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USING MACHINE LEARNING AND IMAGE RECOGNITION TO EVALUATE WATER QUALITY

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Abstract – This research project explores the application of machine learning in assessing water quality through image recognition. The study leverages a diverse dataset of water samples collected from various sources across Mumbai, encompassing ponds, lakes, water outlets, and sewage points. Multiple parameters, including pH, conductivity, turbidity, and dissolved oxygen content, are examined in relation to the resulting HEX colour code,which serves as a visual representation of water quality.The central hypothesis posits that employing machine learning algorithms can reliably predict water safety based on these environmental parameters through image recognition of the colour gradient of the water samples. A systematic approach to data collection, standardisation, and logistic regression modeling has been employed.Results demonstrate the effectiveness of the logistic regression model in predicting water safety with an 85% accuracy rate, highlighting its potential for real-time water quality monitoring and risk assessment. Nevertheless, this study recognises its limitations and the need for further research to refine the model's predictive accuracy and address variations across different geographical regions and water sources. This research aims to contribute to the development of innovative approaches for water quality assessment and therefore, environmental preservation.

***Key Words*: Machine learning, water sources, pH, conductivity, turbidity, dissolved oxygen, HEX colour code, logistic regression**

1.INTRODUCTION

Clean water and adequate sanitation are vital for human existence, environmental sustainability, and economic development. However, the irresponsible disposal of industrial effluence has emerged as a significant threat to water quality in major world cities including Mumbai, a particularly urbanized region.This research paperaimsto investigate how pollutants—measured through various water quality parameters such as pH, turbidity, dissolved oxygen and conductivity—affect the colour gradient of various water bodies and therefore, the overall water quality.

1.1 PROBLEM STATEMENT

Whilewater qualityusingtheaforementionedparameters (pH, conductivity, turbidity, and dissolved oxygen) has been tested and analysed in the past, this research paper looks into the feasibility of using image recognition and machine learning as a way of predicting water quality - in essence using technology to look at a very widely prevalent, yet fundamental community problem. The fusion of machine learning with water quality assessment has immense potential to make water safety evaluations more widely accessible.

2. BACKGROUNDINFORMATION

The World Wildlife Fund (WWF) defines water pollution as "toxic substances entering water bodies such as lakes, rivers, oceans and so on, getting dissolved in them" ("Water Pollution").

EFFECT OF WATER ON FOUR WATER QUALITY PARAMETERS

Effect of Water Pollution on Electrical Conductivity: Electricalconductivityisameasureofhowwella substance allows the flow of electric charges, typically in the form of electrons or ions.

Water pollution often introduces various charges into aquatic ecosystems. For example, agricultural runoff, industrial discharges, and urban runoff can contain ions like sodium, chloride, nitrate, sulfate, and heavy metal ions.Theseionsincreasetheelectricalconductivityofwater as they are capable of carrying electrical charges[5].

Importantly, there is a relationship between pH and electrical conductivity. Heavy metals found in water pollution affect pH (discussed in earlier paragraphs), and consequently, these changes in pH can affect the dissociation of ions, potentially impacting electrical conductivity. Acidic conditions, for example, can lead to the release of hydrogen ions (H+), which can alter the conductivity.

EffectofWaterPollutiononTurbidity:

Turbidity is a measure of the cloudiness or haziness of a fluid caused by the presence of suspended particles,which scatter and absorb light. Turbidity is an essential parameter in environmental and water qualitymonitoring, as it can indicate the presence of contaminants or impurities in a liquid [3].

Pollutants such as sediment, clay, organic matter, and debris can be introduced into water bodies through various sources, including erosion, industrial discharges, and sewage runoff. These particles can increase turbidity, making the water appear cloudy or visibly spoilt. Industries that release effluents containing fine particles, chemicals, heavy metals, and other contaminants can significantly increase turbidity in nearby water bodies. Construction sites in Mumbai, are also the cause of such particles entering water bodies (Tembhekar et al.).

A point to note is that with greater suspended particles in a water sample, there is a higher chance of finding metals inthewater.Thisisnotablebecausewithahigheramount of suspended particles, the impurities containing ions allow electricity to be easily conducted. Hence, turbidity and electrical conductivity have a direct relationship, wherein, the increase in the value of one will result in the increase of the other.

