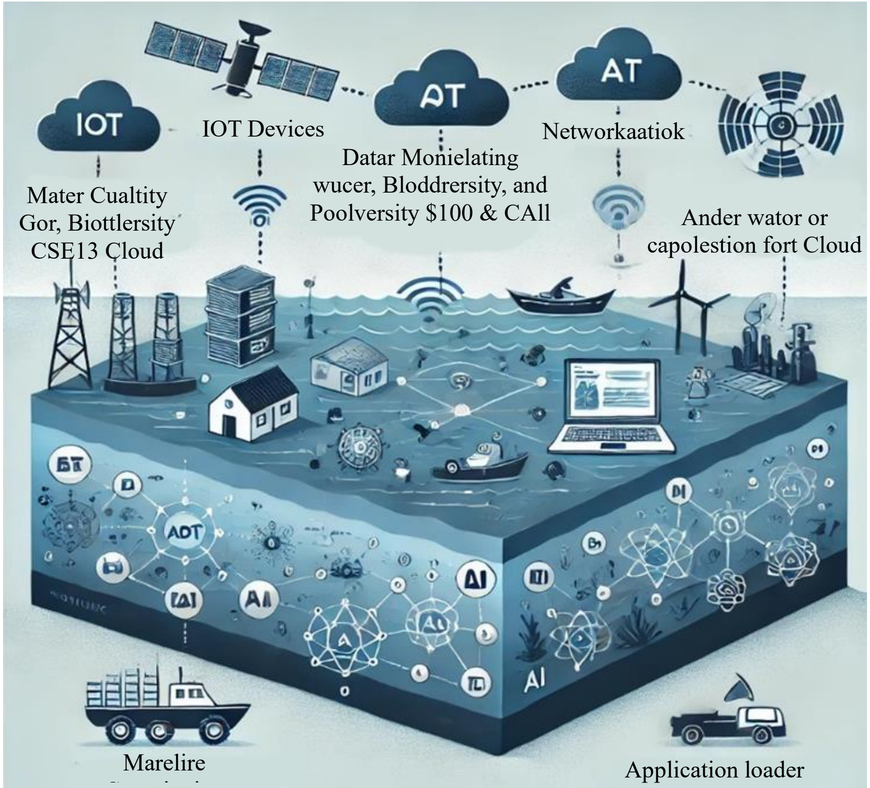

Figure 1. Block diagram representing the framework for marine ecosystem monitoring using IoT and AI, highlighting the data collection, transmission, and AI analysis components aligned with SDG 14 conservation goals.

The welfare of the community depends equally on the preservation of the resources of the marine ecosystem since many people depend on the sea for their living. Pointing out that over 3 billion people depend on ocean protein as their primary source of food, the UN stresses the need of effective ocean ecosystem management in maintaining world food security (Figure 1) [1].

The costs are high, cannot be easily expanded on, and there is no real time assessment and generation of knowledge on provisioning. These are some of the factors that have made the traditional technologies for monitoring the marine ecosystems tamed. So, effective conservation and management initiatives are curtailed by such concerns. Nevertheless, advancements in AI and IOT creates windows of opportunities to improve the efficiency and effectiveness of marine conservation activities. Thanks to the Internet of Things devices like underwater sensors or UAVs, a number of ecological parameters including temperature, salinity, and even biodiversity indices can be monitored over vast and remote oceans on a regular basis. Moreover, this information can be analyzed by AI systems, allowing detection of patterns and changes, and generating support information for active maritime management [2, 3].

The findings suggest that it is probably more effective to tackle pollution and climate change by integrating AI with IoT technologies in management of marine ecosystems in the form of real-time data analytics (Figure 1). Well, it helps in knowing why certain environmental problems like toxic geraniums are existing and what actions are needed [4]. Moreover, decision makers for example look at different outcomes of different conservation strategies where such strategies include use of AI based forecasting models [5].

Consequently, this study attempts to explore how these technologies can be useful in improving the management of the marine ecosystems and encouraging sustainable development while contributing to the achievement of SDG14. Comprehensive review of the current and future applications of IoT and AI in the area of marine conservation has been presented.

