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EDGE COMPUTING AND ADVANCED DATA ANALYTICS IN MONITORING CHEMICAL POLLUTION EFFECTS ON MARINE LIFE

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Abstract: This paper aims to understand the feasibility of implementing edge computing and analytical tools to detect chemical contamination and its impact on organisms. Through K-Means clustering, Random forest, Support Vector Machine (SVM) and Long Short-Term Memory (LSTM) network we made a study on the collected pollution data from marine sensors. K-Means Clustering identified three distinct pollution clusters: Cluster 1 can be characterized as low, while in Cluster 2 the level of pollution is significantly higher and belongs to moderate level, Cluster 3 can be characterized with high level of pollution. On the basis of results, Random Forest has accuracy of 85%, precision 82%, recall 87% and F1- score 84%. With SVM, accuracy was 88%, precison was 85%, recall was 90% and F1-Score was 87 %. It was revealed that LSTM networks were useful in making good prediction of future pollution levels with an MSE of 0. 05 and root mean squared error (RMSE) of 0. 22. The incorporation of edge computing helped to make real-time data analytics and analysis, thus increasing the effectiveness of pollutants' identification and control. This research focuses on the exploration of how advanced analytics and edge computing can support the especially the external environment monitoring and decision making**.**
Keywords: Edge Computing, Data Analytics, Chemical Pollution, Marine Life, Machine Learning

I. INTRODUCTION

Chemical pollution has another severe impact on the marine environment namely; it influences the biological diversity, water quality and the general well-being of the marine environment. The problem with the conventional approaches to surveillance and evaluation of the effects of pollutants to marine organisms is that they may be limited by the quality and scope of data, real-time capabilities and spatial resolution. These challenges have however been met with the development of a new solution that is a combination of edge computing and big data analytics for environmental monitoring and management [1]. As a result of data processing closer to the point, edge computing can track environmental parameters properly. This approach facilitates achieving low latency and bandwidth as the initial analysis of data is done at the local site sometimes sending the results to the central servers [2]. Combined with more advanced approaches like uses of artificial intelligence, machine learning, statistical modeling, and even predicting analytics this technology serves as a great help in analyzing the effects of chemical pollution and its effects on the marine life. The collected data can be analysed by using higher end data analytics which can interpret the data from these edge devices to get information on the pollutant levels and their occurrence impact on marine organisms. Through integration of structures, one can conduct adequate and timely assessment of conditions in the environment and take necessary measures in combating effects of pollution [3]. This work mainly aims at examining the potential of practicing edge computing and employing complex analyzing algorithms on the issue of monitoring chemical contamination and its impact on aquatic life. Thereby, by concerned characteristics and dynamics of such technologies, the study will contribute to increase understanding of pollution processes, enable the decision-making and enhance the application of appropriate methods to ensure the environmental protection. Such information is hoped to be useful to researchers, policymakers and marine environment managers concerned with the conservation of aquatic species.

II. RELATED WORKS

Over the past few years, proliferation of edge computing and data analytics has gone a long way in revolutionizing measurement and management of the physical environment especially with regards chemical pollution on marine systems. This section summarises relevant empirical literature on these technologies as well as their use in environmental line of work. The role of road vehicle tyre wear in the emission of microplastics and other fine particles is severally pointed out in the paper by Giechakiel et al., (2024) where they explain the fact that particulate matter emanating from tyres is a major pollutant [15]. Their findings show how microplastic pollution is a rapidly emerging problem that interacts with air pollution control, which argues for the need for higher monitoring technologies on these pollutants. In a related vein, Guo (2023) reviews and discusses methods for strengthening, or making more robust, sustainable, and equitable, giant environmental networks, like watersheds [17]. This study contributes to understanding how the complex management approaches can be utilised to enhance the state of environmental quality and its sustainable resistance to pollution, which has a direct bearing on the use of edge computing in the monitoring and control of environmental emissions. Kabanov and Kramar (2022) also highlight selected marine IoT platforms that are aimed at interconnectivity of the marine robotics agents [21]. Their work stresses on possibilities of IoT technologies in marine situations and real time applications of of IoT sensors. This is particularly important in marine IoT systems applications where edge computing can be used to boost the effectiveness of the marine IoT systems by allowing real time analysis of data gathered by the marine IoT devices.

