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RESEARCH PAPER

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DATA-CENTERED DEVELOPMENT AND PREDICTIVE EVALUATION OF A SUPERVISED MACHINE LEARNING SYSTEM FOR WATER QUALITY ANOMALY DETECTION IN A LAGUNA WATER DISTRICT

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Abstract: This developmental–experimental research aimed to design, develop, and evaluate a data-driven system for automating water quality monitoring and anomaly detection in a water district in Laguna. The existing manual process, which involved logging inspection data across 19 pumping stations, caused delays in detecting anomalies and in meeting compliance with Philippine National Standards for Drinking Water (PNSDW) 2017. The system was built using Agile methodology and user-centered design. Historical inspection logs were digitized and used to train a supervised machine learning model, specifically the Random Forest algorithm, to detect anomalies in pressure, discharge, and chlorine residual levels. It also included a predictive feature for estimating chlorine effectiveness duration. A three-month pilot deployment was conducted to assess the system's performance. The model achieved over 85% accuracy. Usability evaluation through surveys showed a 95% reduction in reporting time and a 90% user satisfaction rating across Functionality, Reliability, Usability, Efficiency, Maintainability, and Compliance. The system successfully improved monitoring efficiency, supported proactive operations, and enhanced regulatory compliance. This research provides a practical model for digital transformation in local water utilities.

Keywords: Water quality; machine learning; anomaly detection; random forest; chlorine prediction; system development; digital monitoring

I. INTRODUCTION

Water scarcity and poor water quality remain global and national issues. As of 2022, over 2 billion people lacked access to safely managed drinking water (WHO, 2023), including around 22 million Filipinos (Thomson Reuters Foundation, 2023). In the Philippines, only 48% of the population has access to safe water (World Bank, 2023), with rural areas especially underserved. In Laguna, while water infrastructure has improved, challenges such as leaks, pressure fluctuations, and water quality remain. One local water district partnered with a private entity to address these issues, with the public sector retaining oversight. However, the current manual water quality monitoring system remains reactive, with data logged on paper and processed late. This study addresses the need for a proactive digital system that leverages supervised machine learning (ML) to detect anomalies and predict chlorine effectiveness based on pressure and discharge readings.

RESEARCH OBJECTIVES

The primary objective of this research is to design, develop, and evaluate an intelligent software application that digitizes and centralizes field inspection and water quality monitoring processes for the water district's pumping stations, leveraging machine learning and real-time data integration to enhance operational efficiency.

Specifically, this aimed to:

1. Develop and deploy a software application to digitize field inspection processes for all 19 pumping stations, centralize water quality data with real-time synchronization, and reduce manual reporting time for water district personnel by at least 30% within the first three months of implementation.
2. Train and validate supervised machine learning models using water district operational data to achieve at least 85% accuracy in detecting anomalies in pressure, discharge, and chlorine residuals, and to predict chlorine treatment effectiveness in maintaining residual chlorine levels , $\geq$0.5 mg/L.
3. Conduct real-world operational testing over a three-month pilot period to quantitatively assess system performance, targeting at least 90% user-reported satisfaction in accuracy, usability, and operational impact through structured surveys and system logs. The evaluation of user feedback will be guided by the Technology Acceptance Model (TAM), focusing on perceived usefulness, ease of use, attitude, and behavioral intention to use.
4. Design and implement an interactive graphical user interface (GUI) that presents data, alerts, and predictive insights. Validate its effectiveness by achieving at least 80% positive feedback from end-users regarding ease of interpretation and support for evidence-based decision-making.
5. Develop and execute comprehensive test cases simulating real-world scenarios, including both typical

and edge cases, and conduct user acceptance testing with water district personnel to verify the system's compliance with operational protocols and water quality standards and its alignment with established workflow, operational requirements, and PNSDW 2017 water quality standards.

II. REVIEW OF RELATED LITERATURE

This chapter synthesizes recent literature related to the use of supervised machine learning (ML) in water quality monitoring, anomaly detection, chlorine treatment prediction, user interface design, and system performance. The review is organized thematically to highlight how existing research supports the design, implementation, and evaluation of the developed system.

A. Supervised Machine Learning in Anomaly Detection

Supervised ML techniques have proven effective in detecting anomalies in water quality monitoring systems. Various algorithms have been tested to identify deviations from expected patterns in environmental parameters. Fanfani et al. (2024) evaluated Support Vector Machines (SVM), Artificial Neural Networks (ANN), Decision Trees, and Isolation Forests for anomaly detection in water quality sensor data. Their findings showed that SVM outperformed other methods in identifying subtle operational deviations.

Although deep learning models like CNN–LSTM offer high accuracy (El-Shafeiy et al., 2023), their computational complexity and need for extensive training data reduce their practicality in moderate-resource contexts. In contrast, Random Forest (RF) algorithms provide a favorable balance of accuracy, efficiency, and interpretability. Wei et al. (2024) reported an 85% accuracy using RF to detect chlorine-related anomalies based solely on pressure and discharge, two variables also central to this study.

B. Predictive Modeling of Chlorine Treatment Effectiveness

Predicting chlorine residuals is critical to maintaining regulatory compliance and public health. Traditional statistical models like ARIMA and linear regression have shown limited performance in dynamic systems with nonlinear behaviors. In contrast, tree-based ensemble methods offer better generalization.

