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Wastewater recycling integration with IoT sensor vision for real-time monitoring and transforming polluted ponds into clean ponds using HG-RNN

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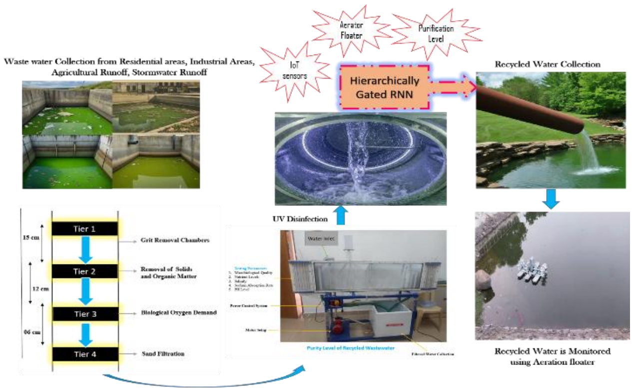
Graphical abstract



Abstract

Wastewater recycling will protect the environment by reducing the quantity of contaminants released into water bodies, safeguarding aquatic ecosystems, and averting water pollution. The objective is to transform polluted ponds into clean water sources through real-time monitoring and efficient treatment by tracking water quality parameters such as pH, dissolved oxygen, turbidity, and biological oxygen demand using plotted IoT sensors. The IoT sensors continuously transmit real-time data to a cloud-based system, where the HG-RNN algorithm models complex relationships between water quality metrics to predict and optimize treatment processes. The HG-RNN is trained on historical data to predict future water quality trends and identify potential issues. Based on these predictions, appropriate treatment strategies can be implemented in real-time, such as adjusting chemical dosages or activating filtration systems. This proactive approach ensures optimal water quality and prevents further pollution.

Keywords: Wastewater Recycling, Gated Linear Unit, Hierarchically Gated Recurrent Neural Network, Vision Pond Skimmer, Machine Learning, IoT Sensors, Cloud Environment

1. Introduction

In the 19th century, the first wastewater treatment plants were established as a reaction to concerns about public health. The primary objective of these initial systems was to eliminate solid waste and minimize unpleasant odors Periyasamy A.P. *et al.* (2024). The technological progress of the 20th century resulted in the development of more advanced treatment methods, such as biological and chemical treatment. Water reuse is becoming prevalent in agricultural and industrial sectors. The increasing scarcity of water and growing environmental concerns in the 21st century have made water recycling a key focus of sustainable development Baskar G. *et al.* (2024). Ponds operate as natural, economical wastewater treatment systems that cleanse water, promote public health, and enhance environmental sustainability. If compared to other systems, ponds need little capital investment and operating expenses, use natural processes, facilitate nutrient recovery, and are environmentally friendly; yet, they exhibit longer treatment times than mechanical and biological treatment facilities. Inadequately maintained ponds might result in odor and pest problems. Advanced technology such as membrane filtering and desalination has extended water reuse options. Aeration floaters are crucial in diverse aquatic environments, ranging from aquaculture to wastewater treatment. They have a vital function in oxygenating water bodies, enhancing water quality, and sustaining aquatic life. wastewater from diverse sources including residential areas, industrial facilities, and runoff from agriculture. Before pouring the wastewater into the pond, it is necessary to pre-treat it to eliminate any large debris, sediments, paper, plastic covers, wood sticks, and dangerous compounds. This precaution decreases the burden on the pond's inherent purification mechanism and safeguards the integrity of the aquatic ecology Raveena Selvanarayanan *et al.* (2024), Thomsen L.B.S. *et al.* (2024) and M Venkatraman (2024). Sensors are placed in the pond at different zones to monitor water quality parameters such as physical parameters (temperature, conductivity, turbidity), chemical parameters (pH, dissolved oxygen, biological oxygen demand), and biological parameters (algal bloom, bacterial presence). Sensors can promptly identify changes in water quality indices, enabling timely measures to avert further deterioration. A quick decline in dissolved oxygen levels might activate alarms, notifying authorities of possible fish fatalities.

A sensor network is created by connecting multiple sensors that provide data to a central system for ongoing analysis. Analyzed data are collected and transferred to wireless transmission to a cloud-based platform. Preprocessing and data analysis The Hierarchical Gated RNN model is used for data cleaning (missing values, outliers, noise reduction), data normalization, feature engineering, and Exploratory Data Analysis (EDA) Sundarapandi A M S. *et al.* (2024) and M Venkatraman (2023). Cloud-based environments are connected to the IoT device plotted near the pond to monitor and collect real-time data on wastewater quality, flow rates, and treatment processes. Pond skimmers are devices mainly used to remove floating debris and scum from wastewater treatment ponds using camera integration to capture images, image processing analyze water change, anomaly detection learn and train abnormal patterns in water. Aerator floaters are designed to distribute optimal oxygen transfer and treatment efficiency. There are several types of paddle aerator floaters designed to move across the wastewater surface, ensuring even aeration coverage Periasamy, S *et al.* (2024) and Selvanarayanan, R. *et al.* (2024). They can be either manually or automatically controlled.

Monitoring and optimization are essential for effective and dependable wastewater treatment. Sensors gather real-time data on essential parameters, allowing remote monitoring, predictive maintenance, and process optimization. The Internet of Things (IoT) technology enables data transmission and control, whilst software processes data, issues warnings, and enhances operational efficiency. This comprehensive strategy guarantees the safeguarding of public health, the sustainability of the environment, and the economical administration of wastewater treatment facilities. In real-time industrial wastewater treatment facilities for Supervising industrial discharges for adherence to regulatory criteria, detecting and mitigating pollution sources, and enhancing treatment methodologies to reduce environmental repercussions. The dependability of IoT sensors may be influenced by variables like climatic conditions, power supply, and maintenance. Sensor malfunctions or calibration inaccuracies may result in erroneous data and diminished model efficacy. The framework of the above article is as follows: Section 2 provides a comprehensive examination of previous research on Hierarchical Gated Recurrent Neural Networks with the Internet of Things, using Machine learning. Section 3 provides a comprehensive explanation of the planned HG-RNN, vision pond skimmer technique. Section 4 provides an overview of the experimental configuration and the outcomes obtained. Section 5 examines the findings and contrasts HG-RNN with current approaches. The work is concluded in Section 6, which also covers future research topics.