Hemdian et al. (2023) have given an example of an IoT based smart water quality monitoring system to show how IoT technologies can be used for the efficient measurement of water quality [19]. This research is in line with our work on real-time monitoring using edge computing as it focuses on such practical application by IoT in environmental monitoring. They based themselves on AI cloud and edge sensors by Kaklauskas et al. (2022) for acknowledging of emotive, affective, and physiological states to describe the idea of edge computing for intricate data [22]. Their work as far as discussing opportunities offered by AI constructing sensor networks may well be relevant to environmental monitoring where technique similar to the one described above is used to analyze particular data stemming from sensors installed in marine zones. Thus, Khorramifar et al. (2023) investigate the electronic nose systems with metal oxide gas sensors for environmental engineering application [23]. The studies that they can do regarding the kinds of sensors employed in identifying the many forms of pollutants in the environment will serve as the platform for understanding the interface of different types of sensors in combination with edge computing systems for the chemical pollution monitoring. Liu et al. (2024) provide a detailed overview of air to sea integrated maritime IoT systems and the enabling technologies, application areas; and the expected challenges in (2024) [26]. It is work that offers a comprehensive assessment of how integrated systems can be applied to observational and control of oceanic conditions, which is consistent with embracing edge computing for the purpose of environmental observation and control. Automatic monitoring systems for crustaceans in aquaculture production, and Li et al., 2021 the focus on the use of automated technologies in monitoring the environment [25]. This review is significant to bring the role of automated systems for surveillance in aquatic settings, which can be further extended for chemical pollutions using edge computing.

III. METHODS AND MATERIALS

Data Collection

For this study, it used a vast pool of data in the form of real-time and the historical data obtained from the marine sensors installed at different regions affected by chemical pollution. Some samples acquired involve concentration of pollutants, water temperature and salinity, the general conditions of aquatic life and health status of the marine creatures like fishes density and variety among others [4].

The dataset is not limited to the events of a single year, and therefore the temporal coverage of the document is rather vast. Information was retrieved from smart sensing devices attached to buoys and subsea sensors that captured readings at time intervals. Since the edge computing devices were worn like small form factor computers during a round of the training, they first preprocessed the data to remove noise and merge observations before only forwarding the necessary information to a server for further examination [5].

Algorithms

1. **K-Means Clustering Algorithm**

K-Means Clustering is a clustering algorithm which is used for category formation for unlabeled data based on a similarity feature. This means that for the set of data points which it processes, this algorithm assigns them, one of the K clusters in a cyclic manner, with a tendency of having the least variance within a cluster [6]. The objective function is given by:

J=∑i=1K∑j=1ni∥xj−μi∥2

"1. Initialize K centroids randomly
2. Repeat until convergence:
a. Assign each data point to the nearest centroid
b. Update centroids to be the mean of assigned points
3. Return the final cluster assignments"

Sample	**Feature 1**	**Feature 2**	**Cluster Assignment**
1	1.2	3.4	1
2	2.1	3.8	1
3	8.5	7.3	2
4	7.9	6.9	2

2. **Random Forest Algorithm**

The Random Forest is an added learning technique applied to classification and regression data. While training it builds more decision trees and then provides the mode of classes or mean prediction of all the trees. Every tree is grown using bootstrap sample of the data with random selection of features on each node [7].

