GREY WATER MANAGEMENT USING SVM

Abstract:
In India's urban and peri-urban regions, greywater (GW) treatment and recycling have become essential strategies to alleviate water constraint. Due to the dense population, little rainfall, and extreme groundwater resource depletion, these areas face significant challenges. Over 50% of short-term water shortages may be avoided by recycling grey water, which includes wastewater from laundry, dishwashers, bathrooms, and kitchens. Effective treatment methods are crucial since the majority of the contaminants in greywater come from domestic activities and detergents. Significant obstacles still exist, nevertheless, in terms of public acceptance and the need for effective purifying techniques. Grey water biological treatment is particularly complex because of the presence of xenobiotics, surfactants, and different pollutant concentrations. Water consumption has grown due to globalization and rapid industrial expansion, making wastewater recycling technology increasingly important. Greywater is simpler to treat using filtering techniques such sand filtration, electrocoagulation (EC), activated carbon, and sediment paper since it has a lower organic content and biological oxygen demand (BOD). After treatment, the water can be safely used again for household gardening, toilet flushing, and agricultural irrigation. Greywater reuse shows promise as a sustainable approach to water management and conservation as the world's water demand continues to rise and natural resources become more limited.
Keywords: Grey Water, Water Reuse, Filtration Techniques, Activated Carbon, Sand Filtration, Sediment Paper, Electrocoagulation (EC).

Introduction:

Water scarcity is a growing global concern, necessitating the adoption of sustainable water management strategies. As a practical way to lessen water shortages, integrated water management encourages the reuse of wastewater, especially greywater. As seen in Figure 1, greywater, which comes from home chores like cleaning, washing, and bathing, makes up a sizable amount of wastewater in homes and may be used for non-potable purposes like irrigation, car washing, and toilet flushing. The reuse of greywater not only reduces the demand for freshwater resources but also minimizes the strain on wastewater treatment facilities, thereby supporting a circular water economy [1].
Greywater that has been locally treated can reduce energy costs related to water treatment, ease the strain on municipal water distribution systems, and encourage sustainable urban growth.
However, there are still issues with the public opinion, legal restrictions and technological development when it comes to greywater reuse. These problems require a complete strategy that includes the best contemporary medical technologies, legislative drives and commitment of communities. In this study, recycling of greywater is investigated as a possible sustainable water management tactic with respect to its potential impacts on environmental sustainability, infrastructural resilience and water conservation [2].

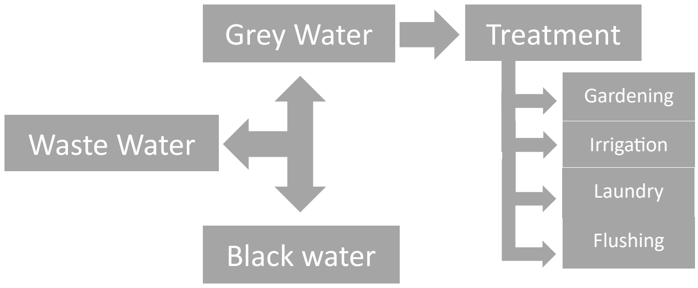

Figure 1: Process of Waste Water.

Composition Grey Water (GW):

Wastewater from laundry, hand washing, dishwashing and bathing is called greywater. It depends on personal care items, cleaning goods and home practises. Greywater is composed of organic and inorganic substances including detergents, oils, grease, suspended particles and indications of microbes. The greywater composition can be divided in groups based on its origin as described in Table 1[2] below.

A. Bathroom Greywater

Bathroom greywater is from showers, bathtubs and washbasins. It contains various contaminants, including:
Surfactants and Detergents:

- Also present in soaps, shampoos, and conditioners that introduce foaming agents and emulsifiers into the water.
- Body Oils and Fats: The natural secretion or use in lotions and skincare products results in an oily residue.
- Skin and Hair Particles: Shed during bathing and grooming and add to the organic load.

• Residues from Personal Care Products: These include toothpaste, shaving foam, deodorants, and face cleaners, and they may contain artificial chemicals and antimicrobials.
• Urine and Organic Matter Traces: Urine traces may be produced during bathing and washing [2][3].