2. Literature survey

Aeration floaters occupy a crucial role in diverse aquatic environments, ranging from aquaculture to wastewater treatment. They have a vital function in oxygenating water bodies, enhancing water quality, and sustaining aquatic life. The objective of this review of the literature is to present a comprehensive analysis of the current body of research on aeration floaters, with a specific emphasis on their design, performance, uses, and environmental consequences. Saeed T *et al.* (2024), wastewater treatment systems that integrate floating wetlands with septic tanks. The improvement of bioenergy output and nutrient removal is the main focus. Floating wetlands offer extra treatment and habitat, and two-stage septic tanks enhance the decomposition of organic materials. Biogas production and microbial activity can both be enhanced by the oxygen from outside sources. Through regulation of flow and nutrient transfer, circuit coupling between systems maximizes treatment efficiency. Choosing the right plant, operational factors, and system design are crucial for maximum efficiency and power output. Adhikari, K *et al.* (2020), The Pond-In-Pond (PIP) system shows great potential as a viable option for the treatment and reuse of wastewater. The system combines anaerobic and aerobic ponds to improve the effectiveness of the treatment process. Research suggests that PIP systems are successful in significantly reducing Biochemical Oxygen Demand (BOD) to levels that are appropriate for reuse. CFD models have been used to enhance the performance of PIP design through optimization. Although PIP systems provide cost-effective and energy-efficient treatment, additional research is required to establish uniform design parameters and investigate their suitability in different climatic settings. Kelestemur, Guluzar T *et al.* (2024), Pond aeration systems essentially aim to improve the efficiency of oxygen transmission. Research has investigated many techniques for aeration, such as surface and subsurface aerators. The oxygenation efficiency is influenced by several key aspects, including impeller design, air flow rate, water depth, and pond features. Scientists frequently utilize experimental configurations to quantify the amounts of dissolved oxygen and determine the speeds at which oxygen is transferred. The objective of optimization studies is to identify the most efficient system designs for various pond conditions. Although some progress has been achieved, additional study is required to enhance the efficiency and sustainability of aeration methods. Tong, C *et al.* (2024), aeration in recirculating aquaculture systems (RAS) is the levels of dissolved oxygen (DO), which have a substantial impact on the health and growth of fish. Prior research investigates different aeration techniques, such as surface and subsurface aerators, and their influence on water quality factors. There is an increasing fascination with aeration systems that are both energy-efficient and cost-effective. However, research is scarce on innovative aeration device designs that are specifically customized for RAS (Recirculating Aquaculture Systems). Important factors to consider in the design include the efficiency of oxygen transfer, the amount of energy consumed, the degree of noise produced, and the ability to resist biofouling. Gaining a comprehensive understanding of the interplay among aeration, water quality, and fish physiology is essential for maximizing the performance of a Recirculating Aquaculture System (RAS) as follows in **Table 1**.

3. Materials and methods

The research focuses on wastewater recycling system which involves multiple treatment stages tier 1 grid removal, tier 2 removal of solids and organic matter, tier 3 biological oxygen demand (BOD) reduction, and tier 4 sand filtration. UV disinfection kills harmful bacteria and viruses Figure 0. IoT sensors and vision cameras are placed near the pond to monitor the purity of recycled water. Collected information is transferred to a cloud environment. The proposed algorithm Hierarchically Gated RNN monitor and predict the performance of the wastewater treatment system continuously. Aeration floaters are used to monitor the purity level of the recycled wastewater. They help maintain oxygen levels and prevent stagnation in the water body.

Table 1. Existing Work is Compared with the Proposed Work

Author	Algorithm	Methodology	Result	Future Scope
Ji, Mingdong *et al.* 2024	Mathematical Model	Aeration flow rates, dissolved oxygen (DO) measurements, water quality parameters, and hydrodynamic simulations.	Development of a mathematical model to predict DO distribution and oxygen transfer rate.	Aeration system design for different fish species and stocking densities.
Wu, Ye, Lingfeng Zhang et al ., (2024)	Oxygen Mass Transfer Coefficient	Economic analysis	Assessed the economic feasibility of the intelligent oxygenation system.	Develop predictive models for oxygen demand based on environmental factors.
Roy, Subha M *et al.*., (2024)	Cascade Aeration System	Comparative analysis with other aeration systems. Economic evaluation. Life cycle assessment.	PPCSC offers high performance and lower operational costs compared to traditional systems.	Aquaculture scales. Development of hybrid aeration systems.
Tien Nguyen, N *et al.* (2024)	Mechanical aeration, Bubble diffusion Oxygen injection Bioaugmentation	Combination of aeration and wastewater treatment, Optimization of system parameters	Improved dissolved oxygen levels, enhanced shrimp growth, and reduced disease outbreaks.	Development of more sophisticated models incorporating complex interactions between biological, chemical, and physical factors.
Qiu, Y *et al.* 2024	Computational Fluid Dynamics (CFD)	Two-phase flow model, gas-liquid mass transfer, biokinetic model	Evaluation of design and operational boundary conditions	Develop advanced statistical methods for model validation
Samsuri, E. R *et al.* (2024)	Microbubble aeration	Biofloc technology, microbubble aeration, water quality parameters (DO, pH, temperature, salinity, ammonia, nitrite, nitrate), shrimp growth, survival rate, feed conversion ratio	Improved water quality, enhanced shrimp growth and survival, reduced water exchange	Optimize microbubble size and aeration intensity,

3.1. Evaluation setup

Paddlewheel Aerator- model AM-G001, 2024. IoT setup as shown in **Figure 1**. Python 3.6, Data Visualization Tools Matplotlib, Cloud platform AWS, DC Power Supply, Wi-Fi communication module - Permits linking to a nearby Wi-Fi hotspot for web surfing. Axis Communications PTZ Dome Network Camera Q3615-E Features High-resolution imaging, pan-tilt-zoom capabilities, weatherproofing, and night vision. Underwater camera Sea Vision HD 1000 with Waterproof housing, high-definition imaging, and LED lighting for low-light conditions. Personal Computer (PC) with the following specifications Processor: operating system Windows 11, Graphics Card: Nvidia GeForce 1050Ti 4GB, Intel Core i5-8600, Storage: 250 GB SSD (fast boot and program loading) + 1 TB HDD (large data storage), RAM: 16 GB. The proposed model is evaluated using True Positive, True Negative, False Positive, and False Negative, and metrics using the Hierarchical-Gated Recurrent Neural Network.

