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Wastewater recycling to enhance environmental quality using fuzzy embedded with RNN-IOT for sustainable coffee farming

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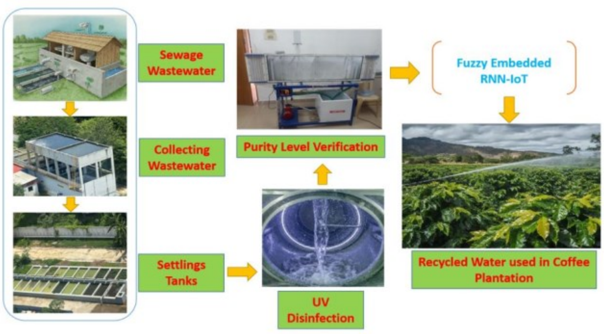
Graphical abstract



Abstract

Wastewater pollution is a major concern due to organic matter, pesticides, and other contaminants. Untreated discharge of this wastewater can pollute water resources and harm the environment. A data-driven approach for optimizing wastewater treatment systems and ensuring recycled water's safety and effectiveness by calculating energy, chemical, and greenhouse gas emissions. According to this study, the process of system optimization decreases the negative influence on the environment. This suggested research looks at the potential for reusing wastewater and purifying it so it can be used in coffee plants. A variety of methods for cleaning and disinfecting substances are detailed in the article. A wide range of physical, chemical, and biological processes can be utilized in these treatments. The primary objective of sewage wastewater treatment is to develop effective methods that ensure the safety and effectiveness of treated reused water for use in agriculture. data analysis using sensors Connected sensors that measure nutrients, pollutants, salinity, pH, organic matter, and toxins are being used to track various water quality measures. Fuzzy-based data processing utilizing FRNNs to handle uncertainties inherent in sensor data through fuzzy logic techniques. Recurrent neural networks capture temporal dependencies in the wastewater data, allowing for more accurate predictions. Compared with the other existing algorithms, the proposed method has the efficient treatment of wastewater and its safe reuse for coffee cultivation, promoting water conservation and sustainable agricultural practices.

Keywords: Wastewater treatment, data analysis, fe-rnn, iot sensors, purity level indicator, motor and power control system

1. Introduction

The increasing urbanization and population of India have made water scarcity and stress a major issue in the nation. To save water from being wasted, it is crucial to recycle and reuse wastewater. Greywater, which includes water from sources such as showers, bathtubs, hand basins, washing machines, laundry troughs, and kitchen trash, is the most common kind of wastewater. Black water–toilet waste. sewage–a mix of greywater waste, black waste, and trade waste. industrial wastewater–all wastewater waste except sewage. Sewage water irrigation increases plant growth and reduces the need for chemical fertilizers (Awasthi *et al*. 2024). There are main two types of coffee plantations for the cultivation of coffee beans such as Arabica coffee soil conditions thrive in well-drained, volcanic soils rich in organic matter. The optimal pH range is 6.0 to 6.5. These conditions are frequently encountered at elevated altitudes (about 3,000 feet and higher) with temperate temperatures and abundant precipitation. Water necessitates a constant level of wetness, but it is vulnerable to water logging. Precipitation is essential, with optimal levels falling within the range of 60-100 inches per year (Selvanarayanan *et al*. 2024). Still, soils that are well-drained and have a slightly acidic pH (at approximately 5.5 to 6.5) are preferred. Robusta is capable of thriving in lower altitudes (approximately sea level to 2,000 feet) and can tolerate elevated temperatures. Water requirements Robusta coffee is more drought-tolerant than Arabica and can endure lower levels of precipitation (approximately 40-60 inches per year). Nevertheless, optimal growth and production are still facilitated by consistent moisture. A balanced supply of macronutrients and micronutrients is necessary for water constituents (Cargnin and Joao, 2024). On the other mutually beneficial ways, Robusta's unique needs could change slightly depending on the soil type. Regular soil testing will help you determine the best nutrient profile for your Robusta plantation. The treatment and disposal of this effluent will determine its environmental repercussions. The presence of dangerous bacteria along with additional pathogens in untreated sewage effluent poses a threat to the health of both humans and animals. Algae bloom and ecological disturbances caused by an overabundance of nutrients in water sources are further potential outcomes. The environmental impact of the effluent treatment system can be evaluated through data analysis. This encompasses the assessment of variables such as greenhouse gas emissions, energy consumption, and chemical usage. The environmental impact can be reduced by optimizing the system by this analysis.

Data Quality ensures high-quality sensor data covering various operating conditions (e.g., water flow rate, nutrient levels, contaminant concentrations). Data Preprocessing is to clean and pre-process the data by handling missing values, and outliers, and scaling sensor data to a common range. Environmental benefits of reusing sewage water Cultivating a sustainable future can alleviate water stress, reduce pollution, promote public health, increase food output, conserve energy, mitigate climate change, and restore habitat (Alotaibi *et al*. 2024). Maintaining nutrient levels is critical since recycled water contains high levels of specific nutrients such as nitrogen and phosphorus. To prevent harm to coffee plants, it is necessary to monitor nutrient levels and adjust watering operations accordingly. Water quality monitoring systems utilize IoT sensors to assess many physical attributes, including temperature, pH, conductivity, turbidity, and total dissolved solids (TDS) in the form of sand (Dahiya *et al*. 2024). Heavy metals, phosphates, nitrates, and chlorine are all part of the chemical characteristics. Algae, bacteria, and other little creatures are all part of the biological parameters. The IoT makes it easy to link sensors to the web, which allows for real-time data collecting and processing. Fuzzy Embedded Recurrent Neural Networks (FE-RNNs) are commonly employed to improve the efficiency of wastewater recycling processes. Comparing past and present statistics. During training, the model discovers the complicated correlations between different parameters. Once trained, the FE-RNN can forecast water quality using real-time sensor data from influent wastewater (Selvanarayanan *et al*. 2024).

