2023 International Conference on Data Science and Network Security (ICDSNS)

Water Quality Analysis from Satellite Images

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***Abstract*—Remote sensing has proven to be an efficient tool for monitoring water quality due to characteristics such as high coverage and less time consuming. Because of its capacity to capture the possible association between water quality metrics and satellite imagery, machine learning has increasingly been applied for water quality retrieval. This study focuses on the usage of Sentinel-2 images for qualitative water quality analysis of four different saline water bodies – Arabian sea, Bay of Bengal, Lonar lake and Arabian sea near the southern coastal region of Indian subcontinent. The proposed work calculates normalized difference chlorophyll, turbidity and salinity index and classifies the water quality using ML classification algorithms. The study also performs comparative analysis of five different classification algorithms: Random Forest, K-nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree, and Naive Bayes. According to the results, Random Forest outperformed the other four algorithms with 94% accuracy in classifying the water quality into good or poor category. The key findings demonstrates that Bay of Bengal region is comparatively less contaminated and saline as compared to the Arabian sea and Lonar lake which shows high amount of salinity and chlorophyll-a concentration ranging from 25 to 30 mg m^{-3}.**

Keywords—Sentinel-2, Chlorophyll-a, turbidity, salinity, qualitative water quality, remote sensing.

I. Introduction

Water quality generally refers to the extent to which water is fit for a specific use and whether or not pollutants in the water are a threat to the environment. Complex and varied water quality challenges demand immediate worldwide attention. Due to its intrinsic potential to significantly affect the hydrological cycle, the reduction in water quality has become a global problem. Even the changes in the saline water bodies results in drastic effect on the biological diversity and environment. Due to the enormous rise in population and the quick rate of urbanization, there is a significant impact on the environment. Water's spectral characteristics fluctuate with wavelength of incident radiation due to both its molecular makeup and contaminants in the water body. Water quality evaluation is accomplished by comparing the water's physiochemical and biological properties or characteristics to a set of standards. Water quality assessment can be defined as "the evaluation of the physical, chemical, and biological state of the water in relation to its natural state, anthropogenic effects, and future uses."

To monitor water quality using remote sensing, the relationship between spectral reference and water quality indicators must be established. Water quality evaluation can make use of the benefits of remote sensing, such as synoptic coverage, development of databases in close to real time, and the availability of multispectral and multi-temporal data. Electromagnetic radiation from the earth's surface, such as reflected sunlight or emitting thermal infrared rays is detected by remote sensors. Remote sensing delivers high spatial and temporal resolution water quality data and aids in the assessment of environmental issues by analysing changes in water quality.

The proposed work focuses on the data obtained from Sentinel 2 satellite. With a returning period of 10 days, it provides multi-spectral data in 13 bands over the visible, near-infrared, and short wave infrared spectrums. The Sentinel-2 twin satellites were used to monitor water quality due to their superior spatial resolution (10-20-60 m) and open data policy. In order to meet the operational requirements of the Copernicus Programme, the European Commission (EC) and European Space Agency (ESA) developed the Sentinel-2 multispectral imaging mission that aids coastal and inland waterway surveillance, soil and water cover monitoring, etc.

The significant contributions of the proposed work can be described with the help of below points:

- Analysis of water quality using remote sensing helps to reduce the need of in-situ observations of water quality parameters which is labour-intensive and time-consuming.
- Satellite images provide time-series data which can be used to study recent state of the water body. The proposed work collects sentinel-2 data of Arabian sea, Bay of Bengal and Lonar lake to analyse and compare the quality of these saline water bodies.
- Normalized difference chlorophyll index (NDCI) and normalized difference turbidity index (NDTI) altogether provides efficient method for qualitative assessment of water quality where no in-situ data is present.
- The extracted water quality parameters can be used to categorize a water body into good-quality or poor-quality categories using classification algorithms.

The elucidation of the proposed work has been structured and organized into different sections and sub-sections such as related works (literature survey and limitations of existing systems), methods, results and discussion, conclusion and references.

II. RELATED WORKS

A. Literature survey

- Using Landsat 8 satellite data and virtually real-time in situ measurements, A.K. M. Azad Hossain et al. [1] developed a numerical turbidity estimation model for the Tennessee River and its tributaries in Southeast Tennessee. When there is a lack of in-situ data, researchers often turn to qualitative investigations to make educated guesses about the turbidity levels. In cases where precise projections aren't needed, such qualitative forecasts may be helpful in gauging the state of the water. It highlights the development of the Normalized Difference Turbidity Index (NDTI) as a turbidity metric for qualitative study.

