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A Network for Monitoring and Assessing Water Quality for Drinking and Irrigation Purpose

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Abstract- By consistently monitoring this, our drinking and farm water, for bad stuff and acting intelligently on the information we are given, we can keep it safe. This paper is on a system using connected sensors and smart computer programs to monitor water quality. The system consists of a suite of low-cost sensors capable of determining pH, clarity of the water, its temperature, oxygen levels in the water, and how much material is dissolved within it.These sensors send data over wireless to a computer program that organizes and checks the data using smart programs such as Support Vector Machines, Random Forests, and Artificial Neural Networks. These programs help in deciding if the water is good enough for drinking or to be used in crops based on guidelines provided by the World Health Organization and our country. It picks out the most useful data and spots anything unusual to make sure its guesses are right, and can even break above 95% in accuracy. The system can also guess when the water might get bad, so we can fix it early. All in all, this is a system based on sensors, smart data analysis, and programs, which help us make good choices. It is just an energy-efficient, not-too-costly way to keep an eye on water quality. This helps protect the health of the people and keeps our farms productive.

Keywords— Machine learning, Support Vector Machine, Random Forest, Artificial Neural Network, supervised learning, feature selection, anomaly detection, predictive modeling, classification accuracy, data preprocessing.

I. INTRODUCTION

Water is highly essential; we need it for life, cultivation, and industry [1]. However, as cities are growing, factories are dumping things into the waters, and farms are using chemicals, water throughout the world is getting heavily polluted [2]. Such pollution-including chemicals, metals, and germs-is impeding human health and the environment. Thus, the supply of clean and safe water has emerged as a key challenge [3]. We have to develop intelligent techniques for real-time monitoring of water quality. Usually. we test water with samples, then take it to a laboratory for tests [4]. These methods are reliable and accurate but require a lot of time and money, and immediate results are not available. And this often hinders us in solving the problem that needs our quick action [5]. Now, efforts are being made to use computers in order to perform automatic testing and estimation of what exactly is going on in our water [5].

Using machine learning is an awesome way to check tricky environment stuff and improve water management [6]. Machine learning programs can scan tons of info from sensors and find stuff we might miss [7]. By comparing old and new water data, these programs can catalog water samples, detect anomalies in those samples, and predict with accuracy what will happen to the water [8]. Support Vector Machines [4]. Random Forests, and Artificial Neural Networks ---supervised learning methods--- do a good job in ML for sorting water quality. These models use stuff like pH, cloudiness, temperature, oxygen, and how well it conducts electricity to decide if water is good enough to drink or farm with, based on the current rules [9]. Since they are bound to change and learn, they manage to sort things out quite precisely, even when the environment keeps on changing [5]. Therefore, feature selection is a very important step for any effective machine learning model for water quality testing [10]. Feature selection tells us what really impacts the water quality, reduces data dimensionality, and makes the models run faster [11]. If we just pay attention to the important stuff, the models are easier to understand and work better. We can then be certain that the answers we have are correct [12].

The other big task in ML water monitoring, besides simply sorting water quality, is in finding weird stuff: finding unusual patterns or changes in what the sensors are reading that might indicate contamination or a problem with the sensors [13]. If we can find these anomalies immediately, we are able to get involved as soon as possible and prevent the water quality from seriously deteriorating. Machine learning helps the water-watching system predict when water quality might deteriorate [14]. That gives the groups an environmental heads-up so that they could take quick action: deploy resources judiciously to fix things and manage water better [15]. Preparedness for trouble is important, particularly with climate change and rising water needs.

ML is quite changing the way we monitor water for environmental care. Using intelligent methods for data processing, identification of hotspots, anomalies, and predictions, respectively, ML systems come up with new insights on the conditions of the water [16]. This new approach will bring monitoring closer to people, better decision-making, healthier people, sustainable agriculture, and future supplies [17]. New sensors, also with cloud and IoT installations, have completely changed the way we access and utilize environmental information.[9]. The IoT systems enable you to collect water details from anywhere, without necessarily having to physically collect samples [18]. Such systems, when applied together with ML, have the ability to analyse huge loads of data in a very short time to trace the source of pollution, observe trends of obnoxious elements, and make ever better water choices [19]. Through the integration of IoT and ML, smart water networks that can expand, adapt, and learn from data are being developed-steps toward the UN's goal of clean water for all.