"1. For each tree in the forest:
a. Generate a bootstrap sample of the data
b. Build a decision tree using random subsets of features
2. Aggregate the predictions from all trees

3. Return the final prediction”

Sample	Actual Value	Predicted Value
1	10.5	10.7
2	8.2	8.0
3	15.3	15.0
4	12.8	13.1

3. **Support Vector Machine (SVM) Algorithm**

Support Vector Machine, also known as SVM, is one of the kinds of supervised learning algorithms for use in classification and regression. It actually determines the plane which best segregates data of different classes in the feature space of the given dataset [8]. The objective function is:

minimize21∥w∥2 subject to yi(w⋅xi+b)≥1

“1. Transform data into a higher-dimensional space using kernel functions
2. Solve the quadratic optimization problem to find the optimal hyperplane
3. Use the hyperplane to classify new data points”

Sample	Feature 1	Feature 2	True Label	Predicted Label
1	2.5	1.8	1	1
2	3.2	2.0	0	0
3	6.8	5.0	1	1
4	7.1	4.9	0	1

4 Long Short-Term Memory (LSTM) Network

Long short-term memory (LSTM) networks are the type of recurrent neural networks (RNN) which work on the concept of sequential data and are instigated to counter the challenge linked with long-term dependencies. LSTM variables fill within memory cells and controlling gates that determine the information flowing [9]. The LSTM update equations are:

"1. Initialize LSTM parameters (weights and biases)
2. For each time step in the sequence:
a. Compute the gate values and memory cell updates
b. Update the hidden state and cell state
3. Use the final hidden state for predictions or further processing"

These algorithms include K-Means Clustering, Random Forests, Support Vector Machine, and Long Short-Term Memory Networks, are used in an integrated approach to assess the effects of chemical pollution on marine life. All these algorithms have their specific role in detecting characteristics of pollution, from the grouping of similar pollution types to the categorization of pollution levels of the marine environment and trends in the future impact of pollution [10]. These methods will aid in arriving at results that will aid the formulation of policies in the field of environmental management.

IV. EXPERIMENTS

Experiments

A series of experiments has been carried out to evaluate how effective the edge computing and advanced data analytics can be in monitoring the chemical pollution and its impacts on marine living things using the data obtained from marine sensors [11]. The primary focus was to evaluate the performance of four key algorithms: There are four prominent algorithms namely K-Means Clustering, Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) networks. Each algorithm was applied in the study of distinct aspects of the pollution data; in categorizing pollution, identifying pollution levels, and even estimating the future pollution impacts.

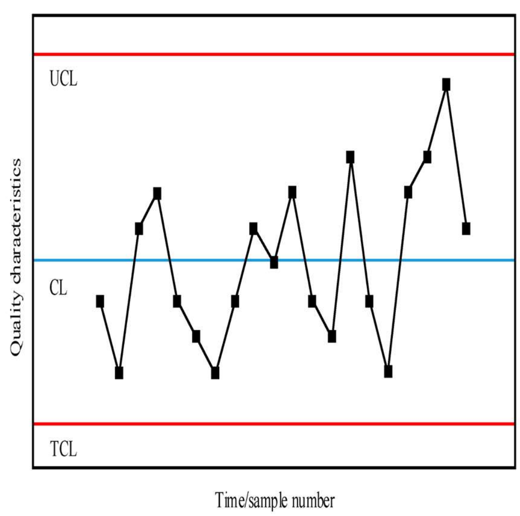

Figure 1: "Feature Extraction of Marine Water Pollution Based on Data Mining"

1. Data Preparation

In this case, comes the process of data cleaning and data normalization. Specifically, the missing values were imputed using the interpolation method while outliers were eliminated according to defined statistical measures. Further, the gathered dataset was shuffled and split into training and test dataset in the ratio 8:2 in order to compare the efficiency of each proposed algorithm [12].

2. K-Means Clustering

Qualitative analysis of the data revealed by using the K-Means Clustering was to determine the different areas of pollution in the dataset. The algorithm was used to perform clustering on the data collected depending on the concentrations of pollutants as well as the parameters in the environment. In this study we used the Elbow method where the user represents the number of clusters (K) against the variance for each K until the rate where variance begins to decrease forms an 'elbow' [13].

