UNIVERSITI TEKNOLOGI MALAYSIA

FINAL YEAR PROJECT II:

DESIGN AND DEVELOPMENT OF MONITORING SYSTEM USING RASPBERRY PI FOR PALM OIL MILL EFFLUENT (POME) IN DARK ENVIRONMENT OF ANAEROBIC DIGESTER

MUHAMMAD NAJMI BIN ZAHARI
A21EE0157

SUPERVISED BY DR KHAIRUL HAMIMAH

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PROJECT BACKGROUND

- **Palm Oil Industry in Malaysia**
  - 2nd largest global producer, contributing RM 35 billion (2.4% of GDP, 2022).
  - Accounts for 25.8% of global production and 34.3% of exports.
- **Palm Oil Mill Effluent (POME)**
  - Highly polluting byproduct of sterilization and clarification processes.
  - Contains residual oil, suspended solids, and soil particles.
  - BOD and COD are 100x greater than municipal sewage.
- **Environmental Challenge**
  - In 2004, 30 million tonnes of POME were generated.
  - Untreated sludge leads to system inefficiencies and ecological hazards.
- **Anaerobic Digestion for Treatment**
  - Microbes digest organic matter in low-light conditions.
  - Sludge monitoring is critical for process efficiency.
- **Project Aim**
  - Develop a monitoring system using Raspberry Pi integrate with sensor and machine learning to predict the sludge level/density.
  - Overcomes the limitations of **camera-based systems** in dark environments.
  - Automates sludge detection, reduces supervision, and enhances wastewater treatment.

PROBLEM STATEMENT

How can we monitor turbidity to correlate with sludge concentration of Palm Oil Mill Effluent (POME) in a dark anaerobic digester environment to effectively track sludge formation, ensure proper sludge management, and prevent system inefficiencies and environmental hazards?

SCOPE

Constrained sample size and experimental setup under laboratory conditions

Stirring samples at a fixed rpm when measuring the characteristics to ensure consistency

Using Raspberry Pi 4 as MCU

Parameters to be measured are only turbidity and voltage.

OBJECTIVE

01

To study the correlation between turbidity, temperature and concentration of Palm Oil Mill Effluent (POME)

02

Implement machine learning model in raspberry pi based system to predict sludge level

03

To integrate the sensor-based monitoring system into a lab-scale anaerobic digester for real-time sludge detection

LITERATURE REVIEW

LITERATURE REVIEW

Title	Observation	Objective	Gaps
Palm Oil Mill Effluent (POME) from Malaysia Palm Oil Mills: Waste or Resource	POME is a resource-rich byproduct with high concentrations of total solids, volatile solids, and organic acids, but it is also a major pollutant due to its high BOD, COD, and acidic nature. Advanced technologies like anaerobic digestion (e.g., POMETHANE) are effective in treating POME and recovering biogas as a valuable byproduct.	Explore cost-effective and sustainable technologies to treat POME while minimizing environmental impacts and recovering useful byproducts like biogas and fertilizers.	Focused on industrial-scale systems; lacks emphasis on small-scale, real-time sludge monitoring or predictive modeling for lab-scale setups.
Real-Time Turbidity Measurement in Sludge Processing Units	IoT-based turbidity sensors used for real-time monitoring in sludge processing plants, enabling early detection of anomalies.	Develop a low-cost, real-time IoT turbidity monitoring system for sludge.	Focused on large-scale systems; lacks attention to sludge characteristics like density or formation, especially under lab-scale conditions.
Analysis of Machine Learning Models for Wastewater Treatment	Machine learning models like Random Forest and Support Vector Machines (SVM) demonstrate promising results in predicting sludge volume and wastewater parameters.	Identify effective machine learning models for accurate prediction of sludge formation.	Limited application to sludge formation in anaerobic digesters; lacks consideration of additional factors like pH, temperature, and retention time.