3.2. Wastewater collection and pre-treatment process

Wastewater is gathered from a multitude of origins, which may encompass, residential areas generate domestic wastewater, which consists of sewage and grey water from sinks, showers, and washing machines in homes. Industrial facilities generate process water and effluents that can potentially contain chemicals, oils, heavy metals, and other pollutants. Agricultural runoff refers to the water that originates from farms and may contain fertilizers, pesticides, and organic waste. Stormwater runoff entails rainwater that accumulates contaminants as it travels across urban or agricultural areas (**Figure 2**). The wastewater collection structure consists of underground sewage networks that collect wastewater from residential, industrial, and commercial areas. Pumping stations are used in cases when the inherent flow of wastewater is insufficient. These pumping stations elevate the wastewater to higher elevations to facilitate its transportation to the treatment facility. Drainage systems have Storm water and agricultural runoff are often collected using drainage systems that direct the flow toward treatment facilities or ponds. Conveyance to the treatment facility or reservoir: Once collected, the wastewater is transported via pipes or channels to the pre-treatment plant and straight to the pond.

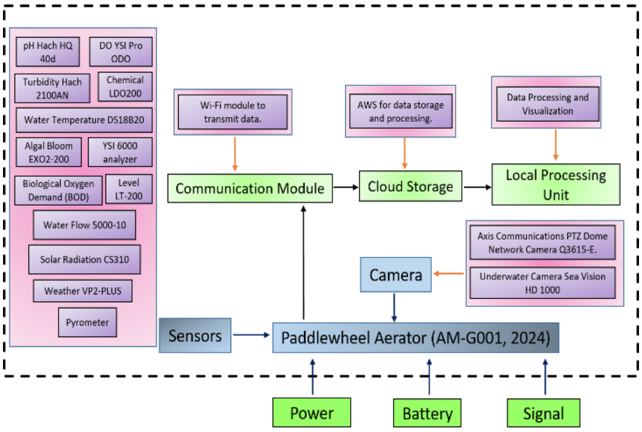


Figure 1. Block Diagram of Data Collection using IoT Devices.

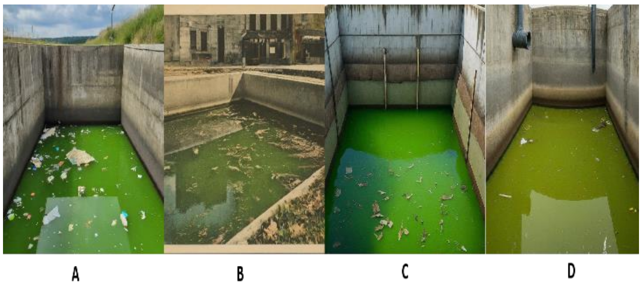


Figure 2. Wastewater is collected from various sources such as A. residential areas, B. Industrial Areas, C. Agricultural Runoff, D. Storm water Runoff.

Aeration floater contains a motorized aeration mechanism, such as a diffuser and propeller, which enhances oxygen diffusion and circulation. Collected data as shown in **Figure 3**, are stores the given data in a dictionary format. Converts the dictionary into a pandas Data Frame. Saves the Data Frame as a CSV file named water quality data.csv. Displays the Data Frame to the console.

3.3. IoT sensors installed in the pond

IoT sensors are designed for monitoring real-time water quality to ensure the pond remains healthy and clean. As illustrated in **Figure 4**, water quality sensors such as pH sensors measure the acidity or alkalinity of the pond water. These sensors are usually placed underwater in various sections of the pond to observe changes throughout the pond's surface. Dissolved oxygen sensors measure the concentration of oxygen dissolved in the water, DO sensors are strategically positioned at different depths to monitor oxygen levels across the entire pond, particularly in places sensitive to low oxygen levels. The purity of water is measured by turbidity sensors, which detect suspended particles. Algal blooms or pollutants can cause high turbidity. For water clarity monitoring, these sensors are placed around the pond. Temperature sensors measure water temperature, which influences aquatic creature metabolism and oxygen solubility. To fully assess the pond's thermal characteristics, temperature sensors are installed at the surface and various depths. Conductivity sensors evaluate water's ability to conduct electricity, which is connected to ion concentration (salts, minerals). Distributed over the pond, these sensors detect high dissolved solids concentrations. Nitrates, phosphates, ammonia, heavy metals, and organic substances are detected using chemical sensors.

Sample Data:

	Date	pH	DO	Turbidity	Temp	Conductivity	Chemical \
0	05-22-2024	5.8	4.5	80	50°C	1800	9.2
1	05-23-2024	6.0	4.9	72	47°C	1789	9.1
2	05-24-2024	6.1	5.0	66	42°C	1642	9.0
3	05-25-2024	6.3	5.0	60	38°C	1500	8.9
4	05-26-2024	6.7	5.0	55	35°C	1478	8.7
5	05-27-2024	7.0	5.0	50	33°C	1347	8.6
6	05-28-2024	7.1	5.3	45	30°C	1224	8.2
7	05-29-2024	7.1	5.5	40	27°C	1141	7.7
8	05-30-2024	7.3	5.7	35	33°C	1021	7.5
9	05-31-2024	7.3	5.9	31	33°C	987	7.5
10	06-01-2024	7.4	6.2	27	33°C	921	7.4
11	06-02-2024	7.5	6.2	25	33°C	897	7.4
12	06-03-2024	7.6	7.0	21	33°C	842	7.3
13	06-04-2024	7.3	7.5	19	33°C	811	7.3
14	06-05-2024	7.3	7.9	15	33°C	751	7.2
15	06-06-2024	7.3	8.4	15	27°C	712	7.1
16	06-07-2024	7.5	8.6	14	27°C	645	7.1
17	06-08-2024	7.5	8.9	12	33°C	601	6.9
18	06-09-2024	7.5	9.7	10	33°C	550	6.5
19	06-10-2024	7.7	9.9	8	31°C	521	6.2

