Ocean of Things: Marine Environment Monitoring using Discriminatory Model

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Abstract. It is generating complex Marine Environment monitoring models for the ocean-based on data from Discriminant Analysis. The Ocean of Things (OoT) is adopted in this paper to help interface multiple sensors to predict climate conditions for Aquatic life monitoring. This study, therefore, contemplates five years of climate observations in two oceans. An effort is made to study the temperature, salinity, current of water, how it varies with relation to the ocean, and the reasons for differences in the location parameters. The findings are based on Canonical correlation, Lambda of Wilks, and characterization in general. It is found that the generated model is useful for weather forecasting and aquatic life monitoring.

Keywords: Ocean of things, Underwater Internet of Things, Canonical correlation, standard deviation, Discriminant function

1. Introduction
Smart cities and oceans have developed recently. One of the most powerful instruments that can use for this development is the "Internet of Things (IoT)," which is also known as "The information society infrastructure" [1]. In 1985, found the principle of IoT [2] [3], then the Internet of Underwater Things (IoT) was first taken up in 2012 [3]. IoT defines the "network of smart interconnected underwater objects." "Ocean of Things (OoT)" is a new IoT category and an important part of smart Oceans' evolution. OoT is a research development used to fill the technological gap by deploying smart, low-cost vessels that serve as a decentralized sensor network. In the literature, growing attempts have been made to emphasize the importance of OoT [3-5]. Three key reasons are provided. First, more than 72 percent of the land on earth is occupied by water, even though some of the marine areas remain undiscovered. Secondly, IoT / OoT is predicted to have multiple changes in the platform. Third there have been more advanced stages of waterproofing developments for underwater communication and facilities. This is also a good time for IoT / OoT research to be performed.
Since it is commonly used in numerous aquatic and coastal ecosystems [6], OoT has gained much interest in the proliferation of various marine activities. Typical IoT applications include monitoring of the ocean environment, aquatic species tracking, tactical surveillance, aquaculture oversight, etc. [7,8,10,11]. Usually, there are multiple sensors and source nodes in the IoT. Underwater sensor nodes send sensed information to source nodes usually placed on the top of the water surface. Sink nodes then send data collection to offshore equipment such as ships and vessels. Computational-intensive data processing operations must be performed in mobile data processing hubs, typically located far enough from the connectivity area. However, building and maintaining the IoT and onshore data center link
infrastructure is not cost-effective.

Figure 1. Model of IoT in Marine Environment

The IoT model, shown in Figure 1, typically includes surface nodes for underwater sensors, "Autonomous Underwater Vehicles (AUVs)" computes the node for underwater transmission modules for underwater processing and transmission and modules for base station seashore and coastal control. Valuable ocean data is obtained from underwater sensor nodes by a large number of individuals. The resulting data fusions are accomplished with the information from intelligent computation and when transmitted by sub-water AUVs and nodes. Underwater and AUVs nodes can use many deepwater networking technologies to relay data to shore processing and transmitting systems. Several Surface, Underwater Edge servers analyze useful surface data for aquatic applications and transmit it to cloud or offshore control centers through radio communication. Offshore control hub produces intelligent solutions based on data obtained from cloud Repositories from the ocean and the Internet to enable human ocean operations. Another essential feature of the IoT is an underwater wireless sensor network that provides marine data and enhances users' effectiveness to monitor and predict events in the underwater environment [12]. The description of this article's conduct can be summarized as follows.

- The various advances in the field of IOUT are discussed based on different literature surveys.
- The benefits of the Ocean of Things and its role in the present and future research field are explained.

The challenges faced in the IoT are summarized based on the underwater environment with its research issues.

An Underwater system architecture based on the Internet of Things is elaborated with the discriminant results for monitoring marine environment applications.

2. Advances in IOUT

The IoT's functions and structure are identical to IoT. Besides, the IoT has its particular network characteristics, and the IoT, for instance, is a complex network, sparse in density, a large-scale network. The network and its channels for communicating underwater are poor. Such features make the IoT a network of new forms, which demands more research. The key differences between the IoT and the IoT are found in [13].
Five-layer device architecture, including the application, network layer, and layer of awareness, is shown in figure 2. The authors of [14] summarize IoT, introducing realistic underwater applications, disparities between UWSNs, and wireless terrestrial networks for sensors. Finally, they tested the model is analyzed in the underwater acoustic channels. The following are unique studies by the IoT. The MAC-layer packet scheduling for the IoT, defined in [15], has been studied in the studies. A role-based scheduling protocol for sender-receiver high computing utilization and high energy efficiency is designed in this paper, using spectrum spatial-temporal reuse to facilitate smart underwater data transmission. For climatic monitoring underwater [16], the concept of the IoT-based architecture and data analytics were presented in five system modules: remote-operated devices, a moveable water sensor, an observation system for coral reefs, a quality examination system, a data analytics processing platform, and Wireless Mesh Networks communication. In the [13] protocol for data processing and power consumption optimization in IoT's core network, the authors proposed an improved channel-aware routing.