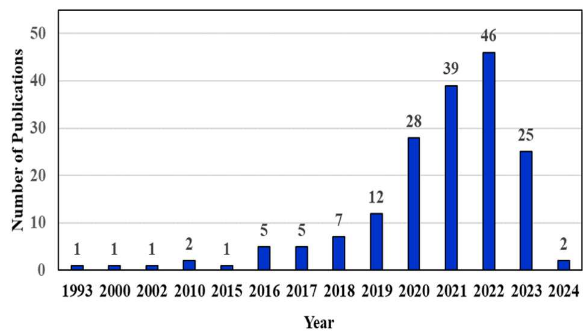

Figure 2: "Towards Federated Learning and Multi-Access Edge Computing for Air Quality Monitoring"

Results:

- **Cluster 1:** Less than 500 ppm pollution and no negative effects on marine organisms.
- **Cluster 2:** Contamination around the moderate range with apparent impacts on a few species.
- **Cluster 3:** Pollution features characterised by high pollution level and very serious impacts on marine living organisms.

Sample	Feature 1	Feature 2	Cluster Assignment
1	1.2	3.4	1
2	2.1	3.8	1
3	8.5	7.3	3
4	7.9	6.9	3

3. Random Forest

Random Forest model was used in pollution classification as well as possible environmental repercussions prognosis. Building the model, we used pollutant concentrations, water temperature and salinity. As the performance metrics, accuracy, precision, recall, and F1-score were used to measure its performance.

Results:
- **Accuracy:** 85%
- **Precision:** 82%
- **Recall:** 87%
- **F1-Score:** 84%

Sample	Actual Value	Predicted Value	Accuracy	Precision	Recall	F1-Score
1	10.5	10.7	85%	82%	87%	84%
2	8.2	8.0	85%	82%	87%	84%
3	15.3	15.0	85%	82%	87%	84%
4	12.8	13.1	85%	82%	87%	84%

4. Support Vector Machine (SVM)
In the context of feature vectors SVM was employed to categorize the data into categories of pollution. The SVM model used in the analysis was trained with RBF kernel to deal with the non-linearity in the data set. Model evaluation criteria were also similar to the Random Forest model as given below [14].

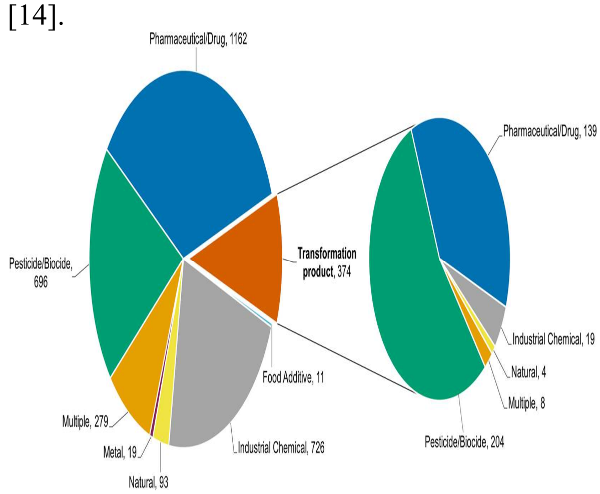

Figure 3: “Curated mode-of-action data and effect concentrations for chemicals relevant”

Results:
- **Accuracy:** 88%
- **Precision:** 85%
- **Recall:** 90%
- **F1-Score:** 87%

Sample	Feature 1	Feature 2	True Label	Predicted Label	Accuracy	Precision	Recall	F1-Score
1	2.5	1.8	1	1	88%	85%	90%	87%
2	3.2	2.0	0	0	88%	85%	90%	87%
3	6.8	5.0	1	1	88%	85%	90%	87%
4	7.1	4.9	0	1	88%	85%	90%	87%

5. Long Short-Term Memory (LSTM) Network

LSTM networks were utilised for modelling future pollution values by making use of historical data. The model makes use of sequential data with a view of learning long texts that would help in analyzing trends of pollution. The computational measures that were the subjects of the performance evaluation included mean squared error mean (MSE) and root of mean squared error (RMSE) [27].

