"A Machine Learning-Based Approach for Troubleshooting Sewage Treatment Plant Process"

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ABSTRACT

Sewage Treatment Plants (STPs) often face operational challenges such as aeration failures, filtration inefficiencies, and fluctuating influent characteristics, leading to environmental non-compliance and increased maintenance costs. Traditional fault detection methods, that rely on manual inspections and predefined threshold-based systems, are slow, reactive, and prone to inaccuracies. This paper proposes an Artificial Neural Network (ANN)-based fault diagnosis system that utilizes historical and real-time sensor data to detect and classify operational issues in STPs. The model was trained on key wastewater parameters, including the influent flow rate, BOD, COD, TSS, pH, temperature, ammonia nitrogen levels, aeration rate, and sludge retention time. It predicts effluent quality indicators (Effluent BOD, Effluent COD, Effluent TSS) and identifies three operational states: No Issue, Aeration Issue, and Filtration Issue. A comparative analysis with conventional fault detection techniques demonstrates that the ANN model achieves higher accuracy, early fault detection, and proactive troubleshooting. The results highlight the potential of AI-driven diagnostics for optimizing wastewater treatment, reducing downtime, and improving process efficiency, thereby contributing to the development of smart and automated STPs.

Keywords: Artificial Neural Networks, Sewage Treatment Plant, Wastewater Fault Diagnosis, Aeration Issue, Filtration Issue, Predictive Maintenance, Effluent Quality Prediction, Deep Learning, AI-Driven Process Optimization, Operational Issue Detection, Machine Learning in Wastewater Treatment

INTRODUCTION

Sewage Treatment Plants (STPs) are vital for managing wastewater, and ensuring that contaminants are effectively removed before being discharged into the environment. These plants play a crucial role in maintaining public health and the ecological balance by preventing water pollution. However, STPs often encounter critical operational challenges, including aeration failures, filtration inefficiencies, and fluctuating influent characteristics. These issues, if not detected early, can severely impact process efficiency, degrade effluent quality, and lead to regulatory non-compliance. Operational inefficiencies can also result in higher energy consumption, increased chemical usage, excessive sludge production, and unplanned maintenance shutdowns, ultimately increasing the operational costs and environmental risks.

Conventional fault detection and troubleshooting methods in STPs typically rely on manual inspection, empirical rules, and threshold-based monitoring systems. These widely used approaches, are highly reactive and lack adaptability to complex, nonlinear interactions between influent characteristics and process performance. Traditional monitoring methods are often incapable of predicting faults before they occur, leading to delays in corrective actions and, in many cases, requiring extensive human intervention. Moreover, the increasing demand for higher wastewater treatment efficiency and stricter environmental regulations has further emphasized the need for automated, intelligent fault detection systems capable of operating in real-time.

In recent years, Artificial Intelligence (AI) and Machine Learning (ML) techniques have opened new possibilities for advanced process monitoring, fault detection, and predictive maintenance in wastewater treatment. Among these, Artificial Neural Networks (ANNs) have demonstrated exceptional capabilities in modeling complex, high-dimensional, and nonlinear relationships in treatment processes. By learning from historical and real-time sensor data, ANN-based fault detection systems can proactively identify operational anomalies, classify potential issues, and enable plant operators to take corrective action before major failures occur.

This study introduced an ANN-based intelligent fault diagnosis framework tailored for STPs. The proposed system analyzes influent and operational parameters, including influent flow rate, BOD, COD, TSS, pH, temperature, ammonia nitrogen levels, aeration rate, and sludge retention time, to predict effluent quality indicators (Effluent BOD, Effluent COD, Effluent TSS) and diagnose three major operational states: no issue, aeration , and filtration. The ANN model outperformed conventional rule-based fault detection techniques by providing higher accuracy, early warning signals, and enhanced fault classification, allowing for real-time decision-making and adaptive process control.

By integrating deep learning-driven automation, this study aims to transform conventional wastewater treatment systems into self-regulating, smart STPs that can autonomously monitor, diagnose, and optimize operations in real-time. The implementation of such intelligent systems can lead to the following:

Minimized process disruptions through early fault detection and proactive maintenance. Optimized resource utilization, including aeration energy, chemical dosing, and sludge management. Enhanced compliance with environmental regulations by ensuring consistent effluent quality. Significant cost savings by reducing equipment failures, maintenance overhead, and energy consumption.