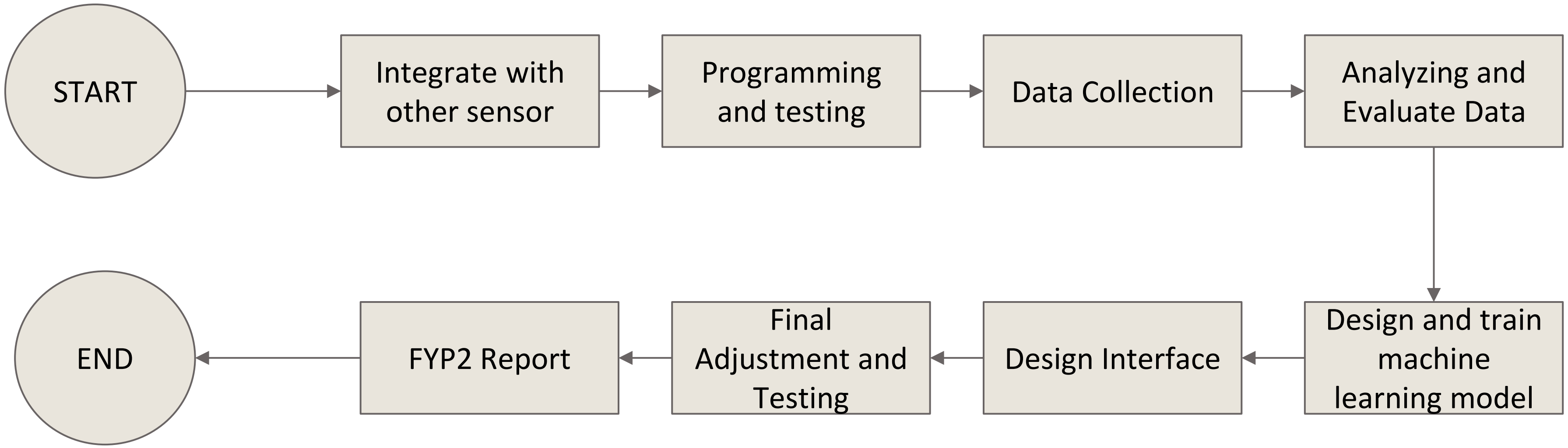
LITERATURE REVIEW

Title	Observation	Objective	Gaps
Turbidity Detection Using Image Processing	Digital image processing can be used to measure turbidity by capturing water sample images and comparing them with a pre-stored database for turbidity characterization.	To use image processing techniques for turbidity detection, enabling faster and more accurate measurements.	Requires high-quality images and extensive database calibration; not feasible in low-light environments like anaerobic digesters.
Turbidity Measurements as a Tool for Monitoring and Control of the SBR Plant Effluent	Turbidity strongly correlates with effluent quality but not directly with sludge formation or density.	Investigate how turbidity can serve as an indirect measure of sludge density and formation	No consideration of complex environments like dark anaerobic digesters, where turbidity sensors may face operational limitations.
Machine Learning as a Support Tool in Wastewater Treatment Systems	Machine learning aids in optimizing wastewater treatment processes, reducing errors, and improving decision-making.	Incorporate machine learning to streamline sludge formation prediction and improve process	Models lack integration of real-time sensor data (e.g., turbidity, temperature, and pH) to predict sludge density.
Machine Learning Methods for the Prediction of Wastewater Treatment Plant Influent Characteristics	Regression models predict influent wastewater characteristics like BOD, COD, and TSS to optimize treatment processes.	Leverage machine learning to enhance sludge formation prediction in dynamic wastewater environments.	Does not address sludge-specific conditions in controlled or dark environments like anaerobic digesters.

