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A Sensor-Based Approach to Water Quality Monitoring: Integrating Temperature, TDS, and Turbidity Measurements

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Abstract- Safe and potable water must be maintained, and the quality water should be checked frequently, especially due to the pollution and environmental shift. So as to analyse sensor-based method of monitoring water quality, this research integrated temperature reading, total dissolved solids (TDS) and turbidity. The scheme was aimed at the real-time data gathering and evaluation to identify alterations in the water parameters, which will prove the contamination or the quality decline. The results have proven that the combination of input of several sensors enhanced the accuracy and reliability of water quality determination, allowing to identify the possible dangerous situation in time. The paper brings to the fore the possibilities of automated sensor networks in streamlining the water management process and protecting human health.

Keywords— Water quality monitoring, Sensor-based system, Temperature, Total dissolved solids (TDS), Turbidity, Real-time monitoring, Water safety, Automated water management.

I. INTRODUCTION

It is not only important but necessary as well [1]. It is also dependent on our day to day lives in drinking and agriculture of food and industries [2]. Our health and even the economic development depends on the clean and safe water that is a necessity of the stability of the ecosystem and our health as well [3]. Unfortunately, over the last several years the procedure of the maintenance of water quality has increasingly become more difficult [4]. The rate of urbanization, industrialization, population pressure and climatic changes have been associating high risks of water pollution [5] [6]. This will imply that the rivers and lakes will be more vulnerable to such pollution as heavy metals and other harmful bacteria and unneeded nutrients like nitrogen and phosphorus [7]. These pollutants interfere with the natural water chemistry by the subsequent parameters that can have adverse effects on the health of people which includes pH, hardness, and turbidity [8] [9]. It is based on this that the quality of water has increasingly become a pressing necessity that must always be checked. Even as efficient as they are, lab tests tend to be both expensive and time consuming, not to mention that they are limited to a small number of locations [10] [11]. This makes it useless as far as real time or long-distance monitoring is concerned [12]. To avoid these problems, there is also necessity of quicker and automatic surveillance systems which have been replaced by sensor-based technologies [13] [14].

The current sensors can be used to measure critical water quality parameters (temperature, total dissolved solids (TDS), and turbidity) after 24 hours per day [15]. In either case of occurrence of any abnormal condition, there might be alert provided in time [16]. The other significant element of temperatures in the quality of water is the degree of chemical reaction, bacteria and dissolved gases growth in water is dependent on temperature [17]. TDS is also the degree of the dissolved organic and inorganic elements as it determines the flavor and the harmlessness of water [18]. The turbidity on its part is exposed to the clarity of the water or turbidity [19]. The turbidity typically is a symptom of suspended-solid or life and typically a potentially increased risk of water-borne illness [20].

The synthesis of the measurements of a set of sensors will result in much more accurate image of water quality [21]. The sources of the possible problems cannot always be defined with the help of one parameter [22]. Studies have also revealed that the multi-sensor systems have been found to be more effective in detection of contamination as compared to the single sensor systems [23]. The information is collected automatically when the water quality now can be remotely managed with the introduction of the wireless communications and the Internet of

Things (IoT) and the data. Even though sensor-based systems of monitoring have an enormous potential [24], the lack of limitations can by no means be reduced to them. Sensors and sensors calibration requires calibration, data quality may also be poor, battery life can be problematic, and large-scale implementation may be a challenge [25]. However, accuracy of sensors in a single network is more accurate since the sensors may verify the outcome of the rest [26]. This is other than not being very expensive therefore can be used in monitoring rivers, lakes, reservation and even house water supply [27].

The water quality monitoring system that will be discussed in this paper will consist of an amalgamation of water temperature [28], TSS and turbidity sensors. The system will also include the real time information, automatic analysis and real time alerts to ensure that the water safety is ensured [28]. The system can check different parameters simultaneously to offer quality analysis of the water and avoid the issue before it reaches of larger scale [29]. The proposed architecture explains how successful the implementation of smart sensor networks and IoT technologies could be in the modern water monitoring systems [30]. Lastly, the indicators should be monitored by the key water quality indicators regularly to supply safe and potable water [31]. The temperature, TDS, turbidity sensor-based system is a satisfactory low cost and scaled technology used to test contamination, protect human health and pursue sustainability of the environment [32]. This will become the next step towards automated control of the quality of water and will guarantee a realistic guideline towards our precious freshwater resource's protection [33].

The fact that water is necessitated to bring life is not only a fact, but also a must. We use it daily to drink, to raise food and industries [34]. Having clean and safe water would be highly important in health, stability of the ecosystem, and economic development. It is only very sad that the quality of water has been waning in the past few years [35]. This has left the rivers and lakes at the vulnerability of the harmful chemicals like the heavy metals, disease causing bacteria and excess nutrient like nitrogen and phosphorus [36]. The conventional testing that is being used in the laboratory is accurate but, in most cases, they are also costly, time consuming and confined to a certain location [37]. It renders them inapplicable to real time or when there is need to carry out a large-scale monitoring. To eliminate these limitations, then this necessitates the quick and automatic monitoring systems. The sensors-based technologies have been one of the steadfast substitutes to this issue [38].