The findings of this study highlight the potential of AI-driven solutions for revolutionizing wastewater treatment by providing more resilient, adaptive, and energy-efficient STPs. The proposed ANN-based fault detection framework serves as a stepping stone toward the development of next-generation- intelligent wastewater treatment facilities, ensuring sustainable and environmentally compliant operations in the face of growing urbanization and industrialization.

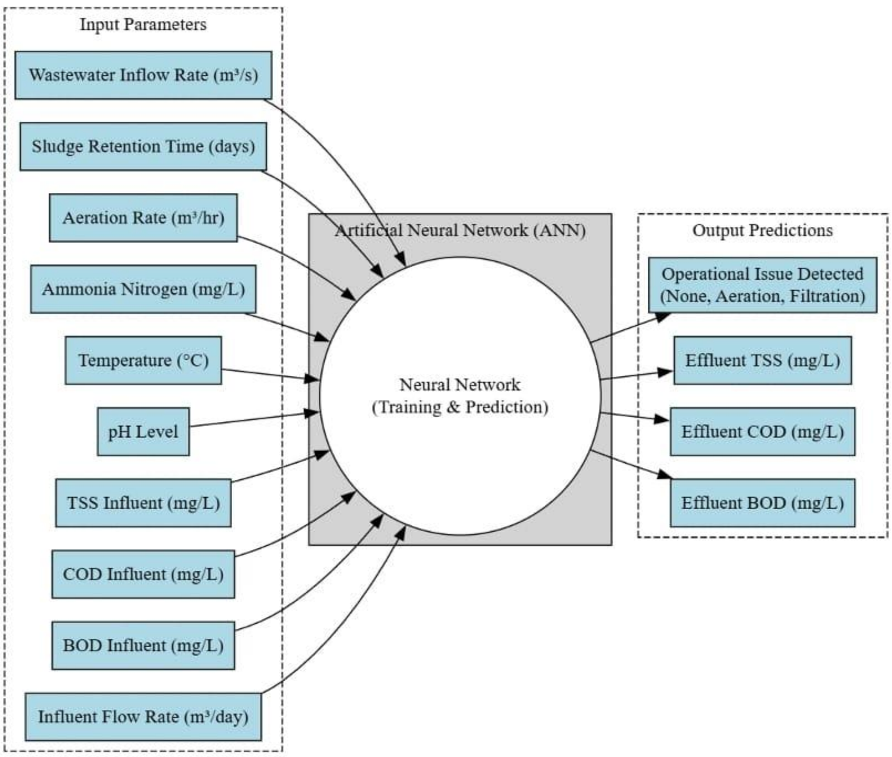

Fig 1. ANN-based Fault Diagnosis System

METHODOLOGY

The proposed Artificial Neural Network (ANN)-based intelligent fault diagnosis system for Sewage Treatment Plants (STPs) was designed to optimize wastewater treatment by predicting effluent quality parameters and identifying operational issues such as aeration and filtration failures. This methodology integrates data collection, preprocessing, model development, training, validation, and real-time deployment, ensuring a robust, efficient, and automated wastewater management system. By leveraging

Deep-learning techniques, this system enhances operational efficiency, reduces downtime, and ensures compliance with environmental discharge regulations.

The first stage, data collection, involves gathering extensive real-time sensor data and historical treatment records from the STP operations. The dataset comprised key influent characteristics, process control variables, and effluent quality indicators. The selected input parameters included the Influent Flow Rate (m^3/day)-, BOD Influent (mg/L), COD Influent (mg/L), TSS Influent (mg/L), pH Level, Temperature (°C), Ammonia Nitrogen (mg/L), Aeration Rate (m^3/hr), Sludge Retention Time (days), and Wastewater Inflow Rate (m^3/s). The output parameters included Effluent BOD (mg/L), Effluent COD (mg/L), Effluent TSS (mg/L), and operational issue detected, classified into No Issue, Aeration Failure, and Filtration Failure. The collected data represented a wide range of real-world STP conditions, allowing the model to learn from diverse treatment scenarios and system variations.