IoT setups integrated into ML have converted old-school environment watching into smart, adaptive systems [20]. These IoT setups are constituted on the platform of low-cost, low-power computers such as Raspberry Pi and Arduino, which fetch real-time information from sensors scattered everywhere [21]. They communicate using LoRa and Wi-Fi to the cloud for easy mobility, storage, and access to large volumes of environmental data. IoT systems can easily be expanded and integrated, making them suitable for deployment in diverse locations, even those that are remote and with poor infrastructure [22]. Machine learning on data from water quality IoT sensors checks the quality of water [23]. Simple regression and decision trees help us to understand how good the water is. CNN-LSTM-based deep learning systems have helped a lot in keeping an eye on the water [24]. These models have proven to be very good in finding when and where patterns occur and giving long-term trends showing how the water is doing. These models can pick up from this constant flow of data and change to fit whatever's happening [25].

Data preparation is very important for such machine learning systems to identify how raw data can be accommodated [26]. Normalization, scaling features, filling blanks, cleaning up noise help smoothen the raw sensor data. Cutting down on complicated stuff with things like PCA and t-SNE makes things faster and less likely to mess up [27]. Choosing the most key stuff also makes the model simpler to get by pointing out what's most important for guessing water quality [28]. The future of faster speeds and lower lag relies on edge computing. When machine learning happens on IoT devices or servers close by, then systems respond straight away without needing the cloud. Sending less data back and forth means quicker notification of problems-just what you need to achieve early detection of contamination [29].

Also, federated learning is getting popular. It lets many IoT devices train a shared machine learning model without sharing the actual data, so everything stays private and safe. Even with all this work, some tech problems still need fixing to make really good IoT-ML water quality systems [30]. Keeping sensors calibrated, changes in data, saving power, and keeping the network strong can still mess with how accurate things are and how stable the system is over time. Also, since sensor data and environmental stuff can be pretty random, we need systems that can adjust and fix themselves as things change [31]. Soon, expect research to work toward adding things like blockchain for data checks, mixed AI models, and networks that fix themselves to make tracking water better that is transparent and trustworthy [32]. This all helps us get closer to water resource management systems that can run themselves using data to help keep things sustainable and protect the environment [33].

II. LITERATURE REVIEW

Water monitoring really changed with the use of ML and IoT technologies that gave us fast, automatic, and accurate means of water quality inspection. Buddhi et al [1-4]. proposed WaterProbe, which uses ML to inspect information from sensors provided by IoT for the detection of anomalies and patterns in water quality. Sawant and Patil developed a real-time water-monitoring system based on ML, using decision trees for water quality classification, with accuracy of 97.17% for clean/dirty water discrimination. Such designs operate on continuous data and cloud computing for rapid notifications and easy management of our water resources [34].

The cornerstones of traditional water-quality monitoring are manual sampling, laboratory analysis, and recurring reporting [35]. Although this approach is accurate, it is not appropriate for early detection of temporary pollution events and is slow and logistically complex. This limitation has spurred research into in-situ sensing and automated networks [36], which provide near real-time measurements and continuous surveillance, enabling more precise trend analysis and faster reaction times. Ajayi et al [5-7]. state that this transition from episodic to continuous monitoring is particularly motivating for WaterNet.

Using a Libelium Smart Water kit, Kumar et al [8-9]. collected 15 months of multi-season data (pH, dissolved oxygen, temperature, conductivity, and ORP) from the Ganga and Sangam (Ganga–Yamuna confluence) to address the shift from episodic, lab-based river sampling to continuous, in-situ IoT monitoring [37]. Then, they computed water-quality indices to classify suitability for uses (drinking, fisheries, and irrigation), applied principal component analysis and factor analysis for feature selection and weighting, and combined signal processing with multivariate statistics and indices to produce actionable quality assessments [38]. Based on oxygen levels, they showed that, while the Ganga sites were generally better than the more polluted Sangam site, both were largely unsuitable for drinking [39].