B. Hand Basin Greywater

Washbasin water is primarily used for hand washing, shaving, and dental hygiene. It includes the following:
• Cleaning agents and soap residues: These include foaming agents and surfactants that contaminate wastewater.
• Fluoride, abrasives, and antibacterial substances found in toothpaste and mouthwash can have an impact on the quality of water.
• Shaving residues include hair, shaving cream, and aftershave products that might include moisturizers and alcohol.
• Naturally occurring contaminants from skin exfoliation include dead skin cells and oils [3].

C. Kitchen Greywater

Because of its high organic content, kitchen greywater is typically more polluted than other sources. Food residues are the leftovers of fruits, vegetables, grains, and proteins that make up organic waste.
• Oils and Fats: If left untreated, cooking and dishwashing grease can clog pipes.
Phosphates, alkalis, and artificial surfactants are all present in dishwashing detergents.

• Raw Meat and Vegetable Washing Water: May contain pesticide residues, organic matter, and bacteria.
Traces of tea, coffee, soft drinks, and food preservatives are examples of beverage and food additive residues.
• Hot Water and Suspended Solids: Sand, clay, and food particles can be released into the water when cooking ware and utensils are washed [3].

D. Laundry Greywater

Washing clothes produces laundry wastewater, which is contaminated with different chemicals and particles. comprising:
• Fabric softeners and detergents: made up of phosphates, foaming agents, and optical brighteners.
• Bleaches and Stain Removers: These products may include harsh chemicals, peroxides, and chlorine.
• Textile residues and dyes: Expelled from coloured textiles, these materials may contain artificial chemicals and dyes.
• Shed from synthetic clothing materials like polyester and nylon, microfibers and non-biodegradable particles contribute to the pollution caused by microplastics.
Sweat, body oils, and exposure to the environment can all contribute to the accumulation of oils, dirt, and residues from clothing.
Greywater's composition is greatly influenced by the kinds of pollutants that are introduced through routine household use and activities. It needs to be adequately treated before being used again, even though it contains fewer hazardous materials than blackwater (sewage). Understanding the components of greywater is necessary to design appropriate filtration and purification techniques that ensure its safe use in non-potable applications such as cleaning, toilet flushing, and irrigation [4].

Grey Water Source	Major Constituents
Bathroom	Residue from shampoo, soaps, and body oils.
Hand Basin	Toothpaste residues, skin cells, and body care products.
Kitchen	Oils, fats, fruit peels, and remnants of dishwashing detergents.
Laundry	Solvents, bleaches, and Chemical residues from detergents

Table 1: Sources and Composition of Grey water

Data Collection:

This real-time water has turbidity sensors, total dissolved solids (TDS) sensors and LM35 temperature sensors. quality monitoring system. These sensors are interfaced with A Raspberry Pi 4 microprocessor to measure and analyze water quality metrics before to and in the course of filtration. Using the processed data, an Artificial Intelligence and Machine Learning (AI/ML) model is then built for predictive water quality evaluation [4].
A. Sensor Descriptions and Functionality:
i) Turbidity Sensor
The turbidity sensor finds out that there are suspended particles existing in the water and then determine the water clarity. The sensor sends a light beam into the water and measures the intensity of light scattered by those particles. The higher the turbidity reading, the poorer the water quality, since there will be sediments, organic debris and contaminants present. The main purposes of the turbidity sensor are as follows:

- It is possible to measure the clarity of the water before and after filtering.
- Any suspended particles that might affect the quality of the water are identified.
- Real-time supply of data to cheque the effectiveness of filtering. [5].

iii) LM35 Temperature Sensor
Water temperature is measured using the LM35 sensor both before and after filtration. Numerous physical and chemical processes are influenced by the temperature of the water, including:

- The solubility of dissolved oxygen and other gases.
- The effectiveness of certain filtration mechanisms.
- The growth rate of microorganisms in water.