2. Literature survey

The study of enhancing water quality through the salvaging of sewage wastewater has been actively researched throughout history. W. Janczukowicz *et al*. introduced a sustainable water management practice. Algorithms such as Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) can be employed to examine past data on meteorological conditions, soil moisture levels, and crop water requirements. Satellite and aerial images can be utilized to monitor the well-being of crops, determine the moisture content of soil, and identify regions that may be experiencing water scarcity. The availability and quality of data are constrained (Janczukowicz and Rodziewicz, 2024). A. Joaquin *et al*. (2024) introduced an adsorption method that entails the gathering of contaminants in water (adsorbates) on the surface of a solid material (adsorbent), either by physical or chemical mechanisms. This approach efficiently eradicates a wide range of pollutants, including dyes, heavy metals, chemical compounds, and pharmaceuticals. The effectiveness of adsorption depends on factors such as the characteristics of the adsorbent, the properties of the pollutants, and the current operating circumstances (Joaquin *et al*. 2024). M.M Syeed *et al* proposed doing a comprehensive assessment of surface water quality by the analysis of several physical, chemical, and biological parameters to evaluate the overall state of the water body. The Water Quality Index (WQI) technique combines multiple water quality factors into a single numerical score, making it easier to understand and communicate water quality situations. The Pollution Index (PI) is a specialized tool used to detect and quantify the levels of pollution in surface water, similar to the Water Quality Index (WQI). Statistical techniques, such as correlation analysis, principal component analysis (PCA), and cluster analysis, are employed to detect patterns, relationships, and potential causes of pollution in water quality data (Syeed *et al*. 2023). P. Chang, *et al*, provide an innovative soft-sensing model for wastewater treatment operations. Soft-sensing involves the estimation of challenging-to-measure indicators of effluent, such as 5-day Biological Oxygen Demand (BOD), by utilizing easily accessible sensor data for other parameters. This methodology provides instantaneous monitoring and enhanced regulation of the therapy procedure (Chang *et al*. 2023). The work by H. Shabanizadeh *et al* utilizes Response Surface Methodology (RSM) to enhance the procedure. Response surface methodology (RSM) is a statistical technique used to examine the relationships and effects of several variables on a specific outcome. In this scenario, RSM is used to optimize the factors that affect the removal effectiveness of COD (Chemical Oxygen Demand) and turbidity. The criteria are expected to encompass the dosage of pomegranate seed powder, the initial pH of the effluent, and the duration of mixing time (Shabanizadeh and Taghavijeloudar, 2023). T. Mkilima *et al*. introduced an innovative method for treating slaughterhouse wastewater by integrating Microbial Fuel Cells (MFCs) and Electro-Fenton (EF) systems, resulting in improved treatment efficiency. The fundamental concept is to exploit the advantages of both technologies: MFC bio-electrochemical systems employ electroactive bacteria to transform organic substances in wastewater into electrical energy. Microorganisms break down contaminants while also producing an electric current. EF systems utilize electrochemically produced hydroxyl radicals (OH•) to degrade organic pollutants in wastewater. These extremely reactive radicals efficiently break down intricate chemical compounds (Mkilima *et al*. 2024). J. Wang *et al* (2023) suggested a concentration on appraising the water quality and estimating the pollution levels of Weishan and Luoma Lakes, situated in Xuzhou, Jiangsu Province, China. Evaluating water quality is essential for comprehending the condition of a water source and its appropriateness for different purposes, such as consumption, leisure activities, or the survival of aquatic organisms. Pollution evaluation helps identify the sources and types of contaminants impacting the water quality (Wang *et al*. 2023). L. Sulistyowati proposed an Importance-Performance Analysis (IPA) technique to assess stakeholder perceptions of various water quality parameters. Stakeholders rate the importance of each parameter for maintaining good water quality and the performance of the current efforts in addressing those parameters. Parameters that have a significant impact but are currently performing are crucial areas for enhancement. The Terrain Analysis technique employs geographical data, including elevation and slope, to identify regions with a significant likelihood of water pollution. These regions are frequently linked to higher levels of water flow accumulation, rendering them more vulnerable to pollution runoff resulting from activities such as agriculture or industry (Sulistyowati *et al*. 2023). Using criteria for water quality that have been measured, C. Chawishborwornworng put out a WQI model. Measurement mistakes, oversimplifications, and random fluctuations in water quality are some of the sources of the inherent inaccuracies in these models. To overcome this, the bootstrap method generates many "pseudo-datasets" that are resampled using the actual data as a replacement. The bootstrap method improves our understanding of model uncertainty and its effect on anticipated WQI values by training independent WQI models on each pseudo-dataset and evaluating the ensuing variations. (Chawishborwornworng *et al*. 2024). Wastewater from the coffee processing industry often contains herbicides, organic debris, and other contaminants. The environment and water supplies are vulnerable to contamination from this wastewater if it is not treated before discharge. By reducing wastewater treatment requirements to an acceptable level, the fuzzy-embedded RNN-IoT system provides a long-term, environmentally friendly solution as shown in Table 1.

