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Decentralized Wastewater Treatment and Reuse for Sustainable Water Management in a Nigerian University

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Abstract

Wastewater management remains a critical environmental challenge in many developing countries, where untreated domestic effluents contribute to groundwater contamination and environmental degradation. This study evaluates the effectiveness of a decentralized wastewater treatment system (WWTS) implemented at Dr. Aderemi Makanjuola Hall of Residence, Edo State University Iyamho, for sustainable water quality management and potential non-potable reuse. Laboratory analyses were conducted to determine the physicochemical characteristics of wastewater samples, including pH, Total Dissolved Solids (TDS), Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Dissolved Oxygen (DO), Total Suspended Solids (TSS), chloride ions, temperature, and sulphate. Conventional treatment processes comprising coagulation, sedimentation, filtration, and chlorination were applied to reduce pollutant concentrations. Significant reductions in BOD, COD, and TSS were observed after treatment, indicating effective removal of organic pollutants and suspended solids. However, TDS values increased significantly after treatment, highlighting the limitation of conventional methods in removing dissolved salts. A machine learning classification model developed using the MATLAB Classification Learner App was compared with a Markov chain model for short-term prediction of wastewater quality states. The optimized Support Vector Machine (SVM) model achieved an accuracy of 79.2%. The findings demonstrate that

decentralized wastewater treatment systems can improve water quality for non-potable reuse in institutional settings. However, additional advanced treatment processes are required to address dissolved solids and ensure safe reuse.

Keywords: Decentralized Wastewater Treatment, Support Vector Machines (SVM), Markov Chains, Non-Potable Water Reuse, Organic Pollutant Removal.

Introduction

The management of wastewater remains a major environmental challenge in many developing countries. In Nigeria, ineffective wastewater disposal practices contribute significantly to ground water contamination, surface water pollution and public health risks.

Domestic effluents generated from residential buildings contain suspended solids, organic matter and dissolved contaminants that can negatively impact surrounding ecosystems if not properly treated. Contemporary studies have revealed the grave consequences of prolonged exposure to these effluents when not managed properly, including the development of specific health issues like gastrointestinal diseases, skin infections, eye infections, and other waterborne diseases (WHO, 2006; Dickin *et al.,* 2016)

According to Silva (2023), much of wastewater comes from homes, industries, and businesses. In homes, water from sinks, showers, bathtubs, dishwashers, toilets, and washing machines is often channeled through collection pipes to sewage treatment plants (Fito & Van Hulle, 2021). A study by Adewumi & Oguntuase (2016) highlights that wastewater reuse is an appealing option for pollution abatement and can provide an alternative water supply for many activities that do not require drinking water quality such as toilet flushing and clothes washing. The integration of effective, efficient and eco-friendly wastewater management practice into the life cycle and operation of the urban system would be a step towards achieving Sustainable Development Goal (SDG), particularly goal 6, which will ensure a healthier environment for everyone. Wastewater management has proven to be a reliable and effective tool for achieving sustainable development, by serving as a means of pollution prevention, source of alternative water for non-potable uses and disease prevention (Oji *et al.,* 2018). There is limited public awareness about the benefits of treated wastewater, compounded by cultural and societal perceptions that discourage its reuse (Iheukwumere *et al.,* 2021). The absence of a comprehensive policy framework to guide wastewater treatment and reuse in Nigeria hinders progress in this critical area (Lakai, 2021). University campuses generate significant volumes of wastewater from hostels, cafeterias and sanitation facilities. Without appropriate treatment systems, these effluents are often discharged directly into nearby water bodies, resulting in environmental degradation. Wastewater treatment and reuse therefore represent a

viable strategy for sustainable water resource management. This study evaluates the implementation of a decentralized wastewater treatment system (WWTS) at Dr. Aderemi Makanjuola Hall of Residence (Hall 2), Edo State University Iyamho. The study analyzes the physicochemical characteristics of untreated and treated wastewater and applies predictive modelling techniques to evaluate future water quality conditions. The findings are expected to assist in implementation of WWTS in other hall of residences, hereby abating water scarcity and mitigate the environmental impact. A study by Omosa, *et al.* (2012) discusses the significant lack of proper wastewater treatment in most African countries. Untreated wastewater effluent is one of the most common types of pollution found around urban rivers and in groundwater sources in many African cities. Nigerian cities are expected to participate in the global trend of sustainable environmental improvements or innovations that focus on projects such as water supply and sanitation, solid waste management, air pollution, environmental health, and access to means of livelihood.

Water pollution is described as any physical, chemical or biological change in water quality which adversely impacts on living organisms in the environment or which makes a water resource unsuitable for one or more of its beneficial uses (Iheukwumere *et al.,* 2021). Some of the major categories of beneficial uses of water resources include public water supply, irrigation, recreation, industrial production and nature conservation. Occasionally, pollution may derive from natural processes such as weathering and soil erosion. In the vast majority of cases, however, impairment of water quality is directly, or indirectly the result of human activities (Adetunji & Olaniran, 2021). Recent research has limitations on how the advancements in digitalization and technology integration in waste management can be applied at university campuses to improve wastewater handling (Borchard *et al.,* 2022). The absence of a wastewater treatment plant at the university highlights the need for research into prototype development and framework design tailored to the institution's specific requirements. While chemical and microbiological tests, such as BOD, COD, and Escherichia coli detection, are essential for wastewater quality assessment (Medeiros *et al.,* 2020), studies on how these tests can inform a practical and cost-effective treatment solution for the university are lacking. Addressing this gap is vital for ensuring compliance with environmental standards and mitigating pollution.