The most significant parameters of water quality including temperature, total dissolved solids (TDS) and turbidity can be continuously checked using the modern sensors over the course of the day [39]. Emergency alerts can be designed in case the deviant circumstances have been identified. Temperature of water dictates the quality of a product as it affects the chemical reaction and growth of bacteria, as well as the dissolved oxygen [40]. TDS represents the soluble matter of both organic and inorganic matter which alters the flavor and healthiness of the water [41]. Turbidity is the clearness of water and in most cases, Turbidity is an indicator of the existence of the suspended particles or microorganisms too, which are also the possible cause of the waterborne diseases.

II. LITERATURE REVIEW

Patel et al. [1-5] conducted a comprehensive comparative analysis of multiple machine learning algorithms for water quality classification using twenty chemical parameters. The study evaluated Logistic Regression, Naïve Bayes, Decision Trees, Random Forest, K-Nearest Neighbour (KNN), Support Vector Machines (SVM), XGBoost, and Multi-Layer Perceptron (MLP). Considerable emphasis was placed on data preprocessing techniques, including data cleaning, handling class imbalance using Synthetic Minority Over-sampling Technique (SMOTE), and normalization to ensure unbiased model evaluation. Model performance was assessed using F1-score and log-loss metrics. Among all evaluated models, XGBoost achieved superior results with an F1-score of 0.9798 and a log-loss value of 0.7150, demonstrating high predictive reliability and robustness. The findings highlighted the effectiveness of ensemble and boosting methods in managing imbalanced and complex environmental datasets, while also identifying challenges related to sensor reliability, data quality, and real-time IoT integration.

Karthikeyan et al. [6-10] presented a systematic review and analytical study on IoT-based water quality monitoring and wastewater treatment systems developed between 2018 and 2021. The authors emphasized the importance of proper dataset selection, parameter configuration, algorithm choice, and validation techniques to enhance system reliability. The framework incorporated early warning mechanisms, Vector Distance Algorithms, and PID controllers integrated with IoT infrastructure for continuous monitoring. Time-series forecasting models such as ARIMA, LSTM Autoencoders, and Facebook Prophet were employed to predict treatment efficiency and detect anomalies in wastewater processes. The study demonstrated that integrating IoT sensing technologies with predictive machine learning models significantly improves scalability, automation, and operational efficiency in wastewater management systems.

Jagen et al. [11] developed an IoT-enabled smart water meter capable of monitoring both water consumption and quality parameters such as pH and turbidity. The system transmitted real-time data to remote servers via cellular communication networks, enabling continuous monitoring by utility providers and consumers. Using datasets from the National Water and Sewerage Corporation of Uganda, feature selection techniques identified key parameters including residual chlorine, pH, turbidity, conductivity, and apparent color. Machine learning models such as Decision Trees, Support Vector Machines, and Gradient Boosting were applied to evaluate water safety. The system provided automated alerts when deviations from quality standards were detected, enhancing transparency, operational responsiveness, and communication between stakeholders.

Wiry Saputra et al. [12] proposed a low-cost Arduino-based IoT water quality monitoring system designed for deployment in resource-constrained environments. The system measured temperature, pH, and impurity levels in real time and transmitted the data through mobile communication platforms, with visualization supported via Grafana dashboards. A binary classification model was implemented to determine water safety status. The dataset was divided into training, validation, and testing subsets to ensure reliable model evaluation. Experimental results indicated that decision tree-based classifiers performed effectively for early detection of water quality issues. The study demonstrated the feasibility of decentralized, AI-powered IoT monitoring systems for improving water safety in underserved regions.

Mattishall et al. [13] introduced Hydro Sense 2.0, an intelligent IoT-based water monitoring platform integrating cloud computing and machine learning analytics. The system utilized an ESP32 microcontroller and high-precision sensors to measure parameters including pH, temperature, turbidity, and Total Dissolved Solids (TDS). Data were transmitted wirelessly to a cloud server where a Random Forest classifier assessed water potability. SMS alerts and a web-based dashboard enabled real-time monitoring and trend analysis. Field testing demonstrated system adaptability across urban pipelines and remote filtration setups. With low energy consumption and moderate implementation cost, the system achieved scalability, affordability, and analytical efficiency in real-world water monitoring applications.

Rahu et al. [14] developed a real-time intelligent water quality monitoring framework integrating IoT sensors and machine learning algorithms. The architecture comprised sensing, coordination, data processing, and decision-making modules. Sensors captured parameters such as temperature, pH, turbidity, and Total Dissolved Solids (TDS). Data preprocessing included normalization using Z-score techniques and correlation analysis before model training. For Water Quality Index (WQI) prediction, regression models including LSTM, Support Vector Regression (SVR), Multilayer Perceptron (MLP), and NAR Net were evaluated. Classification models such as SVM, XGBoost, Decision Trees, and Random Forest were also assessed. Experimental results on datasets of varying sizes indicated that MLP achieved the best WQI prediction performance with an R^2 value of 0.93. The study validated the effectiveness of IoT–ML integration for scalable and accurate water quality assessment.