Table 1. Existing work compared with the Proposed work

Author	Concept	Algorithm	Disadvantage	Future Scope
Jin *et al*. (2020)	Assessing risks and benefits of reuse	LCA (Life Cycle Assessment)	Public perception, potential for pathogen contamination	Develop standardized guidelines & regulations
Wu *et al*. (2019)	Optimizing treatment processes for irrigation	Membrane filtration, reverse osmosis	High operational costs, energy consumption	Explore cost-effective advanced treatment technologies
Qadir *et al*. (2010)	Managing salinity issues	Salinity modeling, leaching practices	Salinity buildup in soil, potential for soil degradation	Develop salt-tolerant crop varieties, improve irrigation management
Pichel *et al*. (2021)	Microbial risk mitigation strategies	Pathogen detection methods, disinfection techniques	Uncertainty of long-term health effects	Implement robust monitoring programs, research on novel disinfection methods
Hussain *et al*. (2019)	Economic aspects and social acceptance	Cost-benefit analysis, social surveys	Public education, capacity building programs	Develop economic incentives for wastewater reuse in agriculture

3. Materials and method

The research focused on developing a more reliable method for treating recycled sewage water for coffee cultivation as indicated in Table 2. Current water quality assessments, based on outdated guidelines, often produce inaccurate results. The research addressed the Fuzzy Embedded RNN-IoT algorithm, which provides a more predictable way to transform wastewater into a sustainable and nutrient-rich irrigation source for coffee plants as shown in Figure 1.

3.1. Sewage wastewater samples collection from coffee plantation

Sewage wastewater from a coffee plantation that instigates from bathrooms and restaurants is also referred to as domestic wastewater (Fecal matter, Toilet paper, Food scraps, and Graywater (wastewater from showers, sinks, dishwashers, and washing machines). The wastewater flows into a settling tank these are large tanks that allow solids to settle out of the wastewater by gravity. The settled solids, called sludge, can then be removed and disposed of properly. Settling tanks are a simple and effective way to remove a significant amount of organic matter from wastewater.

Once the wastewater is settled Ultraviolet (UV) is shown in Table 3. Disinfection is a method for disinfecting water and surfaces using ultraviolet light, particularly a specific wavelength within the UV-C spectrum (around 254 nanometers). This light disrupts the DNA of microorganisms like bacteria, viruses, and protozoa, rendering them unable to reproduce or infect. DNA Disruption structure of microorganisms within the wastewater. Damaged DNA prevents them from reproducing, essentially rendering them inactive. The UV-treated wastewater is free of harmful pathogens and can be safely used for irrigation on the coffee plantation. Unlike chlorination, UV disinfection doesn't involve adding chemicals to the water. This eliminates the risk of harmful disinfection byproducts (DBPs), safe for the environment.

Table 2. Wastewater Recycling Treatments Suitable for Coffee Plantation

Treatment Stage	Type of Treatment	Depiction	Detriment	Fuzzy Logic and RNN Integration
Preliminary	Screening and Grit Removal	Removes large objects like rags, sticks, and debris. inorganic materials like sand and gravel	Reduces maintenance issues	Sensors can track incoming water flow rate. The fuzzy system can adjust screen mesh size and grit removal frequency to optimize capture while minimizing energy usage.
Primary	Sedimentation	Allows suspended solids to settle out of the wastewater through gravity settling in large tanks	Removes a significant portion of organic matter and solids.	Sensors can track sludge blanket depth and effluent turbidity.
Chemical	Neutralization	Adjusts the pH of wastewater to a neutral range (pH 6.5-8.5) using acids or bases.	Creates optimal conditions for biological treatment and protects equipment.	The RNN can analyze historical data to predict upcoming influent with high or low pH
Biological	Trickling Filters	Sprays wastewater over a fixed bed	Simpler operation compared to activated sludge.	The RNN can analyze historical data to predict future trends in organic matter content.
Disinfection	Ultraviolet Disinfection	Exposes wastewater to UV light to inactivate bacteria and viruses.	Effective disinfection, no chemical residual.	Sensors can track UV lamp intensity and effluent flow rate.