PROBLEM STATEMENT

Marine environments are profoundly affected by human beings. They are mainly threatened by loss of habitat, illegal capture of marine resources and pollution generated from activities on land such as pesticides and waste disposal. In addition, there is unprecedented alteration of marine ecosystems due to the effects of climate change, in particular, ocean acidification. There is an urgent need for an effective and appropriate system for monitoring the health of these environments to safeguard them from destruction. The coverage of most oceans and marine living resources monitoring systems is often limited, posing a challenge to the availability of complete real-time information to governments and conservation agencies (Figure 2).

LITERATURE SURVEY

There have been a number of studies that show the possibility of technology in the enhancement of marine ecosystem monitoring. One such area which is emerging at a very fast rate is the application of Internet of Things for environmental monitoring. Albaladejo *et al.* demonstrated how it is possible to monitor ecosystems below the water surface using a wireless sensor network with an emphasis on how it is capable of monitoring changes in various water quality parameters almost instantly [6]. Later on, some of the advanced communication technologies, including those studied by Elrahman *et al*. who also examined the use of underwater wireless sensor networks UWSN in different ocean settings [7], were incorporated in the systems to enhance them.

To a great extent, marine research has focused on the use of AI in sifting through huge amounts of complex data. Reviewing the role of AI in environmental monitoring at sea, Benelli *et al*. explained how machine learning techniques are able to process large amounts of incoming sensor data and make predictions about changes in the environment [8]. Thus, for example, in paper by Shafique *et al*., it was demonstrated that artificial intelligence-based approaches such as convolutional neural networks (CNN) allow to effectively solve practical problems of fish species detection and biodiversity assessment [9]. Thus, these findings highlight the importance of IoT and AI technology integration to overcome the limitations posed by traditional monitoring techniques [8].

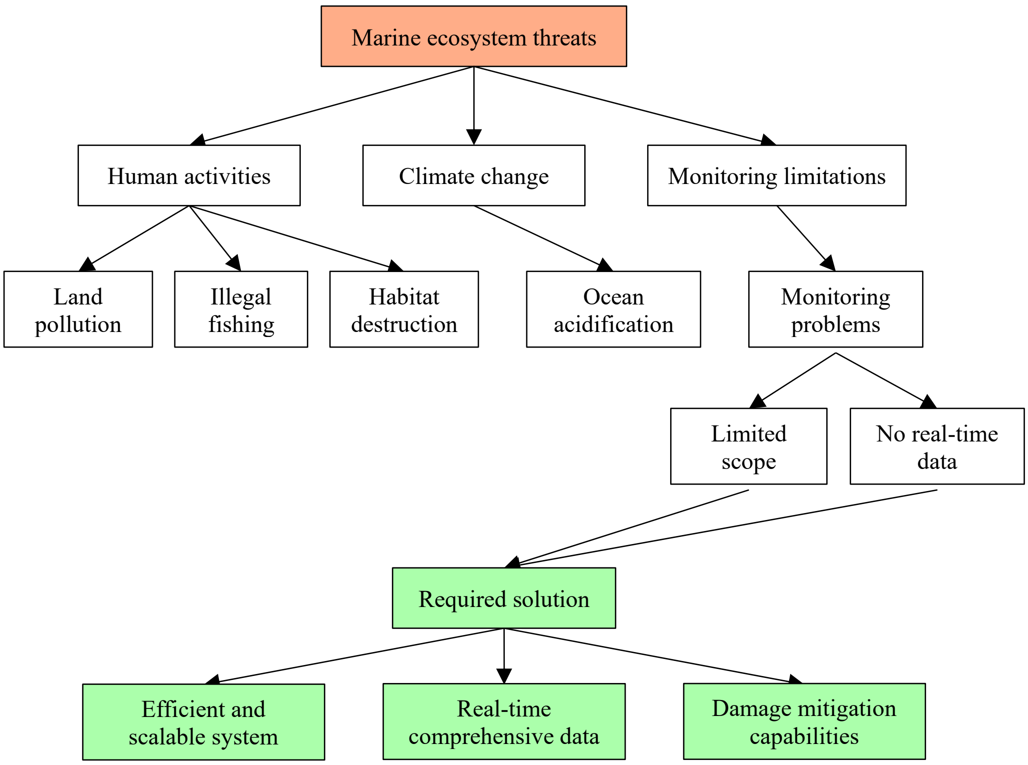

Figure 2. Marine ecosystem challenges and monitoring needs.