- In accordance with the concept proposed by Vaibhav Garg et al. [2], an analysis of the change in the turbidity of river water quality was conducted using only Sentinel-2 multispectral remote sensing data. Using this data, the visible area changes in the spectral reflectance of water along the river in Haridwar, Prayagraj, Kanpur, and Varanasi was analysed. According to the findings, the red and NIR wavelengths can be used to detect turbidity because they are the most sensitive. Improved spatial, spectral, and temporal resolution datasets, would enhance the accuracy of remote sensing.

- In their study [3], Kaire Toming et al. explored the potential of employing Sentinel-2 Multispectral Imager (MSI) data to map a variety of lake water quality metrics. Sentinel-2 Level-1C and atmospherically corrected Level-2A images were used to build band ratio algorithms that were compared to in-situ measurements of chlorophyll-a, water color, colored dissolved organic matter (CDOM), and dissolved organic carbon. One limitation of this work is the inability to formally evaluate the effectiveness of Sen2cor atmospheric correction due to lack of up-to-date field radiometry data.

- In their work, researchers Yuanhong Li et al. [4] wrote about what they did to measure amounts of nitrogen, phosphorus, bacteria, and total solids. To show these connections, they used machine learning to train three different estimators, including ridge regression (R-PLS), stochastic gradient descent (SGD), and normal equation linear regression (LR). The method described in this piece can only be used with a small subset of lagoon effluent contamination indicators. Some things cannot be checked for heavy metal pollution based on signs that cannot be seen.

- It was proposed in a paper by Xidong Chen et.al. [5] to use time-series data to create a cloud-free composite image of China during the summer of 2015. The first 30-meter-resolution Forel-Ule index (FUI) water colour product in China was developed using the newly-created BAP composite and the Google Earth Engine platform. The research had a flaw that in optically shallow regions, the influence of bottom reflectance could alter the observed water color. Since there is currently no system for properly identifying shallow pixels on a global scale, signals from the silt and plants at the bottom of the sea may also contribute to the reflectance above water.

- Ersan Batur et.al. [6] suggested research describing the PCA model for monitoring the surface water quality in Gala Lake. The model created in this study was entirely based on the surface water quality features of Lake Gala observed during the summer since surface water quality models are only applicable to the relevant site and season. It is required to gather and evaluate lengthier measurements to create a model that works for all time periods. Ingenious models have been developed to more accurately forecast surface water quality metrics using band ratios and long-term data.

- Hendrik Jan Van Der Woerd et.al. [7] proposed a research paper in which it is possible to determine the hue color of the body of water, but not all of the colors can be determined with equal accuracy. Despite having only four small bands in the visible spectrum and one large band in the IR, the CZCS sensor proved remarkably good in retrieving the hue angle for the majority of angles.

- Shungudzemwoyo P. Garaba et.al. [8] proposed research where a change in field observation is one potential source of uncertainty; personnel can affect FUI observations because the human eye's perception of color varies greatly. Water depth and FUI colors don't appear to be correlated in any obvious way. Due to the FUI scale's restriction to discrete numerical values, clustering will have an impact on correlations with other continuous water constituents.

- The research to assess the viability of the Sentinel-2 imaging for lake monitoring during the 2020 Pacific typhoon was proposed by Caballero and G. Navarro [9]. The Case-2 Regional CoastColour processor is used to provide water quality parameters such total suspended matter and chlorophyll-a. Results demonstrate that compared to pre-storm conditions, Typhoons Goni and Vamco delivered large suspended sediment loads to the reservoir. Additionally, the Google Earth Engine platform uses the normalized difference chlorophyll index (NDCI) for near-real time monitoring.

- R. Sivakumar's use of satellite remote sensing techniques to evaluate the water quality [10] indicated that there had been an improvement in lake water quality throughout the lockdown. i.e., an improvement of 30.60% in lake water clarity. During these challenging periods, it may be possible to estimate the lake water quality using satellite image processing techniques.

- The research by Hasab, Jawad, Dibs, Hussain, and Ansari [11] focuses on Al-Hawizeh wetland of Iraq. Due to post-war events and human activities, this marsh's water quality has drastically declined in recent decades. Based on the construction of mathematical models for salinity and minerals, Landsat-8 data was utilised to forecast and assess the geographical fluctuation and map distributions of the salinity, SO4, and CaCO3 within Al-Hawizeh Marsh over the two seasons in 2017.