This study focuses on the different wastewater treatment technologies that will be adopted in removing pollutants and contaminants present in wastewater at Edo State University Iyamho Hall of Residence. It primarily involves the qualitative and quantitative analysis of wastewater, evaluating its physical, chemical and biological characteristics, and the assessment of treated wastewater for reuse in various applications. This study further identifies the potential risks and challenges associated with wastewater reuse, as well as developing strategies for mitigation. This study extends to the design and implementation of a wastewater treatment system (WWTS) utilizing natural and engineered processes for treatment and reuse in non-potable applications.

Despite growing interest in decentralized sanitation, a significant technical barrier remains in the lack of empirical data regarding the performance of low-cost prototype systems under the highly fluctuating, high-volume generation cycles typical of West African student hostels. Furthermore, while chemical metrics like BOD and COD are standard, there is an unresolved operational challenge in how to deploy low-compute, short-term predictive modeling architectures that can accurately forecast wastewater quality dynamics with sparse data footprints, preventing system failure and accidental exposure during non-potable reuse applications.

METHODOLOGY

The study was conducted at Dr. Aderemi Makanjuola Hall of Residence, Edo State University Iyamho, Edo State, Nigeria, situated precisely at latitude 7.133495^0 N and longitude 6.297081^0 E. The hall of residence accommodates approximately 1,400 students across 268 rooms and generates domestic wastewater from sanitation, laundry and kitchen activities. The hall has an outlet river which serves as a recipient for effluents discharged from the nearby sewage collection structure. The effluents generate the wastewater around the structure having major impacts such as pollution of water sources in the environment, reducing air quality, and increase in waterborne diseases. It is essential to access the composition of these discharges, considering major factors such as pH, temperature, chemical content and volume of discharge. Comprehensive analyses will help in formulating effective treatment strategies for wastewater management and environmental sustainability.



Figure 1: Map of Edo University Hostel

Wastewater Treatment Technologies

This study evaluates wastewater treatment methods, including physical, chemical, and biological treatment processes. The effectiveness of each method is analyzed based on pollutant removal efficiency and operational feasibility at the university scale. Comparative analyses were carried out through coagulation, sedimentation, filtration and chlorination (Zhang *et al.,* 2021). Alum was used as coagulant to facilitate the aggregation of suspended

particles. The filtration unit was designed using layered filtration media consisting of sand, activated carbon and gravel.

The sand filtration layer had a depth of 40cm and served as a primary medium for removing suspended particles. A 30cm activated carbon layer was incorporated to enhance adsorption of organic contaminants and improve water clarity. A gravel support layer consisting of 20mm aggregate size was placed at the bottom of the filter unit to provide structural support and ensure proper drainage. Chlorine (in pebbles, 3mg) of little measurable quantity was added as a disinfectant to help destroy all harmful microorganisms present in the treated wastewater. The process flow diagram of wastewater treatment system is shown in Figure 2 below.

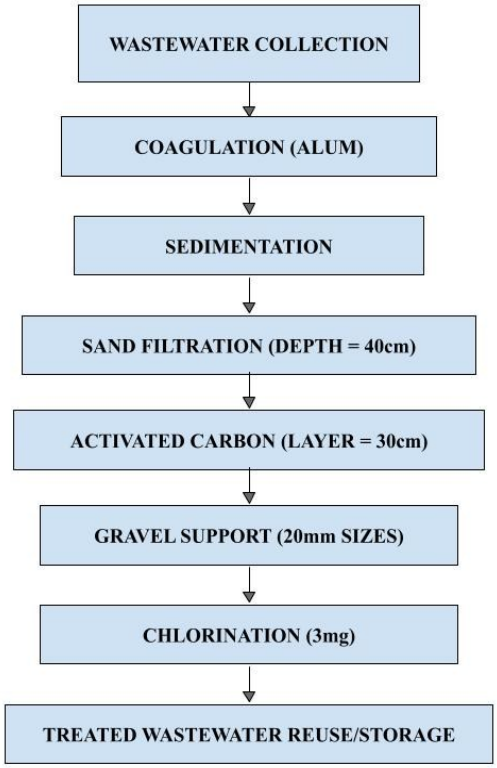


Figure 2: Process Flow Diagram of Wastewater Treatment System

Determination of Biochemical Oxygen Demand (BOD)

The determination of Biochemical Oxygen Demand (BOD) follows the stringent guidelines outlined in ASTM D6238, reflecting a commitment to industry-standard methodologies. The BOD analysis commenced with the addition of 10ml wastewater samples in two 250 ml BOD bottles. To facilitate this test, a nutrient buffer solution is used in diluting the samples to an appropriate concentration range. This solution, consisting of magnesium sulfate, calcium chloride, phosphate buffer, and ferric chloride, ensured that the samples were prepared under optimal conditions for the accurate determination of BOD. The diluted sample is sealed tightly in the BOD bottle, avoiding presence of air bubbles. This process resulted in the incubation of

the diluted sample in the BOD bottle, adhering to the specified conditions of 20℃ over a 5-day period. This extended incubation duration ensured a comprehensive assessment of the oxygen-consuming capabilities of the sample, allowing for a thorough understanding of its biodegradable organic content.