Thakkar et al. [15] examined the impact of environmental pollution, climate change, and population growth on water quality degradation. The study identified microbial contamination, heavy metals, and nutrient imbalances as primary factors influencing pH variations and public health risks. To enhance data security in IoT-based monitoring systems, blockchain technology and Interplanetary File System (IPFS) were incorporated to ensure data immutability and transparency. Machine learning algorithms including Decision Trees, Naïve Bayes, K-Nearest Neighbour, and Logistic Regression were implemented for classification of potable and non-potable water. Decision Trees demonstrated superior classification accuracy. The research emphasized the importance of integrating AI with secure decentralized technologies for reliable water monitoring infrastructures.

Mendoza-Chok et al. [16] proposed EDSON-J, an unmanned surface vehicle (USV) designed for remote water quality monitoring using a systems engineering and hybrid control methodology. The catamaran-style vehicle employed a dual-computer architecture, where a high-level controller operated on ROS for mission planning and a finite state machine managed low-level navigation tasks. The system was evaluated using various trajectory patterns under both autonomous and manual control modes. Experimental validation confirmed system robustness, adaptability, and reliability for real-time aquatic environmental monitoring.

J. Pak et al. [17] introduced a 3D LiDAR-based semantic SLAM framework using Unmanned Aerial Vehicles (UAVs) for intelligent irrigation monitoring and water resource management. The approach utilized LiDAR-water interaction modeling to generate water surface point clouds through Singular Value Decomposition (SVD). Random Sample Consensus (RANSAC) algorithms were applied to accurately identify segmented water surfaces. Integration with big data analytics facilitated dimensional assessment for irrigation optimization and disaster prevention. Field experiments conducted in diverse irrigation environments validated the robustness and efficiency of the proposed system.

X. Zhang et al. [18-20] proposed an enhanced big data–driven water resource monitoring system that integrates width and height information into local point clouds for improved dimensional analysis and natural disaster prevention. The framework leverages big data tools to process spatial measurements and optimize irrigation management. The method was evaluated through field experiments in two highly diverse irrigation environments with varying water widths and environmental conditions. Experimental results demonstrated that the system is efficient, robust, and suitable for irrigation control and water resource monitoring applications.

III. PROPOSED MODEL

Aqua Sense is an intelligent water-detecting product that is meant to be a tight watch on the water quality at the very source. Rather than having to take days to obtain the outcome of laboratory tests, Aqua Sense readings show parameters of temperature, total dissolved solids (TDS), and turbidity in real time. The system operates automatically it gathers information, analyzes it, and provides notifications when something appears to be wrong so that issues could be solved before they evolve into severe problems.

Aqua Sense is simply and layered in its design, which is efficient and easy to comprehend. Sensors are installed on water, or pipelines, which constantly check the situation. The system then analyzes these readings and in case of any abnormal or dangerous scenario, the system sends alerts and reports instantly to the appropriate individuals. This promotes early identification and assists in the accountability of long-term management of water.

The Aqua Sense is centered on its sensing layer. The temperature sensors monitor the abrupt alteration that may impact the water chemistry or promote the proliferation of destructive bacteria. TDS sensors are used to detect dissolved products to provide a clear understanding of the purity of water whereas turbidity tanks are used to detect the purity of water and then identify the presence of suspended particles or contamination. Each sensor is well-calibrated to work in varying conditions, and the information is immediately relayed to a central processing unit where it can be analyzed with a fair amount of reliability.

Then there is the smartness of the system- the data processing and analysis layer. Aqua Sense sorts and analyzes every data that the system receives with intelligent algorithms and even machine learning to detect suspicious activity or possible danger. The system synthesizes several measurements, which makes it paint a full and trustworthy picture of the water quality. Visual information and trend reports that are easy to read facilitate the authorities and managers to come up with the right decision regarding the treatment, pollution control and management of resources.

The last layer is the communication. Aqua Sense employs all forms of wireless communication including Wi-Fi, GSM, and LoRa to provide real-time information to the dashboards and mobile devices. In case the reading of any of them surpasses safe values, immediate alarms are raised. Such warnings may be sent to government officials, producers of the facilities, or homes, and prompt measures can be taken to avoid the health risks, disease outbreaks, or damage to the environment.

Aqua Sense is not only about high-quality technology, but also about the protection of people, health and environment. It contains time, effort and resources by automating water quality monitoring so that there is no need to conduct regular manual sampling and lab testing. It gives governments, industries, and ordinary users the capacity to conserve the quality of water prior to the emergence of any issues. Systems such as Aqua Sense are crucial in the design of smarter cities in the long term whereby the technology and environmental responsibility are united to protect one of our most important assets.