B. *Limitations of the existing systems*

After studying the related work, it was observed that the existing systems considered the relation between in-situ data and values extracted from satellite images. For instance, the study by C. Lal and S. Kumar [12] demonstrates combination of remote sensing and field observations. However, this approach proves to be less significant where there is no in-situ data available. Therefore, the proposed work focuses on analyzing water quality parameters such as turbidity, Chlorophyll-a and salinity of Arabian sea, Bay of Bengal, Lonar lake and Arabian sea near the southern coastal region of Indian sub-continent using NDCI, NDTI and NDSI to determine qualitative water quality for comparison. Due to the limitations imposed by Landsat 8's revisit period and cloud pollution, it cannot be used to continuously track changes in water quality throughout the year. Therefore, this proposed system uses Sentinel-2 with lower revisit period as compared to Landsat 8. Sentinel-2 also provides atmospherically corrected data which can be used to obtain more accurate images.

III. METHODS

The proposed system can be viewed as a series of steps such as selecting the region of study, Sentinel-2 data collection, data processing and applying ML models to classify the extracted values into good or poor quality. It also performs comparative analysis of classification algorithms.

A. *Region of study*

The proposed work focuses on deriving qualitative water quality parameters of four regions as described in Fig. 1 to Fig. 4 – Arabian sea along the western coastal region surrounding Mumbai, Lonar lake, Bay of Bengal and coastal water near the southern Indian region. Strong seasonal oscillations in biological production are a feature of the Arabian Sea, one of the significant water bodies on earth. Goes and Gomes found that chlorophyll-a levels in the Arabian Sea have been rising gradually during the 1990s—as much as four times higher — using ocean color data from NASA in a 2020 research study [13]. According to the literature survey, the Arabian Sea has a higher concentration of chlorophyll in comparison to the Bay of Bengal region [14]. The salinity parameter has a slight variation among each other as all the regions possess high alkaline levels. Scientists from many different fields have been interested in Lonar Lake for a long time. It is an inland salt crater in the Buldhana district of Maharashtra. Scientists looked at the physicochemical qualities of water samples and found that the water is high in alkalinity, sulphate, sodium, total dissolved solids, magnesium, chloride, and dissolved oxygen. It also has a high pH.

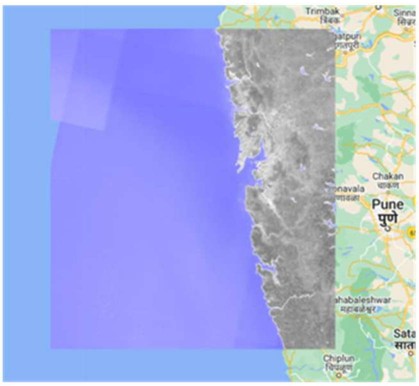

Fig. 1. Arabian Sea

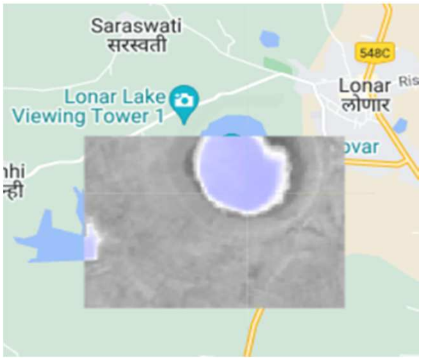

Fig. 2. Lonar lake

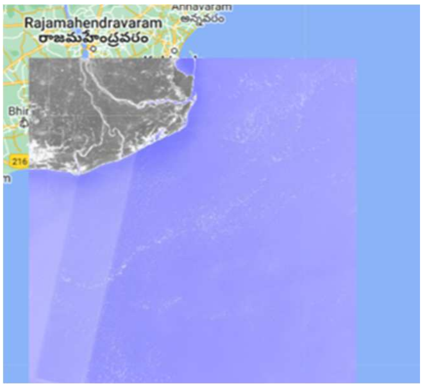

Fig. 3. Bay of Bengal

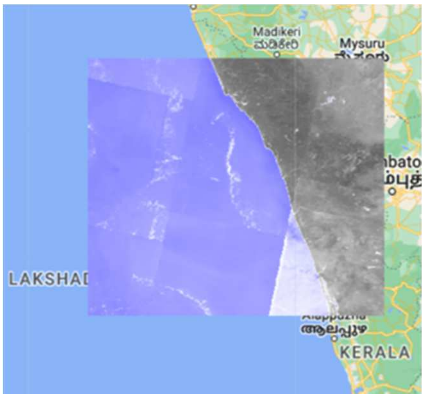

Fig. 4. Arabian sea near southern coastal region of India

The proposed work determines quality of water on the basis of the following parameters-