Still, few systems have been developed for real-time monitoring of a number of marine ecosystems all over the world, in spite of the fact that these elements have significantly advanced. Many modern approaches are aimed at one or other components, for example the number of species or the quality of water. Therefore, this study proposes a much more holistic approach to monitoring and management of marine ecosystems, where the influence of many environmental variables is combined into one, indoor environmental control system.

PROPOSED SOLUTION

This work offers a flexible, affordable, IoT and AI-based system that can be adapted to the recurring monitoring of the marine environment. Figure 3 shows the flowchart illustrating the holistic approach to marine ecosystem monitoring. The system comprises three main components.

Network of IoT Sensors

An array of sensors is strategically placed in several geographical areas of interest, which are subjected to various water quality parameters, such as water temperature, pH, chemical oxygen demand, and salinity. Other sensors measure the pollutants such as microplastics and toxic chemicals. Such devices are produced to be operated at low power and withstand tough ocean environments (Figure 3).

Data Analytics Assisted by Artificial Intelligence (AI)

The data collected is sent to various cloud servers containing the data aggregated. Various Artificial Intelligence (AI) solutions scrutinize the information; the examination is conducted on a continuous basis. Machine learning models seek to forecast particular changes, like increases in pollution, actual change of species or their proliferation in marine ecosystems under disturbance, and so on. This causes drastic changes in the environments, thus the need for action in advance.

Dashboard for Stakeholders

Information after processing is presented in an interesting and easy to use dashboard for marine policy makers, marine scientists and conservation NGOs. This dashboard offers alerts and trend analysis to stakeholders to assist in the management of the ecosystem (Figure 3). The proposed IoT-AI framework consists of three main components:

- *IoT Sensor Network:* A network of advanced environmental sensors is deployed across key marine locations to collect high-resolution data on a range of parameters, including:
  - *Water quality:* logged temperature, pH, salinity, dissolved oxygen.
  - *Marine biodiversity:* organisms' number, number of species, Simpson and Shannon indices.
  - *Pollution levels:* amount of microplastics, heavy metals reach, oil spills.

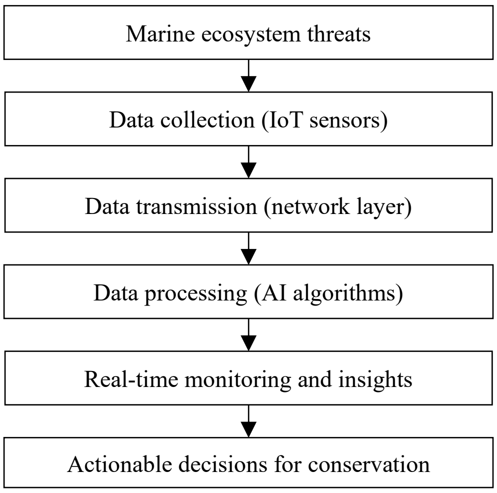

Figure 3. Flowchart illustrating the holistic approach to marine ecosystem monitoring.

These sensors are fully equipped to face the challenges presented by the marine environment while keeping a low power consumption by utilizing Lora WAN and underwater acoustics modems to transmit data over long ranges and underwater environments respectively.