Effect of Water Pollution on Dissolved Oxygen:

INSTRUMENTS MEASURING PARAMETERS

1. pHMeter–pH:scalefrom1-14
2. Conductivity Meter - Electrical Conductivity: expressed in microsiemens per centimeter (µS/cm).
3. Turbidimeter - Turbidity: expressed in Nephelometric Turbidity Units (NTU) or Parts Per Million (PPM).
4. Nephelometer (DO meter) - Dissolved Oxygen: expressed in milligrams per liter (mg/L) or parts per million(ppm)

HOW PARAMETER SAFF ECTHEX COLOUR

pH can influence the colour of water indirectly byaffecting the solubility and speciation of certain substances.For example,water with a low pH(acidic) can cause the leaching of metals like iron and manganese, leading to discolouration in the form of reddish-brown or yellowish tints. Extreme pH values can also impact the colour perception, making the water appear more or less translucent.

Conductivity measures the concentration of ions in water, mainly due to the presence of salts and minerals. While high conductivity can be indicative of dissolved ions, it does not influence the colour of the water directly. High ion concentrations can affect the taste and odor of water, but they do not define the colour.

Turbidity is a measure of the cloudiness or haziness of water due to suspended particles. The presence of suspended particles in water can scatter and absorb light, leading to variations in the water's appearance.
High turbidity can make water look cloudy or murky, which can affect the perceived colour.

The dissolved oxygen content does not have a direct impact on the colour of water. However, it can indirectly affect the health of aquatic ecosystems and the growth of algae or other organisms that may impart differentcolours to water, such as greenor brownhues. Changes in dissolved oxygen levels can influence the biological activity and the presence of organic matter in water,which may impact the water's overall appearance.

3. SCIENTIFIC LITERATURE REVIEW

Groundwater quality is assessed through various parameters such as turbidity, pH, dissolved oxygen (DO), and conductivity. Recent studies have also explored the application of machine learning in predicting and managing water quality. This literature reviewcategorizes the selected research into these themes to provide a cohesive understanding of the topic.

4. VARIABLES

IndependentVariables:

The independent variables in this study are represented by the various water bodies from which water samplesare procured. These water bodies serve as distinct categories or groups for the machine learning algorithm's analysis. Within each category, the parameters, including pH, conductivity, turbidity, and dissolved oxygen content, are measured and act as the features or characteristics used for the machine learning algorithm. These parameters are the focus of the study particularly concerned with their relationship to the HEX colour code, and the different water bodies, from different locations, are the independent variable..

5. HYPOTHESIS

The utilization of a machine learning algorithm for predicting water safety based on the parameters of pH, conductivity, turbidity, and dissolved oxygen content, within various water bodies, will result in a reliable and efficient method for assessing water quality, as represented by the corresponding HEX colour code.

SupportingEvidence:

pH levels influence the colour of water indirectly by affecting the solubility and speciation of certain substances. For instance, low pH (acidic) can lead to the leaching of metals

like iron and manganese, which can result in reddish- brown or yellowish tints, thus affecting the HEX colour code. Conductivity measures ion concentration in water, impacting its taste and odor. High conductivity does not directly affect the HEX colour code, but it can indirectly influence water quality which in turn may have an effect on the colour composition of water. High ion concentrations can alter water characteristics, potentially impacting the HEX colour code. METHODOLOGY

The research employed a systematic approach to collect and analyse water samples from diverse sources across Mumbai and develop a logistic regression model for water quality assessment.

1. SampleCollection:

60 water samples were collected from various locations, including ponds, lakes, water outlets, and sewage sources throughout Mumbai, to ensure a broad spectrum of water sources and conditions. The collection was carried out using a bucket and a rope. Each sample was collected in individual sample cups to maintain sample integrity. 3-5 samples of the same source were collected.