3. Benefits of Ocean of Things
The OoT software will support various communities by generating analytics for actions for both ecological data products and maritime data products. Ecological goods are sold at high-density levels in wide areas. Surface temperature, for instance, which can enable a better view of weather patterns, can improve the fundamental oceanographic systems of atmospheric shifts [17]. For instance, it improves the precision of satellite derivatives in far-field measurements. In-situ measurements can also deliver more accurate results for particular primary models alongside remote sensing data measurements. This enhances our knowledge of marine life. The distribution of organisms for better aquatic management of fisheries and tools is one advantage of OoT. Acoustic data can be obtained on a fine Spatio-temporal scale capable of quantifying, labeling, characterizing, and tracking marine mammals and detecting background noisescapes. This can be used to improve our understanding of sea mammals in coastal bodies of water.
By obtaining a more reliable and precise detection method, observing the appearance of aquatic animals near sea lanes, mammals, and shipping could mutually benefit both industries. This initiative will also create algorithms for the automatic identification, registration, and detection of nearby vessels and vessels. Identification of new, unusual maritime activity criteria, unlawful fishing practices are a significant part of the challenge addressed by OoT [15].

4. Challenges
Realizing IoT’s vision is not an easy job since it has many problems to deal with. The major hypotheses and primary methodologies are demonstrated for the first time in constructing the future smart ocean IoT networks. The key challenges in the underwater network are presented in this paper. The paper also presents the IoT-based open problems, and the difficulties in the various fields are discussed. In oceanography, Major hypotheses of the ocean are included, which may impact the IoT design, such as optics of the ocean, the ocean’s acoustics, marine Electromagnetics, and the nature of the ocean [10]. In the principal theories of the underwater, the network should be considered when constructing the portion of the IoT underwater network that has the regulation of underwater topology, underwater topology, protocols for routing, the architecture of the underwater network, and underwater repairing a network. These theories may provide ideas for design and theoretical research to develop the underwater segment in IoT. Three major difficulties and open problems are discussed as follows, as per our research of the characteristics of the marine ecosystem and in the most previous surveys of an underwater network:

- Underwater Insecure Channel disrupts with Performance Communication by Underwater.
- In smart Oceans, UWC is introduced for more Speed and Large distance coverage.
- Node Versatility and Equipment uniformity affect the Underwater Networking performance.
- Extremely reliable and self-assertive production of networking for the technique of large-Scale IOUT.

Transmission technologies from the media are these main issues. Although optical and radio signals are possible neither for UWSNs to transport data or from terrestrial wireless sensor networks (TWSNs) is feasible. High attenuation and absorption of radio signals are present in High frequencies in underwater conditions. At low levels, the frequencies can transmit radio signals for longer distances. However, it needs high transmitting power and large antennas. Underwater conditions also make it difficult owing to the increase in absorption and scattering of optical signals in the IoT; optical signals can only be propagated for a very long time in the normal case. In underwater conditions, greater attenuation and absorption of acoustic signals can travel even longer distances to transmit optical signals (than both radio and radio). As a result, UWSNs use acoustic signals for the transport of awareness in most instances. These issues can have a major influence on communication and communication protocols applied to the IoT, but they cannot be specifically applied to the IOUT[17]. It is important to establish communication protocols for IoT; therefore, in table 1, IoT problems are summarized.

Table 1: Challenges of IoT

| Parameters                  | Challenges                      |
|-----------------------------|---------------------------------|
| Propagation Speed (Delay)   | ~ 1500m/s                       |
| Reliability                 | Low and Unstable                |
| Transmission Rate (BW)      | ~ 10 – 100kbps                  |
| Battery (Energy)            | Difficult to replace/ recharge  |
| Mobility                    | It depends on the water current.|

5. System Structure
Environmental monitoring for weather forecasting and Aquatic life monitoring is explained in figure 3. The sensors sense the ocean data, and the sensed data is transferred to the connecting device using IoT.
The transferred data is then communicated to the network, which is then analyzed using the discriminant model. The data analyzed is used for monitoring applications and weather forecasting.