METHODOLOGY

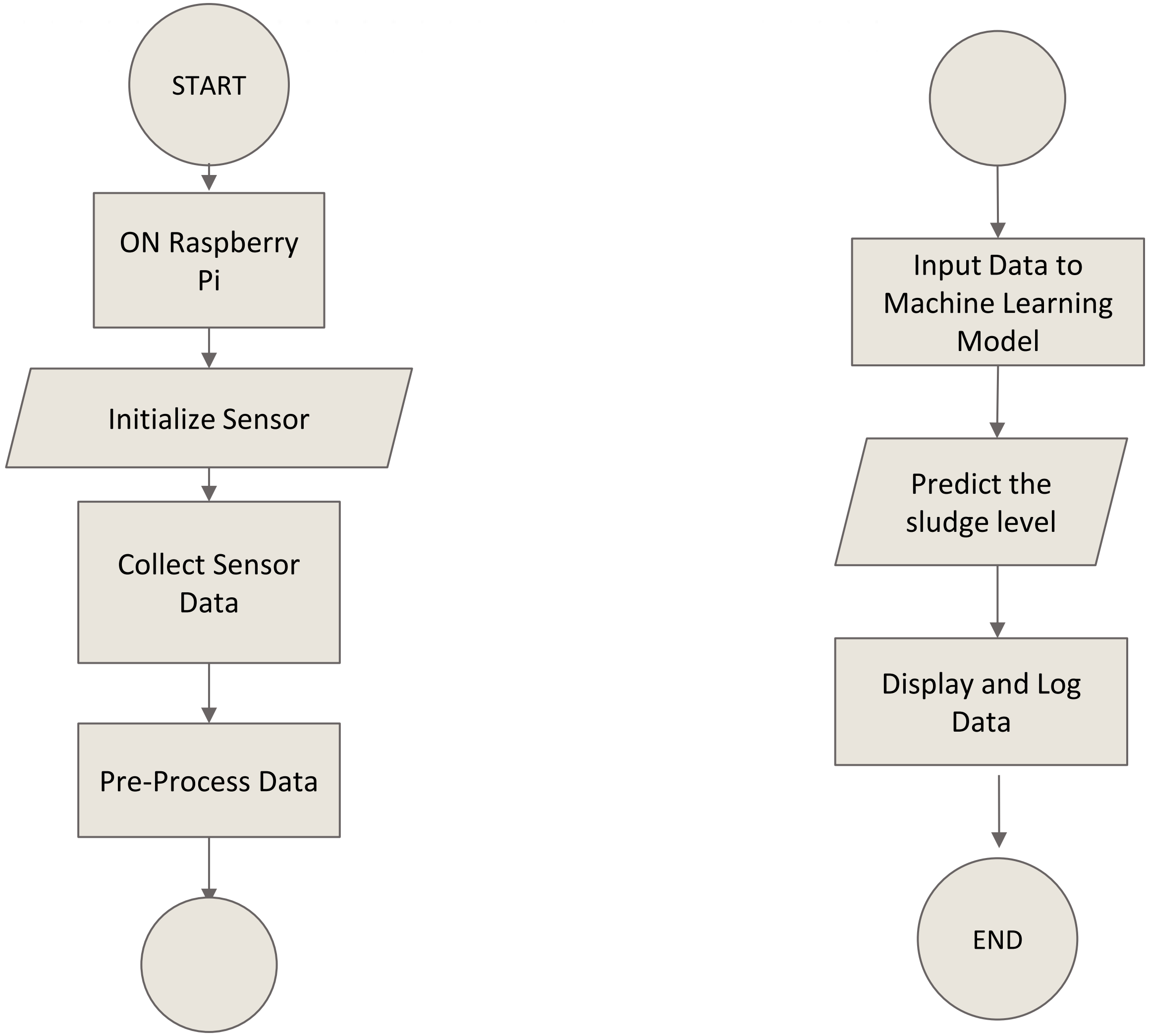
METHODOLOGY

Project Plan



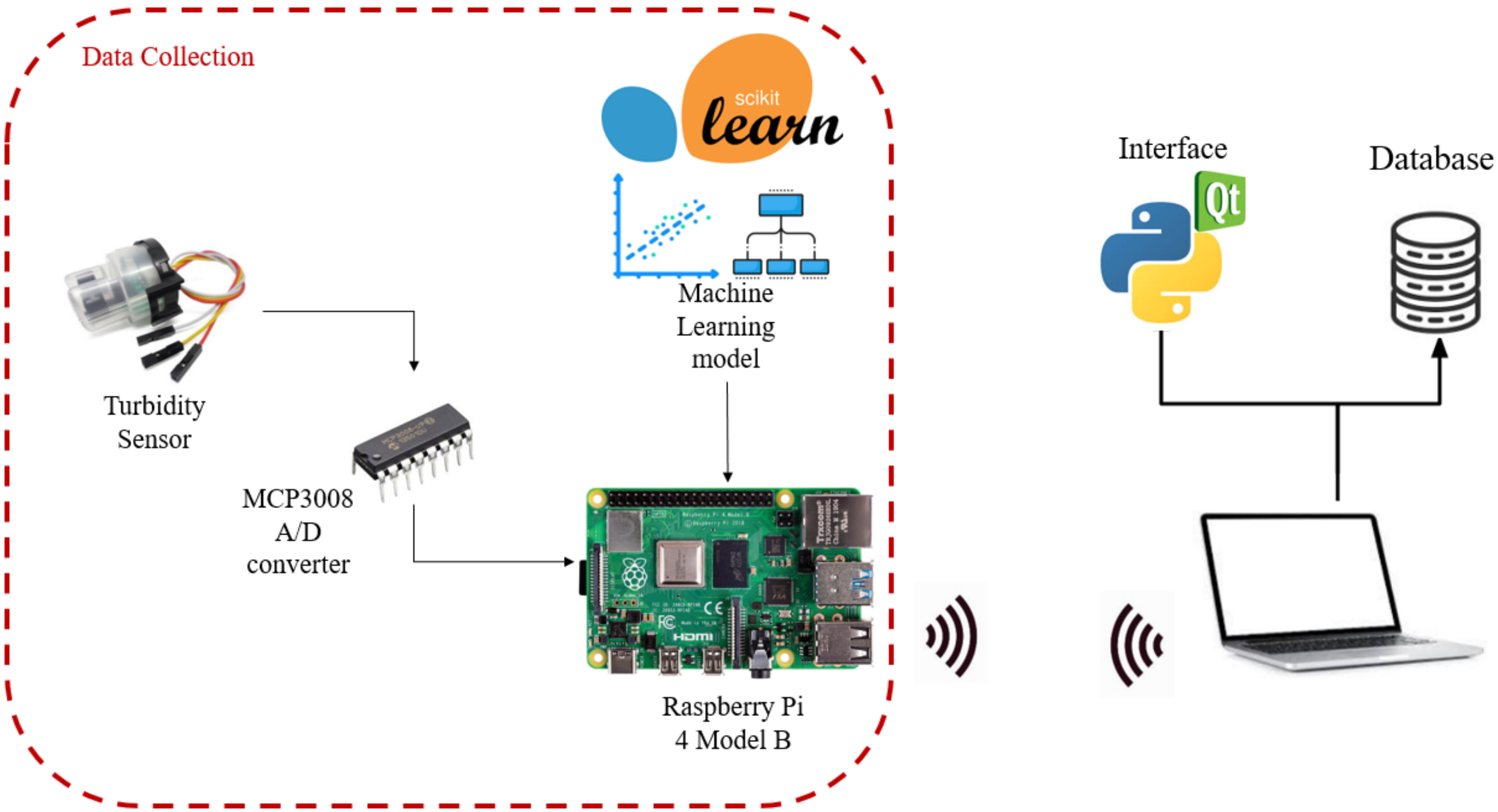
METHODOLOGY

System Flowchart



METHODOLOGY

Conceptual Block Diagram