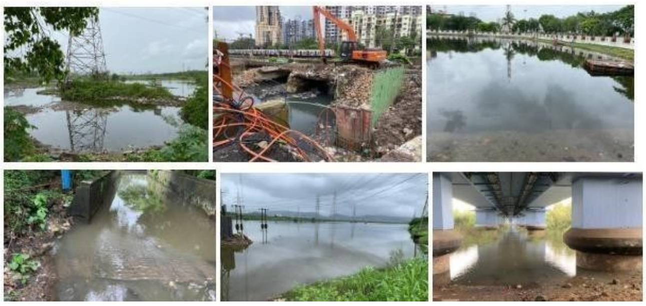

Fig.6.1-6.6:PicturesofVariousPonds/IndustrialSites Across Mumbai from which Samples were Collected

2. DataCollection:

Multiple water quality parameters were measured for each collected sample. The IONIX 7 in 1 multiparameter instrument was used to gather data on pH, electrical conductivity, and turbidity. The Lutron Do-5509Dissolved Oxygen Meter was used to collect data for dissolved oxygen. Both instruments were calibrated and standardized before use. Three trial measurements for each sample were taken.

Fig.6.7:DataCollectionusingaDigitalMultiparameter and a Nephelometer

3. Data Analysis & Standardization: The collected data, including pH, conductivity, turbidity, and DO values, was transferred to an Excel spreadsheet for analysis. This data was organized and averaged to prepare it for the development of a logistic regression model. Standard values for drinking water from secondary sources, mentionedinthebackgroundresearch,allowedfora

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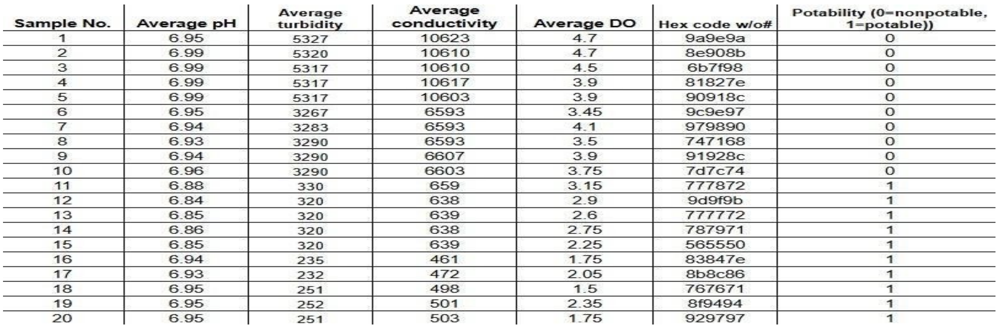
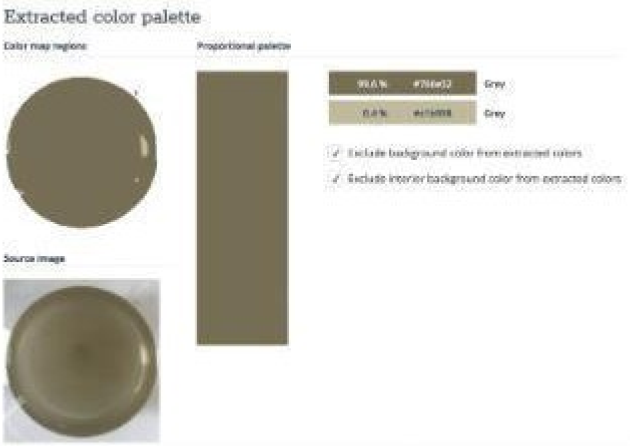


Sample No.	Average pH	Average turbidity	Average conductivity	Average DO	Hex code w/o#	Potability (0=nonpotable, 1=potable))
1	6.95	5327	10623	4.7	9a9e9a	0
2	6.99	5320	10610	4.7	8e908b	0
3	6.99	5317	10610	4.5	6b7f98	0
4	6.99	5317	10617	3.9	81827e	0
5	6.99	5317	10603	3.9	90918c	0
6	6.95	3267	6593	3.45	9c9e97	0
7	6.94	3283	6593	4.1	979890	0
8	6.93	3290	6593	3.5	747168	0
9	6.94	3290	6607	3.9	91928c	0
10	6.96	3290	6603	3.75	7d7c74	0
11	6.88	330	659	3.15	777872	1
12	6.84	320	638	2.9	9d9f9b	1
13	6.85	320	639	2.6	777772	1
14	6.86	320	638	2.75	787971	1
15	6.85	320	639	2.25	565550	1
16	6.94	235	461	1.75	83847e	1
17	6.93	232	472	2.05	8b8c86	1
18	6.95	251	498	1.5	767671	1
19	6.95	252	501	2.35	8f9494	1
20	6.95	251	503	1.75	929797	1

Fig.6.8:Digitisationofdataandstandardizationof samples

Simultaneously, using the colour extraction algorithm the HEX code values and the respective intensity percentageof those HEX code values were extracted. These values were accounted for in the data sheet as they play a crucial role in the development of a supervised machine learning algorithm. Below is an example of one of the samples that underwent this process.