- Turbidity: Water clarity is gauged by turbidity (i.e., transparency). Water can seem cloudy or murky when suspended particles, such as silt, algae, plankton, and sewage, are present. Instead of allowing light to pass through the water directly, these particles scatter and absorb light waves. A greater turbidity rating denotes cloudier, "thicker," and more particle-filled water. The turbidity of water is low when it is clear.
- Salinity: Salinity is an indicator of how much salt is in a body of water. The majority of the salt in seawater is sodium chloride (NaCl). A mixture of dissolved ions, including sodium, chloride, carbonate, and sulphate, can result in some lakes having a high salinity level. Water used for irrigation or drinking can have a worse quality due to salts and other impurities.

- Chlorophyll: The concentration of phytoplankton is determined by the amount of chlorophyll present in a water sample. These metrics help us comprehend the system's overall biological "health," including its trophic status and primary output. Chlorophyll measurements can forecast hazardous algal blooms and identify algal bloom occurrences and their impacts on water quality.

B. Sentinel-2 Data collection

Typically, satellites utilize sensors to gather electromagnetic radiation reflected from land and oceans as they orbit the Earth, some of which pass over a certain region every day. The most pertinent wavelengths for measuring the quality of water bodies are visible and near-infrared light. TABLE I describes various satellites with their respective sensors and resolution.

TABLE I. SATELLITES WITH THEIR RESPECTIVE SENSORS

Satellites	Sensors	Resolution
Landsat 7	Enhanced Thematic Mapper (ETM+)	185 km swath; 15 m, 30 m, 60 m; 16 days revisit
Landsat 8	Operational Land Imager (OLI)	185 km swath; 15 m, 30 m, 60 m; 16 days revisit
Terra & Aqua	Moderate Resolution Imaging Spectroradiometer (MODIS)	2330 km swath; 250 m, 500 m, 1km; 1-2 days revisit
Sentinel 2A & 2B	Multi Spectral Imager (MSI)	290 km swath; 10 m, 20m, 60 m; 5 days revisit
Sentinel 3A	Ocean and Land Color Instrument (OLCI)	1270 km swath; 300 m; 27 days revisit

The work that is being proposed acquires the data from Sentinel-2A, which has a Multispectral Imager (MSI) sensor. The Copernicus programme has image dataset and the related information. As the satellite moves along its orbital path, the sensor picks up new information. The incoming light beam is split by a beam splitter and focused on two different focal plane units inside the instrument, one for Visible and Near-Infrared (VNIR) bands and one for Short Wave Infrared (SWIR) bands. The spectral separation of each band is split into individual wavelengths by stripe filters that are placed on top of the detectors. TABLE II describes Sentinel-2A bands with its resolution and description.

TABLE II. SENTINEL-2A BANDS

Band	Resolution	Description
B1	60 m	Ultra Blue (Coastal and Aerosol)
B2	10 m	Blue
B3	10 m	Green
B4	10 m	Red
B5	20 m	Visible and Near Infrared (VNIR)
B6	20 m	Visible and Near Infrared (VNIR)
B7	20 m	Visible and Near Infrared (VNIR)
B8	10 m	Visible and Near Infrared (VNIR)
B8a	20 m	Visible and Near Infrared (VNIR)
B9	60 m	Short Wave Infrared (SWIR)
B10	60 m	Short Wave Infrared (SWIR)
B11	20 m	Short Wave Infrared (SWIR)
B12	20 m	Short Wave Infrared (SWIR)

C. Data processing

In the proposed work, a normalized difference chlorophyll index (NDCI) is used to forecast chlorophyll- a (chl-a) content in aquatic bodies using remote sensing data. The results of the research and literature survey indicates that NDCI can be utilized to quantitatively monitor chl-a in inland coastal waters. In the absence of ground truth data, NDCI may be utilized to detect algal blooms and subjectively estimate chl- a concentration ranges in remote coastal waters. The study of NDCI by Sachidananda Mishra and Deepak R. Mishra associates the relationship between NDCI and real values of Chlorophyll [15] which is described in TABLE III.