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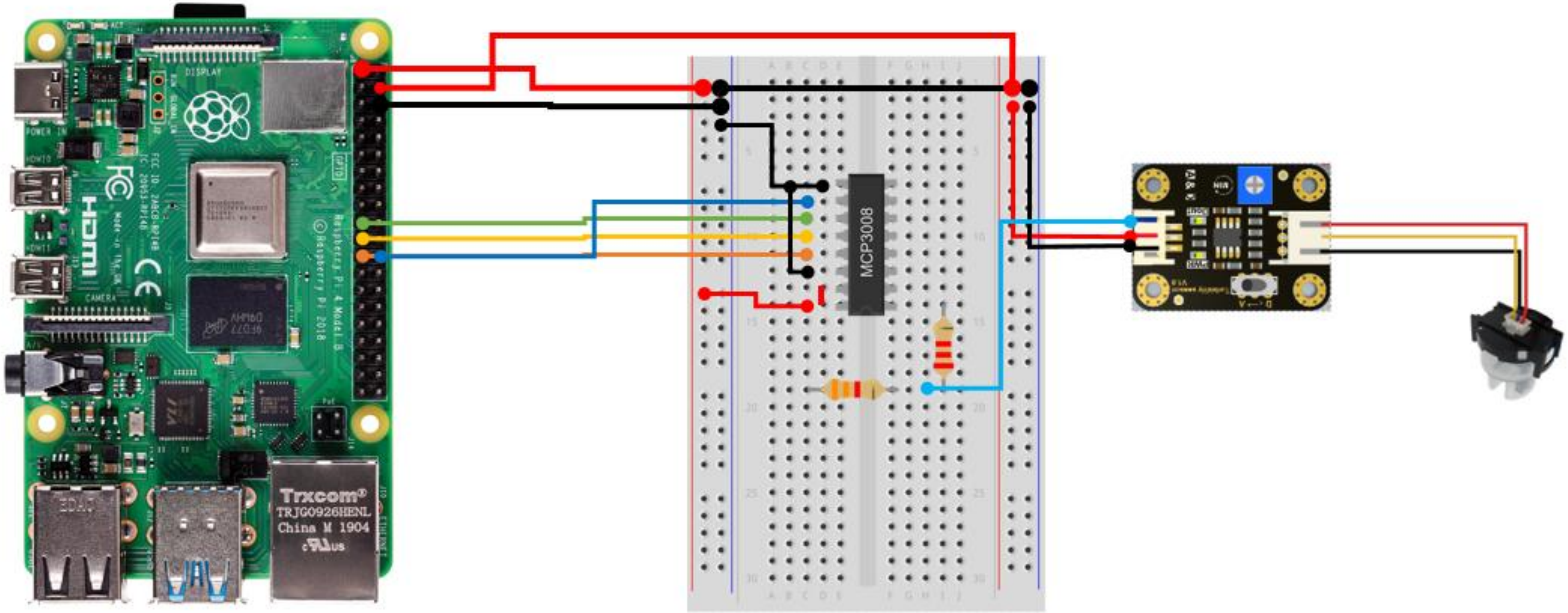
METHODOLOGY

CIRCUIT DESIGN



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