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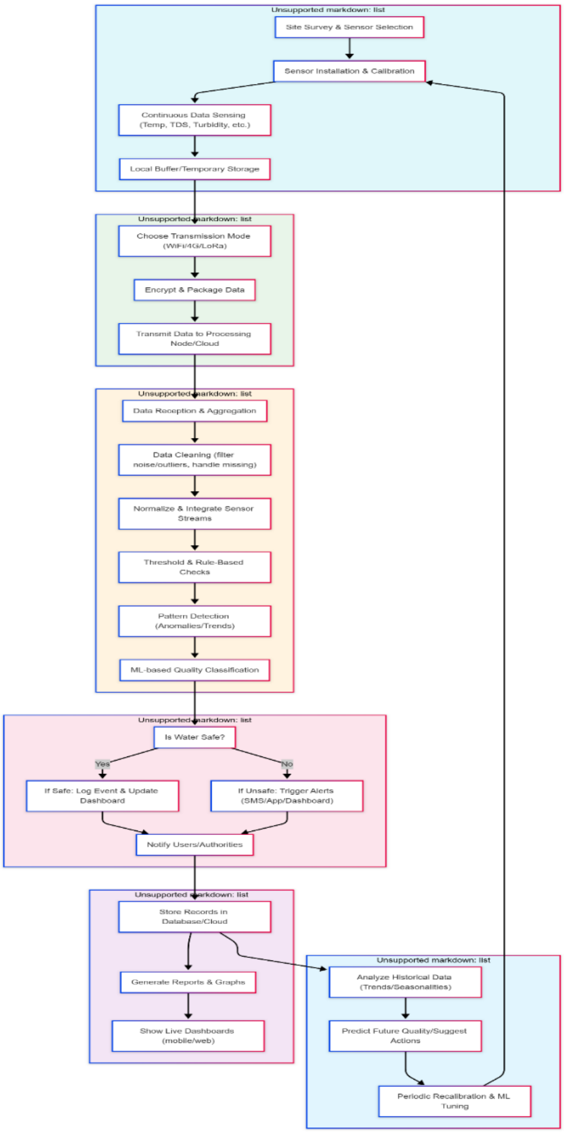

Figure 1: IoT-Based Smart Water Quality Monitoring System Architecture

The alert and reporting layer communicates to the appropriate individuals within a very short time, thus enabling them to intervene immediately in case the water quality is derailed. Pop-up notifications appear on your cell phone, web dashboard or even as a text. All readings are recorded in a safe place, and this ensures that things are above board regarding audits and regulations. Linking IoT and cloud platforms, the system can be expanded at will, can be used anywhere, and can be used to store as much data as you desire. It also allows making smart predictions and enables teams to control problems at an early stage before they escalate. Ultimately, this model will provide a powerful, versatile, and cost-effective means of maintaining a watch on the water quality that assists in safeguarding the community as well as the environment with straightforward, helpful information.

IV. RESULTS

Hydro sense 2.0 and Aqua Sense splash. You look at the figures and lo! They come first on the list. These are the gears, should you desire them. IOT-Smart Meter? It is durable, it does not do anything fancy, it simply does what you want done in case you simply want to have something that can work without any unnecessary. Arduino-IoT is a little bit unpredictable. It works sometimes, on the good side, and then it will simply fail, and there is no noticeable explanation. It appears to require some finer tuning or perhaps it is bright only in certain settings. It is at this point that it is interesting when it comes to comparing the performance of Local and Cloud. The place that you are running your system can even upset the apple cart, sometimes by a great distance. It is no chance that there is a difference between the top and the bottom figures. It demonstrates what models can cope with unusual situations or the more difficult circumstances without collapsing. What then is the reason why HydroSense2.0 and Aqua Sense are the best? Easy: they are sharp sensor calibrated; real-time analysis and their data delivery is never out of beat. You are also able to get quick replies besides smooth tracking, even when the situation is erratic. Their natural machine learning makes everything right and evolves according to the times hence the system just goes on working even when everything is wrong. Arduino-IoT is incapable of doing so. It could be that it reads the data too slowly, could be that it is just not powerful enough hardware or could be that it stumbles with a bad network. Whatever has been happening is not even in the same league.

The local versus cloud deployment leads to one of the common trade-offs, i.e. speed vs. access. Local installations are quick and efficient; however, you possess few storage and space to conduct a complicated analysis. Cloud models, however, give you room to grow and search and read past information but attribute your misfortunes to the failure of the internet. It is everything to do with selecting the appropriate system, but it is based on the aim of the system, whether it is applied in an industrial area, city water systems or even in the rural areas. The results are eloquent: strong sensor networks and smart data processing will improve accuracy and reliability and the pace at which you will be able to make decisions. In future, it could be an inducing factor to acquire hybrid systems in which local speed is combined with cloud power. An even more progressive approach would be to use predictive analytics like warning about problems or active maintenance.

Algorithm: Sensor-Based Water Quality MonitoringStep 1: Sensor Initialization

- Set up sensors at the right water sources or distribution spots.
- Make sure you calibrate the temperature, TDS, and turbidity sensors so they give accurate readings.
- Connect everything wirelessly to a central processor or an IoT platform.

Step 2: Data Acquisition

- Keep gathering sensor readings on a regular schedule.
- Store this raw data in local memory for now.