TABLE III. RELATIONSHIP BETWEEN NDCI AND REAL VALUES OF CHLOROPHYLL-A

NDCI range	Chl-a range (mg m^{-3})
<-0.1	<7.5
-0.1 to 0	7.5 – 16
0 to 0.1	16 – 25
0.1 to 0.2	25 – 33
0.2 to 0.4	33 – 50
0.4 to 0.5	>50
0.5 to 1	Severe bloom

The proposed work concluded a high value of chlorophyll-a for the Lonar lake which was 0.18 as compared to the other coastal regions which has 0.005 to 0.012 values. NDCI is calculated using red spectral band B4 and Near Infrared band B5 using the equation “(1)”.

$$NDCI = \frac{(B5-B4)}{(B5+B4)} \tag{1}$$

An index of water quality called the Normalised Difference Turbidity Index (NDTI) is used to calculate how turbid a body of water is. The cloudiness or haziness of water brought on by suspended particles, such as sediment or algae, is measured as turbidity. NDTI is calculated using the red spectral band (B4) and green spectral band (B3). The significance of the red and green spectral bands for qualitative turbidity prediction in the absence of in situ data is shown by A. K. M. Azad Hossain, Caleb Mathias and Richard Blanton in a study on remote sensing of turbidity in the Tennessee river using Landsat 8 [1]. It is calculated using “(2)”

$$NDTI = \frac{(B4-B3)}{(B4+B3)} \tag{2}$$

The Sentinel 2 satellite is used to evaluate water quality using a remote sensing technique called the Normalized Difference Salinity Index (NDSI). However, NDSI is a proxy for salinity rather than a direct measurement of salinity. The NDSI results must be converted to salinity levels using calibration algorithms. By comparing the NDSI results to field salinity measurements, the calibration equation is created. Moreover, other elements like suspended silt and organic debris can have an impact on the NDSI. Consequently, it is crucial to consider these elements when utilizing the NDSI to evaluate the quality of the water. NDSI is calculated using the following equation "(3)".

$$NDSI = \frac{(B11-B12)}{(B11+B12)} \tag{3}$$

D. Classification algorithms

The primary objective of a classification algorithm is to determine the category of a given dataset, and these algorithms are primarily employed to forecast the results for categorical data to categorize water quality into two different classes – good and poor.

- Random Forest: Multiple decision trees are built using various randomly selected subsets of the data and features in a random forest classification. In deciding how to categorize the data, each decision tree acts as an expert.
- Support Vector Machine (SVM): SVM categorizes data points even when they are not otherwise linearly separable by mapping the data to a high-dimensional feature space.
- K-Nearest Neighbor (KNN): In order predict the class or value of a new data point, it finds the K nearest points in the training dataset and uses their class to do so.
- Decision Tree: The objective is to learn simple decision rules based on the data features in order to build a model that predicts the value of a target variable.
- Naïve Bayes: There is less training data needed. It manages data that is continuous and discrete. With regard to the quantity of predictors and data points, it is quite scalable.

IV. Results and Discussion

- System Requirements: To run this model you may need to have a mid-tier CPU as it can be CPU intensive at times, No other requirements.
- Software Requirements: Google Colab/Jupyter Notebook or any other Python IDE.

This section illustrates the results of the water quality analysis using satellite images. The normalized difference chlorophyll, turbidity and salinity index is calculated with the help of Sentinel-2A bands. These values are then compared with quantitative values and it signifies that Bay of Bengal region is comparatively less contaminated and saline as compared to other saline regions. The higher concentration of chlorophyll-a for the Lonar lake (0.18) as compared to the other coastal regions which has 0.005 to 0.012 values, indicates poor water quality. TABLE IV highlights the parametric values obtained after processing sentinel-2A images. After extraction of water quality parameters, a classification model is applied to these values in order to predict the category of the water quality. This classification model is trained using dataset containing NDCI, NDTI and NDSI values and a categorical label – good and poor. The output 0 indicated poor quality and 1 indicated comparatively better quality. Fig. 5. describes the predicted output.