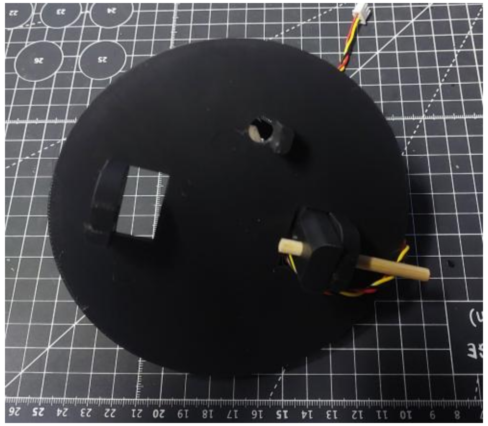
CIRCUIT DESIGN

Black box simulates dark anaerobic digester conditions.

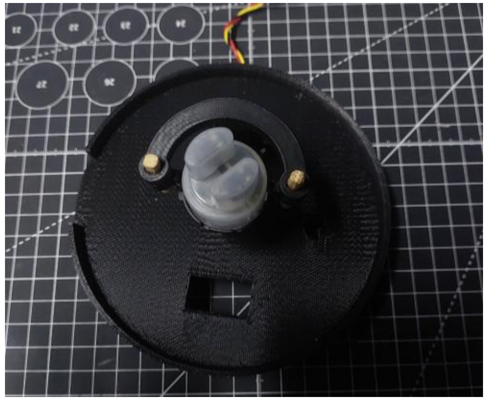
Magnetic stirrer used for uniform sample mixing.