	Algae Bloom	BOD	Weather
0	27000	800	50°C
1	25000	789	45°C
2	24000	777	42°C
3	22000	745	38°C
4	20000	712	35°C
5	19000	701	31°C
6	17000	699	30°C
7	15000	691	27°C
8	13000	689	33°C
9	11000	677	33°C
10	10000	645	30°C
11	9000	632	33°C
12	9000	632	35°C
13	8500	622	33°C
14	8200	612	33°C
15	8200	603	27°C
16	8150	599	27°C
17	8000	578	33°C
18	7200	566	33°C
19	7000	545	31°C

Figure 3. Collected Dataset from the Pond

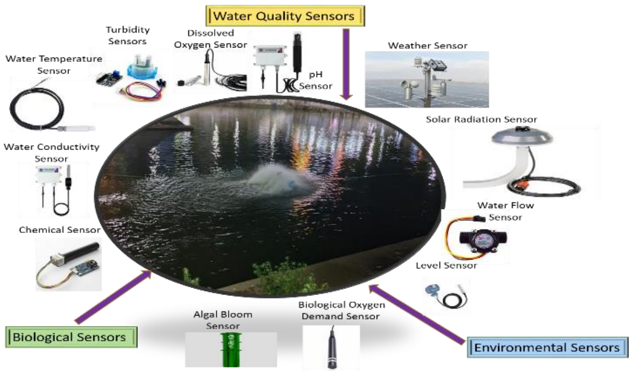


Figure 4. Various IoT Sensors Are Installed in the Pond to Monitor Recycling Wastewater

Chemical sensors are positioned near wastewater inlets and runoff points to prevent pollution from entering the pond. Environmental sensors such as weather sensors measure air temperature, humidity, wind speed, and rainfall **Table 2**. Such things can affect water quality. These sensors monitor the pond's environment from poles or platforms. Solar radiation sensors measure sunlight entering the pond, affecting aquatic plant photosynthesis and algae growth. Usually over the pond with weather sensors. Water flow sensors assess pond water entry and exit rates to understand water exchange and dilution. Installed pond inlets and outlets to monitor water flow. Level sensors at set sites around the pond measure water level, evaporation rates, rainfall influence, and inflow/outflow balance. Biological Sensors such as Algal Blooms detect hazardous algal blooms (HABs) that create toxins in the water. These sensors are at the surface where algae grow. Biological oxygen demand (BOD) sensors measure organic pollution by measuring the oxygen aerobic bacteria need to break down water organics. BOD sensors are put near inlets to detect organic pollution.

Table 2. Before cleaning the pond sensor readings and status with comments

Sensor Type	Unit	Typical Range in Pond	Current Sensor Reading	Status	Acceptance Limits	Comments
pH Sensor	pH Units	6.5-8.5	5.8	Red	Green (6.0-9.0) Yellow (5.8 -9.2) Red (< 6.0 or > 9.0)	pH is too low; water is too acidic for most aquatic life
Dissolved Oxygen (DO) Sensor	mg/L	5.0 - 14.0	3.0	Red	Green (5.0-14.0) Yellow (4.5) Red (< 4.0)	Low DO indicates potential hypoxic conditions
Turbidity Sensor	NTU	1 - 50	120	Red	Green (1-50) Yellow (60-80) Red (>100)	High turbidity, likely due to suspended particles or algae
Water Temperature Sensor	°C	10 - 30	28	Green	Green (10-35) Yellow (36) Red (< 10-> 35)	Within acceptable range for aquatic life
Water Conductivity Sensor	µS/cm	100 - 2000	2500	Red	Green (500-1500) Yellow (1600) Red (>2000)	High conductivity, indicating elevated ion levels
Chemical Sensor	mg/L	Varies by chemical	N ()	Red	Green (6.0-9.0) Yellow (5.8 -9.2) Red (< 6.0 or > 9.0)	High ammonia level, toxic to aquatic organisms
Algal Bloom Sensor	Cells/mL	0 - 20,000	35,000	Red	Green (0-20,000) Yellow (25,000) Red (>30,000)	Algal bloom detected, potential risk of eutrophication
Biological Oxygen Demand (BOD) Sensor	mg/L	mg/L	550	Red	Green (20-500) Yellow (550) Red (>600)	Very high BOD, indicating significant organic pollution
Level Sensor	cm or m	Site-specific	100 cm	Green	Green (100) Yellow (150) Red (200)	Normal water level
Water Flow Sensor	L/s or m^3/h	Varies by system size	5 L/s	Green	Green (5) Yellow (7) Red (9)	A low flow rate could indicate low inflow or stagnation
Solar Radiation Sensor	W/m^2	0 – 1000	6.0	Green	Green (6.0-9.0) Yellow (5.8 -9.2) Red (> 9.0)	Adequate sunlight may influence algal growth
Weather Sensor	Varies	Site-specific	60°C RH	Green	Green (32°C) Yellow (60°C) Red (70°C)	Warm and humid conditions could affect water temperature and DO levels

3.4. Real-time data collection and transmission to the cloud environment

Improving wastewater quality to protect the environment using IoT sensors, Node MCU, Arduino, and cloud environment. Universal Asynchronous Receiver-Transmitter (UART) is a communication protocol. A transmitter, denoted as T, is transmitting a continuous sequence of bytes to a receiver, denoted as R. T is a faster gadget compared to R, and R is unable to match its speed. Before continuing to receive data, it is necessary to either do data processing or clear certain buffers. R needs to instruct T to temporarily cease transmission. Flow control is the concept that is relevant in this context. Flow control enables additional signaling to indicate to the transmitter when it should cease (pause) or start (resume) the transmission. Multiple types of flow control are available. Hardware flow control employs additional wires to determine whether the transmitter should continue transmitting data or halt, based on the logic level of these wires. Software flow control involves the sending of certain characters across the regular data channels to initiate or terminate the transmission.