The BOD assessment involved measuring the dissolved oxygen (DO) concentration at pre-incubation and post-incubation phases, leveraging a precise DO probe. This involved the analysis of the dissolved oxygen in the remaining sample, blank bottles, and incubated samples. The determination of dissolved oxygen (DO) in the diluted Biochemical Oxygen Demand (BOD) samples is executed with precision, by employing established methods such as, the Winkler titration method as stipulated by ASTM D888. The prompt assessment of initial dissolved oxygen levels unfolded immediately after the meticulous preparation of the BOD samples. The Winkler titration method, known for its reliability and accuracy, involves a series of carefully orchestrated chemical reactions to quantify the concentration of dissolved oxygen in the sample.

This process required the use of reagents like manganese sulfate, alkaline iodide-azide, and sodium thiosulfate. The titration process commenced with the addition of these specific reagents to the sample. The subsequent steps involved the dissolution of the precipitated floc by mixing with concentrated sulfuric acid. This methodical process prepared the sample for titration against a standard 0.025N sodium thiosulfate solution, with starch indicator employed to detect the first disappearance of the characteristic blue colour. The subsequent step is the determination of the final dissolved oxygen (DO) levels after the 5-days BOD incubation period, using the same procedures before incubation of the Winkler titration method.

The difference in DO concentrations before and after the incubation period was then used to calculate the BOD. The Biochemical Oxygen Demand (BOD) was determined using the equation below:

$$BOD(mg/L) = \frac{D_1 - D_0}{B} \quad 1$$

where D_0 is the initial dissolved oxygen (immediately after preparation), D_1 is the final dissolved oxygen (after 5 days of incubation) and B is the fraction of sample used.

Determination of Dissolved Oxygen

This assessment adheres to the Winkler method as outlined by ASTM D888, ensuring precision and reliability in DO measurements. The analysis commences with meticulous sample collection, executed with utmost care to avoid agitation and prevent the inadvertent introduction of atmospheric oxygen. The addition of manganese sulfate solution and alkaline iodide-azide reagent initiates the reaction, forming a precipitated floc. The subsequent titration phase involves the introduction of standard 0.025N sodium thiosulfate solution, a process meticulously conducted until the first disappearance of the blue color. This endpoint, discerned with the aid of a starch indicator, marks a critical juncture in the titration and ensures accuracy in determining the amount of sodium thiosulfate required to neutralize the remaining oxygen-consuming agents in the sample. This assessment provides valuable insights into the

environmental conditions of the study area, crucial in prediction analysis of the wastewater. The dissolved oxygen (DO) was determined using the equation below:

$$DO(mg/L) = \frac{16000 \times M \times V}{\left(\frac{V_2}{V_1}\right)} \quad 2$$

where M is the molarity of thiosulphate used, V is the volume of thiosulphate, V_1 is the volume of bottle of stopper and V_2 is the volume of aliquot taken for titration.

Determination of Chemical Oxygen Demand (COD)

This was conducted in strict accordance with ASTM D1252 by employing an open reflux colorimetric method to ensure precision and consistency in COD measurements. The analysis unfolded with the careful extraction of a 2 ml sample aliquot, which then undergoes reflux in the presence of an excess of 0.025 N potassium dichromate ($K_2Cr_2O_7$) solution and concentrated sulfuric acid. After the reflux process, the unreacted excess dichromate is titrated against ferrous ammonium sulfate, and the amount consumed in the reaction is quantified.

The flask is cleaned with a 250ml borehole water warmed to a temperature of 27°C. The incubation process commences with the addition of 1ml of $KMnO_4$ 0.0125M and 10 ml of 20% volume of sulfuric acid. This solution was mixed gently and incubated at 27°C for 4 hours. The mixture was examined at intervals, when the pink colour of permanganate tends to disappear, 10ml of KMnO4 was added. After 4 hours, 1ml KI solution was added and titrated with 0.0125M SO_4 using starch as an indicator, until the blue colour just disappeared. The Chemical Oxygen Demand (COD) was determined using the equation below:

$$COD(mg/L) = \frac{[(ml\ of\ Blank - ml\ of\ required\ sample) \times 1000]}{A \times volume\ of\ sample\ used} \quad 3$$

where A is the total volume of $KMnO_4$ 0.0125M added to the sample

Programming and Mathematical Model

The Classification Learner app in MATLAB was used to train and test classification models without extensive coding. Markov chain was used in the analysis of different state of wastewater during the current period in order to predict the behavior of these states in the future in any later periods (Hasan, 2015). The water quality parameters obtained from Classification Learner Prediction Model is adopted as the initial state in Markov Analysis. Due to limited monitoring data, the Markov model was implemented as a preliminary predictive framework rather than a fully validated stochastic model. The workflow diagram of machine learning-based wastewater quality prediction system is shown in Figure 3 below:

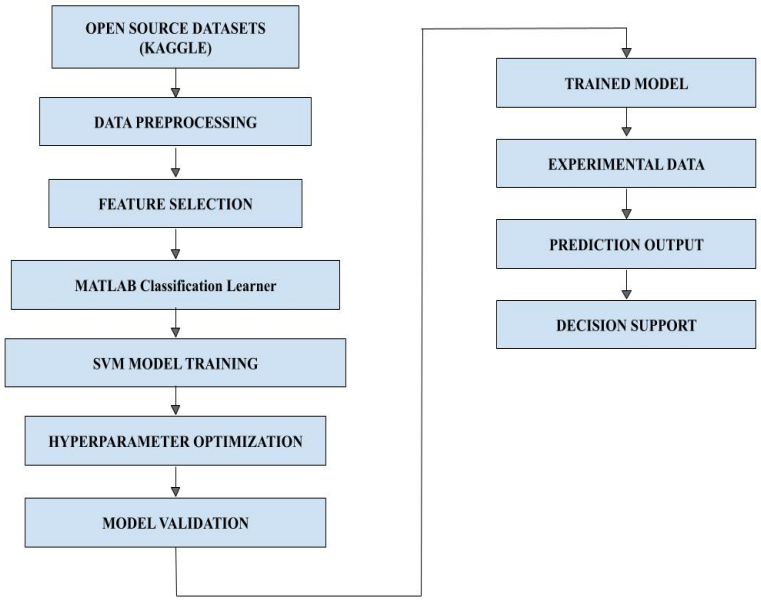


Figure 3: Workflow Diagram of Machine Learning-Based Wastewater Quality Prediction System.

The workflow diagram illustrates the integration of an open-source wastewater dataset with experimental data obtained from the treatment system. The process begins with data preprocessing and feature selection, followed by model training using a Support Vector Machine (SVM) within the MATLAB Classification Learner App. The model undergoes optimization and validation before being applied to predict the quality classification of treated wastewater samples. This framework supports decision-making for safe non-potable water reuse within the university environment. The SVM model was selected due to its effectiveness in handling nonlinear relationships in environmental datasets.

Table 1: Initial State

Parameter	Value in week 1	Value in week 2	Initial State
BOD (mg/L)	0.8	0.4	Moderate
COD (mg/L)	21.63	26.45	Moderate
TSS (mg/L)	15.4	15.3	Moderate

a. The Initial state matrix x_o

The Initial State is given as:

$$x_o = \begin{bmatrix} Good & Moderate & Bad \\ 0 & 1 & 0 \end{bmatrix} \quad \text{(a)}$$

b. Transition matrix

The Transition Matrix is given as:

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (b)$$

Applying Laplace smoothing with α = 1 (add 1 to each element):

$$\begin{bmatrix} 0+1 & 0+1 & 0+1 \\ 0+1 & 1+1 & 0+1 \\ 0+1 & 0+1 & 0+1 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Normalizing each row, we have:

$$\begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/4 & 2/4 & 1/4 \\ 1/3 & 1/3 & 1/3 \end{bmatrix} = \begin{bmatrix} 0.33 & 0.33 & 0.33 \\ 0.25 & 0.5 & 0.25 \\ 0.33 & 0.33 & 0.33 \end{bmatrix}$$

c. Transition Matrix P:

$$P = \begin{bmatrix} 0.33 & 0.33 & 0.33 \\ 0.25 & 0.5 & 0.25 \\ 0.33 & 0.33 & 0.33 \end{bmatrix} \quad (c)$$

d. Weekly probability formula

Where $x_i = x_n P$, and x_i is the number of weeks (i = 1,2,3…), x_n is the probability of each states and P is the transition matrix. We calculate for the weekly probability of each state:

Week 0 (initial): $x_o = [0 \quad 1 \quad 0]$ (d)

Week 1: $x_1 = x_o P = [0.25 \quad 0.5 \quad 0.25]$

Week 2: $x_2 = x_1 P = [0.2917 \quad 0.4167 \quad 0.2917]$

Week 3: $x_3 = x_2 P = [0.2972 \quad 0.4056 \quad 0.2972]$

Week 4: $x_4 = x_3 P = [0.2981 \quad 0.4037 \quad 0.2981]$

Week 5: $x_5 = x_4 P = [0.2984 \quad 0.4033 \quad 0.2984]$

Week 6: $x_6 = x_5 P = [0.2984 \quad 0.4032 \quad 0.2984]$

The stationary (long-run) distribution $\pi = [\pi_1, \pi_2, \pi_3]$ such that $\pi = \pi P$ and $\pi_1 + \pi_2 + \pi_3 = 1$.

e. Transpose of Transition matrix

Where π is the transpose of the Transition matrix (P), which is given as:

$$\begin{cases} \pi_1 = \frac{1}{3}\pi_1 + \frac{1}{4}\pi_2 + \frac{1}{3}\pi_3 \\ \pi_2 = \frac{1}{3}\pi_1 + \frac{1}{2}\pi_2 + \frac{1}{3}\pi_3 \\ \pi_3 = \frac{1}{3}\pi_1 + \frac{1}{4}\pi_2 + \frac{1}{3}\pi_3 \end{cases} \quad (e)$$

where $\pi_1 = \pi_3 = a, \ then \ \pi_2 = b$, substituting we have

$$a = \frac{1}{3}a + \frac{1}{4}b + \frac{1}{3}a$$

$$b = \frac{1}{3}a + \frac{1}{2}b + \frac{1}{3}a$$

$$a = \frac{2}{3}a + \frac{1}{4}b; a - \frac{2}{3}a = \frac{1}{4}b; \frac{1}{3}a = \frac{1}{4}b; a = \frac{3}{4}b$$

Since $\pi_1 = \pi_3 = a, \ then \ \pi_2 = b$ and $\pi_1 + \pi_2 + \pi_3 = 1$. by normalizing, we have

$$2a + b = 1; \left(2 \times \frac{3}{4}b\right) + b = 1; \frac{5}{2}b = 1; b = \frac{2}{5}$$
$$a = \frac{3}{4}b = \frac{3}{4} \times \frac{2}{5}; a = \frac{3}{10}$$
$$\therefore \pi = [0.3, 0.4, 0.3]$$

RESULTS AND DISCUSSION

The physicochemical analysis of wastewater samples demonstrated that the treatment system significantly improved several water quality parameters. BOD, COD, and TSS values decreased substantially after treatment, indicating effective removal of biodegradable organic matter and suspended particles.