Electronic components

Casing



Top view



Bottom view

METHODOLOGY

Sample Preparation

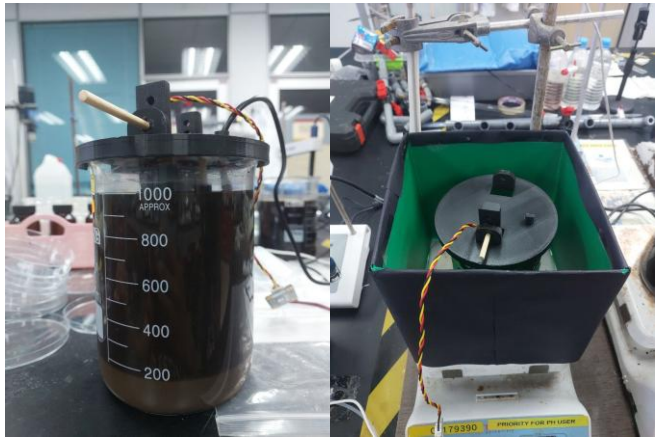
- Started with 100% raw POME as the base.
- Distilled water was used to dilute the raw POME to desired concentrations (e.g., 20%, 40%, etc.).
- Total volume fixed at 1000 ml for each sample.
- Example (20% concentration): 200 ml raw POME + 800 ml distilled water.
- Used the dilution formula: $\boldsymbol{M_1V_1 = M_2V_2}$

  $M_1 = Initial\ Concentration$

  $V_1 = Volume\ of\ \text{raw POME}$

  $M_2 = Desired\ Concentration$

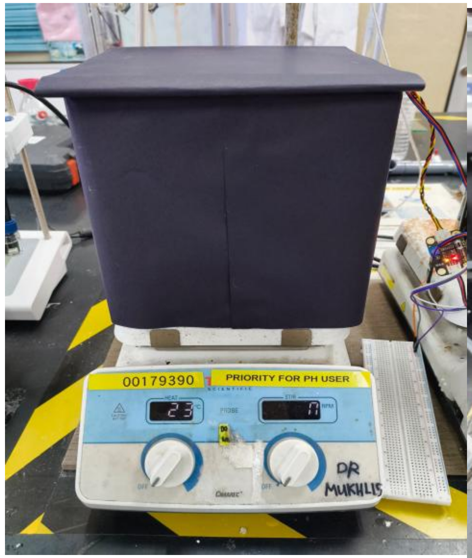
  $V_2 = Final\ Total\ Volume$
- Example (20% concentration): 200 ml raw POME + 800 ml distilled water.



Setup

- **Turbidity sensors** mounted in a custom casing.
- Casing placed on top of a beaker containing the sample.
- Beaker enclosed in a **black box** to simulate **anaerobic digester** conditions.

METHODOLOGY

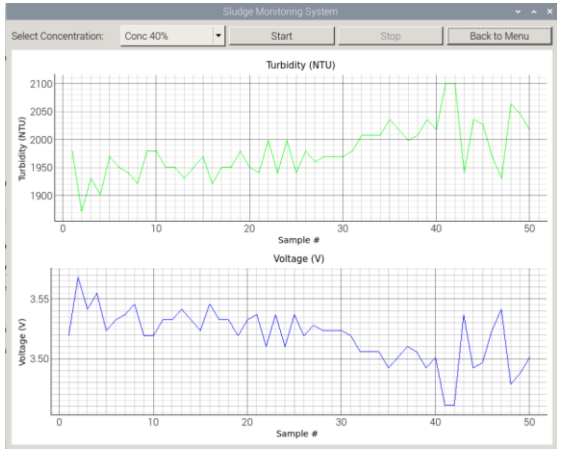


Measurement

- The system **fully covered**, with the Raspberry Pi and sensor electronics mounted externally.

- A **magnetic stirrer** was used at a constant speed (130 RPM) to keep the **POME** sample consistent across readings.