![Block Diagram of IoT for Marine Applications](image)

**Figure 3.** Block diagram of IoT for Marine applications

The IoT is a complex structure containing various heterogeneous system networks; the design of a scalable layered structure is critically important. Several IoT system architectures know the researchers' needs, and the industry focuses on such needs. The basic three-layer architecture of IoT, consist of the operation layer, the communication layer, and the perception layer, has been proposed. The five-layer IoT structure architecture consists of two elements, as shown in Figure 2, both underwater and non-underwater. Application, merger, networking, collaboration, and layer sense are included in the IoT system. There is an independent architectural feature and usability on each layer of the device. These technologies have a considerable impact on growth. IoT is considered a model for establishing a uniform set of configurable cloud services computing services with invisible, easy, on-demand network access. Fog computing on the cloud server of [12] is much more time-sensitive than cloud services, a virtualized system for computing, storage networking between end devices and conventional devices. Machine Learning in Artificial Intelligence algorithms can tackle many IoT problems, such as artifact selection, object tracking, file transfer, channel detection, protection, and service quality. The concept of machine learning is implementing computational techniques by sensing accuracy and identifying and planning data patterns to improve the machine's effectiveness.

### 6. Results and Discussions

The significance for the analysis of different types of ocean and its results are discussed under various subtitles.

#### 6.1. Basic statistics

The two oceans' Indian and Arctic Ocean statistics are explained in the following table with their mean and the standard deviation. Table 2 shows a huge variation in the temperature and the salinity in the Indian and Arctic oceans. This is because the Indian Ocean plays a key role in monitoring the Asian monsoon's average climate and stability and the tropical dynamics.

| Ocean          | Temperature (°C) | Salinity (ppt) |
|----------------|------------------|----------------|
| Indian Ocean   | 28.0             | 32-37          |
| Arctic Ocean   | 0.0              | 30             |

The Central-East Indian Ocean characterizes a warm pool with sea surface temperatures (SST) greater than 28.0°C during the summer. This temperature variation also lies in the variation in the salinity of the ocean, which is 32-37ppt. Since the Arctic Ocean lies in the middle of the northern part, its salinity is the lowest 30 ppt of all the 5 major oceans. The water current is compared in both the cases of the Indian and Arctic oceans. The Indian Ocean is the warmest compared to the Arctic. Because, The Sun in the Arctic is always low on the horizon, even in the middle of summer. In winter, the Sun is so far below the horizon that it doesn't come up at all for months at a time. So the ocean remains cold throughout the year. As the warm water moves fast compared to cold water, the Arctic Ocean has a 2.5m/s water current. The statistical analysis states that the Indian Ocean has a fast transmission rate compared to the Arctic Ocean since it remains cold throughout the year.
### Table 2: Group Statistics

| Oceans          | Parameter   | Mean  | Std.deviation |
|-----------------|-------------|-------|---------------|
| 0(Indian Ocean) | Temperature | 24.9973 | 1.99986       |
|                 | Salinity    | 34.8318 | 1.64493       |
|                 | Water current | 13.0272 | 1.72398       |
| 1(Arctic Ocean) | Temperature | 0.8488  | 0.53052       |
|                 | Salinity    | 27.9978 | 2.28170       |
|                 | Water current | 247.9395 | 4.62495       |

6.2. Test for Equality of group means and Correlation

The correlation matrix is calculated for the values that are observed in the Oceanic conditions. From table 3, the result obtained for all the parameters does not exceed 0.5 of the variables observed, which shows that there is no occurrence of high inter-correlations among the independent variables in this model. The group matrices state that the possibility of correlation is less by using the Discriminant model.

### Table 3: Group Matrices

|         | Temperature | Salinity | Water current |
|---------|-------------|----------|---------------|
| Correlation | Temperature | 1.000    | 0.21          |
|         | Salinity    | 0.021    | 0.005         |
|         | Water current | -0.002  | 0.005         |

6.3. Standardized Canonical Discriminant Function Coefficients

Table 4 gives the result of a standardized canonical discriminant model whose function is given as:

\[
D = (-0.160) \times (temperature) + (-0.021) \times (salinity) - (0.278) \times (watercurrent) - (-33.546) \ldots \ldots \ldots (1)
\]

The standardized model D's discriminant function is the variable's values per day obtained in the Indian and Arctic oceans shown in table 4.

### Table 4: Standardized Group Matrices

| Parameter      | Function (1) |
|----------------|--------------|
| Temperature    | -0.160       |
| Salinity       | -0.021       |
| Water current  | 0.278        |
| Constant       | -33.546      |

6.4. Summary of canonical discriminant functions

As shown in Table 5, the discriminant function for Eigenvalue is 1202 is explained with a 100% variance. The canonical correlation coefficient is 0.936, and its squared value is 87.6%. This clearly shows that the discriminant model explains 100% of the variation between the two oceans.
Table 5: Eigenvalues

| Function | Eigenvalue | % of values | Cumulative % | Canonical Correlation |
|----------|------------|-------------|--------------|-----------------------|
| 1        | 1202.294   | 100.0       | 100.0        | 0.936                 |

Table 6: Wilks’ Lambda

| Test of functions | Wilks lambda | Chi-square | Degrees of freedom | sig. |
|-------------------|--------------|------------|--------------------|------|
| 1                 | 0.001        | 25871.054  | 3                  | 0.000|

In table 6, Wilks’ lambda shows the importance of the built discriminant function. The value of Wilks’ Lambda is 0.001. The Chi-square statistic is 25871.054 with 3 degrees of freedom, and the p-value is 0.000. As the value of p is less than 0.05, we can infer that the discriminant function is efficient in monitoring.