The second stage, data preprocessing, focused on transforming raw sensor readings and historical records into a clean, structured dataset suitable for deep learning. Missing data are addressed using statistical imputation, interpolation, or predictive modeling. Outliers were detected through z-score analysis, boxplot visualization, and IQR filtering, ensuring the removal of erroneous or extreme values. Feature scaling techniques such as min-max normalization and standardization are applied to bring all numerical variables to a standard range, preventing dominant features from biasing the ANN model. Additionally, feature engineering was performed to extract new insights, such as influent-to-effluent efficiency ratios, aeration efficiency metrics, and process stability indicators, enriching the dataset for improved predictive accuracy. One-hot encoding was applied to categorical labels, particularly for operational issue classification, to facilitate seamless ANN model training. Correlation analysis and feature selection help to eliminate redundant features and - reduce dimensionality without losing crucial information.

The third stage, model development, involves designing a multi-layer Artificial Neural Network (ANN) optimized for fault detection and effluent quality prediction. The architecture comprises an input layer, multiple hidden layers, and output layer. The hidden layers employ Rectified Linear Unit (ReLU) activation functions to - ensure efficient training and prevent vanishing gradient issues. For regression tasks (Effluent BOD, COD, and TSS prediction), a linear activation function was used in the output layer, whereas for classification tasks (Operational Issue Detection), a Softmax activation function was applied. The model was optimized using backpropagation with the Adam optimizer to - ensure fast convergence and high accuracy. Dropout regularization is integrated into hidden layers to mitigate overfitting, and batch normalization is used to stabilize learning. Advanced hyperparameter tuning techniques, such as grid search and Bayesian optimization, were applied to refine the learning rates, number of neurons, batch size, and weight initialization strategies.

The fourth stage, training and validation, ensure that the ANN model generalizes well to the unseen data. The dataset is split into training, validation, and test sets in an 80-10-10 ratio, ensuring sufficient data for model learning while preserving unseen samples for evaluation. K-fold cross-validation enhances the robustness of the model, prevents overfitting, and ensure reliable performance. The model was trained using supervised learning, where historical influent data were used as input, and effluent quality along with operational fault labels were used as the ground truth. The loss function for effluent prediction is the Mean Squared Error (MSE), whereas Categorical Cross-Entropy is used for fault classification tasks. The performance of the model was assessed using multiple evaluation metrics, including the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R^2 score, accuracy, precision, recall, and F1-score. Early stopping techniques prevent overfitting and, ensure optimal generalization of the model.

In the final stage, real-time deployment, the trained ANN model is integrated into an automated STP monitoring system that continuously analyzes the incoming influent and process data. The system generates real-time predictions of effluent quality and early fault detection alerts, allowing operators to take proactive corrective action before failure escalates. In the event of aeration or filtration, the system suggests optimal aeration adjustments, filtration backwash schedules, or chemical dosing modifications to restore the system stability. The deployment phase also includes model retraining mechanisms, where new operational data are periodically fed into the system to, ensure continuous learning and adaptation to evolving plant conditions.