Table 3. Measuring Inland surface water, Total Suspended Solids, biochemical, chemical, Oxygen

Parameter	Units	Relative Weight	Date of Measurement	Measured Value	Weight	Stand. Value
(BOD, COD)	mg/L	0.35, 0.20	05.27.2024-0.5.30.2024	0.15-0.20	3.5, 2.0	≤30,≤250[ISW]
(Na), (Cl)	mg/L	0.01	05.27.2024-0.5.30.2024	0.05, 0.10	0.08	≤10,≤50[ISW]
pH	-	0.15	05.27.2024-0.5.30.2024	0.20	1.5	6.5-8.5[ISW]
(TSS)	mg/L	0.15	05.27.2024-0.5.30.2024	0.10	1.5	≤100[ISW]
(TN)	mg/L	0.10	05.27.2024-0.5.30.2024	0.10	1.0	≤90 [ISW]
(TP)	mg/L	0.05	05.27.2024-0.5.30.2024	0.10	0.5	≤70 [ISW]

3.2. Purity level verification in recycled sewage water

Untreated sewage water can harbor harmful pathogens like bacteria, viruses, and parasites. These can cause diseases in coffee plants, reducing yields and impacting bean quality. Safeguarding public

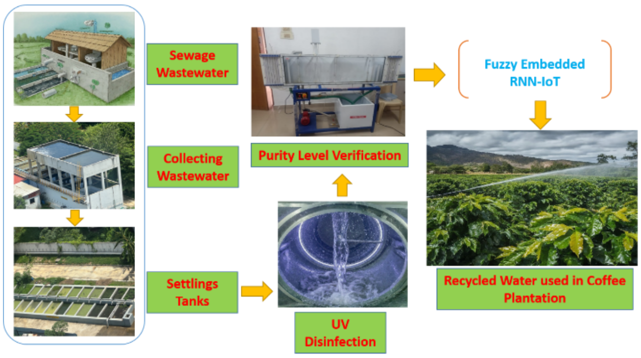


Figure 1. Proposed Model for Recycling Sewage Wastewater

health coffee beans irrigated with contaminated water can become carriers of pathogens. Consuming such coffee can pose health risks to humans. Many countries have regulations governing the use of recycled wastewater for irrigation, often specifying acceptable levels of contaminants like bacteria, heavy metals, and salinity indicating the purity level of water and whether water can be used for the coffee plantation or not. High levels of salts and sodium in inadequately treated wastewater can accumulate in the soil over time, negatively impacting its fertility and hindering future crop growth. Enhance the soil micro and macro nutrients needed. Macronutrients such as Nitrogen (N) are crucial for strong vegetative growth and abundant fruit sets. Deficiency leads to stunted growth and yellowing leaves. Phosphorus (P) promotes root development and overall plant health. Deficiency results in poor root growth and weak stems. Potassium (K) enhances disease resistance, water regulation, and fruit quality as indicated in Figure 2. As shown in Table 4 Micronutrients such as Magnesium (Mg) and Sulfur (S) both are essential for various plant functions and impact yield. Zinc (Zn) and Boron (B) are particularly important during flowering for good berry set and overall yield potential. Deficiency can lead to poor flower development and reduced fruiting.

Always ensure a proper pH level in the irrigation water (between 6.0 and 7.0) for optimal nutrient availability to the coffee plants (Selvanarayanan and Rajendran, 2023).

Figure 2. Wastewater Purification Setup

3.3. UV disinfection in recycled water

Ultraviolet (UV) disinfection is a method that uses ultraviolet light, particularly a specific range called UV-C, to kill or inactivate microorganisms like bacteria, viruses, fungi, and protozoa. UV disinfection utilizes ultraviolet (UV) light, specifically a wavelength of around 254 nanometers (nm). UV light disrupts the DNA of bacteria, viruses, and other pathogens in the water, rendering them inactive and unable to reproduce. The water flows through a chamber equipped with UV lamps, ensuring proper exposure to the germicidal light. UV light disrupts the DNA or RNA of microorganisms (Alotaibi *et al*. 2024), preventing them from reproducing and causing infection. The effectiveness of UV disinfection is determined by the UV dose, which is the product of UV intensity (I) and exposure time (T) as illustrated in eq 1.

$$\text{UV Dose}\left(\frac{\text{uWsec}}{\text{cm}^2}\right) = \text{I}\left(\frac{\text{uW}}{\text{cm}^2}\right) \text{x T}(\text{sec}) \quad (1)$$

Where I (uW/cm²): Effective UV lamp intensity reaching the target microorganism in the water. This value depends on lamp characteristics, water quality (turbidity, organic matter content), and lamp aging. T (sec). Exposure time is the time the water is exposed to the UV light within the disinfection chamber. This depends on the flow rate of the water and the design of the chamber (Surendran *et al*. 2023).

3.4. Built iot sensor network to monitor water quality

The sensor measures the quality of the water after passing from the UV Disinfection panel. IoT Sensors as shown in Table 5 fixed in the pipe while water passes through water purity can be measured. IoT sensors such as pH Sensor Measure the acidity or alkalinity of the water where the range for water is between 6.5 and 8.5. Temperature Sensor Measures the temperature of the water. Water temperature can impact the amount of dissolved oxygen and the growth of bacteria. Low-Power Wide-Area Network (LPWAN) is ideal for battery-powered sensors as it consumes minimal power and offers long-range communication. Conductivity Sensor: Measures the electrical conductivity of the water, which can be an indicator of the presence of dissolved salts and minerals. Dissolved Oxygen (DO) Sensor Measures the amount of dissolved oxygen in the water. Oxygen is essential for aquatic life and can be impacted by pollution as shown in eq 2. Turbidity Sensor Measures the clarity of the water. Turbidity can be caused by suspended particles such as sediment, algae, or bacteria. Chlorine Sensor Measures the amount of chlorine in the water. Chlorine is a disinfectant that is used to kill bacteria.