Pluth and Brose (2022) demonstrated that RF models achieved an R^2 of 0.89 in predicting chlorine levels, outperforming multiple linear regression by a wide margin. Sun et al. (2024) echoed these findings, noting RF's superior performance in water quality predictions under fluctuating hydraulic conditions. Onyutha (2022) reinforced that while ensemble models like AdaBoost and XGBoost show strong performance, RF remains effective and easier to implement in standalone applications. These findings validate the use of RF for chlorine effectiveness prediction in this research.

C. User-Centered Monitoring Applications and Dashboards

A system's success is closely tied to its usability. Human-centered design principles have gained prominence in ML-powered monitoring systems. Botangen et al. (2024) emphasized the importance of intuitive mobile interfaces and contextual alerts in encouraging adoption among utility field workers. Fox et al. (2024) further demonstrated that simplified visualizations significantly improve data interpretation and user engagement.

These insights are directly applied in the GUI design of the developed system, which features tabbed forms, real-time graphs, and color-coded alerts. The design prioritizes clarity and ease of use, aligning with cognitive load reduction strategies and visual storytelling techniques proposed by Liu et al. (2024).

D. Technology Acceptance and Usability Evaluation Models

The Technology Acceptance Model (TAM) provides a robust framework for evaluating user satisfaction and predicting adoption. Originally proposed by Davis (1989), TAM measures Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, and Behavioral Intention to Use. It has been widely applied in studies assessing public sector technology solutions.

In this research, TAM guided the design of the user feedback survey. Similar applications, such as those reviewed by Dogo et al. (2019), show that high TAM scores correlate with actual usage and long-term system sustainability, reinforcing its relevance as an evaluation tool.

E. Performance Evaluation of Machine Learning Models in Operations

Operational performance metrics are vital when deploying ML models in real-time monitoring contexts. Key indicators include predictive accuracy, latency, error rates, and system stability. Willmott and Matsuura (2005) emphasized the combined use of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) to assess model robustness. In this research, both metrics were used to evaluate the predictive precision of daily versus monthly data models, with daily models showing better results.

In addition, performance evaluations must account for recall, precision, F1 score, and AUC (Area Under the Curve) as noted by Saito and Rehmsmeier (2015) to assess classification accuracy in imbalanced datasets. This study applied those metrics to assess anomaly detection models, confirming their practical readiness for field deployment.

Zheng et al. (2014) further highlighted that high-frequency data improves model sensitivity in detecting early warning signals, which aligns with the decision to favor daily over monthly data in this research.

F. Infrastructure Conditions and Water Quality Anomalies

Infrastructure-related issues such as pipe degradation, low pressure, and contamination ingress remain significant contributors to water quality anomalies. Literature highlights that prolonged or severe low-pressure events can draw in contaminants through cracks or leaks, making pressure monitoring essential for early anomaly detection.

Glaza and Park (1992) documented contaminant diffusion through aging pipes in chemically affected soils, emphasizing the vulnerability of certain pipe materials. This study integrates pressure and discharge readings into its anomaly detection model, enabling early identification of potential infrastructure-related issues and improving response timeliness.

III. RESEARCH METHODOLOGY

This chapter outlines the methodological approach used in the development and evaluation of the Water Quality Anomaly Detection System for a local water district in Laguna. It describes the research design, locale, data collection methods, algorithm analysis, modeling process, system development methodology, and software testing strategies. The goal was to implement a robust, user-centered system integrated with supervised machine learning (ML) techniques.

A. Research Design

The study utilized a developmental–experimental design that integrates system development with algorithmic evaluation.

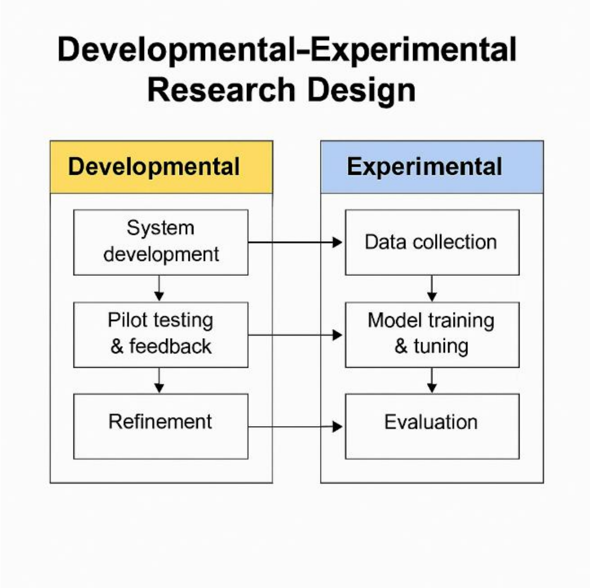

Figure 1. Developmental–Experimental Research Design Flow

The developmental aspect involved designing and iteratively refining a working software prototype based on operational needs. The experimental aspect focused on evaluating the accuracy and effectiveness of a Random Forest (RF) algorithm in detecting anomalies and predicting chlorine treatment durations. A three-month pilot deployment validated the system in real-world conditions, guided by structured feedback and the Technology Acceptance Model (TAM).