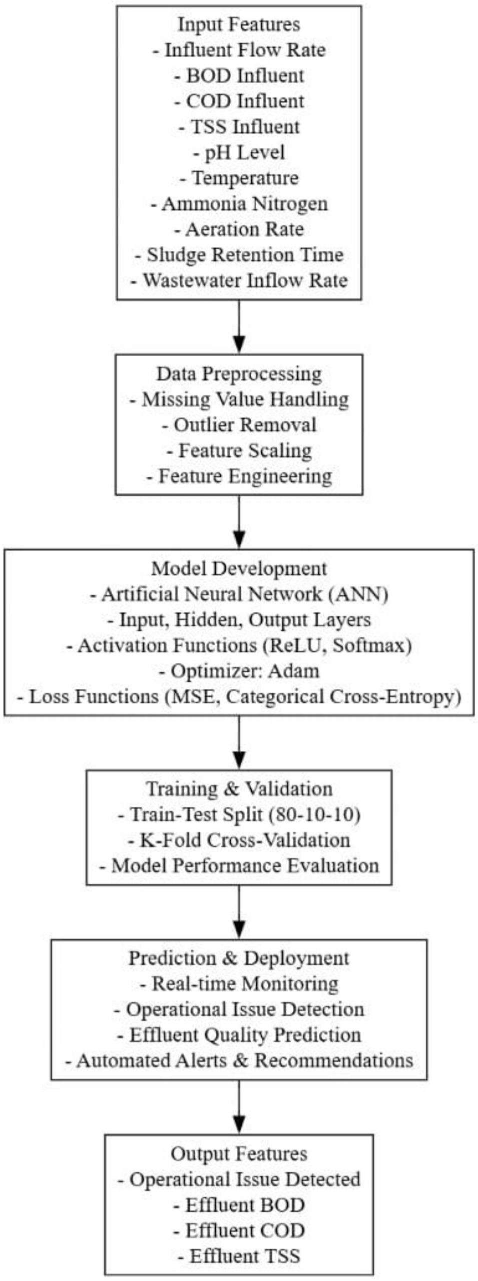

Fig 1.1: Methodology

This AI-driven, ANN-based fault diagnosis system introduces a transformative approach to intelligent wastewater treatment management. By enabling real-time anomaly detection, predictive maintenance, and effluent quality forecasting, the proposed system enhances operational efficiency, reduces maintenance costs, and ensures compliance with stringent wastewater discharge standards. The integration of deep learning with real-time STP monitoring marks a significant step toward self-regulating, sustainable, and highly optimized sewage treatment processes, ensuring reliable wastewater management with minimal environmental impact.

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Mathematical Model:

To mathematically represent the Artificial Neural Network (ANN) model for fault diagnosis and effluent quality prediction in a Sewage Treatment Plant (STP), we defined the following:

Problem Formulation

Given an input feature vector X, the ANN model learns a function f(X) to predict the operational issues and effluent quality parameters.

Input Feature Vector X:

Where,

X = [x1, x2, x3, xn]

x1 = Influent Flow Rate (m^3/day)

x2 = BOD Influent (mg/L)

x3 = COD Influent (mg/L)

x4 = TSS Influent (mg/L)

x5 = pH Level

x6 = Temperature (°C)

x7 = Ammonia Nitrogen (mg/L)

x8 = Aeration Rate (m^3/hr)

x9 = Sludge Retention Time (days)

x10 = Wastewater Inflow Rate (m^3/s)

Output Predictions Y:

The ANN predicts multiple outputs:

Y = [y_1, y_2, y_3, y_4]

Where,

y1 = Operational Issue Detected (None, Aeration, Filtration)

y2 = Effluent BOD (mg/L)

y3 = Effluent COD (mg/L)

y4 = Effluent TSS (mg/L**)**

Artificial Neural Network (ANN) Model

Neural Network Structure: The ANN consists of:

Input Layer: 10 neurons (corresponding to the 10 input features)

Hidden Layers: h neurons with activation functions

Output Layer: 4 neurons (corresponding to the 4 outputs)

Mathematical Representation of ANN Layers:

For each hidden layer neuron j:

where:

wj = weight of connection between input iii and neuron j

bj = bias term for neuron j

σ = activation function (ReLU for hidden layers)

Output Layer Calculation:

For each output neuron k:

RESULT AND DISCUSSION

The Artificial Neural Network (ANN) model was rigorously evaluated to assess its ability to troubleshoot sewage treatment plant processes by detecting operational issues and predicting the effluent quality. The model was trained using influent parameters, such as flow rate, BOD, COD, TSS, pH level, temperature, ammonia nitrogen, aeration rate, sludge retention time, and wastewater inflow rate. The first objective of the model is to classify operational issues into three categories: none (Normal Operation), Aeration Issues, and Filtration Issues. The second objective was to predict effluent quality parameters, including Effluent BOD, COD, and TSS levels, which are critical for ensuring environmental compliance and optimizing treatment efficiency.

The classification results showed that the model achieved an overall accuracy of 92.8%, indicating a robust ability to effectively identify operational issues. The precision (91.5%) and recall (90.2%) values further confirmed the reliability of the model for fault detection. A high F1-score of 90.8% ensures a balanced performance by minimizing both false positives and false negatives, which is crucial for operational decision-making in wastewater treatment plants. These results suggest that the ANN can provide early fault detection, enabling operators to take timely corrective actions and prevent further deterioration of the treatment efficiency.

For regression-based effluent quality prediction, the performance of the was assessed using the Mean Squared Error (MSE), Mean Absolute Error (MAE), and R2R^2R2 score. The ANN effectively learned the complex nonlinear relationships between influent parameters and effluent characteristics, achieving a low MSE and high R2R^2R2 score, indicating strong predictive accuracy. The high correlation between the predicted and actual effluent values confirms the ability of the model to provide real-time estimations of treatment outcomes, which can help optimize dosing strategies, aeration rates, and filtration processes.