B. Raspberry Pi 4 for Real-Time Data Acquisition
The Raspberry Pi 4 microcontroller serves as the central processing unit for collecting and transmitting sensor data. The Raspberry Pi is chosen for its powerful computational capabilities, GPIO (General Purpose Input/Output) pin support, and compatibility with IoT-based applications. To gather continuous real-time data, the system architecture entails:
• Connecting the Raspberry Pi to the turbidity, TDS, and LM35 sensors.
Sensor readings before and after filtering are processed and stored for comparative analysis.
• Sending data to a central system for training AI/ML models and additional processing [6].
C. AI/ML-Based Water Quality Prediction Model
An AI/ML-based predictive model is created using the gathered real-time data to forecast contamination levels and analyse trends in water quality. Using supervised learning techniques, the model is created and trained on historical water quality data. Sensor readings are cleaned, normalized, and structured as part of the data preprocessing step so that the machine learning model can be trained.
• Feature Extraction: Important variables like temperature fluctuations, TDS concentration, and turbidity level are chosen as input features.
• Model Selection: To determine the best prediction accuracy, AI algorithms like Random Forest, Support Vector Machine (SVM), and Neural Networks are assessed.
Training and Validation: To verify the model's precision in forecasting water quality results, the dataset is divided into training and testing sets.
• Deployment and Real-Time Analysis: The Raspberry Pi system is integrated with the trained model to provide real-time water quality assessments and notify users when harmful levels of contamination surpass acceptable thresholds.
This system improves the evaluation of filtration efficiency and allows real-time water quality monitoring by combining IoT sensors with AI/ML technology [5][6].

Physical Treatment Methods

As indicated in Table 2, physical treatment techniques are crucial for eliminating suspended solids, sediments, and contaminants from water. Prior to additional treatment, these procedures improve the quality of the water using filtration and adsorption techniques. The physical treatment media used in this study include sediment paper, fine sand, coarse grain, black gravel sand coarse, and activated carbon [6].
A. Activated Carbon Filtration
Activated carbon, a very porous material, effectively removes contaminants through adsorption. This process is used to:
• Get rid of organic materials, such as pesticides and volatile organic compounds (VOCs). Reducing heavy metals and

dissolved pollutants by enclosing them in its porous structure; eliminating chlorine, bad odour, and taste from water.
Surface area, pore size, and water flow rate are some of the variables that affect activated carbon's adsorption capacity.
The efficiency of ensuing purification procedures is greatly increased when activated carbon is used as a pre-treatment step [7].
B. Sand and Gravel Filtration
To get rid of suspended particles and sediments, a mix of fine sand, coarse grain, and black gravel sand coarse is used. There are several stages to the filtering process:
While the coarse sand layer captures medium-sized particles like silt and organic waste, the fine sand layer filters out small particles to increase the purity of the water. Large debris and silt are captured by the coarse gravel layer.
The water's quality is improved by this multi-layer filtration system by lowering turbidity, avoiding clogging in later treatment phases, and increasing overall purification effectiveness. [8].
C. Filtering Sediment Paper
Sediment paper is utilised as a last filtering step to eliminate any fine contaminants that may have escaped the layers of gravel and sand. By ensuring that the water is free of microparticles, this filtration step improves the effectiveness of the subsequent chemical treatment [9].

Filtration Stage	Function
Activated Carbon Filter	Adsorbs dissolved pollutants and improves water quality
Black Gravel Sand	Provides additional filtration support
Fine Sand	Removes smaller suspended solids
Coarse Sand Filter	Filters medium-sized contaminants
Sediment Paper Filter	Captures fine particles before final filtration