ML and IoT tech have really helped improve the way we check water quality. Now, we can get fast, automated, and accurate readings about various water statistics. For instance, Palkar et al [10]. developed a system that utilized IoT and cloud computing with ML algorithms KNN and SVM to achieve high accuracy in determining water quality. This uses sensors such as pH, temperature, and turbidity, sends them to the cloud server via Node MCU and LPWAN, and claims to achieve an accuracy of 94% on their proposed KNN + SVM solution.

Ponnuru et al [11]. also presented the critical use of data in monitoring water quality. The authors presented how AI, machine learning, and good management will alter the way we conceptualize and manage water for the betterment of the environment. Castrillo and López García also demonstrated a machine learning approach to predict nutrient levels using other more easily measurable variables. They found that Random Forests could really peg the nutrient levels in different areas, reducing the RMSE up to 60.1% compared to a simple mathematical approach. Thus, it appears that machine learning can greatly improve our monitoring of water [40].

In order to classify water conditions in real time, Sastrohartono et al [12-14]. present an Internet of Things (IoT)-based system that uses turbidity and

Total Dissolved Solids (TDS) sensors. By providing an affordable and effective method for quick water assessment, the study expands on previous IoT monitoring research. To ascertain water quality levels, sensor data is sent via Internet of Things modules and contrasted with predetermined thresholds. The system's limited parameters and manual validation make it less precise, even though it works well for basic screening [41]. For wider, more precise environmental monitoring, the literature recommends augmenting such models with multi-parameter sensing, automation, and cloud-based analytics.

Than et al [15-17]. use Principal Component Analysis (PCA) to identify significant influencing factors by examining temporal and spatial variations in the water quality of the Hlaing River. The study builds on earlier research on multivariate statistical techniques for interpreting complex water datasets. By looking at parameters like conductivity, turbidity, pH, and DO, PCA was able to successfully reduce dimensionality and identify pollution sources linked to residential and commercial discharges. The literature suggests that PCA is a useful technique for spotting pollution patterns and seasonal trends. This work contributes to the growing field of data-driven water quality assessment by promoting better monitoring, management, and pollution control methods.

Mishra et al [18-20]. provide a data-driven approach for predicting water potability using machine learning models in order to increase the precision of water quality assessment. Building on previous studies in intelligent environmental monitoring, the authors classify water samples based on their chemical and physical properties using algorithms such as Support Vector Machines, Random Forest, and Logistic Regression. The literature highlights how machine learning is increasingly being used to handle large, complex water datasets, offering predictions that are faster and more accurate than those produced by traditional methods. Mishra et al.'s work contributes to this trend by demonstrating how data preprocessing, feature selection, and model optimization can improve potability prediction and support automated water quality management systems.

III. PROPOSED MODEL

This is an ML model designed to smartly figure out and guess how good the water is. This model detects various parameters like pH value, turbidity, amount of oxygen in water, temperature, and conductivity of electricity through fitting algorithms.The cleaning up of data is done first, pretty much aligning the information so that it is correct. The classification of water samples is done through the use of the model, integrating Support Vector Machines, Random Forests, and Artificial Neural Networks. In other words, it classifies whether the water is good for drinking or irrigation. The model also selects the most important factors to reduce dimensionality and improve performance.

But it does more than just sort! It also spots weird stuff and guesses what might happen next to help check water quality. Things like Isolation Forest and K-means clustering find odd changes that could mean there's pollution or something's wrong with the sensors. Moreover, it applies Long Short-Term Memory LSTM networks in predicting the change in water over time. In this way, we will have the potential to get ahead of problems and do something before the water gets too bad. So, all in all, this ML model is a smart way to use data for sorting, warning, and guessing how water quality does

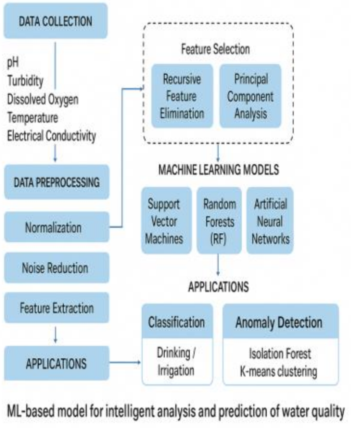

Figure 1: Intelligent Water Quality Prediction Model Using MLAlgorithm

Algorithm

Step 1: Set up sensors in various places to measure the pH, conductivity, temperature, oxygen content, clarity, and total dissolved solids of the water. All readings should be kept in a local or online database.