Dissolved Oxygen levels increased after treatment, reflecting improved water quality conditions. However, Total Dissolved Solids (TDS) values increased after treatment. This observation suggests that conventional treatment processes are ineffective at removing dissolved salts. Additional advanced treatment technologies such as reverse osmosis or ion exchange may therefore be required for applications requiring lower salinity levels. The result of the analysis obtained are summarized in Table 2 below.

Table 2: Comparative Table of Sample Properties

Parameters	Sample 1 (Untreated)	Sample 2 (Treated)	Sample 3 (Treated)	ASTM Limit	FMENV Limit	Average
BOD (mg/L)	6.1	0.8	0.4	20	15	0.6
COD (mg/L)	245.85	21.63	26.45	80	80	24.04
DO (mg/L)	2.35	5.33	5.55	≥ 4-5	≥ 5	5.44
Turbidity (NTU)	0.36	0.18	0.16	1	5	0.17
Colour	6	1	1	15	15	1
pH	7.2	7.69	7.69	6.5-8.5	6-8	7.69
Temp (°C)	30.6	28.6	28.6	31	30-33	28.6
Chloride (mg/L)	31.2	8.863	8.863	250	250	8.863
Sulphate (mg/L)	6	23.62	23	250	100	23.31
TDS (mg/L)	50.1	3542	3542	500	500	3542
TSS (mg/L)	33.6	15.4	15.3	30	30	15.35

Prediction Model

An open source dataset was used to train the prediction model. Following this, the trained model was used to test the datasets gotten from the treatment plant. The various parameters used for model prediction were BOD, COD, TSS, DO and quality class (states) of the wastewater parameters. The optimized model is the SVM Coarse Guassian model, typically prediction model 1.16 on the MATLAB Classification Learner App. The trained model plot

shows that 100% of samples with water quality classification of good and bad are misclassified, so the 100% in the moderate row and column is the True Positive Rate for correctly classified parameters in this model.

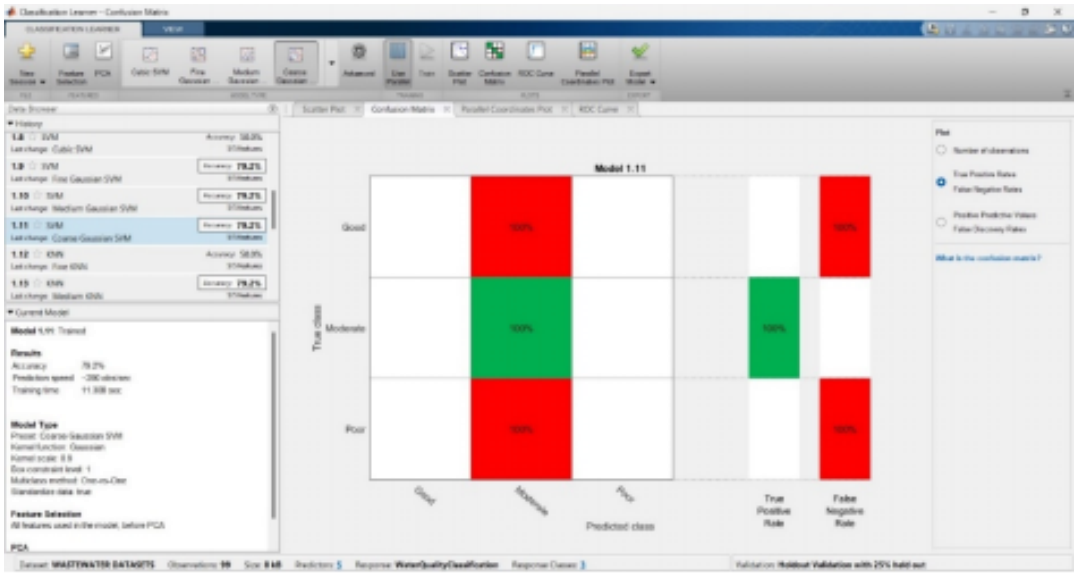


Figure 4: True Positive Rates of trained model

The confusion matrix shows summary rows of the Positive Predictive Value in green for the correctly predicted parameters in each state. The graph shows a 79% Positive Predictive Value in the moderate water quality class, and a sum of 21% False Discovery Rates along the moderate state.