Algorithm 1: Sensor readings are stored

```
    Int sensor value;
    Serial. begin (9600);                    [Serial monitor for debugging]
    Serial1.begin (9600);                    [Serial-1 for sending data]
void loop ()
    Sensor value = analog Read (sensor pin);    [Read sensor value]
    if (sensor value > 100)     [Send data only if sensor value exceeds a threshold]
String message = "Sensor value: " + String (sensor value);  [Combine text and sensor data]
    Serial1.println(message);
    if (Serial. Available () > 0)
```

3.5. Hierarchical-gated RNN

The Hierarchically Gated Recurrent Neural Network (HGRNN) is a new structure created to improve the abilities of normal Recurrent Neural Networks (RNNs) in tasks involving the modeling of sequences. HG-RNN has a unique capability to discern both short-term and long-term intricate patterns in wastewater quality metrics. The hierarchical structure encapsulates both detailed and broad temporal relationships, allowing the model to discern complex patterns across several time scales, essential for comprehending the dynamic characteristics of wastewater quality. In comparison to analogous algorithms like LSTM, which is computationally intensive, GRU does not capture as intricate relationships, CNN is less appropriate for sequential data, and the hybrid model (CNN-LSTM) entails a complicated design and heightened computational expense. Gated Linear Units (GLUs) are used for channel-wise fusion, allowing the network to choose and proprietarily determine certain properties Peng-Fei, Lv. *Et al.* (2024). Hierarchical Gated Recurrent Units (HGRUs) are the essential building blocks of the HGRNN. Their main purpose is to capture and store temporal correlations. The authors suggest using a hierarchical forget gate system to control the transmission of information across different time steps and layers. The forget gates in HGRUs have a learnable lower limit, which guarantees the retention of knowledge across longer sequences (**Figure 5**).

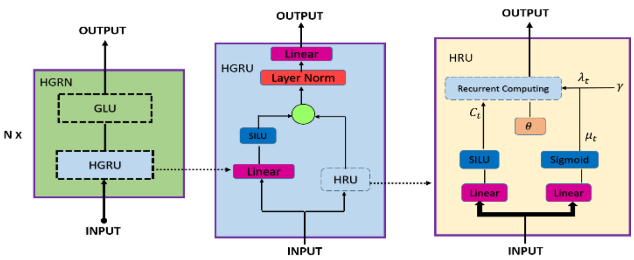


Figure 5. Proposed Algorithm Hierarchically Gated Recurrent Neural Network (HGRN)

A multi-HGRU-layer, GLU-unit, and output-layer HGRNN take in the input sequence as wastewater quality parameters such as (temperature, pH, humidity, and dissolved oxygen level) are collected over time. Sequential data and their temporal dependencies are captured and processed in the first HGRU layer, which handles the input. A GLU unit is used for channel-wise mixing and receives the GLU output from the HGRU layer. Linear and layer norms are the production of the GLU that is transformed by a linear layer and then normalized using Layer Norm. SILU normalized output is passed through a SILU activation function. HRU output is fed into the next HGRU layer, which captures longer-term dependencies Eq 1. HGRU layers are repeated for subsequent results. The final production of the HGRN is generated based on the outputs of the last HGRU layer, potentially passing through additional linear and activation layers.

$$h_t^l = \mathrm{HGRU}\left(h_{\{t-1\}}^l, x_t, W^l, U^l, b^l\right) \tag{1}$$

Where this is the hidden state at time step t for layer l., x_t is the input at time step t. W^l, U^l and b^l are the weight matrices and bias for layer l. HGRU represents the Hierarchical Gated Recurrent Unit function.

$$\mu_t = \sigma\left(W_\mu * x_t + U_\mu * h_{\{t-1\}} + b_\mu\right) \tag{2}$$

$$\lambda_t = \gamma + (1-\gamma) \odot \mu_t \tag{3}$$

$$i_t = \sigma\left(W_i * x_t + U_i * h_{\{t-1\}} + b_i\right) \tag{4}$$

$$c_{tilde_t} = \tanh\left(W_c * x_t + U_c * h_{\{t-1\}} + b_c\right) \tag{5}$$

$$c_t = \lambda_t \odot c_{\{t-1\}} + i_t \odot c_{tilde_t} \tag{6}$$

$$g_t = \sigma\left(W_g * x_t + U_g * h_{\{t-1\}} + b_g\right) \tag{7}$$

$$y_t = g_t \odot x_t + (1-g_t) \odot h_{\{t-1\}} \tag{8}$$

Where Eq 2- Eq 8, x_t Input vector at time step t (e.g., wastewater quality measurements), h_t Hidden state at time step t, C_t cell state at time step t, W, U, V: Weight matrices, b: Bias vector, σ: Sigmoid activation function, tanh: Hyperbolic tangent activation function.

Algorithm 2: Build HGRN model and Training Loop

Step 1: HGRU Cell

Function HGRU_Cell (input, previous_hidden_state, previous_cell_state):

Calculate gates and cell state updates based on HGRU equations

Update hidden state and cell state

Return updated hidden state and cell state

Step 2: HGRNN Layer

Function HGRNN_Layer (inputs, number_of_units):

Initialize hidden state and cell state with zeros

For each input: update hidden and cell states using HGRU_Cell and store the output.

Return output as a numpy array.

Step 3: Build the HGRNN Model

Function Build_HGRNN_Model (input_dimension, hidden_units, number_of_layers):

Create a list for HGRNN layers.

For each layer: create an HGRNN layer, append it to the model, and update the input dimension.

Return the model.

Step 4: Train the HGRNN Model

Function Train_HGRNN_Model(model, data, learning_rate):

Initialize optimizer.

For each epoch and batch: calculate outputs, compute loss, and update model parameters.

Step 5: Predict with the HGRNN Model

Function Predict (model, input_sequence):

Pass input sequence through the HGRNN layers

Return the final output

3.6. Anomaly detection and prediction using computer vision

Timely identification of anomalies in wastewater quality monitoring is essential for promptly recognizing possible concerns such as pollution, equipment malfunctions, or changes in wastewater composition before they develop into major difficulties. Preventing environmental pollution by quickly spotting abnormalities protects ecosystems and public health. Utilizing process optimization techniques to detect anomalous patterns may enhance the efficiency of wastewater treatment operations, resulting in cost reduction and improved overall performance El-Shafeiy. *Et al.* (2023). The Vision Pond Skimmer is positioned over a tall pole, situated in the center of a pond. The pole is securely fastened to the pond's floor, guaranteeing stability. The gadget is affixed to the top of the pole, positioned to face outward in the direction of the water **Figure 6**. Vision Pond Skimmer technique will monitor and identify atypical patterns in several parameters. Deviation of pH values from typical limits, which indicate acidity or alkalinity, may frequently indicate concerns caused by industrial discharges or equipment faults.