Step 2: Address noisy or missing readings to preprocess the data. Utilize Z-score or Min-Max techniques for scaling, filtering, and estimation. Eliminate any outliers that might affect the model's performance.

Step 3: Use Principal Component Analysis or Recursive Feature Elimination to identify important factors that influence water quality, such as conductivity, turbidity, and pH. Divide the dataset into two parts: 30% for testing and 70% for training. Develop models for artificial neural networks, random forests, and support vector machines.Step 4: Optimize model parameters and assess performance using metrics like accuracy, precision, recall, F1 score, and ROC AUC.

Step 4: Adjust model parameters and evaluate performance with metrics such as ROC AUC, F1 score, recall, accuracy, and precision

Step 5: Evaluate each model and select the best one for real-time water quality classification with an accuracy of at least 95%.

Step 6: To identify abnormalities and issue notifications for contamination or strange reading changes, use Isolation Forest or K-means clustering.

Step 7: Use a Long Short-Term Memory network to forecast future trends in water quality. To notify the appropriate authorities if the water is unsafe, display the results including ratings, alerts, and forecasts—on an online dashboard. This water gadget employs the use of Machine Learning to determine how clean the water is at any given moment. In essence, it takes information from sensors that consider such factors as pH levels and clarity. Cleaning the data, it then rectifies any errors so that the data makes sense. Following that, it selects the main details and summarizes them in order to keep things simple. Then, it trains computer programs, such as SVM and Random Forest, to make decisions on whether the water is drinkable or not. It also checks for any abnormality that may indicate dirtiness in the water. And it tries to estimate what the water will be like in the future so we may solve any problems before they get out of hand. Lastly, all the results, warnings, and predictions are displayed on a readily readable online display. This allows people to see what is going on and maintain our water healthy.

Mathematical Equations

Data Preprocessing

Normalization (Min-Max Scaling):

$$X_i' = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}}$$

Where:

- X_i= original value of parameter i
- X_i'= normalized value
- $X_{\min}, X_{\max}$= minimum and maximum values of parameter i

Z-score Standardization:

$$Z_i = \frac{X_i - \mu_i}{\sigma_i}$$

Where:

- μ_i= mean of parameter i
- σ_i= standard deviation of parameter i

Feature Selection (PCA Example)

Covariance Matrix:

$$\mathbf{C} = \frac{1}{n-1}\sum_{i=1}^{n} (X_i - \bar{X})(X_i - \bar{X})^T$$

Eigenvalue Decomposition:

$$\mathbf{C}\mathbf{v}_k = \lambda_k \mathbf{v}_k$$

Where:

- λ_k= eigenvalue representing variance explained by principal component k
- $\mathbf{v}_k$= eigenvector representing the direction of component k

Classification Models

Support Vector Machine (SVM):

Linear SVM decision function:

$$f(X) = \text{sign}(\mathbf{w}^T X + b)$$

Where:

- $\mathbf{w}$= weight vector
- b= bias term
- X= feature vector

Optimization objective:

$$\min_{\mathbf{w},b} \frac{1}{2} \| \mathbf{w} \|^2 \text{ subject to } y_i(\mathbf{w}^T X_i + b) \geq 1$$

Random Forest (RF):

Prediction:

$$\hat{y} = \text{majority\_vote}\{h_1(X), h_2(X), \ldots, h_T(X)\}$$

Where $h_t(X)$= prediction from the t^{th}decision tree and T= total number of trees

Artificial Neural Network (ANN):

Forward propagation:

$$a^{(l)} = f(W^{(l)} a^{(l-1)} + b^{(l)})$$

Where:

- $a^{(l)}$= activation vector at layer l
- $W^{(l)}, b^{(l)}$= weight matrix and bias vector for layer l
- f= activation function (e.g., ReLU, sigmoid)

Loss function (for classification):