METHODOLOGY

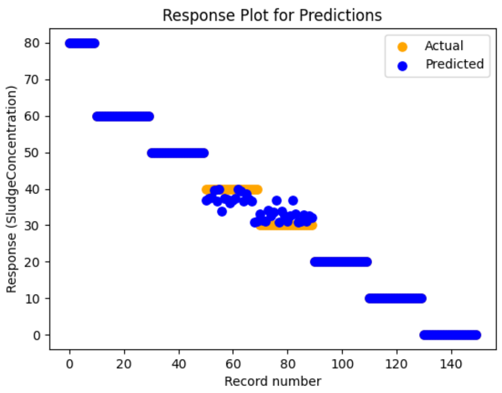


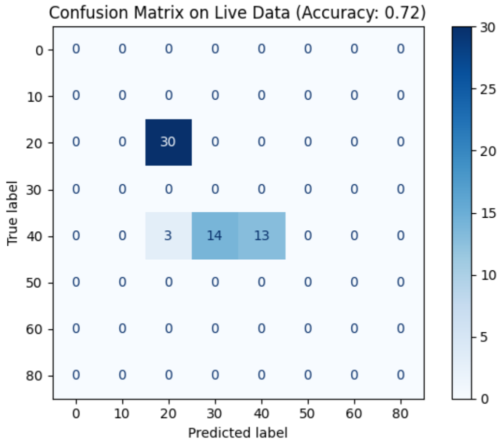
	A	B	C	D
1	timestamp	concentrat	turbidity	voltage
2	9:59:15	Conc 40%	2600.91	1.97
3	9:59:16	Conc 40%	2601.72	1.97
4	9:59:17	Conc 40%	2534.11	1.92
5	9:59:18	Conc 40%	2551.48	1.94
6	9:59:19	Conc 40%	2732.81	2.09
7	9:59:20	Conc 40%	2640.57	2
8	9:59:21	Conc 40%	2609.94	1.97
9	9:59:22	Conc 40%	2668.16	2.02
10	9:59:23	Conc 40%	2707.29	2.05
11	9:59:24	Conc 40%	2606.73	1.97

Data Collection

- After 5 minutes of stirring, turbidity data was collected from the sensor.
- 50 raw readings were taken for each concentration.
- Every 5th data point was averaged (e.g., reading 5, 10, 15...) to minimize noise.
- Around 10 averaged data points per sample were recorded.
- All readings were logged using Python script on Raspberry Pi and saved to a CSV file for analysis and machine learning model training.

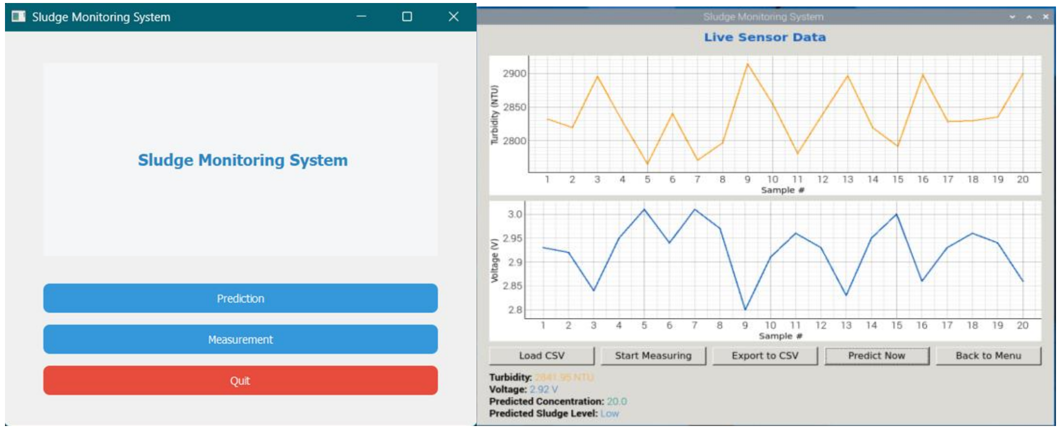
METHODOLOGY





Data Collection

- Developed and trained both **regression and classification models** using the **Scikit-learn** Python library. Multiple models compared based on Test RMSE, MAE, and R^2
- The model with the highest accuracy was selected and embedded into the user interface