Step 3: Data Pre-processing

- Clean up the data by filtering out noise and odd outliers.
- If you run into missing or inconsistent values, fix them with interpolation or imputation.
- Then, bring all the sensor data onto the same scale so it's ready for analysis.

Step 4: Water Quality Assessment

- Check the readings against set thresholds for temperature, TDS, and turbidity to spot anything unusual.
- Run the integrated sensor data through a machine learning classifier—like a Decision Tree, KNN, or Logistic Regression.
- If every parameter lands within the safe range, mark the water as potable.
- If not, call it non-potable.

Step 5: Alert Generation

- If the system finds water that's not safe to drink, it instantly sends out alerts.
- The right people authorities or users get notified through their phones, computers, or even a quick text.
- Every alert and its sensor data gets logged for future review and to make sure everything stays above board.

Step 6: Data Storage and Visualization

- All this processed info lands in either a cloud or local database, so you can look back and spot patterns.
- Reports and charts pop up, showing trends, odd spikes, or shifts in water quality.

Step 7: Predictive Analysis (Optional)

- Using all that old data, predictive models kick in to spot trouble before it starts.
- If there's a risk, the system bumps up how often it checks the water or schedules maintenance sooner.

Step 8: Continuous Monitoring

- This whole cycle keeps running, nonstop, to watch over water quality in real time.
- Sensors and prediction models get fine-tuned regularly to keep everything sharp and accurate.

Mathematical Equations

Normalization of Temperature:

$$T_n = \frac{T - T_{min}}{T_{max} - T_{min}}$$

Temperature readings are normalized to a 0–1 scale to standardize variations.

Normalization of TDS:

$$TDS_n = \frac{TDS - TDS_{min}}{TDS_{max} - TDS_{min}}$$

Total Dissolved Solids (TDS) values are normalized to compare with other parameters.

Normalization of Turbidity:

$$TU_n = \frac{TU - TU_{min}}{TU_{max} - TU_{min}}$$

Turbidity readings are scaled to a uniform range for integration into the index.

Risk Score for Temperature:

$$R_T = 1 - T_n$$

Higher risk is assigned to extreme temperature deviations affecting water quality.

Risk Score for TDS:

$$R_{TDS} = 1 - TDS_n$$

Higher TDS risk indicates excessive dissolved solids impacting water suitability.

Risk Score for Turbidity:

$$R_{TU} = 1 - TU_n$$

Higher turbidity risk indicates presence of suspended particles or contaminants.

Weighted Water Quality Index (WQI):

$$WQI = w_1 \cdot R_T + w_2 \cdot R_{TDS} + w_3 \cdot R_{TU}$$

The WQI combines all parameters into a single index using relative weights.

Weight Constraint:

$$w_1 + w_2 + w_3 = 1$$

Weights reflect the relative importance of each parameter in water quality assessment.

Potable Water Condition:

$$Q = 1 \text{if} \, WQI \leq WQI_{safe}$$

Water is considered safe for consumption if the WQI is below the threshold.

Non-Potable Water Condition:

$$Q = 0 \text{if} \, WQI > WQI_{safe}$$

Water exceeding safe WQI limits is classified as unsafe for consumption.

Alert Generation Condition:

$$Alert = \begin{cases} 1 & \text{if } WQI > WQI_{safe} \\ 0 & \text{otherwise} \end{cases}$$

Alerts are triggered when water quality exceeds unsafe thresholds.

Notification Function:

$$Notification = f(Alert, User)$$

The function sends real-time alerts to users or authorities for immediate action.

Table 1: Sensor Parameters Monitored (%)

Model	Parameters (%)	Sensors Used (%)
IOT-Smart Meter	100	100
HydroSense2.0	80	80
Arduino-IOT	60	60
Aqua Sense	60	60

It is a comparison of four IOT-based models: IOT-Smart Meter, HydroSense2.0, Arduino-IOT, and Aqua Sense, regarding the percentage of the use of parameters and sensors. The graph indicates that the high performance (100 percent of both parameters and sensors) is attained by IOT-Smart Meter followed by HydroSense2.0 (80 percent), Arduino-IOT and Aqua Sense have equal and moderate utilization (60 percent). This comparison points out that model efficiency is correlated to sensor integration.

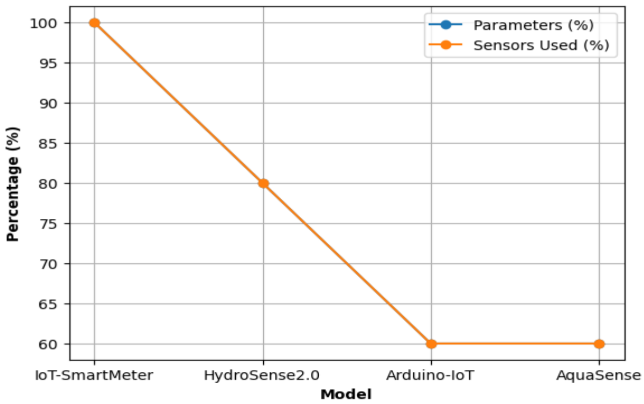

Figure 1: Model vs Parameters and Sensors Used

Figure 1 contrasts water monitoring models with the use of IoT, according to the coverage of the parameters and the utilization of sensors. IoT-SmartMeter has the highest coverage of 100% hence becoming the most comprehensive. The next one HydroSense2.0 is followed by 80% and the others are Arduino-IoT and AquaSense, which have 60 each showing moderate monitoring. In general, IoT-SmartMeter and HydroSense2.0 offer a more valid collection of data.