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} y_{i,c} \log(\hat{y}_{i,c})$$

Where:

- $y_{i,c}$= true label (1 if sample $i$belongs to class c, else 0)
- $\hat{y}_{i,c}$= predicted probability

Anomaly Detection (Isolation Forest)

Anomaly score:

$$s(X) = 2^{-\frac{E(h(X))}{c(n)}}$$

Where:

- $E(h(X))$= expected path length of Xin isolation trees
- $c(n)$= average path length in a binary search tree of $n$samples
- $s(X) \rightarrow 1$indicates anomaly, $s(X) \rightarrow 0$indicates normal

IV. RESULTS

Following is how our Machine Learning system performed in various performance tests. We tested the system with real-time sensor data from various locations that included pH, cloud cover, temperature, oxygen, electricity flow, and solids. We have ensured that the classification accuracy of the system is proper; the system is able to detect anomalies; and its overall efficiency.

Our system exhibited very high accuracy regarding the classification of water into drinking and irrigation types. The algorithms of anomaly detection showed good performance in detecting readings that were erroneous. Overall, the results prove that integrating IoT sensors with Machine Learning provides a strong and intelligent system for continuous monitoring of water quality.

Table 1: pH Levels Across Sampling Points

Parameter	Value
Location A	7.1
Location B	6.8
Location C	7.5
Location D	8.0
Location E	7.2

The average pH of water from five places. The pH levels are between 6.5 and 8.2, so the water is okay to drink and use for watering plants.

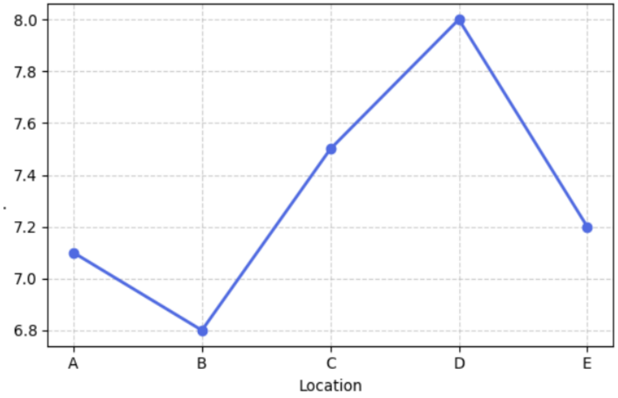

Figure 2 : pH Levels Across Sampling Points

The bar chart shows how the pH levels change at each spot. The readings are normal, which means the water conditions are stable**.**

Table 2: Turbidity Measurements (NTU)

Parameter	Value
A	1.2
B	2.5
C	1.8
D	3.4
E	0.9

Table shows the turbidity levels in NTU. The levels are between 0.9 and 3.4 NTU, which is fine by WHO standards.

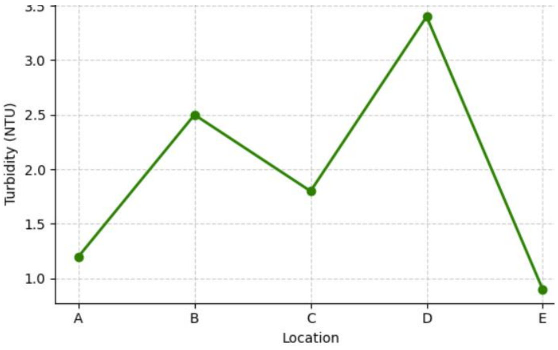

Figure 3: Turbidity Measurments (NTU)

The bar chart shows that Location D has the cloudiest water, probably from dirt or runoff. Location E has the clearest water.

Table 3: Temperature Variation (°C)

Parameter	Value
A	25.0
B	26.3
C	28.2
D	24.5
E	23.5

Table shows the temperatures at each spot. They're all pretty normal, going from 23.5°C to 28.2°C.