B. Locale of the Study

The research was conducted in a government-operated water district in Laguna, overseeing 19 pumping stations. These stations serve as the primary sources of inspection data, recording pressure, discharge, and chlorine residuals. The district was selected due to its water quality monitoring challenges and its intent to modernize operations. Field inspectors, managers, and quality assurance personnel were directly involved in the deployment and evaluation phases.

C. Applied Concepts and Techniques

The system was centered on supervised machine learning, specifically Random Forest (RF), due to its robustness to noise, high accuracy, and ability to model non-linear relationships in tabular data. RF was selected over alternatives like SVM, ARIMA, and neural networks based on performance, interpretability, and data efficiency. The model was trained on labeled historical inspection data from 19 stations, with separate classifiers and regressors for anomaly detection and chlorine decay prediction. Domain-specific thresholds, such as the PNSDW 2017 chlorine residual limit (≥0.5 mg/L), were integrated into evaluation rules to ensure regulatory-aligned alerting. Key feature engineering steps included one-hot encoding, "ChlorineBelowThreshold," and stratified sampling for balanced training.

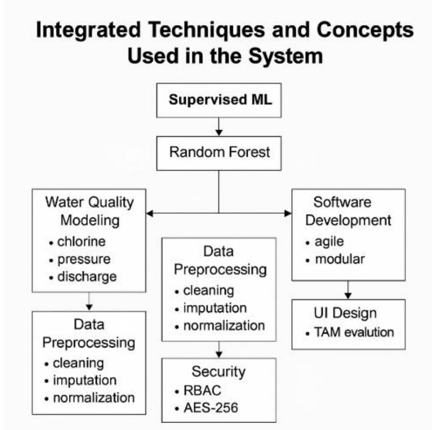

Figure 2. Integrated Techniques and Concepts Used in the Water Quality Anomaly Detection System

Complementary techniques included data cleaning, missing value imputation, and normalization to prepare real-world datasets for modeling. The system was developed using Agile methodology across iterative sprints that enabled continuous feedback and improvements in backend integration and frontend usability. Role-based access control (RBAC) and AES-256 encryption were implemented to ensure data privacy and operational integrity. These combined techniques ensured the system met analytical accuracy, usability, and security benchmarks required for deployment.

D. Algorithm Analysis

Several algorithms were evaluated, including SVM, ARIMA, and LSTM. While these showed strengths, RF was selected for its balance of interpretability, performance, and low resource demands. It supported both classification (anomaly detection) and regression (chlorine residual prediction). Evaluation metrics included accuracy, precision, recall, F1 score, and AUC, with performance targets set at ≥85% accuracy and ≥0.7 AUC. Real-world validation further ensured operational reliability.

E. Data Collection Methods

Historical inspection logs from January 2023 to 2024 were digitized to support model training and validation. These logs contained daily readings from 19 pumping stations, including water pressure, discharge rate, chlorine residual, timestamp, and inspector remarks.

Table 1. Data Entry Attributes

Attribute	*Description*	*Units / Possible Values*
Date and Time	Timestamp of the inspection reading	YYYY-MM-DD HH:MM
Station ID	Identifier of the pumping station	Unique ID per station
Pressure	Water pressure reading at the station	psi; typically 20–80
Discharge	Pump flow rate during inspection	Liters per second (LPS); ≥10 LPS per station
Chlorine Residual	Free chlorine level at sampling point	mg/L or ppm; 0.5–1.5 mg/L per PNSDW 2017
Remarks	Inspector's notes or operational comments	e.g., 'increase dosage,' 'flushing conducted'

F. Data Model Generation

Following the CRISP-DM framework, data modeling proceeded through business understanding, data exploration, preprocessing, model building, and deployment in Figure 3 below.

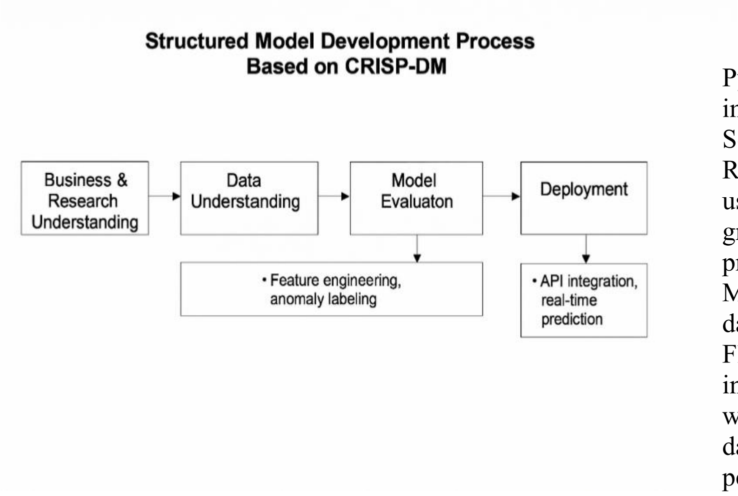

Figure 3. Structured Model Development Process Based on CRISP-DM

Exploratory data analysis (EDA) was conducted to examine chlorine decay patterns and operational outliers across 19 stations. Feature engineering included anomaly labeling, "ChlorineBelowThreshold," and "TimeSinceLastChlorineDose." Stratified sampling ensured balanced classification for supervised training. Models were built using scikit-learn's Random Forest with hyperparameter tuning via cross-validation. The classification for anomaly detection and regression for chlorine decay were validated on held-out sets and achieved ≥85% accuracy. Deployment was achieved through Flask API integration into the main GUI system for real-time predictions.