$$NodeMCU_{Data_{In}} = f\left(Arduino_{Data_{Out}}\right) \quad (2)$$

$$Cloud_{Data_{In}} = f\left(NodeMCU_{Data_{Out}}\right) \quad (3)$$

$$Cloud_{Data_{In}} = f\left(f\left(Arduino_{Data_{Out}}\right)\right) \quad (3)$$

Where Node MCU_Data_In represents data received by the Node MCU from the Arduino as indicated in eq 3, Arduino_Data_Out represents the data transmitted by the Arduino to the Node MCU, and the f () function represents the processing or formatting that might be applied to the data by the Arduino before sending it to the Node MCU. Cloud_Data_In represents the data received by the cloud platform from the Node MCU. Node MCU_Data_Out represents the data transmitted by the Node MCU to the cloud platform. f() function represents any processing or formatting applied by the Node MCU before sending data to the cloud as indicated in eq 4. This could involve data encryption, adding timestamps, or converting data to a specific format required by the cloud platform

Table 4. Recommended Nutrient Concentration in Water for Coffee Plantation

Nutrients	Nitrogen (N)	Phosphorus (P)	Potassium (K)	Magnesium (Mg)	Sulfur (S)	Zinc (Zn)	Boron (B)
Level (mg/L)	20-50	10-20	20-40	4-5	10-20	0.2-0.5	0.1-0.5

Table 5. IoT Sensors Utilized in Wastewater Recycling Process

IoT Sensors	pH Sensor	Temperature Sensor	Conductivity Sensor	Dissolved Oxygen (DO) Sensor	Turbidity Sensor	Chlorine Sensor
Version	Hach HQ40d probe	DS18B20 sensor	HI-8731 sensor	YSI Pro ODO sensor	Hach 2100AN	Myron L Company Pool Lab 1700

Algorithm 1: I2C communication to read data from the sensor at the sensor address

Function: Read Sensor Data (sensor address)

1: Start I2C communication

2: Send sensor address with Read bit (high)

3: Receive data from the sensor

4: Stop I2C communication

5: Return received data

Function: Send Data to Cloud(data) // Connect to the cloud platform (AWS assumed here)

1: Establish a connection with AWS

2: Send data packet containing sensor data; Close connection

Function: Main Loop () // Continuously read sensor data and send to the cloud

1: sensor data = Read Sensor Data (sensor address)

2: Send Data to the Cloud (sensor Data)

3: Delay (desired interval between readings)

Collected information is transferred using the I2C (Inter-Integrated Circuit) Protocol it is a moderate-speed protocol for communication between limited distances and connecting multiple sensors to a single microcontroller. The I2C protocol is connected to the Arduino for communicating via I2C and then sent to the Node MCU to establish a connection to the cloud platform (e.g., Amazon Web Services (AWS)) and transmit the received sensor data.

3.5. Fuzzy embedded recurrent neural network

A Fuzzy Embedded Recurrent Neural Network (FE-RNN) combines the strengths of fuzzy logic and recurrent neural networks (RNNs) to offer improved interpretability and performance in embedded systems as indicated in Figure 3. In data preprocessing, raw sensor data from the environment (wastewater recycling) is collected and undergoes cleaning, normalization, and scaling to prepare it for the FE-RNN. Fuzzification is similar to fuzzy logic systems, the FE-RNN employs membership functions to convert crisp sensor data into fuzzy membership values. These membership functions define input values belonging to a particular fuzzy set (e.g., "high temperature," "low pressure"). The fuzzy Rule Layer leverages fuzzy rules established by the developer. These rules define relationships between fuzzy inputs and fuzzy outputs as shown in eq 5 μ_A(x): Degree of membership of x in fuzzy set A, a, b, c, d: Parameters defining the triangle shape.

$$\mu_{A(x)} = \left\{ max\left(0, min\left(\frac{x-a}{b-a}, 1-\frac{x-c}{d-c}\right)\right), a <= x <= d \right\} \tag{5}$$

An example rule is "if the temperature is HIGH and pressure is LOW THEN water quality is POOR.". Each rule contributes to the overall activation of a fuzzy output set (e.g., "poor water quality") as shown in eq 6. Fuzzy Inference Engine applies the fuzzy rules to the fuzzified sensor data. It considers the activation levels of each rule and combines them using fuzzy operators (e.g., AND, OR).

$$\begin{aligned} &If\,(Temperature\ is\ High)\ AND\,(Pressure\ is\ Medium) \\ &Then\,(Flow\ Rate\ is\ Low) \end{aligned} \tag{6}$$

$$Aggregated\ Fuzzy\ Output = SUM\left(\mu_{i(x)}\right)\ for\ all\ activated\ rules\ i \tag{7}$$

$$Crisp\ Output = SUM\left(\frac{x * \mu(x)}{SUM(\mu(x))}\right) for\ all\ possible\ x\ values \tag{8}$$

Where Multiple activated fuzzy rules contribute to the final fuzzy output, aggregation operators (e.g., SUM, MAX) combine these fuzzy outputs. De-fuzzification is the fuzzy output that needs to be converted back into a crisp value for decision-making. De-fuzzification techniques like the centroid or center-of-gravity methods are used to translate the fuzzy output set into a single numerical value as shown in eq 7&8.