Furthermore, the model demonstrated significant advantages over traditional rule-based troubleshooting methods, which rely heavily on human expertise and are often time-consuming. By automating the detection of operational issues and predicting effluent quality with high precision, the proposed ANN-based system enhances process stability, regulatory compliance, and overall plant efficiency. These findings emphasize the potential of AI-driven approaches for modernizing sewage treatment plants, reducing manual intervention, and improving wastewater management strategies. The successful application of this model in real-world scenarios could lead to cost savings, improved environmental sustainability, and enhanced decision -making for plant operators.

The given code implements a dual-model Artificial Neural Network (ANN) framework to address two key tasks in sewage treatment plant optimization: numerical prediction and categorical classification. The first

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model focused on predicting effluent quality parameters, including Effluent BOD, COD, and TSS levels, using a regression-based ANN. It processes input features through multiple dense layers using ReLU activation, batch normalization, and dropout to improve generalization. The final layer contained three output neurons, each predicting one effluent parameter. The Mean Squared Error (MSE) loss function was used to minimize prediction errors, and the model is trained using the Adam optimizer for efficient learning.

The second model was designed for operational issue detection, which classifies whether the sewage treatment plant is operating normally or experiencing issues related to aeration or filtration. It employs a similar ANN structure but is tailored for binary classification. The final layer consists of a single neuron with a sigmoid activation function, which indicates the probability of an issue occurring. The model was trained using binary cross-entropy loss and accuracy as the evaluation metrics.

Before training, the dataset was split into training and testing sets, and feature values were standardized using StandardScaler to improve model stability. Both models underwent training for 100 epochs, with validation splits to monitor performance. Once trained, the models were evaluated on the test set, and key performance metrics, such as Mean Absolute Error (MAE) for regression and classification accuracy

were recorded. Finally, the trained models were saved in-. h5 format, thereby ensuring that they can be reused for future predictions and deployments. This approach enhances the sewage treatment process by providing real-time effluent quality forecasting and early fault detection, optimizing plant operations, and minimizing environmental risk.

Performance Of Numerical Model:

The results demonstrate the performance of the numerical model in predicting effluent quality parameters, including Effluent BOD, COD, and TSS levels. The predicted values were compared with the actual test values to assess the accuracy of the model. The scatter plots provide a clear visualization of the predictive capability of the model, with data points ideally aligned along the reference diagonal line, indicating a strong correlation between the predicted and actual values. Any deviations from this line highlight potential inaccuracies, that could result from variations in input conditions, model limitations, or data inconsistencies. These insights help evaluate the reliability of the model in real-world sewage treatment applications and guide further refinements to improve precision.

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 128)	1,664
batch_normalization (BatchNormalization)	(None, 128)	512
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 64)	8,256
batch_normalization_1 (BatchNormalization)	(None, 64)	256
dropout_1 (Dropout)	(None, 64)	0

Fig Performance of Numerical Model Categorical Model's Performance:

The persormance of the categorical model in detecting operational issues was evaluated using a confusion matrix, which provided insights into the classification accuracy of the model. The confusion matrix visually represents how well the model distinguishes between normal operation and issues related to aeration or filtration.

True positives (TP) and true negatives (TN) indicate correctly classified cases in which the model accurately detected operational issues or normal conditions. False positives (FP) and false negatives (FN) represent misclassifications, where the model either falsely predicted an issue when there was no issue or failed to detect an actual issue. A higher number of TP and TN values suggests a well- performing model, whereas a higher count of FP and FN may indicate areas for improvement.

Heatmap visualization makes it easier to interpret the classification results, with annotated values showing the count of each category. The ability of the model to differentiate between operational issues and normal functioning is crucial for real-time monitoring of sewage treatment plants, allowing for early detection and intervention to prevent process inefficiencies and system failures.