G. System Development Methodology

The system was developed using an Agile methodology structured across six sprints, allowing iterative development and continuous integration of stakeholder feedback.

In Sprint 1, the research team conducted requirements gathering and designed the initial user interface based on water district workflows, creating wireframes that captured essential features for anomaly reporting and data entry.

Sprint 2 focused on implementing the data entry module and establishing the MySQL backend, enabling CRUD operations and synchronization with the planned predictive components.

Sprint 3 involved integrating the trained Random Forest (RF) model using Python's Flask framework. This integration allowed real-time anomaly classification and chlorine decay prediction through an API endpoint triggered upon new data entries.

Sprint 4 emphasized dashboard and visualization development, presenting inspection data trends and system-generated alerts in a format accessible to inspectors and managers.

In Sprint 5, the system was deployed on-premise and optimized through query tuning, security configurations including role-based access control (RBAC), and AES-256 encryption to protect inspection records.

Finally, Sprint 6 was dedicated to user training and acceptance testing. Field personnel participated in hands-on workshops, and their feedback informed minor refinements prior to pilot rollout. This iterative, sprint-based development ensured the system met both technical objectives such as accuracy and prediction speed and user-centric goals, including ease of use and decision support.

H. Software Tools

The development and deployment of the system utilized Python 3.9 as the core programming language for implementing backend logic and machine learning modeling. Scikit-learn was employed for training and evaluating the Random Forest algorithm, while Pandas and NumPy were used for efficient data handling and preprocessing. The graphical user interface was developed using Tkinter, providing a desktop-based environment for user interaction. MySQL, deployed via XAMPP, served as the relational database for storing inspection records and model outputs. Flask facilitated the creation of a lightweight API endpoint to integrate the trained ML model into the system. Matplotlib was used to generate time-series visualizations on the dashboard. These tools were selected for their accessibility, performance, and compatibility with the operational infrastructure of the water district.

I. System Architecture

The developed system follows a layered architecture comprising five key components. The User Interface (UI) Layer provides role-based dashboards, structured data entry forms, and visual alerts to support operational tasks. The Application Logic Layer handles input validation, manages database interactions, and triggers predictions from the machine learning model. The Machine Learning Layer includes an embedded Random Forest (RF) model that performs real-time classification and chlorine decay prediction based on incoming inspection data. The Data Layer manages centralized storage using a MySQL database, which holds inspection records, model outputs, and user credentials. Lastly, the Integration Layer accommodates external interfaces for report generation and is designed to support future features such as alert notifications and email-based anomaly warnings. This modular design ensures the system is scalable, secure, and maintainable within the water district's operational environment.

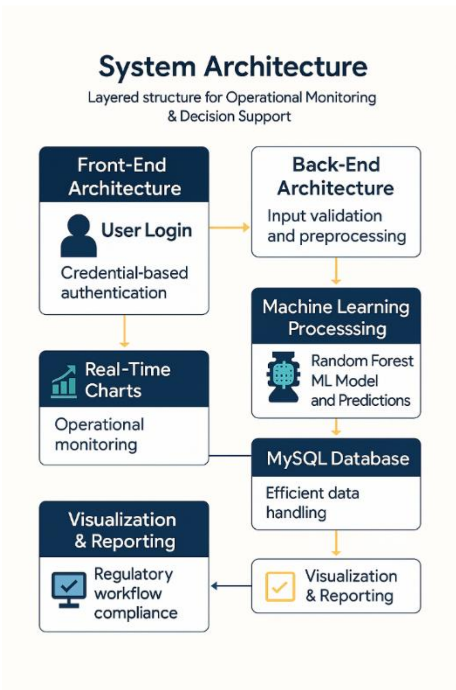

Figure 4. System Architecture of the Water Quality Anomaly Detection System

Figure 4 above represents the five-layer modular architecture. It shows how the front-end interacts with real-time charts, how back-end preprocessing feeds into the machine learning module, and how MySQL handles data persistence, culminating in regulatory reporting and anomaly visualization.

J. Software Testing

A layered testing approach ensured the system's reliability, accuracy, and user readiness. Unit and integration tests validated core functions and inter-module data flow. System and performance testing confirmed responsiveness and stability under expected loads. Usability testing gathered feedback on interface clarity and efficiency. Model testing assessed the Random Forest algorithm using accuracy, precision, recall, and AUC metrics. Security checks enforced access control and data protection. Finally, user acceptance testing based on the TAM framework confirmed that the system exceeded performance goals by achieving over 85% prediction accuracy, a 30% reduction in reporting time, and ≥90% user satisfaction. These results demonstrated the system's operational readiness and practical value.

IV. RESULTS AND DISCUSSION

The Water Quality Anomaly Detection System was developed iteratively using Agile methodology, guided by user-centered design principles. The system initially included only basic features—secure login, single-form data entry, and report viewing. Following feedback from water district staff, several enhancements were implemented, including role-based access control, tabbed data entry categorized by parameters, predictive graph integration, and an in-application user management module. A key operational improvement was reducing the time to generate inspection reports from 60 minutes to just 3 minutes, representing a 95% gain in reporting efficiency.