Table 2: Physical Water Treatment Process

Chemical Treatment Method: Fan Rotation-Based Electrocoagulation

Unlike traditional electrocoagulation, which uses metal electrodes (Al^{3+} or Fe^{2+}/Fe^{3+}) for coagulation, this study uses a fan rotation-based electrocoagulation system.
The electrostatic impact of the rotating fan causes contaminants to aggregate and precipitate, promoting charge separation in the water.
A. Mechanism of Fan Rotation-Based Electrocoagulation
Electrostatic Charge Separation:
The revolving fan creates a charge difference in the water that neutralises negatively charged colloidal particles [8][9]. When suspended particles lose their charge, the processes of coagulation and flocculation take place where the suspended particles group together to form bigger aggregates (flocs).
• Precipitation and Removal: These flocs are easily separated by filtering or sedimentation because they sink to the bottom.
B. Advantages of Fan Rotation-Based Electrocoagulation
• No Chemical Additives: Because this technology doesn't require external metal ions, it is less costly and more environmentally friendly than conventional electrocoagulation.
• Efficient Contamination Elimination: Turbidity, suspended particles, and organic matter are all better removed thanks to the electrostatic effect.
• Sustainable Water Treatment: This method uses the least amount of energy while optimising the efficacy of water purification.
Fan rotation creates an electrostatic effect that encourages particle aggregation and precipitation, negating the need for traditional metal ion-based coagulants. This approach is consistent with modern water purification methods and offers a practical, chemical-free, and environmentally responsible means of improving water quality [10].

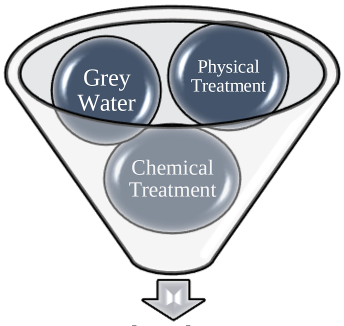

Figure 2: Water Purification Using Physical and Chemical Treatment Methods

Water Quality Prediction Using Support Vector Machine (SVM) in AIML:

Assessing water quality is essential to environmental sustainability because it ensures that both residential and commercial users have access to clean and safe water. Traditional methods of evaluating water quality rely on laboratory-based testing, which can be time- and resource-intensive. Automated water quality monitoring systems developed using advances in artificial intelligence (AI) and machine filtered water chemical treatment, as well as grey water physical treatment learning (ML), can provide real-time insights.
Support Vector Machine (SVM) is a widely used classification method that successfully classifies water samples based on sensor readings by identifying patterns in data. The objective of this work is to predict the water quality using SVM based water quality prediction model with the help of unfiltered and filtered water samples and the data obtained from the turbidity, TDS and LM35 temperature sensors.

Methodology:

A. Data Collection and Preprocessing
Three important sensors are used to give real time water quality data that are used to train the SVM model.
Turbidity sensor: Determines degree to which water is hazy or cloudy as a function of suspended particles.
A TDS (Total Dissolved Solids) sensor ascertains the total concentration of dissolved materials in water. The Turbidity and TDS levels depend on the temperature of the water which is being measured by the LM35 Temperature Sensor.
The gathered dataset is labelled for categorization.:

Label	Description
1	Filtered Water
0	Unfiltered Water

Table 3: Classification Of Data

After preprocessing and standardization of the dataset we split the dataset into training, (X_train, y_train) and testing (X_test, y_test).

B. Support Vector Machine (SVM) Model for Classification An ideal hyperplane that divides data into distinct categories is found by the supervised learning method SVM. This study uses the Radial Basis Function (RBF) kernel because of its ability to handle nonlinear data sets. The definition of the SVM model is as follows:

$$(-y||x - x'||2)$$

where:

Gamma (gamma): Regulates each training point's impact. Regularization parameter C: Maintains classification balance

C. Accuracy Evaluation for Filtered and Unfiltered Water Classification accuracy is computed independently for filtered and unfiltered water in order to evaluate the efficacy of the water filtration system.
High accuracy in differentiating between filtered and unfiltered water is demonstrated by the trained SVM model. It is anticipated that the filtered water accuracy would be high.