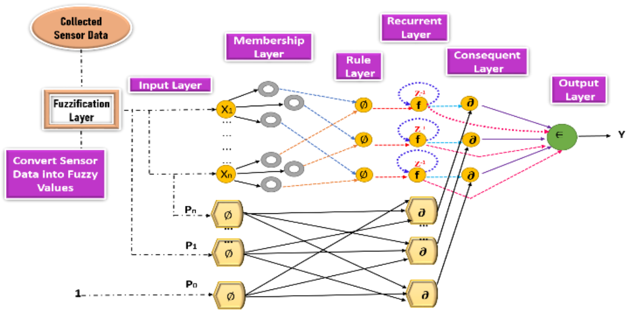


Figure 3. Proposed Algorithm Working Model

Algorithm 2: Map input values to membership degrees for each fuzzy set

```
def fuzzify_inputs(inputs, fuzzy_sets)
    fuzzy_inputs = []; for input_value in inputs:
    fuzzy_input = [];   for fuzzy_set in fuzzy_sets:
    membership_degree = fuzzy_set.membership(input_value)
    fuzzy_input.append(membership_degree)
    fuzzy_inputs.append(fuzzy_input)
return fuzzy_inputs
def create_rnn_model(input_shape, hidden_units, output_shape):
   model = tf. keras.Sequential([
   tf.keras.layers.FuzzyRNN(hidden_units, activation='fuzzy_activation'),
    tf.keras.layers.Dense(output_shape)])
return model
def train_model(model, fuzzy_inputs, targets, epochs):  #appropriate optimizer and loss function
model.compile(optimizer='adam', loss='mean_squared_error')  # Adjust as needed
model.fit(fuzzy_inputs, targets, epochs=epochs) # Train the model on fuzzified inputs and targets
```

4. Implementation and results

In a real-world application, the AI system was deployed by placing Internet-of-Things (IoT) sensors in selected sewage wastewater used for irrigating agricultural fields. These sensors continuously gather real-time water quality data, including moisture content, temperature, pH, levels of various nutrients, and electrical conductivity. A pre-trained FE-RNN model was utilized to forecast specific water properties, such as nutrient content and pH, based on the sensor readings. The gathered data was then fed into the system to identify recurring patterns and trends in water quality, specifically to aid in managing coffee plantations as indicated in Figure 4.

4.1. Evaluation setup

IoT Sensors such as pH Sensor - Hach HQ40d probe, Temperature Sensor–DS18B20 sensor, Conductivity Sensor–HI-8731 sensor, Dissolved Oxygen (DO) Sensor- YSI Pro ODO sensor, Turbidity Sensor–Hach 2100AN, Chlorine Sensor–Myron L Company Pool Lab 1700. Personal

Computer (PC) with the following specifications Processor: operating system Windows 11, Intel Core i5–8600, Graphics Card: Nvidia GeForce 1050Ti 4GB, RAM: 16 GB, Storage: 250 GB SSD (fast boot and program loading) + 1 TB HDD (large data storage). Python 3.6, cloud platform AWS, Data Visualization Tools Matplotlib, DC Power Supply, Irrigation system actuator. Wi-Fi communication module–Enables connection to a local Wi-Fi network for internet access. The suggested model is evaluated using False Negative, True Positive, True Negative, and False Positive metrics using the Fuzzy Embedded Recurrent Neural Network.

Figure 4. Real-Time Working Model Field Setup for Wastewater Recycling

4.2. Performance evaluation compared with FE-RNN

Accuracy reflects the overall effectiveness of the model in correctly classifying samples eq 9. It considers both true positives (correctly identified positive cases) and true negatives (correctly identified negative cases). High accuracy is desirable for wastewater recycling as shown in Table 6.

$$Accuracy = \frac{True\,Positives + True\,Negatives}{Total\,Samples} \tag{9}$$

Precision metric focuses on the proportion of positive predictions that were correct (true positives). It helps identify how good the model is at avoiding false positives, which can be crucial in both applications. For instance, a false positive in plant health monitoring might indicate a healthy plant needs treatment when it doesn't, leading to unnecessary resource use eq 10. Similarly, a false positive in wastewater recycling might suggest cleaner water than it is, posing potential risks.

$$Precision = \frac{True\,Positives}{True\,Positives + False\,Positives} \tag{10}$$

The recall metric emphasizes the model's ability to identify all actual positive cases (true positives). It helps assess how well the model avoids false negatives, which can also be significant eq 11. A false negative in wastewater recycling, a false negative might overlook inadequately treated water, compromising its safe reuse.

$$Recall = \frac{True\,Positives}{True\,Positives + False\,Negatives} \tag{11}$$

The F1 Score metric eq 12 combines precision and recall into a single value, providing a more balanced view of the model's performance. A high F1 score indicates a good balance between identifying true positives and avoiding false positives/negatives.

$$F1\,Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{12}$$

Specificity metric specifically looks at the proportion of negative predictions that were truly negative (true negatives). It's relevant when negative cases are equally important to identify correctly. In wastewater recycling, a high specificity ensures the model can accurately classify safe wastewater for reuse eq 13.