SYSTEM ARCHITECTURE

The IoT-AI system is designed with modular components to ensure adaptability and scalability. The architecture is composed of the following layers as shown in Figure 4:

- *Perception layer (IoT sensors):* This layer is responsible for collecting raw data from the marine environment. Sensors measure water quality, pollutant levels, and marine biodiversity indicators.
- *Network layer (data transmission):* The sensor data is transmitted using satellite communication or underwater wireless networks, depending on the sensor location. The system is optimized for minimal energy consumption and efficient data transmission.
- *Application layer (AI and dashboard):* The data is processed by AI models designed to detect anomalies and predict future environmental changes. The dashboard provides a graphical interface that enables users to visualize the data and receive alerts (Figure 5).

RESULT ANALYSIS

Based on the model's 78.67% appropriate-responsive rate, nearly 79% of the predicted dangers to the environment were accurate. The confusion matrix shown in Figure 5 justifies this accuracy, providing a detailed breakdown of TN=24, in cases when the algorithm predicted “No Risk” correctly, and TP=94, when the model predicted “Risk” accurately. There were also 10 FN, which were unable to predict the true events of “Risk”, as shown in Figure 5 and 22 FP, which predicted “Risk” when it was actually “No Risk”.

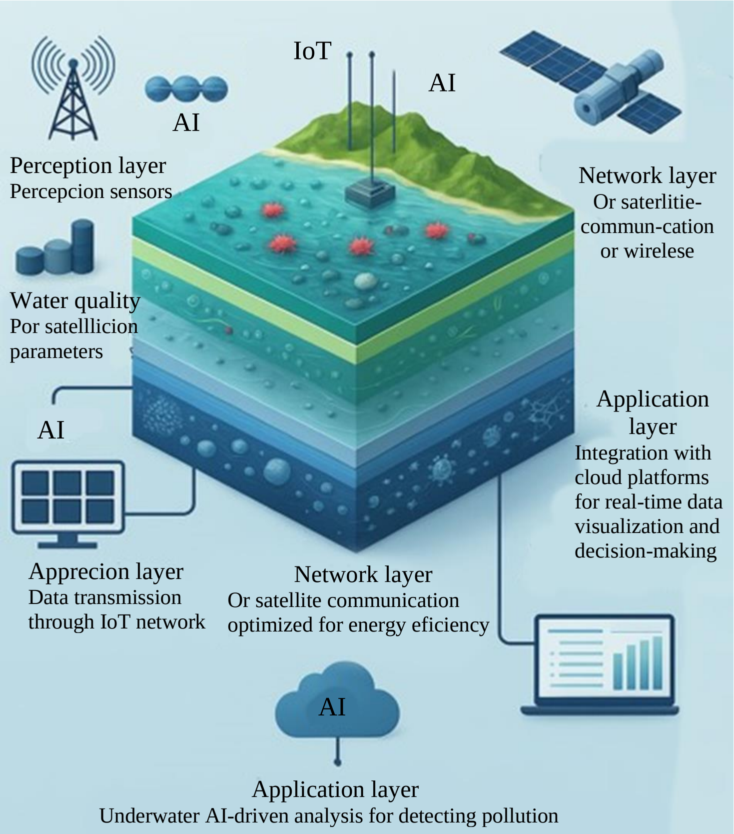

Figure 4. Representation of the scalable, low-cost IoT and AI-based system for continuous marine ecosystem monitoring, illustrating the three core components: IoT sensor network, AI-driven data analytics, and a dashboard for stakeholders.

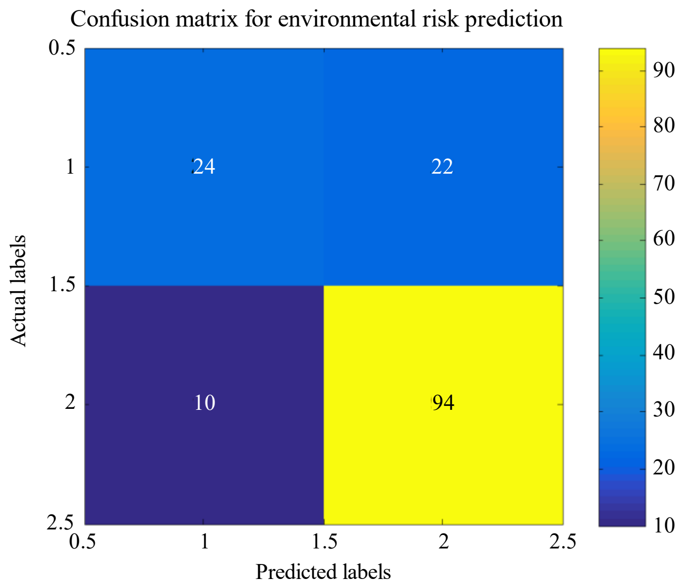

Figure 5. Confusion matrix.