$$Y = f\left(X_1, X_2, \ldots, X_n\right) \tag{9}$$

Figure 6. A Vision Pond Skimmer Approach to Anomaly Monitoring in Wastewater

where, Y is the dependent variable (BOD (Biochemical Oxygen Demand), COD (Chemical Oxygen Demand), pH, Temperature, Dissolved Oxygen, Nutrient levels (nitrogen, phosphorus), Eq 9, Suspended Solids). (X_1, X_2, …, X_n) are the independent variables (Debris collected, battery life, Filter clogging rate, Environmental factors such as Rainfall, Wind speed, Temperature, Sunlight). Temperature variations, particularly abrupt increases or decreases, might potentially suggest the presence of industrial emissions, sources of heat, or inaccuracies in the sensors. Dissolved oxygen (DO) levels, which are essential for the survival of aquatic organisms, may be negatively affected by organic pollutants, biological processes, or fluctuations in temperature. Elevated levels of biochemical oxygen demand (BOD) and chemical oxygen demand (COD) often indicate the presence of organic pollutants, industrial wastes, or inadequate treatment. Industrial discharges, rainwater runoff, or equipment faults may cause an increase in total suspended solids (TSS).

$$\begin{aligned}\mathrm{BOD} = {} & \beta_0 + \beta_1 \times \mathrm{COD} + \beta_2 \times \mathrm{pH} + \beta_3 \times \mathrm{Temperature} \\ & + \beta_4 \times \text{Dissolved Oxygen} + \beta_5 \\ & \times \text{Nutrient Levels} + \beta_6 \times \text{Suspended Solids} \\ & + \beta_7 \times \text{Debris Collected} + \beta_8 \\ & \times \text{Rainfall} + \beta_9 \times \text{Wind Speed} + \grave{o}\end{aligned} \tag{10}$$

Equation 10, developed based on observed data collected from the wastewater system where, β0 is the intercept (the baseline value of BOD when all other parameters are zero). β1, β2…β91 are coefficients that represent the impact of each independent variable on BOD. ϵ is the error term, accounting for variability not explained by the model. Elevated ammonia levels, which serve as an indicator of organic pollution, are often caused by home sewage, industrial discharges, or animal waste. Nitrates and phosphates, which are essential nutrients, may lead to pollution when their concentrations are elevated, usually due to the discharge of fertilizers, animal waste, and sewage. Turbidity, which quantifies the level of purity in water, rises due to the presence of suspended particulates, industrial discharges, and storm water runoff. Ultimately, atypical flow rate variations may be ascribed to precipitation, mechanical faults, or obstructions.

3.7. Aeration floaters device

Paddlewheel surface aerators are designed to improve water quality by increasing oxygen levels, reducing algae growth, preventing fish kills, breaking stagnant water, promoting aquatic life, and improving water clarity **Figure 7**. The shape of floating platforms makes them resistant to different kinds of weather.

Figure 7. Aeration Floaters Device Placed in the Pond for Monitoring Oxygen levels and Water Circulation.

Paddle wheels are made of metal or plastic and turn to stir up the surface. The paddle wheels turn around the vertical shaft of the Central Shaft. The power that turns the paddle wheels comes from the motor. It's made to work with electric, solar, or even wind power.

3.8. Continuous pond cleaning, monitoring and water quality improved

Water Quality can be achieved by regularly monitoring and observing abnormal readings in recycled water using a positioned sensor that can quickly identify deviations from the acceptable ranges **Table 3**. The process of collecting data from the IoT-sensor-based water quality monitoring system involves continuously acquiring key water parameters in real-time. These parameters include BOD (Biochemical Oxygen Demand), COD (Chemical Oxygen Demand), pH, Temperature, Dissolved Oxygen, Nutrient levels (nitrogen, phosphorus), Suspended Solids, Debris collected, battery life, Filter clogging rate, and Environmental factors such as Rainfall, Wind speed, Temperature, Sunlight.

Table 3. After cleaning the pond sensor readings and status with comments

Date	pH	DO	Turbidity	Temp	Conductivity	Chemical	Algae Bloom	BOD	Weather
05-22-2024	5.8	4.5	80	50°C	1800	9.2	27,000	800	50°C
05-23-2024	6.0	4.9	72	47°C	1789	9.1	25,000	789	45°C
05-24-2024	6.1	5.0	66	42°C	1642	9.0	24,000	777	42°C
05-25-2024	6.3	5.0	60	38°C	1500	8.9	22,000	745	38°C
05-26-2024	6.7	5.0	55	35°C	1478	8.7	20,000	712	35°C
05-27-2024	7.0	5.0	50	33°C	1347	8.6	19,000	701	31°C
05-28-2024	7.1	5.3	45	30°C	1224	8.2	17,000	699	30°C
05-29-2024	7.1	5.5	40	27°C	1141	7.7	15,000	691	27°C
05-30-2024	7.3	5.7	35	33°C	1021	7.5	13,000	689	33°C
05-31-2024	7.3	5.9	31	33°C	987	7.5	11,000	677	33°C
06-01-2024	7.4	6.2	27	33°C	921	7.4	10,000	645	30°C
06-02-2024	7.5	6.2	25	33°C	897	7.4	9,000	632	33°C
06-03-2024	7.6	7.0	21	33°C	842	7.3	9,000	632	35°C
06-04-2024	7.3	7.5	19	33°C	811	7.3	8,500	622	33°C
06-05-2024	7.3	7.9	15	33°C	751	7.2	8,200	612	33°C
06-06-2024	7.3	8.4	15	27°C	712	7.1	8,200	603	27°C
06-07-2024	7.5	8.6	14	27°C	645	7.1	8,150	599	27°C
06-08-2024	7.5	8.9	12	33°C	601	6.9	8,000	578	33°C
06-09-2024	7.5	9.7	10	33°C	550	6.5	7,200	566	33°C
06-10-2024	7.7	9.9	8	31°C	521	6.2	7,000	545	31°C

4. Implementation and results

To conduct a comparative analysis between proposed Hierarchical Gated Recurrent Neural Network (HG-RNN) and other commonly used sequence modeling structures (Support Vector Machine, Random Forest, Feedforward Network, K-means Clustering, Logistic Regression, and FE-RNN), Primary language as python for implementation models, pytorch and Scikit-learn performance metrics, and comparing results, Matplotlib for virtualization. Regular ongoing monitoring involves the collection of samples over one year (365 days), totaling around 27 samples each day, resulting in an overall accumulation of 10,000 samples. This situation would need regular monitoring, maybe on a daily or hourly basis, to monitor fast changes in water quality metrics. Batch size of 1000, number of epochs 50, learning rate is 0.01, number of iteration 10. Training set 7000 (70%), testing set 1500 (15%), and validation set 1500 (15%) **Figure 8**. The collected data was then inputted into the system to detect repetitive patterns and trends in the quality of water, especially to assist in the management of pond cleanliness and the quality of recycled water.