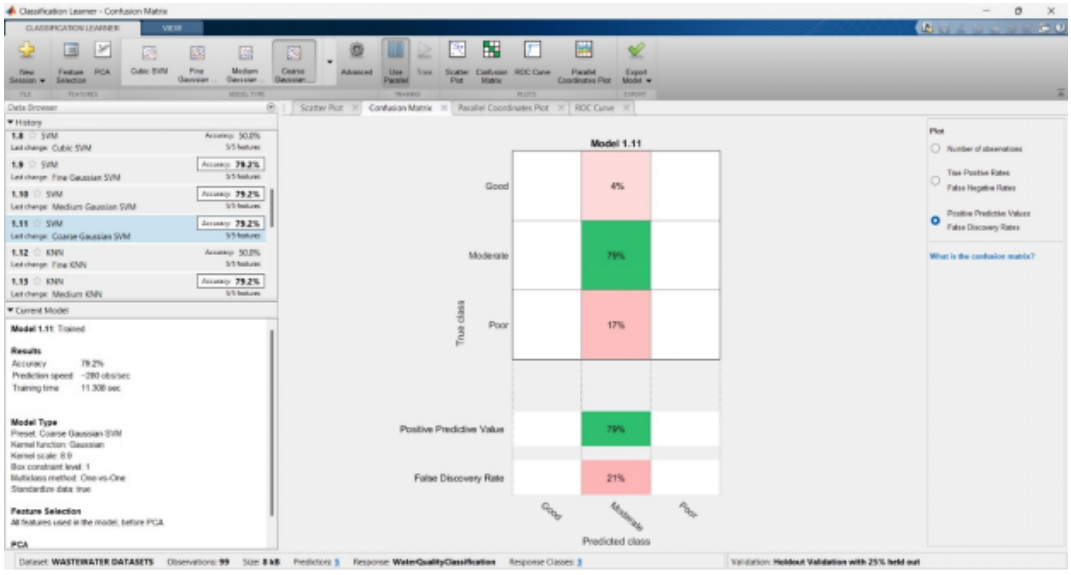


Figure 5: Positive Predictive Values for trained model

The MATLAB Editor Script was used to write a code to produce the water quality classification prediction for the treated wastewater samples shown in Table 2. Parameters such as BOD, COD, TSS, DO, pH and temperature were highlighted. The result achieved classified the water as moderate (Table 1) which implies that it is suitable for non-potable applications.

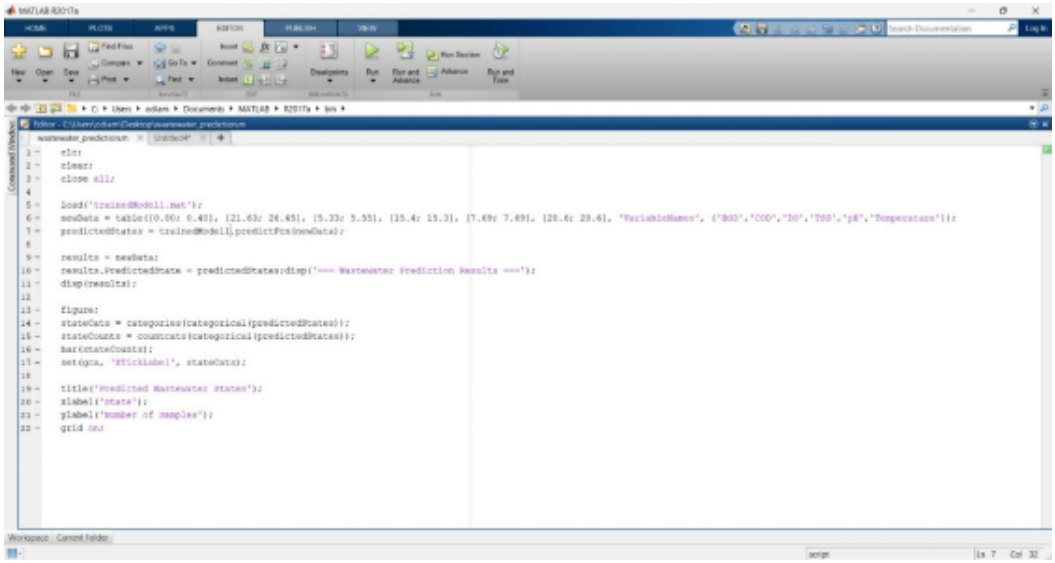


Figure 6: Prediction Model Code

Comparative Analysis between Markov Analysis and Classification Learner

The Markov chain analysis was conducted using the defined initial state matrix (x_o), transition matrix, normalized transition matrix (P), weekly probability formulation, and the transpose of the transition matrix, which collectively describe the temporal evolution of wastewater quality states and provide a probabilistic basis for comparison with the machine learning model. The Classification Learner model demonstrated an accuracy of 79.2%, almost double that of the Markov chain model, which achieved only 40% accuracy. This substantial difference in performance highlights the limitations of Markov models when applied to complex, multivariable wastewater datasets. Markov chains are probabilistic in nature and work best with sequential or state-dependent data. However, their predictive power is constrained when multiple dynamic environmental factors interact simultaneously, as is the case in wastewater treatment. These findings suggest that utilizing Classification Learner for short-term wastewater quality prediction with limited data is more effective than relying on the Markov chain model. By adopting machine learning approaches such as Classification Learner, decision-makers can achieve higher reliability in forecasting water quality parameters, which in turn contributes to improved wastewater management, sustainable water resource planning, and more effective policy implementation.