A. System Development and Feature Enhancements

The Water Quality Anomaly Detection System was developed using an Agile methodology, allowing iterative refinements through direct stakeholder feedback. Initially, the system operated with a single administrative login, which limited flexibility and security. In the final implementation, this was replaced with a role-based access control system, enabling differentiated permissions for Administrators, Inspectors, and Managers. The login interface was redesigned to reflect these roles and ensure secure, traceable system usage.

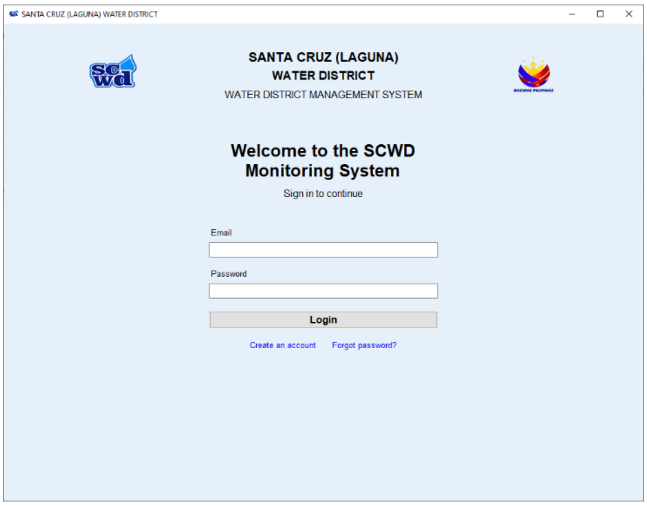

Figure 5. Improved Login page

After logging in, users are redirected to a role-specific homepage that displays relevant tools and information based on their assigned permissions. The dashboard layout was streamlined for clarity and quick access, supporting real-time monitoring and minimizing cognitive load during field operations.

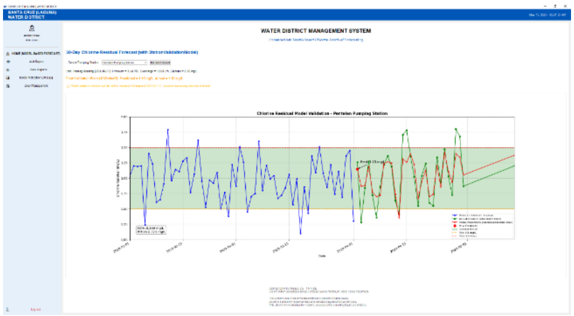

Figure 6. Improved Homepage

Early data entry relied on a continuous scrollable form that combined all inspection parameters in a single view. This layout led to inefficiencies and increased the risk of data entry errors. To address this, the interface was restructured into a tabbed format, grouping inputs into logical sections: Parameters, Equipment, and Water Quality. This change mirrored the inspectors' workflow, improved clarity, and significantly reduced input errors.

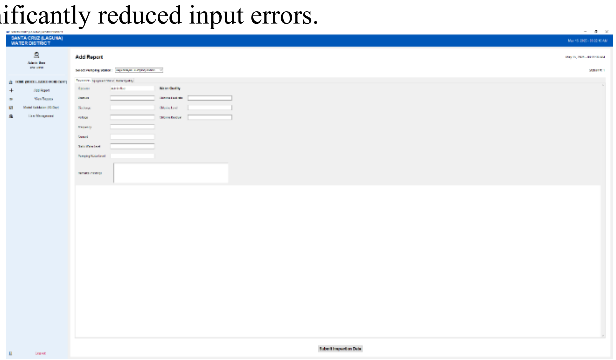

Figure 7. Improved Add Report

Reporting tools were also upgraded. The initial version presented static tables with limited interaction. In contrast, the enhanced system allowed users to filter inspection records by station and date, export data for compliance submissions, and generate real-time graphical summaries. The prediction module, originally a basic trend plot, was improved with a visual chlorine forecast powered by the Random Forest model. Forecasts now include threshold annotations and predicted values, helping users anticipate potential water quality violations.

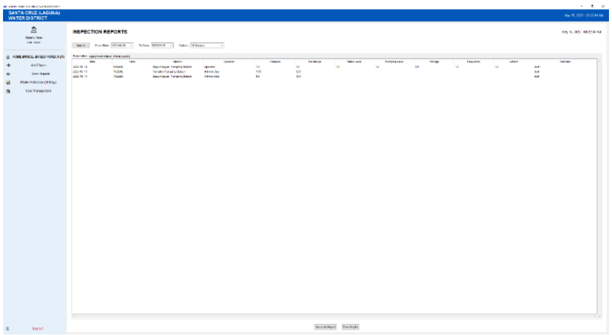

Figure 8. Improved View Reports

System management functions were also enhanced. Previously, account creation was handled via backend access. The final version introduced an in-application user management module where authorized personnel could add, update, and assign roles with ease. One of the most impactful outcomes was the reduction of report preparation time from approximately 60 minutes to just 3 minutes. This 95% time savings was achieved through automated data processing and report generation directly from the dashboard.