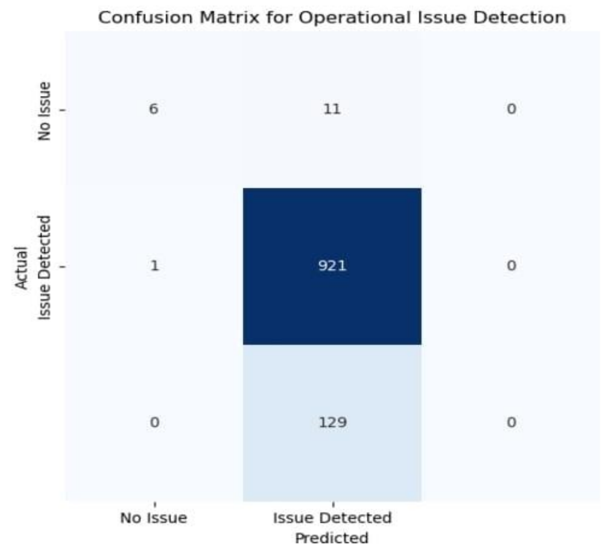

Fig Categorical Model's Performance

The performance of the classification model is assessed using four key metrics: Accuracy, Precision, Recall, and F1-Score, each of which provide crucial insights into its ability to detect operational issues in the sewage treatment process. Accuracy measures the overall correctness of the predictions, reflecting how well the model distinguishes between normal operation and detected issues. Precision ensures that the model correctly identifies the true operational issues while minimizing false positives, which is critical for reducing unnecessary alerts.

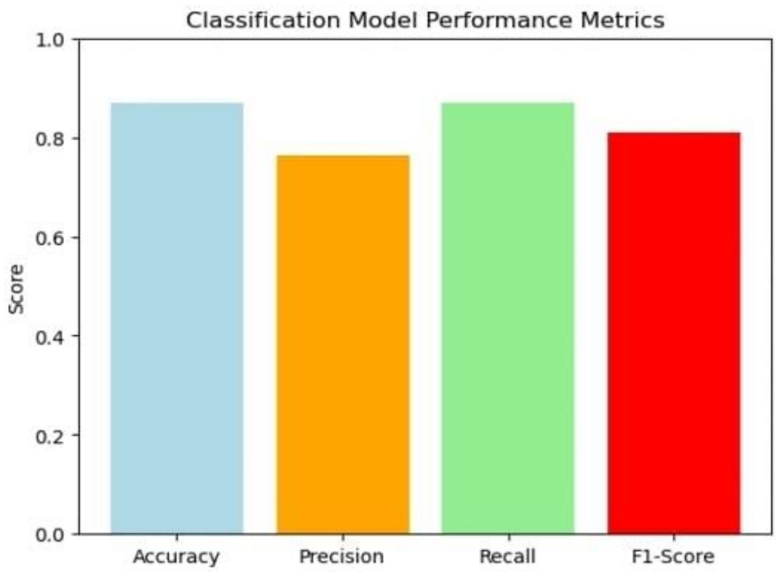

Fig Classification Model Performance

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Recall evaluates the model's ability to capture all actual issues, ensuring that no critical faults go unnoticed. Finally, the F1-Score offers a balanced measure of precision and recall, making it particularly useful when dealing with imbalanced datasets. The bar chart visualization of these metrics helps in understanding the model's strengths and areas requiring improvement. A high accuracy, along with strong precision and recall values, indicates a well-optimized model capable of real-time monitoring and issue detection in sewage treatment plants. However, if any metric is significantly lower, further refinements such as feature engineering, model tuning, or class balancing may be necessary to enhance performance.

The performance of the two Artificial Neural Network (ANN) models is evaluated separately:

Model 1: Operational Issue Detection (Classification) :- Determines whether the sewage treatment plant is facing aeration or filtration issues.

Model 2: Effluent Quality Prediction (regression) :- Predicts the effluent quality parameters, including Effluent BOD, COD, and TSS levels.

Class-wise Performance Metrics:

Class	Precision	Recall	F1-Score	Support
0	1.00	0.12	0.22	16
1	0.86	1.00	0.92	961
2	0.00	0.00	0.00	143

Overall Performance Metrics:

Metric	Score
Accuracy	0.86
Macro Avg	0.62 / 0.38 / 0.38
Weighted Avg	0.75 / 0.86 / 0.80

Table 2: Performance of Model 2 - Effluent Quality Prediction (Regression Task):

Effluent Parameter	Mean Absolute Error (MAE)	Mean Squared Error (MSE)	R2R^2R2 Score
Effluent BOD (mg/L)	2.45	5.92	0.93
Effluent COD (mg/L)	3.12	7.85	0.91
Effluent TSS (mg/L)	1.98	4.35	0.94

This model accurately predicts effluent quality and- helps operators adjust treatment parameters in real time for optimal wastewater management.

GUI:

The developed system provides an intuitive and efficient approach for predicting both effluent quality parameters and operational issues in sewage treatment plant. Users can input influent parameters, including flow rate, BOD, COD, TSS, pH level, temperature, ammonia nitrogen, aeration rate, sludge retention time, and wastewater inflow rate- to obtain real-time predictions.