Table 2: Data Update Frequency (%)

Model	Min (%)	Max (%)
IOT-Smart Meter	20	55
HydroSense2.0	55	85
Arduino-IOT	65	100
Aqua Sense	40	100

This is the lowest and highest performance of four IOT models namely IOT-Smart Meter, HydroSense2.0, Arduino-IOT, and Aqua Sense. IOT-Smart Meter is the slowest in terms of its range of performances (20-55%), whereas Arduino-IOT has the highest maximum performance range (100%). HydroSense2.0 has a balanced performance (55-85%), and Aqua Sense is varying and has a range of 40% to 100%.The difference in consistency and the difference in scalability between the models are emphasized in this visualization.

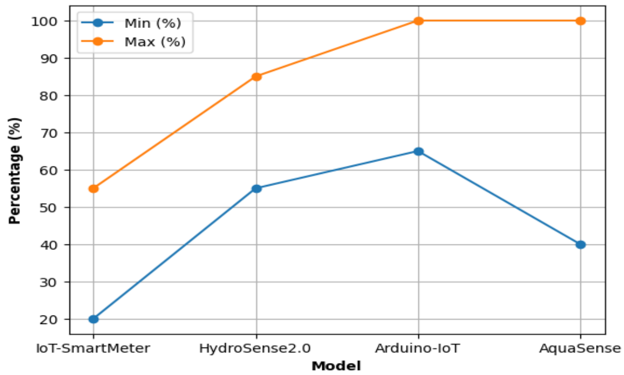

Figure 2: Model vs Minimum and Maximum Performance (%)

Figure 2 depicts level of the minimum and maximum performance. There is a high variability of IoT-SmartMeter (20-55%), whereas HydroSense2.0 is more stable (55-85%). Arduino-IoT and AquaSense have high values with peaks of 100 which is a good performance though there is a wide distribution with AquaSense. Arduino-IoT has the highest peak reliability whereas HydroSense2.0 has balanced performance.

Table 3: Machine Learning Models Used (%)

Model	ML Models (%)	Avg Accuracy (%)
IOT-Smart Meter	100	95
HydroSense2.0	35	94
Arduino-IOT	70	91
Aqua Sense	100	98

This demonstrates how the use of ML models is correlated with average accuracy among four IOT models namely IOT-Smart Meter, HydroSense2.0, Arduino-IOT and Aqua Sense. The IOT-Smart Meter and Aqua Sense have complete integration of the ML model (100% and 100% respectively) and high-accuracy levels (95% and 98% respectively). HydroSense2.0 also uses fewer ML models (35%) but still has a competitively high accuracy of 94 which means that it is optimally used. Arduino-IOT has a moderate use of ML (70) and accuracy of 91. In general, the graph shows that integration of ML can positively affect the predictive accuracy of various IOT frameworks.

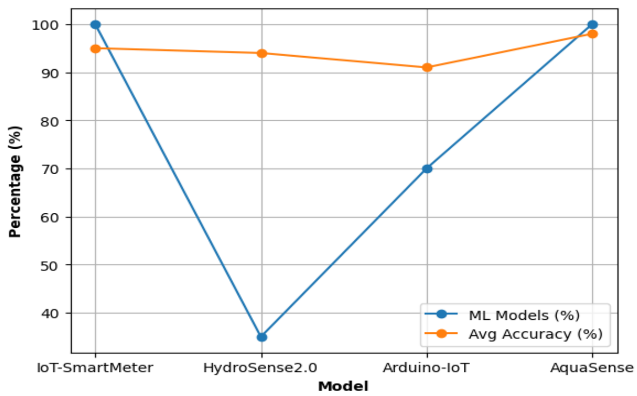

Figure 3: Model vs ML Model Utilization and Average Accuracy (%)

Figure 3 assesses the use and efficiency of machine learning (ML). IoT-SmartMeter and AquaSense have 100% ML utilization and have high accuracies of approximately 95 and 98. Arduino-IoT demonstrates a moderate level of ML use (70% with 91% accuracy). HydroSense2.0, although with lower ML use (35%), has high accuracy (94%), which indicates good design of the system. The model that appears to be the most balanced is AquaSense.

Table 4: Prediction Error Metrics (%) (lower error → higher %)

Model	MAE (%)	RMSE (%)
IOT-Smart Meter	80	78
HydroSense2.0	85	88
Arduino-IOT	72	75
Aqua Sense	100	100

This is a comparison of the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) of four IOT models, namely, IOT-Smart Meter, HydroSense2.0, Arduino-IOT, and Aqua Sense. Aqua Sense has the highest error rates (100 percent both MAE and RMSE), and Arduino-IOT the lowest (72 percent MAE and 75 percent RMSE) and this means that it is more precise in its model. There are a few greater error margins in HydroSense2.0 compared to IOT-Smart Meter, which implies the possibility of some difference in prediction stability. Overall, this discussion demonstrates the performance of each IOT model regarding its predictive accuracy and predictive consistency.