A notable limitation of the treatment system is the significant increase in Total Dissolved Solids (TDS) observed after treatment, reaching values of 3542 mg/L, which exceed both

ASTM and FMENV permissible limits. This increase may be attributed to the addition of treatment chemicals such as alum during coagulation and chlorine during disinfection, which can introduce dissolved ions into the water. Additionally, the breakdown of organic matter during treatment may contribute to increased ionic content. This finding highlights a critical limitation of conventional treatment processes, which are primarily effective in removing suspended and biodegradable pollutants but are not designed to eliminate dissolved salts. The elevated TDS concentration raises concerns regarding the suitability of the treated water for reuse, particularly in applications sensitive to salinity.

Furthermore, the predictive modelling results should be interpreted with caution. Although the SVM model achieved an accuracy of 79.2%, the complete misclassification of "Good" and "Bad" categories indicates class imbalance and limited robustness. This suggests that due to limited sample size and class imbalance, the model may not generalize well under varying environmental conditions, especially given the relatively small and externally sourced training dataset.

CONCLUSION

This study demonstrates that decentralized wastewater treatment systems can significantly improve key water quality parameters, particularly BOD, COD, and TSS, within institutional environments. The integration of machine learning techniques further highlights the potential for predictive monitoring of wastewater quality.

However, the study also reveals important limitations. The substantial increase in Total Dissolved Solids (TDS) after treatment indicates that the current system is insufficient for removing dissolved contaminants, thereby limiting the safety of reuse applications. Additionally, the predictive modelling approach is constrained by limited data availability, model imbalance, and lack of extensive validation.

Therefore, while the proposed system shows promise for non-potable reuse, further optimization of both treatment processes and predictive models is required before large-scale implementation. Future studies should focus on improving treatment efficiency for dissolved solids and enhancing the robustness of data-driven prediction frameworks.

RECOMMENDATIONS

Based on the results obtained from the model analysis and laboratory testing in the study, the following recommendations are proposed:

1. Incorporate a reverse osmosis (RO) polishing unit or ion-exchange resin column downstream of the chlorination stage to effectively remove dissolved salts and reduce TDS levels before reuse.
2. Increase the size and diversity of the dataset used for machine learning to improve model robustness and predictive accuracy.
3. Implement continuous monitoring systems to capture real-time wastewater quality variations for improved predictive modelling.

4. Optimize the coagulation process by carefully controlling alum dosage to minimize the introduction of excess dissolved ions.
5. Develop a full-scale wastewater treatment infrastructure that includes a collection tank, flow measurement system, clarifier, filtration units, and storage facilities for treated water.
6. Conduct further validation of predictive models using larger and locally generated datasets to ensure reliability under varying environmental conditions.

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APPENDIX A: DATASET DESCRIPTION

The prediction model used in this study was trained using an open-source wastewater quality dataset obtained from Kaggle. The dataset includes water quality parameters such as BOD, COD, TSS, DO, pH and temperature. The dataset was used to train and validate the machine learning classification model before testing with the experimental wastewater samples obtained from the treatment system.

Table A-1. Datasets of Trained Model

Predictor Variables					Response Variable
COD	**BOD**	**pH**	**TSS**	**Temperature**	**Water Quality Classification**
55.42609628	3.6200969	6.710113	23.06724747	30.63	Bad
56.40345905	8.0041735	8.128324	15.84023885	30.46	Bad
40.44403677	3.3202566	8.165553	18.74437249	29.595	Moderate
59.63144212	9.1552943	6.642098	7.071843584	30.965	Moderate
58.82546043	8.4532516	7.736163	24.10515188	29.245	Bad
50.76239088	6.7449985	8.069343	21.66500662	30.515	Moderate
49.1323368	5.3056298	7.39483	16.09722309	31.235	Moderate
53.93114637	3.4375431	7.496973	18.08189832	26.955	Bad
51.40587394	9.3475879	8.015574	17.29460482	28.5	Moderate
45.2752659	8.747966	7.148565	27.54379052	29.34	Moderate
43.22753329	9.1904921	6.763189	21.04012461	28.205	Moderate
45.98584561	4.3530329	8.167721	10.10144832	23.76	Moderate
42.01112969	4.7330426	6.765505	22.92929247	29.84	Good
46.18032673	7.597309	8.367967	9.959911072	23.005	Moderate
47.51511053	6.4462107	7.846203	22.79377112	27.995	Moderate
52.45823391	7.8549558	8.419084	12.74375243	29.985	Moderate
54.39416729	5.1866155	8.119129	26.81434699	32.315	Moderate
44.27697498	9.8169638	6.750708	18.02937616	27.645	Bad
50.54310498	5.801057	6.680356	12.39481962	29.63	Moderate
55.344967	6.4656128	8.345817	29.8000194	33.765	Moderate
46.21960783	4.9691703	7.069214	21.03596914	26.225	Moderate
52.88697515	5.7705096	7.352563	24.39733692	30.16	Moderate
40.51781446	4.6547055	7.280767	11.2533974	26.175	Bad
59.37000818	3.3885877	7.42441	19.4008417	29.41	Moderate
50.87607523	6.8301092	7.979636	25.9270821	27.565	Moderate
47.49214144	5.4964786	6.965972	21.29930938	29.7	Moderate
54.61428109	9.6504198	7.065465	6.898046516	25.605	Moderate
56.20232886	6.6832983	7.950276	26.77233627	26.75	Moderate
55.08105423	3.7626394	6.564358	19.08010267	27.315	Moderate
44.27137702	6.9069766	7.336587	8.289445982	33.04	Moderate
59.30150596	4.3949553	6.614092	16.26198679	28.34	Moderate
41.0931619	9.4769758	7.318897	16.82577765	34.255	Moderate
48.96774354	8.2691645	6.556162	14.74513942	26.1	Bad
58.44842407	8.1618405	7.219776	20.79341262	30.12	Moderate
40.55932474	9.4292154	7.363147	12.32150258	25.66	Moderate
47.91435096	4.7621852	7.556513	22.26787076	24.015	Moderate
43.61780288	4.7118155	6.627364	12.84971137	29.185	Good
49.65832044	3.1628762	7.355962	8.577941352	29.405	Moderate
49.50599815	9.8268957	7.973882	27.19773815	25.36	Moderate
53.83714394	3.0522822	7.481119	23.31283139	28.765	Moderate
54.37517596	3.7891467	6.698014	22.87558319	30.48	Moderate
52.30615289	7.5991283	7.849774	9.464948771	27.695	Bad
41.84424158	7.2292516	7.247296	6.305896433	30.39	Moderate
48.74980683	9.2457019	8.491809	18.14729132	30.44	Moderate
50.76810547	5.3047959	8.496302	9.426072364	30.605	Bad
42.86050789	6.7502667	8.158025	22.71954225	28.245	Bad
56.02226869	8.8019645	8.369455	10.90811045	31.345	Moderate
44.2422553	7.5739269	8.30957	26.35268072	29.31	Moderate
40.43057386	3.9351349	7.925647	24.65684731	26.04	Moderate
53.26983457	6.0926006	8.265144	27.06280479	29.28	Moderate
46.93275439	9.8320607	7.467425	28.03587765	27.105	Moderate
46.29752288	5.9888599	8.225354	9.608859571	28.37	Moderate
53.58149036	8.7227687	7.415397	22.50606799	33.01	Moderate
51.10735344	3.2340208	6.680659	22.69674893	31.565	Moderate