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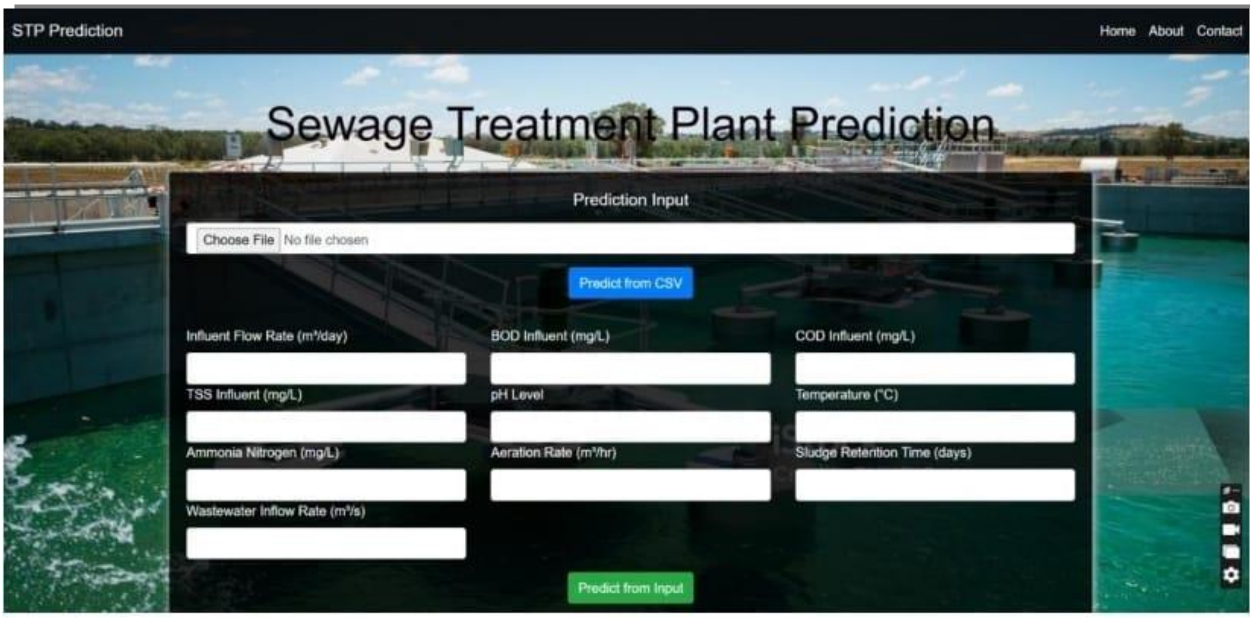
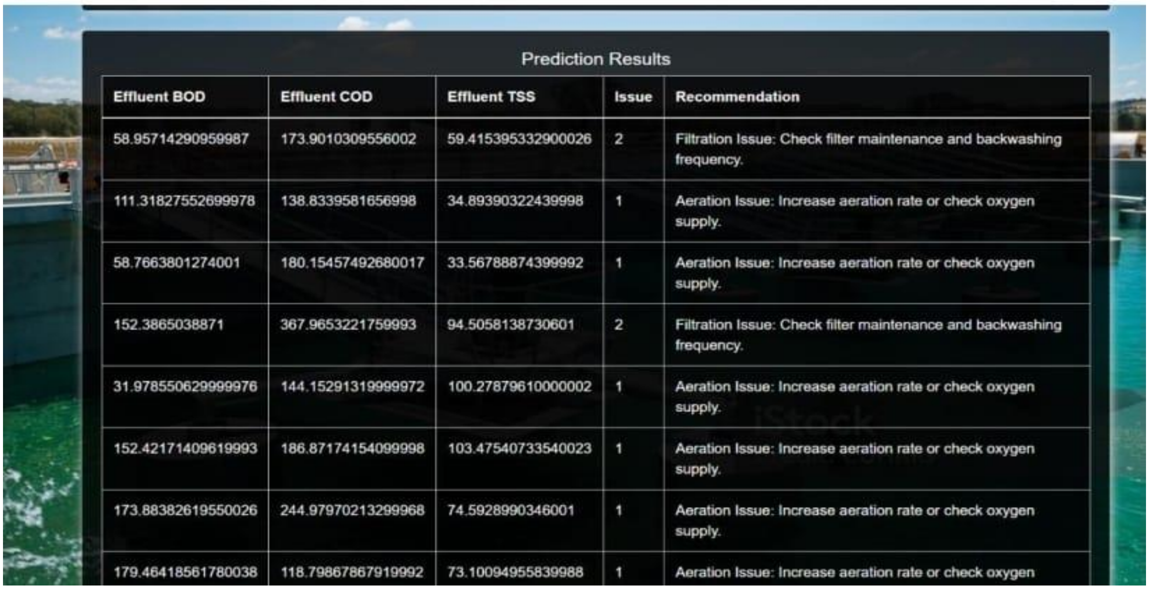