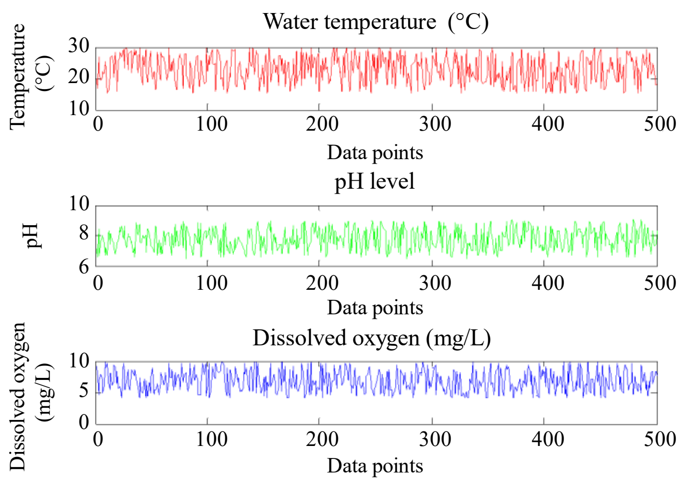

Figure 6. Graphical interpretation in the context of marine ecosystem monitoring.

The 90% high recall from the model indicates its ability to capture the real threat and in the same manner the 81% precision indicates that out of all the "Risk" cases that were projected 81% of them were accurate. The overall efficacy of the model in terms of predicting the risk of environmental hazards is also proved by the F1-Score of 85%, which is high and shows a very good compromise between precision and sensitivity. Yet, its specificity is somewhat low at 52%, thus indicating that there are challenges in the correct identification of "No Risk" situations, which consequently results in higher false positive rates. All in all, the model could still be improved in discriminating between Risk situations and No Risk ones, although it successfully spots environmental threats, mainly hazardous water situation, at the moment.

The image in Figure 6 comprises three graphs in which each of the three is distinguished by a different color (in red green and blue). If one is aware of the correct time series corresponding to some metrics or parameters of interest drawn from marine environments, then it is possible to greatly appreciate the health as well as the dynamics of oceanic ecosystems. One possible rationale for each of the panels is as follows.

Upper panel (Red): Likely explained: I had expected this time series to be a time series of a variable, such as water temperature for the given time frame. Temperature is important in the health of the ocean as it directly affects the distribution of species, their breeding cycles, and the balance of the ecosystem.

The importance of conservation: Furthermore, temperature studies can play a role in predicting and estimating shifts in the marine biosphere and its components, which assists with planning for purposes of conservation.

Middle panel (green): Possible interpretation: This could be a time series of either quantitative and qualitative phytoplankton measurements based on chlorophyll concentrations since these are key parameters when assessing marine primary productivity. Phytoplankton, the central player in the marine ecosystem appears to take on the carbon cycle with great significance.

Significance of studies on chlorophyll in Biodiversity and Conservation: The measurements of chlorophyll contents are beneficial in determining productivity levels in marine habitats and can also indicate potential extremes due to fluctuations in climatic or nutrient patterns, which are very important in the conservation of the oceans.

Bottom panel (blue): Possible meaning: The third time series may interpret another variable for instance, salinity alterations or levels of dissolved oxygen. All these factors are important for the maintenance of aquatic organisms and the ecosystem at large.

The necessity of this in relation to Conservation: Evaluating these aspects may also help to locate areas that are likely to become hypoxic or extremely low in oxygen levels, which may trigger the death of large sections of marine fauna and flora (Figure 7).