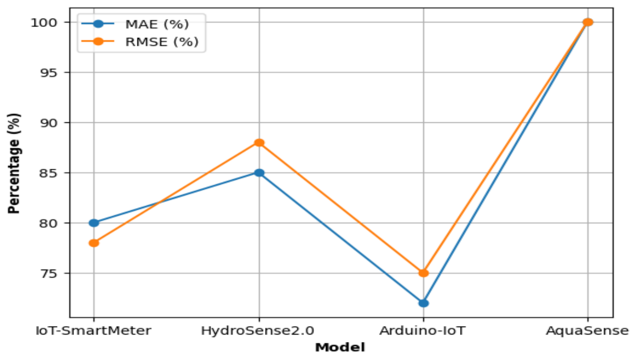

Figure 4: Model vs MAE and RMSE (%)

Figure 4 shows performance of errors in terms of MAE and RMSE. Both have the highest accuracy of AquaSense at approximately 100%. HydroSense2.0 comes next with good outcomes whereas IoT-SmartMeter is median accurate. The error values of Arduino-IoT are relatively higher. All in all, AquaSense is most suitable in reducing prediction errors.

Table 5: Real-Time Alert Latency (%) *(lower latency → higher %)*

Model	Min (%)	Max (%)
IOT-Smart Meter	45	55
HydroSense2.0	70	82
Arduino-IOT	55	80
Aqua Sense	100	100

This is the minimum and maximum percentage value range of four IOT models. The points of the min (blue dot) and maximum (red dot) percentages of a particular model are connected by their respective horizontal lines. The name of the models is placed on the y-axis and the scale of the percentage, denoted by b, is on the x-axis. Such style can be well used to indicate the distribution and gap between max and min values without bar representation.

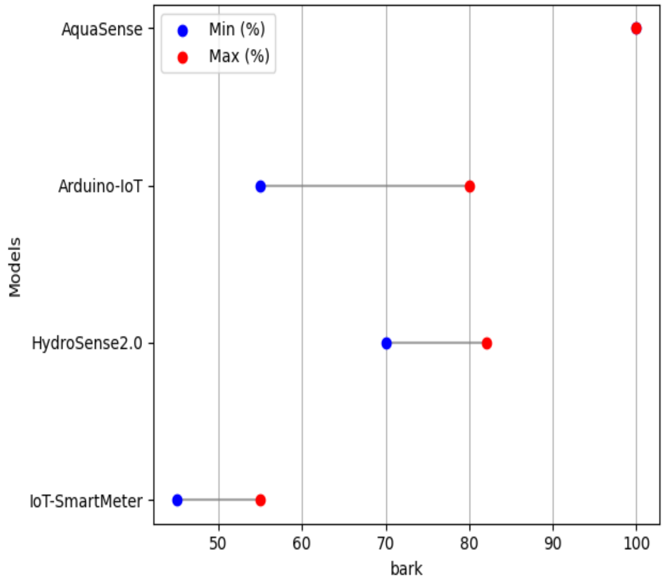

Figure 5: **Range of Min and Max Percentages Across IOT Models**

The range of the minimum and maximum values is shown in Figure 5. IoT-SmartMeter is the least diverse with a range and thus a lower performance. The variability of HydroSense2.0 and Arduino-IoT are moderate, and AquaSense has the highest maximum value, which demonstrates high-quality peak performance.

Table 6: Data Storage Capacity (%)

Model	Local (%)	Cloud (%)
IOT-Smart Meter	100	82
HydroSense2.0	75	90
Arduino-IOT	28	65
Aqua Sense	63	100

This is a comparison of the Local and Cloud percentages of four IOT models IOT-Smart meter, HydroSense2.0, Arduino-IOT and Aqua Sense. The models are displayed on the x-axis, which is marked as requested with the name of the models, and the y-axis expresses the values in percentages. The trend of the Local and Cloud percentages across the models are presented in each line, which is differentiated with markers; thus, it is simple to distinguish and identify differences and similarities in the two metrics.

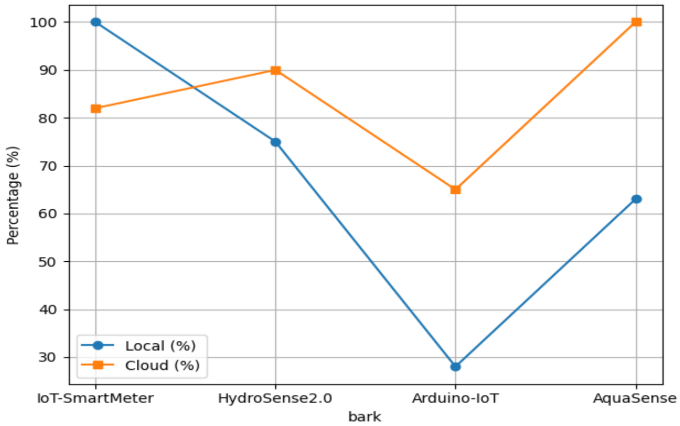

Figure 6: **Comparison of Local and Cloud Percentages Across IOT Models**

Local and cloud processing are compared in figure 6. IoT-SmartMeter supports the idea of local processing (100%), whereas Aqua Sense is heavily dependent on cloud computing (100%). HydroSense2.0 has a balanced hybrid implementation. Arduino-IoT is highly cloud-dependent and less local processing.