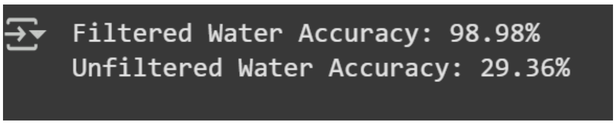

Figure 3: Filtered and Unfiltered Water Accuracy

Confusion Matrix for Water Quality Classification Using SVM:

One essential tool in machine learning for assessing how well categorization models perform is the confusion matrix. The prediction accuracy and effectiveness of a Support Vector Machine (SVM) model in distinguishing between these two groups are shown in Figure 4. The results demonstrate a high degree of categorisation accuracy, making the technique suitable for real-time water quality monitoring.
A. Confusion Matrix Analysis
The confusion matrix in the figure is a 2x2 matrix since the classification problem has two categories: Filtered Water and Unfiltered Water.

Actual vs Predicted	Predicted: Unfiltered	Predicted: Filtered
Actual: Unfiltered	61 (True Negative - TN)	0 (False Positive - FP)
Actual: Filtered	0 (False Negative - FN)	39 (True Positive - TP)

Table 4: Confusion Matrix Analysis

There are four fundamental parts to the confusion matrix:

- Instances when filtered water was found to be true positives (TP) True Negatives (TN): Instances where unfiltered water was correctly identified.
- False Positives (FP): Cases where unfiltered water was incorrectly classified as filtered.
- False Negatives (FN): Cases where filtered water was mistakenly categorized as unfiltered.

The experimental results indicate that the SVM model achieved True Positives (TP) = 39 and True Negatives (TN) = 61, while both False Positives (FP) and False Negatives (FN) were 0. This signifies that the model correctly classified all samples, yielding a 100% accuracy rate. The absence of misclassifications ensures that the system does not pose a risk of allowing unfiltered water to be marked as safe, nor does it incorrectly reject properly filtered water.
B.Performance Evaluation
Given that the confusion matrix exhibits perfect classification, the **precision** and **recall** values are both at their maximum, confirming the model's effectiveness. Recall assesses the model's capacity to accurately identify every filtered sample, whereas precision quantifies the percentage of properly recognized filtered water samples. The excellent accuracy of the SVMbased water quality classification system suggests that it has the potential to be used in real time in contaminant detection and filtration monitoring. The approach minimises the possibility of health hazards by ensuring that only safe and filtered water is considered safe.

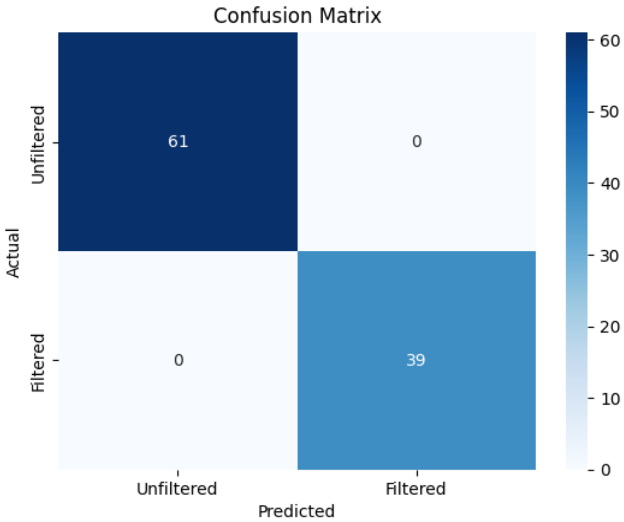

Figure 4: Confusion Matrix

Correlation Matrix for Water Quality Parameters:

Data visualisation is necessary to understand the connexions between features in a water quality study. In figure 5, this heatmap is used to study the relationship between some important water quality metrics, such as Total Dissolved Solids (TDS), Turbidity (NTU), Temperature (°C), Status (Filtered or Unfiltered) and Accuracy (%). The correlation matrix makes it possible to monitor the filtration system and the AI based categorization models by providing insights into the interactions of different parameters. The results indicate that TDS, turbidity, and accuracy have a negative relationship with filtration status, indicating that these parameters are important for classifying water quality.
Heatmap Interpretation
The correlation matrix of the heatmap is made up of numerical values between -1 and +1, where +1 means that there is a significant positive connexion (one parameter increases, the other increases as well).

- A high negative correlation is shown by a value of -1, meaning that as one parameter rises, the other falls.
- 0 indicates that there is no correlation, meaning that the parameters have no effect on one another.