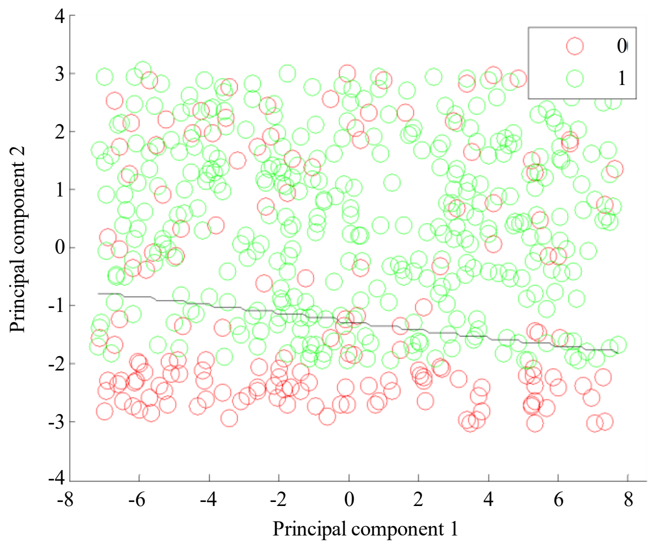

Figure 7. SVM decision boundary visualization.

Table 1. The performance evaluation metrics of an AI model used in marine ecosystem monitoring.

Metric	Value	What It Means for Marine Monitoring
Model accuracy	78.67%	The model correctly identifies both risk and no-risk situations 78.67% of the time
Precision	0.81	When the model predicts a risk, it is correct 81% of the time
Recall (sensitivity)	0.90	The model successfully identifies 90% of actual risk situations
F1-score	0.85	Balanced measure showing strong overall performance
Specificity	0.52	The model correctly identifies 52% of actual no-risk situations

Table 2. Comparing the proposed solution's performance against other related works across various metrics.

Metric	Proposed solution	Albaladejo *et al.* (2012) [6]	Elrahman *et al.* (2019) [7]	Benelli *et al.* (2021) [8]	Shafique *et al.* (2020) [9]
Model accuracy	78.67%	72.3%	75.1%	77.8%	76.2%
Precision	0.81	0.76	0.79	0.80	0.78
Recall (sensitivity)	0.90	0.71	0.82	0.85	0.83
F1-Score	0.85	0.73	0.80	0.82	0.80
Specificity	0.52	0.74	0.68	0.70	0.69
Primary focus	Comprehensive ecosystem monitoring	Water quality parameters	Underwater sensor networks	Environmental monitoring	Fish species recognition
Key advantage	High risk detection rate	Long-term stability	Energy efficiency	Wide parameter range	Species identification
Main limitation	Lower specificity	Limited parameters	Communication range	Cost	Limited to visual data