4.1. Performance compared with HG-RNN

In recycled water quality is monitored using a true positive rate by correctly predicting an anomaly in wastewater quality, a true negative rate by correctly predicting normal wastewater quality, a false positive by incorrectly predicting an anomaly, and a false negative by incorrectly predicting normal water quality. Accuracy measures the overall correctness of the model's predictions. A high accuracy indicates that the model is making correct predictions most of the time Eq 11.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Samples}} \tag{11}$$

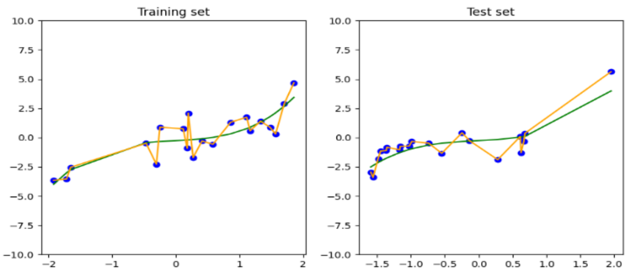


Figure 7. Dataset for Training and Testing Set

Precision measures the proportion of correct positive predictions. A high precision indicates that the model is not making many false positive predictions Eq 12.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{12}$$

Recall measures the proportion of actual positive cases that the model correctly identified. A high recall indicates that the model is not missing many positive instances Eq 13.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{13}$$

F1-Score is a harmonic mean of precision and recall, providing a balanced measure of both. A high F1 score indicates good performance in terms of both precision and recall Eq 14.

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{14}$$

Specificity measures the proportion of actual negative cases that the model correctly identified. A high specificity indicates that the model is not making many false positive predictions Eq 15.

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}} \tag{15}$$

Table 4, shows the overall performance of the Proposed HG-RNN Model compared with other existing algorithm obtains a remarkable accuracy of 96.89%, demonstrating its ability to accurately classify the majority of samples. The F1-Score is a statistic that achieves a balance between accuracy and recall.

The HG-RNN Model demonstrates exceptional performance in this aspect, achieving an impressive F1-score of 95.42%. High recall rate of 96.77%, suggesting its capacity to accurately detect the majority of real anomalies. Specificity of 96.75%, indicating its ability to accurately identify normal samples without generating false alarms. The precision of 96.58%, suggesting that its positive predictions are quite accurate. A pairwise density plot shows the relationship between water quality parameters kernel density estimation (KDE). Eq 16 where, Pij pairwise relationship between two parameters Xi, Xj.

Table 4. Comparison of Different Algorithm with Proposed Model

Performance	Accuracy	F1-Score	Recall	Specificity	Precision
Support Vector Machine	76.66%	73.13%	75.77%	74.21%	71.72%
Random Forest	79.88%	79.24%	79.60%	79.16%	79.44%
Feedforward Neural Network	82.50%	82.61%	82.60%	82.80%	82.02%
K-means Clustering	85.98%	86.23%	87.12%	87.89%	83.12%
Logistic Regression	89.97%	83.23%	85.91%	86.12%	87.73%
FE-RNN	92.40%	92.45%	93.22%	94.78%	92.21%
Proposed HG-RNN Model	96.89%	95.42%	96.77%	96.75%	96.58%

$$\text{Pij} = \text{f}\left(\text{Xi}, \text{Xj}\right) \tag{16}$$

$$f\left(pH, DO\right) = \text{Correlation}\left(\text{pH}, \text{DO}\right) \tag{17}$$

$$\text{f}\left(\text{Turbidity}, \text{Temp}\right) = \text{Correlation}\left(\text{Turbidity}, \text{Temp}\right) \tag{18}$$

$$\text{f}\left(\text{Nitrate}, \text{Conductivity}\right) = \text{Correlation}\left(\text{Nitrate}, \text{Conductivity}\right) \tag{19}$$