Table 7: Power Consumption (%) *(lower consumption → higher %)*

Model	Avg (%)	Peak (%)
IOT-Smart Meter	85	92
HydroSense2.0	92	97
Arduino-IOT	115	107
Aqua Sense	100	100

This is the average and maximum percentages of four IOT models. The models are indicated on the x-axis labelled barks with the percentages indicated on the y-axis. Lower filled region represents the Average percentages and upper translucent region on top represents the Peak percentages that depict the cumulative peak values and the input of average values each model.

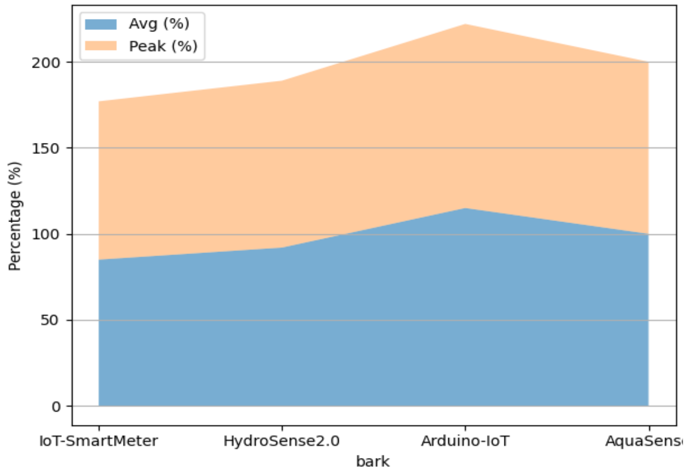

Figure 7: Stacked Area Chart of Average and Peak Percentages for IOT Models

Figure 7 indicates a trend of average and peak performance. The best combined performance is attained by Arduino-IoT, which implies high scalability. IoT-SmartMeter and HydroSense2.0 are rather stable and reliable in terms of trends, whereas Aqua Sense is balanced.

Table 8: Cost per Unit (%) (lower cost → higher %)

Model	Min (%)	Max (%)
IOT-Smart Meter	20	25
HydroSense2.0	40	35
Arduino-IOT	100	90
Aqua Sense	82	62

This represents minimum and maximum percentage values of four IOT models. The models are indicated by the x-axis marked with the word bark and the percentage by the y-axis. The space between zero and Min percentages is filled in solid colour, whereas the space above the space filled in is a stacked area with a translucent fill which is located on the top. Such a layout serves to make comparisons of the values and visualize the sum of Min and Max percentages.

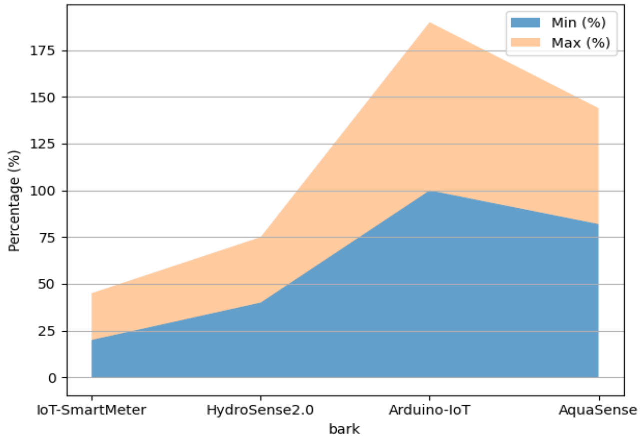

Figure 8: Stacked Area Chart of Min and Max Percentages for IOT Models

Minimum and maximum performance spread is depicted in figure 8. Arduino-IoT displays the broadest scope, which implies that it is highly scaled. Aqua Sense has still strong values, whereas HydroSense2.0 experiences moderate improvement. The lowest range of performance is registered by IoT-SmartMeter.

V. CONCLUSION

In terms of high performance and strong and reliability, HydroSense2.0 and Aqua Sense are the parties which will appear to win. They are suitable in situations where they need to be tough and reliable. IoT-SmartMeter is suitable enough for smaller and not large-scale jobs--no big thing but gets the job done. Arduino-IoT is wildcard. You must make it a little more, or perhaps you want something more special and that is why it is more suited to special situations. The way you handle processing; one of the things you really need to consider. Local disk or data transfer to the cloud changes the rates of efficiency and speed of your system. Finally, it is not necessarily a question of the best, as far as the choice of the proper model of IoT is concerned. It is everything to do with comparing what technology is able to do and what you need in your project.

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