6.5. Standardized Canonical Discriminant Function Coefficients and structure matrix

The standardized canonical discriminant function coefficient from Table 7 can be represented as

\[ D = (-0.235) \times (\text{temperature}) + (-0.46) \times (\text{salinity}) - (0.970) \times (\text{watercurrent}) \]

(2)

The coefficients of the standardized discriminant function are independent of units of measurement. The absolute value of the standardized discriminant function coefficient shows the relative contribution of the variables in discriminating between the Indian and the Arctic Ocean. The results show that temperature is the primary variable between the Indian and Arctic oceans in a significant manner, followed by water current, salinity, and temperature as shown in table 7.

Table 7: Standardized canonical Discriminant Function Coefficient

| Parameters      | Function (1) |
|-----------------|--------------|
| Temperature     | -0.235       |
| Salinity        | -0.046       |
| Water Current   | 0.970        |

6.6. Group centroids and classification matrix

The primary aim of constructing a discriminatory feature is to build a decision model at two different locations to observe the oceans.

We can separately measure the mean discriminant scores for the Indian Ocean and the Arctic Ocean. It’s known as the Centroids Group. It.

The latest average is -34.674 for the Indian Ocean, and +34.655 for the Arctic Ocean indicates that the midpoint of these two is 0.

i. The means for the transformed Centroids Group are shown in table 8.
### Table 8: Functions at Group Centroids

| Ocean       | Function (1) |
|-------------|--------------|
| 0 (Indian)  | -34.674      |
| 1 (Arctic)  | 34.655       |

A classification matrix is constructed, and this matrix shows the summary of correct and wrong classification of observations (days) in both the Oceans based on the developed discriminant model. These results are presented in Table 9. It is to be noted that 97.4% of original grouped cases are correctly classified. The predicted results give 97.4% accurate classification and have the least error rate of 2.6% in Discriminant model prediction.

### Table 9: Classification Result

| Classification | Ocean          | Predicted Group | Total |
|----------------|----------------|-----------------|-------|
|                | Indian         | Arctic          |       |
| Original count | 0              | 1               | 1825  |
|                | 1              | 0               | 1826  |
| %              | 0              | 96.2            | 3.8   |
|                | 1              | 1.3             | 98.7  |

7. **Comparative Analysis**

Table 10. Comparative Analysis of Indian and Arctic Ocean from the Discriminant model

| Parameters                  | Indian Ocean                  | Arctic Ocean                  |
|-----------------------------|-------------------------------|-------------------------------|
| Temperature                 | 22-28°C / 71-82°F             | 1.8°C / 28.8°F               |
|                             |                               | <2°C in winter                |
|                             |                               | 0°C / 32°F in summer          |
| Salinity                    | 32-37 ppt                     | 30-34 ppt                     |
| Water current               | High as compared to Arctic Ocean (∼ 1500 m/s) | Low (2.5 m/s)               |
| Depth                       | ~12,762 ft.                   | ~4500 mts                     |
| Ocean Type                  | Warmest                       | Coldest                       |
| Efficiency for Underwater applications | High                          | It is very less compared to the Indian ocean. |
| Cost for deployment         | High                          | High                          |
| Mobility                    | It depends on the water current. | It depends on the water current. |
| Maintenance                 | High                          | High                          |

The discriminant model is a statistical analysis tool used to classify the environment and justify it in table 10. A comparative analysis is made from the above results that are obtained using the discriminant model. The table tabulates the nature of the Indian and Arctic oceans. The parameters define the feasibility for Underwater Applications using OoT.
8. Conclusion
In the current analysis, the discriminant model for oceanic data structure in two locations is addressed using OoT and IoT. The climate data viz., Temperature (°C), salinity (ppt), and water current (m/s) are observed for 5 years and are analyzed using the discriminant approach for monitoring the marine environment, Aquatic life monitoring, weather forecasting. Its outcome states a greater variation concerning temperature and salinity between the Indian and Arctic oceans. The classification matrix based on the discriminant model reveals that 97.4% of the original classes are correctly classified, useful in Weather Forecasting for the Marine research environment. This model can be extended to predict future weather conditions concerned with the variables like temperature, salinity, water current using the discriminant model.

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