Extracted color palette

✓ Exclude background color from extracted colors

✓ Exclude interior background color from extracted colors

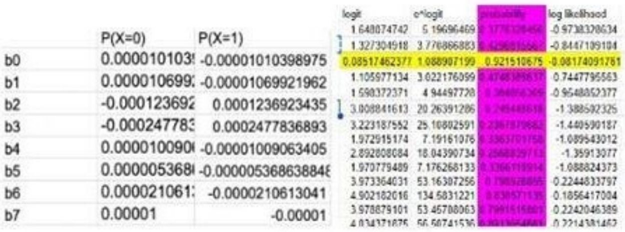
Fig.6.9:Colourextractionofwatersamples

1. ModelDevelopment:

A logistic regression model was created using the processed data. Logistic regression is a type of regression analysis used to predict a dependent variable's outcome based on one or more independent variables. The dependent variable in logistic regression is binary, meaning it has only two possible outcomes (e.g., safe or unsafe water). Unlike linear regression, which predicts a continuous outcome, logistic regression predicts the probability of a certain class or event existing. In logistic regression, each feature (water quality parameter) is assigned acoefficient, which representsitscontribution to the logit (log-odds) of the outcome. The logit function is given by:

$$logit(p) = ln(\frac{p}{1-p}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n$$

Where p is the probability of the outcome being 1 (potable),$\beta_0\beta_0$is the intercept, $\beta_i\beta_i$are thecoefficients for thevariables X_i X_i .Themodelcoefficients($\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n$) were estimated using the maximum likelihood estimation method. This involves finding the values of the coefficients that maximize the likelihood of an accurate model as per standard drinking water conventions. In other words, reducing the numberofoutliers.



	P(X=0)	P(X=1)
b0	0.000010103!	-0.00001010398975
b1	0.000010699:	-0.00001069921962
b2	-0.000123692	0.0001236923435
b3	-0.000247783	0.0002477836893
b4	0.000010090	-0.00001009063405
b5	0.000005368	-0.00000536863884€
b6	0.000021061:	-0.0000210613041
b7	0.00001	-0.00001

logit	e^logit	probability	log likelihood
1.648074742	5.19696469	[illegible]	-0.9738328634
1.327304918	3.770866883	[illegible]	-0.8447109104
0.08517462377	1.088907199	0.921510675	-0.08174091781
1.105977134	3.022176099	[illegible]	0.7447795563
1.598372371	4.94497728	[illegible]	-0.9548852377
3.008841613	20.26391286	[illegible]	-1.388592325
3.223187552	25.10802591	[illegible]	-1.440590187
1.972915174	7.19161076	[illegible]	-1.089543012
2.892808084	18.04390734	[illegible]	-1.35913077
1.970779489	7.176268133	[illegible]	-1.088824373
3.973364031	53.16387256	[illegible]	0.2244833797
4.902182016	134.5831221	[illegible]	0.1856417004
3.978879101	53.45708063	[illegible]	0.2242046389
4.034371875	56.50741536	[illegible]	0.2214381462

Fig.9-10:Setvaluesforparametersthatyield probabilities

The predicted probability of water safety (p) is then obtained by applying the logistic (sigmoid) function to the logit:

$$p = \frac{1}{1 + e^{-logit(p)}}$$

This converts the logit value into a probability ranging between 0 and 1. A threshold of 0.5 was used to classifythe water as safe or unsafe. Probabilities greater than 0.5 wereclassifiedaspotable(1),whileprobabilitieslessthan 0.5wereclassifiedasnon-potable(0).

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0.5wereclassifiedasnon-potable(0).Fig.11:Sigmodfunction(logisticregressioncurve)

3. ModelValidation:

Samples that show discrepancies between theirprobability (0 or 1) and their respective potable factor are highlighted in yellow and are considered anomalies in this model.Thedevelopedlogisticregressionmodelwastested and validatedusing an unknown sampleand predicting its quality. An 85% accuracy rate was attained with the numericals of each parameter described above. These anomalies are highlighted in yellow as shown in Fig. 6.10.