TABLE IV. EXTRACTED WATER QUALITY PARAMETERS

	NDCI	NDTI	NDSI
Arabian sea	0.04	-0.12	0..21
Lonar lake	0.18	-0.02	0.23
Bay of Bengal	0.005	-0.13	0.16
Arabian sea near the southern coastal region	0.12	-0.15	0.19

TABLE V. ANALYSIS BASED ON THE OBSERVATIONS OF REGIONS

REGION	QUALITY
Arabian sea	POOR
Lonar lake	POOR
Bay of Bengal	GOOD
Arabian sea near the southern coastal region	POOR


Lonar Lake (0 indicates poor water quality consisting of high cholorphyll and salinity)

```
X_RF = rf_classifier.predict([[data_ndsi_lonar,data_ndci_lonar,data_ndti_lonar]])[0]
X_RF
0
```

Bay of Bengal (1 indicates better water quality consisting of low cholorphyll and salinity)

```
X_RF1= rf_classifier.predict([[data_ndsi_BOB,data_ndci_BOB,data_ndti_BOB]])[0]
X_RF1
1
```

Arabian Sea near southern part of Indian sub-continent (0 indicates poor water quality consisting of high cholorphyll and salinity)

```
X_RF2= rf_classifier.predict([[data_ndsi_south,data_ndci_south,data_ndti_south]])[0]
X_RF2
0
```

Fig. 5. Prediction on extracted data

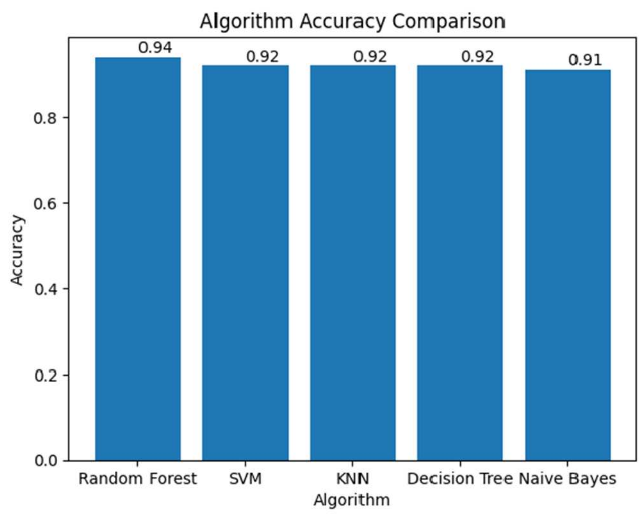

Fig. 6. Comparison of algorithms

To get better results and to test the performance of the ML classification algorithms, the proposed work also performs comparative analysis of these algorithms to determine which one gives more accurate results. The following steps were taken throughout the model creation process: data collection, pre-processing, model construction, model comparison, and assessment. The outcome demonstrates that Random Forest algorithm predicts more accurately, with a precision score of 94%. Instead of depending on a single decision tree, Random Forest gathers the input from each tree and predicts the category using the majority of projections which results in better accuracy.

The prediction accuracy of the Decision Tree, KNN, and SVM algorithms is 92%, while the Naive Bayes approach is 91%. Fig. 6. demonstrates the comparison of these algorithms in terms of accuracy.

V. CONCLUSION

In this study, we have examined the importance of high-quality water and developed methods to determine if the water is good or poor by considering several factors like turbidity, chlorophyll-a, and salinity. The project concludes that Bay of Bengal region is less saline and contaminated as compared to the other saline regions of Arabian sea and Lonar lake. The comparison carried out among several classification model also concludes that Random Forest performs better with comparatively more accuracy.

A. *Limitations*

Capturing appropriate dataset with properly normalized values is very crucial, if in case any atmospheric interference occurs, it may affect the dataset and the accuracy of the model which leads us to the first limitation of the model. Temporal limitations like satellite may not be available at the desired resolution for continuous monitoring of water quality. Also, the accuracy of qualitative water quality assessment as compared to in-situ observations is comparatively less.

B. *Future scope*

Incorporating the Ground Truth In-Situ data can enhance the accuracy and performance metrics of the model. Building a Deep Learning model specifically for Water quality analysis can help do the analysis more efficiently if the dataset grows exponentially. Along with the existing parameters, other factors such as ph can be utilized to efficiently determine water quality. The study of freshwater regions can be undertaken in order to differentiate between saline and fresh water bodies. The future scope can also include creating a dashboard which can be accessed for real-time monitoring of water bodies along with the specified time interval.

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