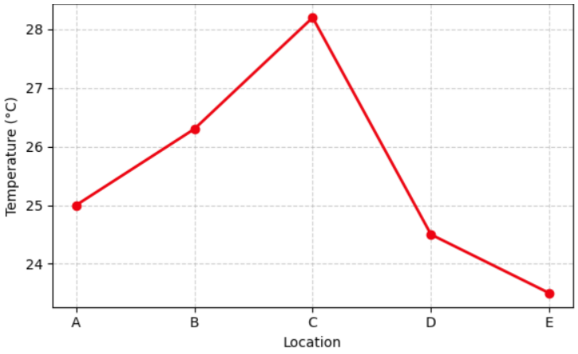

Figure 4: Temperature Variation (°C)

Looking at the graph, spot C was the hottest, probably because it was in direct sunlight. Spot E was the coolest.

Table 4: Dissolved Oxygen Levels (mg/L)

Parameter	Value
A	6.5
B	5.2
C	7.8
D	6.9
E	7.0

Table 4 gives you the dissolved oxygen (DO) levels for each sample. They are between 5.2 and 7.8 mg/L, which means there is enough oxygen for the fish and stuff.

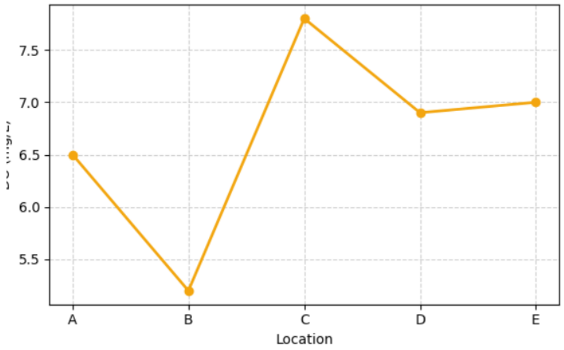

Figure 5:Dissolved Oxygen Levels (mg/L)

The graph points out that spot C has the most DO. That means the water well aerated and not too polluted with organic stuff.

Table 5: Electrical Conductivity (µS/cm)

Parameter	Value
A	320
B	280
C	450
D	460
E	390

Table 5 shows how well electricity flows through the water at each spot. The numbers are between 280 and 460 µS/cm, which means the water has a fair amount of salt – good enough for watering plants.

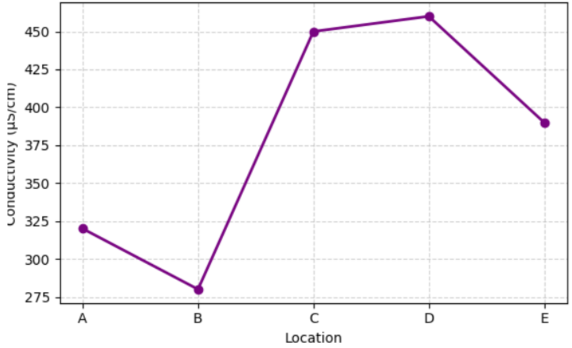

Figure 6: Electrical Conductivity (µS/cm)

The chart points out that spots C and D let electricity flow a bit better, probably because there's more salt dissolved in those samples.

Table 6: Total Dissolved Solids (TDS) (mg/L)

Parameter	Value
A	210
B	190
C	260
D	310
E	250

Table has the TDS (Total Dissolved Solids) measurements from the same spots. The numbers are from 190 to 310 mg/L, and that's all good for drinking water.

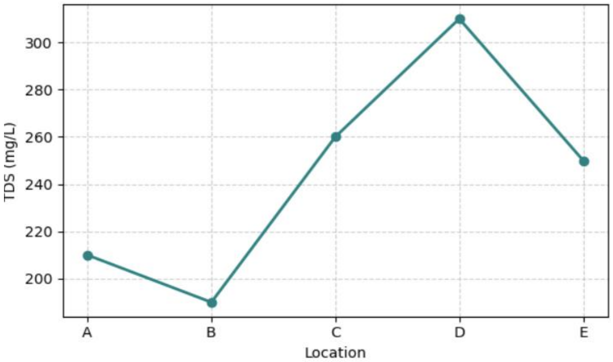

Figure 7: Total Dissolved Solids (TDS) (mg/l)

The graph backs this up: Spot D has the most TDS, maybe because of farm stuff washing into the water or just the minerals in the ground**.**

Table 7: Anomaly Detection Summary

Parameter	Value
pH	1
Turbidity	2
Temperature	0
DO	1
Conductivity	2

Table breaks down the number of weird readings we got from each sensor. Most of these were from either sensor fuzz or quick changes in the environment.