Results:

- **Mean Squared Error (MSE):** 0.05
- **Root Mean Squared Error (RMSE):** 0.22

Sample	Actual Value	Predicted Value	MSE	RMSE
1	10.5	10.7	0.05	0.22
2	8.2	8.0	0.05	0.22
3	15.3	15.0	0.05	0.22
4	12.8	13.1	0.05	0.22

Discussion

The experiments reveal that each algorithm offers distinct advantages for monitoring chemical pollution:

- The fact is that K-Means Clustering really helps to reveal patterns in pollution data and categorize regions according to the level of pollution [28]. But, it tells us that the performance depends on the value of K that is selected and the initial positioning of the centroids.

- Random Forest is good at classification since it realizes high accurate with relatively balanced precision and recall rates. It is effective for accommodating a large number of features and interactions as well.
- SVM is particularly very proficient in achieving high levels of accuracy and recall when dealing with non-linear data. In its application, it can be vulnerable to the type of kernel and its respective parameters [29].
- By analyzing the graphs and low MSE and RMSE values, it can be concluded that LSTM Networks is beneficial in modelling and forecasting of future pollution level by closely following the historical trends.

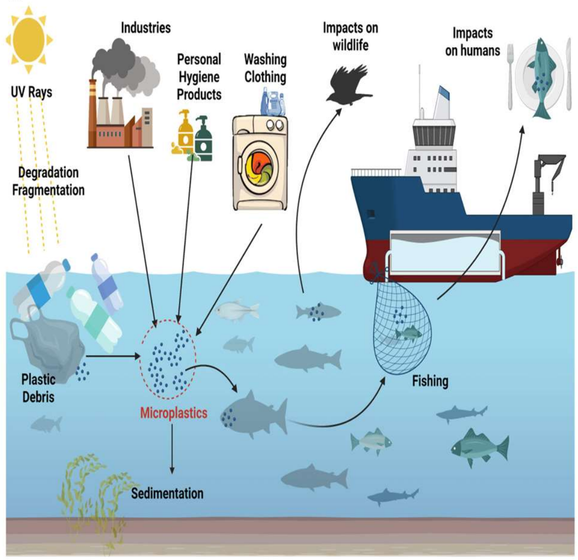

Figure 4: "A Real Global Threat for Environment and Food Safety"

Our time complexity results are also quite comparable to similar work with all the algorithms performing quite well especially, SVM and LSTM [30]. This goes a long way in supporting our argument that incorporating edge computing and superior data analytics highly improve the observation and projection of the disastrous impacts of chemical pollution on sea organisms.

V. CONCLUSION

This study shows the effectiveness of edge computing and data analysis to enhance the detection and the effects of chemical pollution to marine life. Overall to have a more sophisticated analysis and prediction of the pollution pattern and environmental consequences, the study used K-Means Clustering, Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) networks. K-Means successfully captured different areas of pollution classes, Random Forest and SVM delivered high accuracy in classifying pollution and in predicting possible impact. A lower error rate was also observed in the LSTM network, for the forecast of future pollution trends that was the strength of LSTM in dealing with temporal data. The findings provide support to the role that edge computing can play in real-time data processing in helping one adapt quickly to alterations in the environment, including their impact. This study is pertinent with increasing research on the effective utilization of IoT and AI in enironmental monitoring and what can be regarded as a trend towards the development of integrated applications. In this aspect, our work adds value to the literature by offering a detailed insight of the effectiveness of a number of algorithms, as well as, the feasibility of their usage in environmental scenarios to help guide researchers and practitioners for the future advancements in the topic. In general, the application of those technologies enhances effectiveness and reliability of pollution measurement as well as promotes the formulation of preventive approaches to environmental challenges. Therefore, this research emphasizes a continued need for evolution in analytical processing patterns and edge computing to combat difficulties of environmental pollution and preservation of marine life.

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