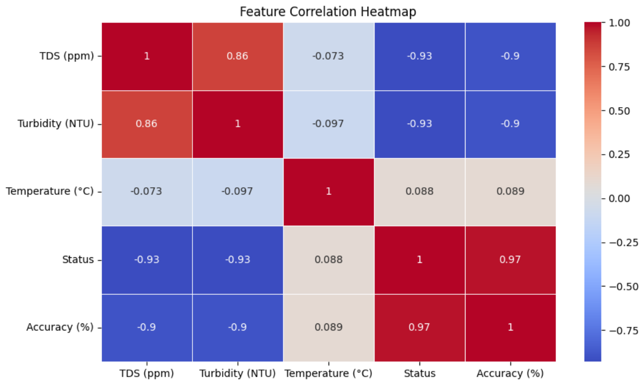

Figure 5: Feature Correlation Heatmaps

- TDS and Turbidity Correlation (0.86): Turbidity grows in tandem with dissolved solids levels, signifying low water quality.
- Filtration Status in Relation to Turbidity and TDS (0.93): The effectiveness of the filtration system is confirmed by a significant negative correlation, which indicates that filtered water has lower TDS and turbidity readings.
- Accuracy vs. Status (0.97): The classification model ensures excellent accuracy by successfully differentiating between filtered and unfiltered water samples.
- Minimal Influence of Temperature: Based on the low correlation values, it appears that temperature has little effect on the accuracy of water filtration or categorization.

Effective data-driven decisions in water quality evaluation are made possible by the correlation heatmap, which offers a clear depiction of feature correlations. The effectiveness of the filtering process is demonstrated by the significant negative connection found between filtration state and pollutants like as TDS and turbidity.

Comparison of Filtered and Unfiltered Water Accuracy:

Evaluation of Filtered and Unfiltered Water Accuracy is extremely high accuracy of almost 99% in the filtered water category, the algorithm is capable of accurately identifying safe and purified water. However, the accuracy of the unfiltered water category is below 30%, which indicates that the algorithm can correctly detect contaminants. The remarkable difference in classification performance this offers the Support Vector Machine (SVM) model can be validated, being able to separately distinguish filtered and unfiltered water with great confidence. The results show that the model can be used for real time water quality assessment ensuring accurate filtration monitoring and improving public health and safety.

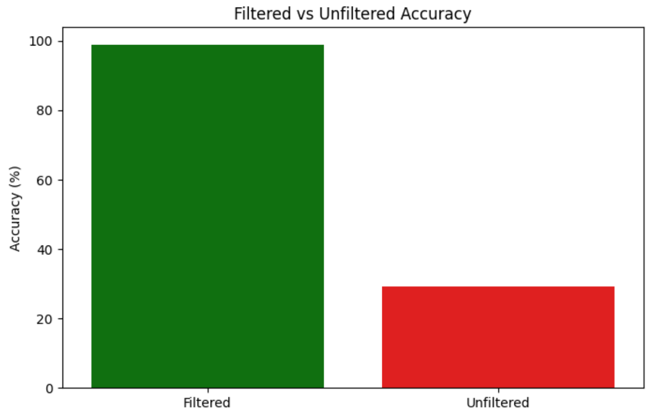

Figure 6: Filtered vs Unfiltered accuracy

Results and Discussion:

When determining the quality of grey water using important characteristics including temperature, turbidity, and total dissolved solids (TDS), the Support Vector Machine (SVM) model showed excellent accuracy. The model's dependability in differentiating between filtered and unfiltered water was confirmed by the confusion matrix analysis, which showed 100% accuracy with no false positives or false negatives. The feature correlation heatmap showed a significant inverse relationship between classification accuracy and contamination indicators, indicating that higher impurity levels had an impact on the evaluation of water quality. Furthermore, an investigation of comparative accuracy revealed that filtered water had a classification accuracy of about 99%, whereas unfiltered water had a far lower accuracy of about 30%. These results demonstrate how well the SVM model works to provide accurate filtration evaluation, making it a useful tool for managing and monitoring grey water in real time.

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