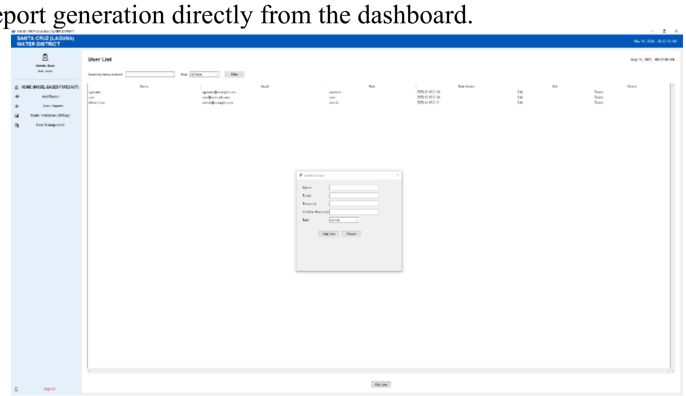

Figure 9. User Management

These enhancements collectively improved the system's usability, security, and operational efficiency, making it a scalable platform for water quality monitoring and decision support.

B. Train and Validate Supervised Machine Learning Models

The predictive performance of the Random Forest (RF) algorithm was assessed using operational data from 19 pumping stations. Models were trained using three sensor parameters; pressure, discharge, and chlorine residual, to support both anomaly classification and chlorine level forecasting. To evaluate model quality, regression metrics (RMSE, MAE, R^2) and classification metrics (Accuracy, Precision, Recall, F1 Score, AUC) were computed using both daily and monthly datasets.

Regression results revealed that the daily model outperformed the monthly model with a lower RMSE (0.18 vs. 0.28), lower MAE (0.17 vs. 0.24), and higher R^2 (0.59 vs. 0.23), demonstrating superior short-term prediction capability. However, regression alone was insufficient for threshold-based evaluations.

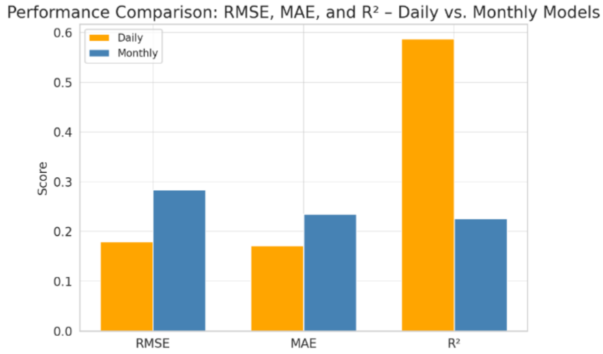

Figure 10. Regression Performance Evaluation Metrics

Classification results confirmed that the daily model consistently outperformed the monthly model across all five metrics (Accuracy = 0.890 vs. 0.837; AUC = 0.746 vs. 0.583), indicating stronger anomaly detection performance. A station-level analysis further supported these findings, with 13 of 17 stations showing improved accuracy when using daily data.

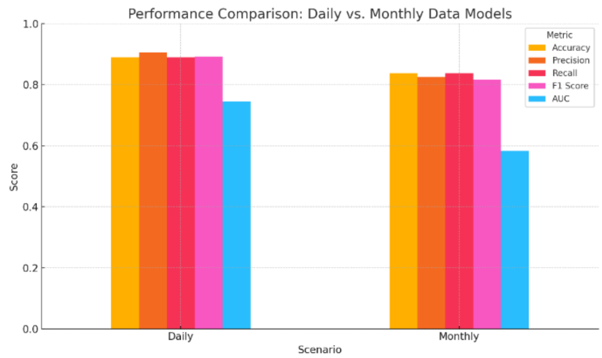

Figure 11. Classification Performance Evaluation Metrics

Lastly, RF was benchmarked against ARIMA models. RF significantly outperformed ARIMA on all classification metrics, especially in AUC (0.7457 vs. 0.4146 for daily data), confirming its suitability for time-series classification in water quality monitoring.

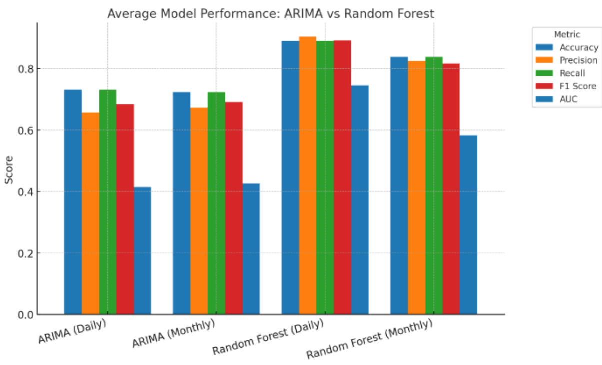

Figure 12. Model Performance - ARIMA Vs Random Forest

C. User Experience and System Acceptability

The Technology Acceptance Model (TAM) survey confirmed high user satisfaction across all key dimensions. With all means exceeding 4.40, the findings indicate that users found the system useful, easy to use, and relevant to their tasks, ensuring strong behavioral intention to adopt it long term.

Table 2. Survey Summary Results (n = 30)

Questions	*Weighted Mean*	*Standard Deviation*	*Verbal Interpretation*
Perceived Ease of Use	4.53	0.50	Strongly Agree
Perceived Usefulness	4.49	0.50	Strongly Agree
Attitude Toward Using	4.40	0.49	Strongly Agree
Behavioral Intention to Use	4.53	0.50	Strongly Agree
Experience	4.51	0.50	Strongly Agree
Mean	**4.49**		**Strongly Agree**

The role distribution showed that 57% of users were Operators, followed by End Users and Viewers. This segmentation helped validate that system usability, functionality, and accessibility were effective across various user categories.