6. RESULTS

The results of this study demonstrated the feasibility of employing a logistic regression model to assess water quality and predict potability based on water parameters within various sources. Water samples from a diverse range of locations across Mumbai, including ponds, lakes, water outlets, and sewage sources, were collected and analysed. Key water quality parameters, namely pH, conductivity, turbidity, and dissolved oxygen (DO), were measured using specialized instruments. Additionally, the HEX colour code values and their respective intensity percentages were extracted using a colour extraction algorithm, providing crucial information for the machine learning model.

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7. CONCLUSION

The findings of this research highlight the potential of utilizing a supervised machine learning algorithm, specifically a logistic regression model, to assess water quality based on key water parameters and the corresponding HEX colour code. The study leveragedwater samples from diverse sources to ensure a comprehensive evaluation of water quality. pH, conductivity, turbidity, and DO were identified as critical factors for water quality assessment, as they influence the HEX colour code. The observed relationships between these parameters and the HEX colour code align with previousresearchfindings,emphasizingtheimportanceof these variables in determining water safety.

It is crucial to note that this research design and modelrely on the relationships observed within the specific water bodies in Mumbai. Variations in geological and environmental conditions in other regions may influence theparameters'relationshipsdifferently.Hence,whilethis logistic regression model is promising for Mumbai, its generalizability to other locations necessitates further investigation.

Moreover, the findings of this study have practical implications for water quality management and public health. The ability to rapidly and accurately assess water safety using machine learning algorithms can facilitate timely actions to protect communities from potentially contaminated water sources. The implementation of this model in real-time monitoring and decision support systems could significantly enhance the safety of water supplies and improve the overall well-being of communities. Future research should focus on validating the model in diverse geographical and environmental contexts to ascertain its broader applicability.

While water quality using the aforementioned parameters (pH, conductivity, turbidity, and dissolved oxygen) has been tested and analysed in the past, this research paper looksintothefeasibilityofusingimagerecognitionand machine learning as a way of predicting water quality - in essence using technology to look at a very widely prevalent, yet fundamental community problem. The fusion of machine learning with water quality assessment has immense potential to make water safety evaluations more widely accessible.

REFERENCES

[1] US EPA, O.(2015, November4). *DissolvedOxygen*. Www.epa.gov. https://www.epa.gov/caddis/dissolvedoxygen#:~:text=colour%3A%20The%20colour%20of%20water

[2] Electrical Conductivity and Electrical Resistivity - ResistivityofMaterials,Formula,Unit,Examplesand FAQs.(n.d.).BYJUS.RetrievedJuly31,2024,from https://byjus.com/physics/resistivity-variousmaterials/#:~:text=Electrical%20Conductivity%2 0is%20an%20intrinsic%20property%20of%20a

[3] Huey,G.M.,&Meyer,M.L.(2010).Turbidityasan IndicatorofWaterQualityinDiverseWatershedsofthe Upper Pecos River Basin. Water, 2(2), 273–284. https://doi.org/10.3390/w2020273

[4] Kang,C.,Lee,T.M.,Wong,B.,&Yoo,J.(2018). Relationship Between Soil pH and Dissolved Oxygen (DO) Concentration in Salish Creek and Canyon Creek. The Expedition, 8. https://ojs.library.ubc.ca/index.php/expedition/articl e/view/191429

[5] pHMeasurement|ElectricalInstrumentation Signals | Electronics Textbook. (n.d.). Www.allaboutcircuits.com. https://www.allaboutcircuits.com/textbook/directcurren t/chpt-9/ph-measurement/

[6] Mathur,A.(2018).Conductivity:WaterQuality Assesment. International Journal of Engineering Research & Technology, 3(3). https://doi.org/10.17577/IJERTCONV3IS03028

[7] Pathak,A.K., Sharma,M.,Katiyar,S. K., Katiyar,S., & Nagar, P. K. (2020). Logistic regression analysis of environmental and other variables and incidences of tuberculosis in respiratory patients. Scientific Reports, 10(1).https://doi.org/10.1038/s41598-020-79023-5

[8] WaterScienceSchool.(2019,October22).pHand Water | U.S. Geological Survey.