$$Specificity = \frac{True Negatives}{True\,Negatives + False\,Positives} \tag{13}$$

Table 6. Performance Analysis for the Proposed Model

Performance	Precision	Recall	F1 Score	Specificity	Accuracy
Support vector machine	79.66	78.23	78.77	80.41	80.72
Random Forest	79.79	80.24	81.60	82.16	81.44
GAN	82.50	82.61	82.80	84.13	82.02
K-means clustering	85.98	86.23	87.12	87.89	86.12
Feedforward Neural Network	84.97	83.23	85.91	86.12	87.73
Logistic Regression	88.23	89.21	90.24	89.77	89.74
Proposed Model FE-RNN	92.40	92.45	93.22	94.78	96.21

Recycled water is crucial for plant growth, and its quality is shown in Figure 5. Plants can't develop without nutrients like nitrogen and phosphorus. Still, there are hazards linked with waste from heavy metals like mercury, so it's important to handle or dispose of it properly. The level of dissolved salts in the effluent is known as salinity (Table 7). The waste's acidity or alkalinity is indicated by its pH. Extremely acidic or basic pH levels harm the environment because they are corrosive.

Keeping an eye on the waste's pH level allows for better management and treatment decisions leading up to disposal. Keeping an eye on the amount of organic matter in trash can tell you a lot about how biodegradable it is and how much methane gas it could produce in landfills. It is possible to gauge the possible effects of certain contaminants on human and environmental health by keeping tabs on them. Some examples are substances that disturb the endocrine system, herbicides, and medications. The proposed method achieved 96.21% accuracy, while Support vector machine, Random Forest, GAN, K-means clustering, Feedforward Neural Network, and Logistic Regression obtained 80.72, 81.44, 82.02, 86.12, 87.73, 89.74. Existing approaches take longer to calculate all datasets. The suggested technique detects events better than current methods.

Table 7. Wastewater Quality Observation and Quality Maintained

Parameters	Measured Method	Value Range	Units
Nutrient Level	Sensors and chemical analysis	Nitrogen (N): 10-50 Phosphorus (P): 2-10	mg/L (milligrams per liter)
Contaminant	Mass spectrometry	Lead (Pb): < 0.5	mg/L (milligrams per liter)
Salinity	Conductivity Meter	Saline water: > 3	dS/m (deciSiemens per meter)
pH Value	pH meter	6.5 - 8.5	pH units
Organic Matter	Chemical Oxygen Demand (COD) test, Biological Oxygen Demand (BOD) test, Total Organic Carbon (TOC) analyzer.	COD: 200–500, BOD: 100–300	mg/L (milligrams per liter)
Pollutant Levels	High-performance liquid chromatography (HPLC)	ng/L	µg/L (nanograms per liter)

Algorithm 3: Choose a defuzzification method (centroid, Bisector, MOM, etc.)

```
def defuzzify_output(fuzzy_output
crisp_output = fuzzy_logic_library.fuzzily(fuzzy_output)
return crisp_output
```

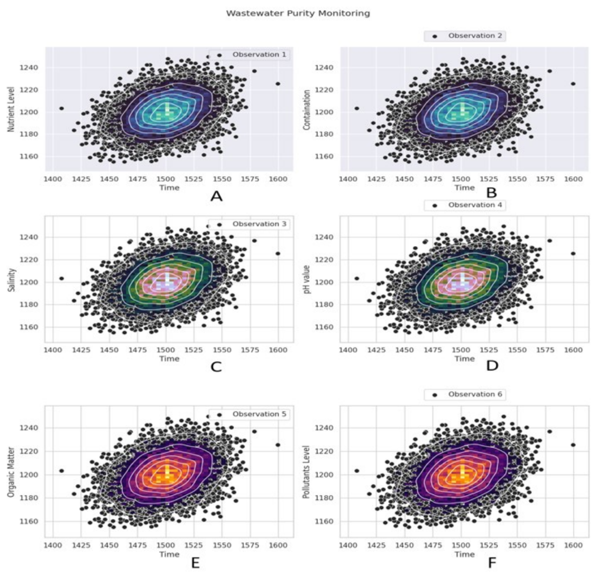


Figure 5. A. Nutrients Level, B. Contamination, C. Salinity, D. pH Value, E. Organic Matter, F. Pollutants Level Monitoring based on Recycling Process over Time

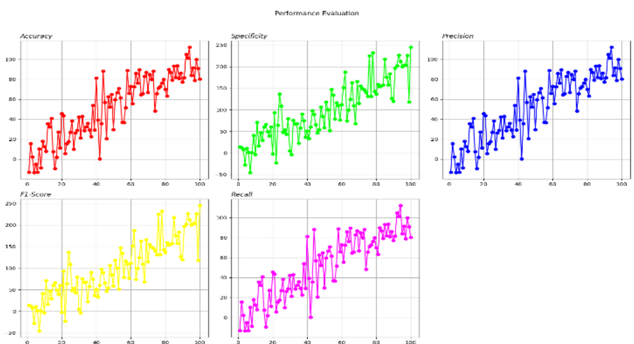


Figure 6. Overall Performance Evaluation

4.3. Optimization of model

Water quality is important for agriculture in coffee plantations any changes in soil, or water fertilizer will affect the growth and flavor of the coffee beans. The conversion of sewage water into agricultural land might cause disease spread to the plants. With the proper monitoring and treatment water can be reused for coffee plantations.