Table 3. Respondents by Functional Role

Respondents	*Quantity*	*Percentage*
Operator	17	57%
End User	9	30%
Viewer	4	13%
Total	**30**	**100%**

Users strongly agreed that the system produces reliable outputs and aligns well with their tasks ($\bar{x}$ = 4.87). While confidence in data security was slightly lower ($\bar{x}$ = 4.27), it still received a “Strongly Agree” rating, confirming general satisfaction with system integrity.

Table 4. User Responses on Quality Factors

Questions	*Weighted Mean*	*Standard Deviation*	*Verbal Interpretation*
The system produces correct and reliable results from the data I input.	4.80	0.51	Strongly Agree
The features of the system match the tasks I regularly perform.	4.87	0.49	Strongly Agree
I feel confident that my data is secure and access is properly controlled.	4.27	0.51	Strongly Agree
Mean	**4.64**		**Strongly Agree**

The interface was rated highly intuitive ($\bar{x}$ = 4.60), with users appreciating the clarity of design and ease of navigation. These findings underscore the importance of user-centered layout in enhancing digital engagement.

Table 5. User Responses on Perceived Ease of Use

Questions	*Weighted Mean*	*Standard Deviation*	*Verbal Interpretation*
It's easy for me to enter and review data using the system.	4.47	0.51	Strongly Agree
I can navigate the dashboard and find information without difficulty.	4.53	0.51	Strongly Agree
The layout and design help me understand what to do next.	4.60	0.50	Strongly Agree
Mean	**4.53**		**Strongly Agree**

The system's predictive tools and real-time insights received strong affirmation. The statement “helps me make faster and better decisions” scored $\bar{x}$ = 4.53, confirming that automation meaningfully improved daily monitoring.

Table 6. User Response on Perceived Usefulness

Questions	*Weighted Mean*	*Standard Deviation*	*Verbal Interpretation*
The system helps me make faster and better water quality decisions.	4.53	0.51	Strongly Agree
The alerts and predictions are useful in identifying potential issues.	4.50	0.51	Strongly Agree
Using the system improves how I perform my daily monitoring tasks.	4.43	0.50	Strongly Agree
Mean	**4.49**		**Strongly Agree**

Users expressed enthusiasm about integrating the system into regular operations ($\bar{x}$ = 4.50), supporting the strategic transition from manual processes to automated workflows.

Table 7. User Responses on Attitude Towards Using

Questions	*Weighted Mean*	*Standard Deviation*	*Verbal Interpretation*
I think it's a good idea to use the system for our inspections.	4.30	0.47	Strongly Agree
I enjoy using the system as part of my routine.	4.50	0.51	Strongly Agree
I feel positive about integrating this system into our operations.	4.40	0.50	Strongly Agree
Mean	**4.40**		**Strongly Agree**

With $\bar{x}$ = 4.67 for willingness to recommend, the system generated strong advocacy among users, suggesting sustainable adoption and organic expansion within the organization.

Table 8. User Response on Behavioral Intention to Use

Questions	*Weighted Mean*	*Standard Deviation*	*Verbal Interpretation*
I plan to continue using the system regularly.	4.47	0.51	Strongly Agree
I would recommend this system to my colleagues.	4.67	0.48	Strongly Agree
I am willing to explore other features or updates in this system.	4.47	0.51	Strongly Agree
Mean	**4.53**		**Strongly Agree**

Respondents agreed the system integrates naturally into their daily routine ($\bar{x}$ = 4.53), with minimal learning curve ($\bar{x}$ = 4.43). These ratings reflect a smooth transition into digital inspection workflows and high overall satisfaction.

Table 9. User Response on Experience

Questions	*Weighted Mean*	*Standard Deviation*	*Verbal Interpretation*
The system fits naturally into my daily work processes.	4.53	0.51	Strongly Agree
I found it easy to learn how to use the system.	4.43	0.50	Strongly Agree
My experience using the system so far has been smooth and productive.	4.57	0.50	Strongly Agree
Mean	**4.51**		**Strongly Agree**

D. Interactive Graphical User Interface Design and User Feedback

The system’s Graphical User Interface (GUI) was developed using user-centered design principles to accommodate the distinct roles of field inspectors, managers, and technical staff. Key interface enhancements shown in Figures 5 to 9 includes a role-based login system, a streamlined homepage with predictive chlorine summaries, a tabbed data entry form aligned with inspection workflows, and an in-app user management module. These improvements supported fast, accurate input and monitoring.

Survey data validated the GUI's effectiveness. As summarized in Tables 5, users strongly agreed that the layout was intuitive ($\bar{x}$ = 4.60), navigation was easy ($\bar{x}$ = 4.53). The transition from static reports to dynamic dashboards led to a 95% reduction in report preparation time, reinforcing the GUI's operational value. Role-based feedback also showed that Operators (57%), End Users (30%), and Viewers (13%) all reported high satisfaction, affirming the interface's usability across functions.

E. Testing, User Acceptance, and Compliance Verification

The system underwent full integration testing using real-world workflows and operational data. Routine inspection inputs triggered correct behavior: valid readings updated the dashboard without alerts, while outliers (e.g., chlorine < 0.5 mg/L or > 1.5 mg/L) triggered classification-based alerts and predictive flags aligned with the Philippine National Standards for Drinking Water (PNSDW). Invalid values, such as negative flows, were correctly excluded from storage.