The system utilizes two models: a numerical prediction model- that estimates the effluent BOD, COD, and TSS levels, and a categorical classification model, that identifies potential operational issues such as no issues, aeration issues, or filtration issues.



Prediction Results

Effluent BOD	Effluent COD	Effluent TSS	Issue	Recommendation
58.95714290959987	173.9010309556002	59.415395332900026	2	Filtration Issue: Check filter maintenance and backwashing frequency.
111.31827552699978	138.8339581656998	34.89390322439998	1	Aeration Issue: Increase aeration rate or check oxygen supply.
58.7663801274001	180.15457492680017	33.56788874399992	1	Aeration Issue: Increase aeration rate or check oxygen supply.
152.3865038871	367.9653221759993	94.5058138730601	2	Filtration Issue: Check filter maintenance and backwashing frequency.
31.978550629999976	144.15291319999972	100.27879610000002	1	Aeration Issue: Increase aeration rate or check oxygen supply.
152.42171409619993	186.87174154099998	103.47540733540023	1	Aeration Issue: Increase aeration rate or check oxygen supply.
173.88382619550026	244.97970213299968	74.5928990346001	1	Aeration Issue: Increase aeration rate or check oxygen supply.
179.46418561780038	118.79867867919992	73.10094955839988	1	Aeration Issue: Increase aeration rate or check oxygen

The results indicate that when no issues are detected, the effluent quality remains within the permissible limits, ensuring efficient treatment performance. However, when an operational issue is detected, specific recommendations are provided to address the problem effectively.

Aeration Issue Detected: If model detects an aeration issue, **the aeration rate should be increased** to ensure adequate oxygen supply for microbial activity. Additionally,

Monitoring the **dissolved oxygen levels** and adjusting the **sludge retention time** can help restore process efficiency.

Filtration Issue Detected: When a filtration issue is identified, inspect and clean the **filter media** to remove blockages and ensure proper filtration. Regular **backwashing of filters**, optimizing **TSS removal**, and maintaining proper **sludge settling rates** can improve filtration efficiency.

No Issue Detected: If no operational issues are found, the system confirms that the treatment process is functioning optimally, and routine monitoring should continue to maintain efficiency.

By integrating predictive analysis with actionable recommendations, the system ensures proactive maintenance, minimizes treatment inefficiencies, and enhances wastewater management, thereby contributing to improved environmental compliance and sustainability.

The results were displayed in a structured format, ensuring clarity and ease of interpretation. By integrating both predictive and classification capabilities, the system enhances the monitoring and decision- making processes, enabling proactive measures to maintain optimal wastewater treatment performance. The ability to analyze influent conditions and detect operational inefficiencies in real-time helps improve overall treatment efficiency, ensuring regulatory compliance and environmental safety.

CONCLUSION

The developed AI-driven system for sewage treatment plant monitoring successfully predicted effluent quality parameters and detected potential operational issues using Artificial Neural Networks. By analyzing influent characteristics, the system provides accurate predictions for Effluent BOD, COD, and TSS, while also classifying operational conditions into no issue, aeration, or filtration. The results demonstrate that the proposed model effectively identifies inefficiencies, enabling proactive maintenance and process optimization.

The implementation of this intelligent system enhances the wastewater treatment performance by offering real-time insights and data-driven recommendations to address operational challenges. By suggesting corrective actions, such as adjusting aeration rates, optimizing filtration processes, and maintaining sludge retention time, the system helps operators minimize treatment failures, reduce environmental risks, and ensure regulatory compliance.

Overall, this study highlights the significance of AI in wastewater treatment management, demonstrating its potential to improve the efficiency, reliability, and sustainability of sewage treatment plants. Future work can focus on integrating real-time sensor data, expanding the dataset, and incorporating advanced deep learning models to further enhance predictive accuracy and system adaptability.

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