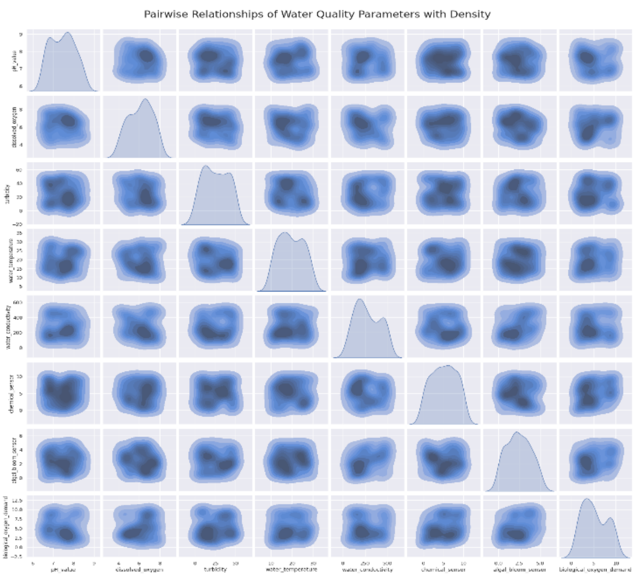


Figure 9. Recycled Water Quality Analysis

The subplots display the density relationships between two parameters in a paired fashion shown in Eq (16) - (19). Most of the data for that parameter combination is concentrated in the shaded blue zones, representing areas of high-density data points. **Figure 9**, The diagonal plots display the pH values, dissolved oxygen, and turbidity levels of the current data, while, the off-diagonal plots illustrate the pH values, dissolved oxygen, and turbidity levels of the historical data. Darker regions indicate more data point density, whereas lighter regions signify lower data point density. Positive Correlations: A concentration of color intensity along a diagonal line from the bottom left to the top right indicates a positive correlation between the two variables. A robust positive association between pH and alkalinity may suggest that elevated pH levels correspond with increased alkalinity. Negative Correlations: A concentration of color intensity along a diagonal line from the top left to the bottom right indicates a negative connection. A negative association between temperature and dissolved oxygen suggests that elevated temperatures result in decreased dissolved oxygen levels. No Correlation: An equal distribution of color intensity throughout the plot indicates a lack of substantial link between the two parameters. As an example: The pH-dissolved oxygen relationship may help measure water ecosystem health. High dissolved oxygen may indicate a certain pH range. Turbidity and water temperature may suggest suspended particles that impact water heating. Chemical sensors monitoring nitrates can be linked with water conductivity, suggesting pollution-induced ionic presence of water quality analysis. **Figure 10**, demonstrates the performance of the proposed HG-RNN model in transforming a pond into a clean-water pond. It is compared with existing algorithms that are most suitable for real-time IoT sensor-based monitoring systems in wastewater recycling. The goal is to ensure accurate predictions, effective detection of contaminants, and optimal intervention in the water treatment process. The **Figure 11**, determine the ideal equilibrium between the rate of oxygen transport and the effectiveness of oxygen utilization. Real-time monitoring of this balance is essential in wastewater recycling, since the oxygen demand in water bodies changes owing to variable amounts of organic contaminants, algae development. The data distribution across various graphs is distinct, indicating that specific conditions substantially influence the oxygen transfer behavior. In certain subplots, the optimum efficiency is achieved at moderate or higher oxygen transfer rates, while in others, it is higher at lower rates. The proposed system could be programmed to optimize aeration rates in ponds or treatment facilities to sustain high oxygen transfer efficiency, thereby ensuring that ponds are transformed into clean water more effectively. A model that learns the patterns in the training data is one with a high training accuracy. **Figure 12**, shows how well HG-RNN performed on unknown data is the validation accuracy statistic, which shows what proportion of validation samples were properly identified. **Figure 11** shows that this improves the model's ability to generalize to new data. The Training Loss metric quantifies the disparity between the predictions made by the HG-RNN model and the actual targets included in the training data. A diminishing training loss signifies that the model is improving its capacity to accurately represent the training data. Loss during the validation process Validation loss, like training loss, quantifies the disparity between predictions and targets using unseen validation data. If the validation loss remains consistent or decreases, it indicates that the model is learning from the training data without overfitting.

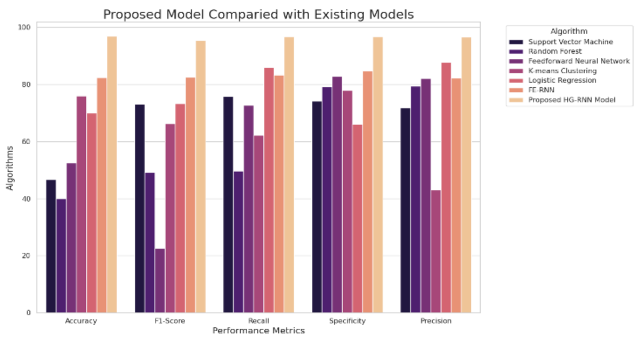


Figure 10. Performance Compared with Existing Algorithms

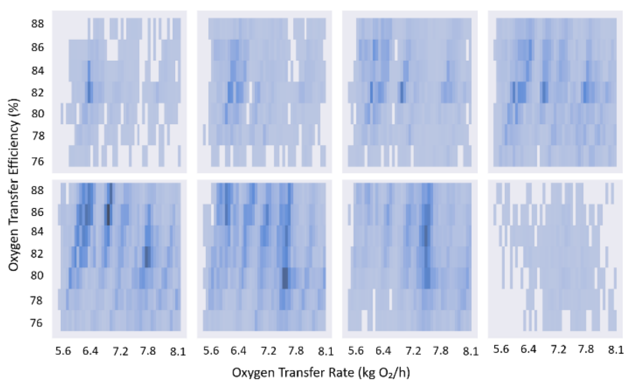


Figure 11. Aerator Monitor Recycled Water Oxygen Level Monitoring

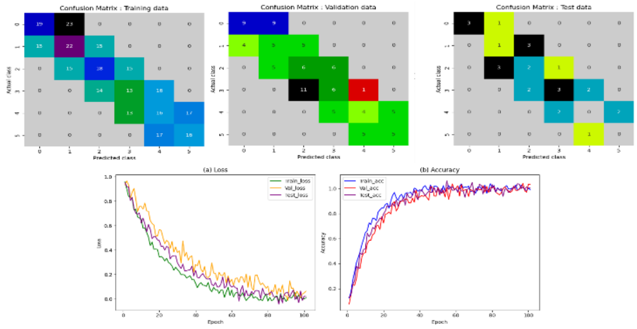


Figure 12. Proposed Model Performance Analysis

5. Conclusion and future direction

Wastewater treatment enables the secure use of water in many fields such as agriculture, manufacturing, and landscaping. This minimizes the pressure on freshwater resources, encourages water preservation, and guarantees the implementation of sustainable water governance. The wastewater originates from several sources, such as residential areas, industrial facilities, and agricultural runoff. Prior to discharging the wastewater into the pond, it is essential to subject it to pre-treatment to remove any sizable debris, silt, paper, plastic coverings, wooden sticks, and hazardous substances. This measure reduces the strain on the pond's natural cleaning system and protects the stability of the aquatic ecosystem. IoT sensors will monitor real-time on wastewater for immediate detection of any issues or deviations from optimal conditions. HG-RNN model is trained on historical data and pre-treatment process of water. Ability to analyze complex data relationships enhances the accuracy of pollutant detection and treatment optimization, ensuring that water quality is maintained at safe levels. Compared with existing algorithm, proposed algorithm HG-RNN achieved accuracy excels in F1-score (95.42%), recall (96.77%), specificity (96.75%), and precision (96.58%), highlighting its robustness in detecting and treating water contaminants in real-time. Future directions could merge reinforcement and deep learning for predicting contamination patterns more effectively and autonomously adjusting treatment parameters.

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