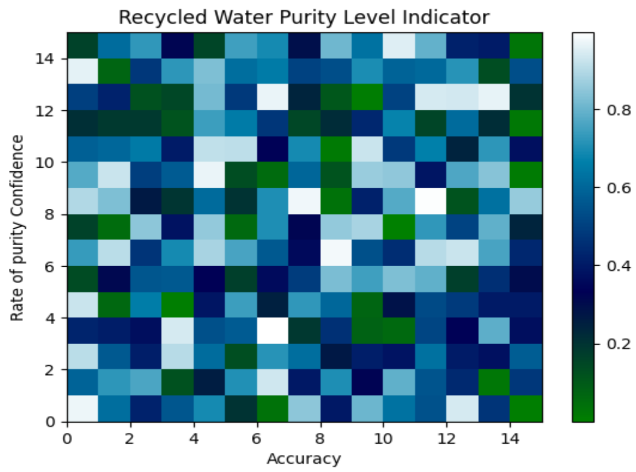


Figure 7. Purity Level Indicator

The dataset is collected using sensors. Training and evaluation are divided into training, validation, and testing sets in the ratio 60:20:20 using the FRNN, the validation set to monitor training progress and prevent overfitting, and the testing set for final performance evaluation. Hyperparameter: learning rate is 0.01, number of hidden layers is 3. Loss Function Selection Choose a loss function appropriate for your task (e.g., mean squared error for regression problems). The loss function quantifies the difference between the FRNN's predictions and the desired outputs achieved 96.21% as shown in Figure 7. As shown in Figure 6 Water Purification Stages has each square depicts a different treatment process, such as Filtration: Removing physical impurities like particles or suspended solids, Chemical Treatment: Using chemicals to neutralize contaminants or adjust water chemistry, Biological Treatment: Employing microbes to break down organic matter, and Disinfection: Eliminating harmful bacteria or pathogens. Color-coded squares of each square might indicate the level of water purity achieved at that particular treatment stage. Dark green is very impure wastewater, Light shade green is partially treated wastewater, dark blue is moderately treated wastewater, light blue is nearly purified wastewater, and white is fully purified wastewater. Training accuracy metric reflects the percentage of training samples the FE-RNN correctly classified during training.

High training accuracy suggests the model is learning the patterns in the training data. The validation accuracy metric reflects the percentage of validation samples the FE-RNN correctly classified on unseen data. It provides a better estimate of how well the model will generalize to new data as shown in Figure 8.

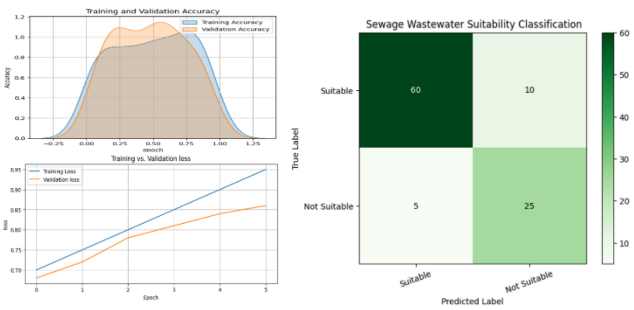


Figure 8. Training and Validation Accuracy, Training and Validation Loss, confusion Matrix of Fuzzy Embedded Recurrent Neural Network

Training Loss metric measures the difference between the FE-RNN's predictions and the actual targets in the training data. A decreasing training loss indicates the model is improving its ability to fit the training data. Validation Loss Similar to training loss, validation loss measures the difference between predictions and targets on unseen validation data. A stable or decreasing validation loss suggests the model is learning without overfitting the training data.

5. Conclusion and future direction

The world faces a serious challenge in water scarcity. With a growing population and uneven water distribution, millions struggle to access this vital resource. Sewage wastewater, once treated, can become a valuable resource and offers several environmental and economic benefits. Sewage wastewater undergoes various treatment stages before reuse. These may include physical removal of solids, biological treatment to break down organic matter, and disinfection to kill harmful bacteria. IoT sensors can continuously measure parameters like pH, conductivity, and nutrient levels. This data is vital for controlling the treatment process and ensuring that recycled water meets quality standards. Collected information is trained and validated using the FE-RNN model. Compared with other existing models the proposed model achieved 96.21% of accuracy, Precision 92.40%, Recall 92.45%, F1 Score 93.22%, specificity 94.78%. Future scope to develop early industrial waste leak detection using sensors can detect leaks in pipes or treatment systems, allowing for prompt repair and minimizing water loss integration with smart irrigation systems.

Data availability

The dataset utilized and analyzed in our research is publicly accessible to the Wastewater Recycling and Quality Monitoring for use in coffee plantation Zenodo communities raveena R. (2024). Wastewater Quality Monitoring. Zenodo. https://doi.org/10.5281/zenodo.12591349 The coding system along with additional data are accessible upon adequate request from the initial and coauthor authors.

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