56.25012017	5.7464509	6.950078	9.69350986	30.185	Bad
56.00266696	9.9918759	8.369974	14.85436886	27.44	Bad
57.92315097	4.0902585	7.253593	13.50122115	24.33	Moderate
43.96521636	4.331103	7.98304	7.223833112	29.725	Good
41.33175705	3.1310806	6.690986	9.050760801	24.24	Moderate
44.13406004	8.8475307	7.738018	6.026966961	31.09	Good
43.84743593	7.6515847	8.318629	8.041408973	31.005	Moderate
45.41010075	5.2311208	6.972612	5.714479857	27.245	Moderate
46.54288719	3.0730152	7.607471	26.48164139	30.795	Moderate
52.72795772	8.388894	7.679617	18.8137686	25.375	Bad
43.61115185	3.089528	8.416309	9.871307932	29.3	Moderate
58.08790729	4.7972557	7.41943	26.62191175	25.99	Moderate
48.88476378	8.7284164	8.40248	26.75093627	28.025	Moderate
53.38920553	7.2169874	7.138915	13.22446764	23.35	Moderate
42.84894602	8.4783826	7.212839	9.781379595	26.02	Moderate
48.12847898	5.744078	7.568825	21.62353717	24.005	Moderate
49.35399184	9.3259362	6.816154	25.68338158	32.2	Bad
47.35089045	3.157022	7.487125	19.40569318	32.525	Bad
41.02632064	6.7542667	7.080524	25.7472964	25.53	Bad
55.20056846	5.126999	8.161295	8.787911272	30.545	Moderate
54.53969573	5.3746661	8.132515	18.73346472	29.665	Bad
53.46971908	5.0953647	7.931696	21.71400093	30.125	Moderate
57.61237958	5.5814659	8.270947	18.48732291	25.335	Bad
43.35347287	8.746302	8.084585	27.83683502	29.61	Moderate
54.38520384	6.2180521	7.424659	16.88381031	32.83	Moderate
51.43936858	9.8113513	8.493756	24.16975101	27.715	Moderate
48.48778336	4.7745505	7.306213	17.25275149	29.715	Moderate
44.16559605	7.3858277	8.245753	23.78411011	24.74	Moderate
43.66252273	8.8464199	7.517001	29.03416397	28.395	Moderate
58.83946692	6.6440739	7.542613	22.63696204	25.46	Moderate
50.06214342	9.8221075	7.81893	7.695456165	28.1	Moderate
49.81333408	7.796079	7.37859	16.24163028	27.245	Moderate
46.74509308	5.7668228	7.857797	13.77896005	29.16	Moderate
59.66033024	9.8717405	8.05767	16.48963063	26.745	Moderate
55.29089417	8.9213286	8.170964	19.10285274	30.425	Moderate
43.99320395	5.9791809	6.571161	26.6132366	25.135	Moderate
57.48385079	6.0011961	7.590697	22.68668883	27.105	Moderate
44.97786392	9.5528488	7.438684	9.808278666	29.885	Moderate
59.05325962	5.8945273	8.376284	10.80559411	29.82	Moderate
41.26134899	3.5157408	8.439614	15.91860753	32.845	Moderate
49.59739873	7.4001934	8.424401	19.88392916	26.77	Bad
58.78212104	5.8684273	7.115478	6.706175718	29.505	Moderate
47.51080243	7.9126095	7.418255	10.42257226	23.295	Moderate
54.29969173	6.8989768	7.05152	16.46471243	33.95	Moderate
56.27021505	4.0331593	7.780495	9.984880207	27.53	Moderate