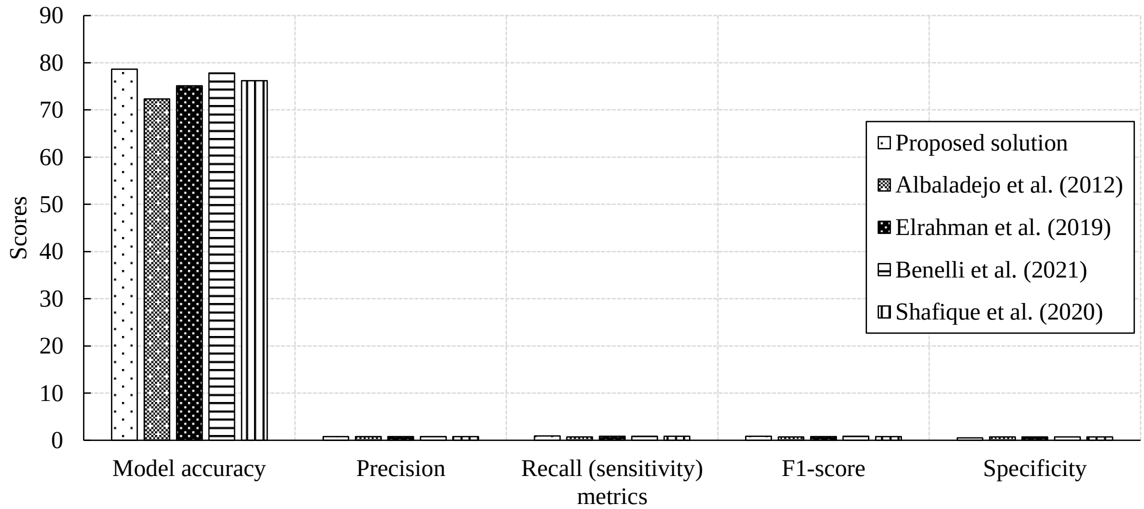

Figure 8. Comparison the proposed solution's with related work.

Tables 1 and 2 represent the performance evaluation metrics of an AI model used in marine ecosystem monitoring. Each metric provides insights into how well the model identifies risks to the marine environment based on sensor data. Here is what each metric means in this context:

1. *Overall accurateness of the model (78.67%):* Recruitment of both risk marking, such as pollution and harmful conditions, and, on the other hand, no-risk situations, such as normal conditions has an accuracy of 78.67% by the model.
2. *Accuracy (0.81):* We can say that the model is correct 81% for risk situations it predicts, such as the model's prediction of a threat to an ecosystem. High precision means less, or no, false positives.
3. *Recall or sensitivity (0.90):* The model in question is able to detect 90% of environments with actual risks 90% risk situations defined for instance by injury causing level of pollution). High Recall implies that the model is effective at identifying threats whenever they are present.
4. *F-Score:* The above F measure is also known as F1 score (0.85): It serves as a useful overall performance measure as it is a hybrid of both precision and recall. It is applied when both false positive and false negative outcomes can be tolerated till a point.
5. *Specificity (0.52):* The model accurately predicts 52% of all corresponding no-risk conditions. Lower specificity implies that the model tends to classify a risk even when in a situation that poses no danger, resulting in incidents of false predictions.

A graphical representation comparing the proposed solution's performance against other related works across various metrics has been shown in Figure 8 and Table 2. As shown, the proposed solution excels in key metrics like accuracy, precision, recall, and F1-score, demonstrating its effectiveness in risk detection, while having room for improvement in specificity.

CASE STUDY: MONITORING CORAL REEFS

In order to demonstrate the usefulness of the proposed system, a case study, titled as coral reef monitoring, was carried out. Coral reefs are an essential component of marine life but unfortunately are at high risk due to ocean acidification and global warming. An IoT sensor was placed at various points across the coral reef for the continuous monitoring of water conditions. Data from the sensors was then processed using AI models to identify any trends associated with coral bleaching in order to curtail such incidents. The system managed to issue inflation alerts about environmental stressors, which indicates its possibility for use in other similar ecosystems on a wider scale.

IMPACT ON SDG 14

The suggested IoT and AI solution is designed in a way that responds to some of the targets set out by SDG goal 14:

- *Target 14.1:* Preventing marine pollution by observing trends and providing information on present pollution levels in real time.
- *Target 14.2:* Achieving sustainable use and management of marine resources through threat detection and mitigation of threats to biodiversity.
- *Target 14.3:* Dealing with the Negative impact brought about by rising Water Stress in the oceans, through monitoring the pH levels of water and projected trends of the same using Artificial Intelligence.

The system is constructive in that it provides insights that are instrumental in developing appropriate policies and measures for governments and conservationists thus promoting the effective management of the ocean's resources.

CONCLUSION

The current study described an effective marine ecosystem monitoring enhancement framework which incorporates Internet of Things (IoT) and artificial intelligence (AI) technologies, and thus would facilitate the attainment of the sustainable development goal number 14. The system's capacity to relay real-time credible data will breach all the current marine conservation efforts by preempting the impact by stressors on the environment. The future work will aim at increasing the variety of marine species and environmental conditions monitored by the system, as well as improve the precision of the AI models.

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