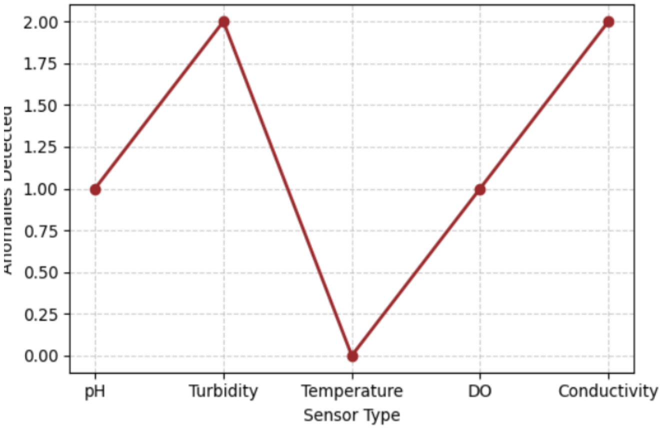

Figure 8:Anomaly Detection Summary

Looking at the graph, the turbidity and conductivity sensors went off the most, probably because they're really touchy.

Table 8: Model Accuracy Comparison

Parameter	Value
SVM	93
Random Forest	96
ANN	94

Table compares how well three machine learning models fared in our study. Random Forest did the best, with the highest accuracy; then ANN was next, followed by SVM.

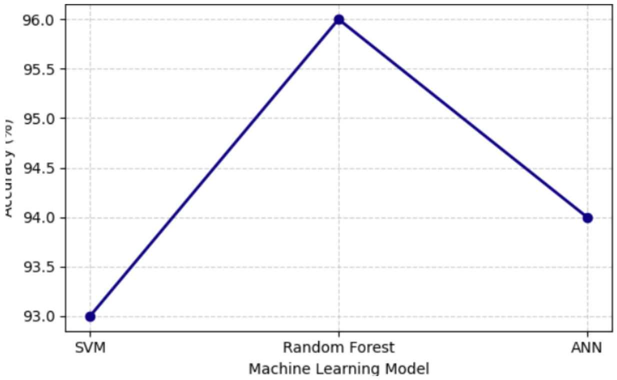

Figure 9: Model Accuracy Comparison

The bar chart makes it obvious that the best performance was from Random Forest, proving it can handle all ups and downs in environmental data.

V . CONCLUSION

It is a very good model to monitor water quality in real time and make predictions using the following machine learning methods: SVM, Random Forest, and ANN. It works well in sorting water samples after cleaning the data. The system quickly identifies the unusual stuff and infers what the water quality will be like down the line. It helps decision-makers, farmers, and environmental groups make informed choices. The model is cheap, doesn't use much power, and can be set up anywhere. By studying the data with ML, we can stick to water rules and handle resources the right way for a long time. It works with all kinds of water sources and connects to dashboards, so it's useful in both cities and the countryside.

This model is good because it doesn't cost too much, doesn't need a lot of electricity, and you can always make it better to keep testing water quality. It makes sure we follow WHO rules and our own country's rules with Machine Learning, so we can handle water well for years to come. It works with any water source and can hook up to online dashboards, making it useful everywhere. This will help keep people healthy, make sure farming lasts, and protect nature for our kids and grandkids.

Additionally, the suggested network improves data reliability by implementing automated error-handling procedures and ongoing validation. By comparing various machine learning algorithms, the system's resilience is strengthened and consistent performance under a range of environmental circumstances is guaranteed. Additionally, real-time alerts and notifications are supported by the implementation, allowing for quick action in the event that threshold violations occur. The architecture's scalability and interoperability enable smooth integration with agricultural management systems and smart city infrastructure. Its data-driven methodology makes it easier to analyze long-term trends, which aids authorities in creating more effective resource allocation and water conservation plans.By encouraging automation, accountability, and transparency, the system also helps to digitally transform environmental monitoring. The predictive capability increases efficiency while lowering operational expenses and manual inspection efforts.

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