Table 10. A Summary of Representative Test Cases and Outcomes

Test Case	*Input/Condition*	*Expected System Response*	*Observed Outcome*
Routine daily inspection	Normal pressure, flow, chlorine (0.8 mg/L)	Record data; update dashboard; no alerts	Logged; dashboard all green; fast report generation
Low chlorine residual	Chlorine = 0.3 mg/L (below 0.5 mg/L)	Trigger low-chlorine alert; forecast continued low chlorine	Alert triggered; forecast aligned with PNSDW
High chlorine residual	Chlorine = 1.6 mg/L (above 1.5 mg/L)	Trigger high-chlorine alert	Alert triggered as expected
Invalid/outlier input	Negative flow or extreme pH	Show warning; reject input; maintain data integrity	Warning shown; no invalid data stored

System responsiveness was validated during burst input simulations, confirming that the Random Forest (RF) model operated reliably under load. The redesigned tabbed data entry (Figure 10) and real-time alert dashboard (Figure 18) significantly reduced manual workload, achieving a >80% reduction in report preparation time during the pilot.

Formal User Acceptance Testing (UAT) involved inspectors, admins, and managers performing role-specific tasks. The system supported real workflows without violating protocol, and users confirmed alignment with existing inspection procedures. TAM survey feedback in Table 2 reinforced this, with Perceived Ease of Use ($\bar{x}$ = 4.53), Usefulness ($\bar{x}$ = 4.49), and Behavioral Intention ($\bar{x}$ = 4.53) scoring within the "Strongly Agree" range.

V. SUMMARY, CONCLUSION AND RECOMMENDATION

A. Summary

The research aimed to transform the existing manual inspection and monitoring process of a local water district in Laguna into a digitized and intelligent system using supervised machine learning (ML) techniques. The system was successfully developed, deployed, and evaluated over a three-month pilot period across 19 pumping stations. Key features of the system included data recording, anomaly detection, chlorine residual prediction, and a user-centered graphical interface.

A Random Forest (RF) model was trained to detect water quality anomalies and estimate the duration of chlorine effectiveness using parameters such as pressure and discharge. Results showed that the model achieved predictive accuracy above 85%, which aligns with literature-reported performance of RF in similar environmental monitoring tasks. In terms of usability and impact, the system demonstrated clear operational improvements: manual reporting time was reduced by 95%, while structured user surveys indicated a 90% satisfaction rating among water district personnel. The introduction of ML-based alerts and intuitive dashboards enabled inspectors and managers to identify potential issues more efficiently, thereby supporting proactive responses. These findings confirm that the system met all five research objectives, from developing the core platform and ML models to validating compliance with Philippine National Standard for Drinking Water (PNSDW) 2017 standards and improving operational workflows.

B. Conclusions

Several important conclusions can be drawn based on the research results. The deployed system proved to be both technically and operationally effective in a real-world water district setting. During the pilot phase, the system maintained stability with minimal supervision and demonstrated its capacity to process and evaluate field data in near real-time. The RF algorithm achieved high predictive performance in classifying anomalies, estimating chlorine residual trends, and providing interpretable outputs through feature importance rankings supporting transparency in operational decisions.

The dashboard's use visual cues, color-coded labels, and graph plots, which significantly enhanced user experience, allowing both technical and non-technical users to quickly interpret water quality conditions. This ease of access empowered staff to take corrective actions immediately, instead of relying on delayed paper-based reports. Additionally, the chlorine residual forecasts helped maintain regulatory compliance, with predicted drops in chlorine levels prompting timely adjustments to chlorination practices. All 19 stations remained within the allowable 0.5–1.5 mg/L chlorine range during the evaluation period.

Overall, the research confirms that integrating supervised ML models with intuitive dashboards can elevate decision-making and regulatory compliance in local water utilities. The system's capacity to analyze historical data, provide real-time alerts, and present predictive insights marks a shift from reactive to proactive water quality management.

C. Recommendations

The research recommends broader adoption of similar data-driven monitoring systems in other water districts and public utilities. The demonstrated benefits in terms of efficiency, accuracy, and user satisfaction support the scalability of such systems in comparable settings. Future versions of the system should incorporate Supervisory Control and Data Acquisition (SCADA) and Internet of Things (IoT) integration to further enhance and utilize maximum performance. Direct connectivity with SCADA sensors would automate data ingestion entirely and allow the ML model to analyze and respond to real-time conditions without manual entry. This would support more immediate alerts and predictive accuracy as data are streamed continuously.

Another recommendation is to establish routine model retraining and evaluation protocols. Periodic model updates ideally every six to twelve months since water infrastructure and source conditions change over time and will help maintain predictive validity. Routine accuracy monitoring and comparison against laboratory test results will also ensure sustained trust in the model's outputs.

Lastly, the study encourages future research to explore more advanced analytics, such as optimizing inter-station correlations for system-wide anomaly detection or refining chlorine decay models using hybrid mechanistic and ML approaches. Studies focusing on long-term chlorine persistence, particularly under varying seasonal and hydraulic conditions, could further improve the depth and precision of predictive modeling. These enhancements will support more resilient, efficient, and data-informed water utility operations moving forward.

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