- Developed using **PyQt5** in Python to provide a simple and interactive GUI.
- Main menu direct prediction page and measurement page.
- Interface display real-time turbidity and voltage from sensor.
- Includes button to start/stop data logging and save data to CSV file.
- Perform sludge concentration prediction base on incoming data

RESULT & DISCUSSION

RESULT & DISCUSSION

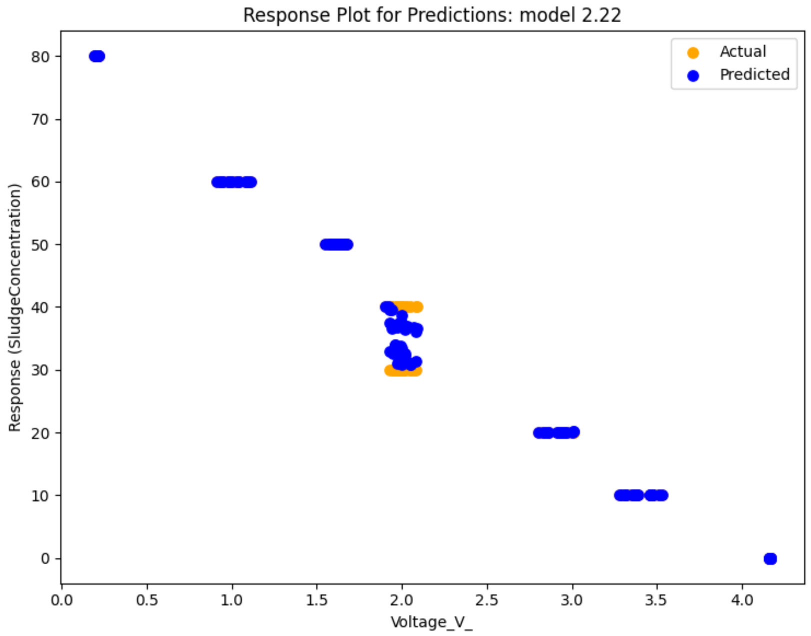
- ## Regression

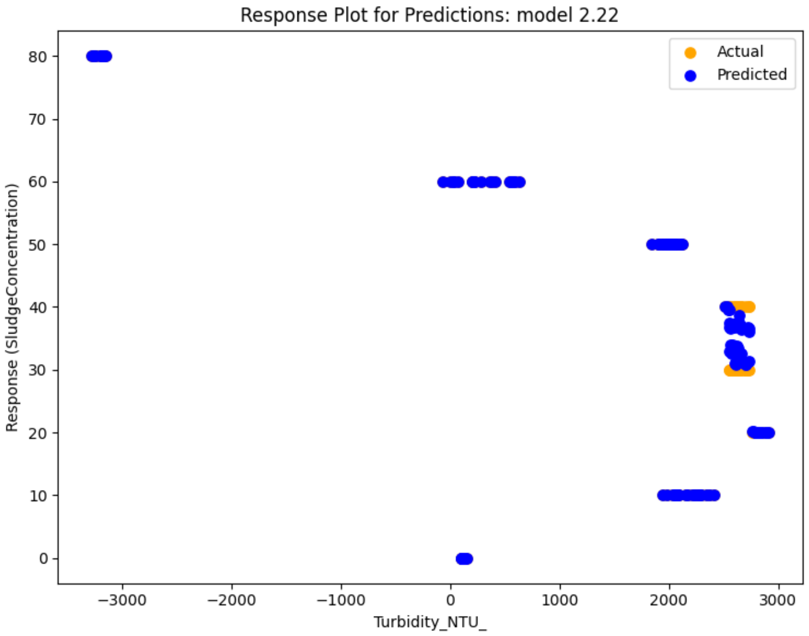
Model	MSE (Mean Squared Error)	RMSE (Root Mean Squared Error)	R^2 (R-squared)
Random Forest	8.36	2.89	0.984
XGBoost	12.03	3.47	0.977
SVR(SVM)	508.7	22.55	0,029
k-NN Regressor	74.00	8.60	0.859

- ## Classification

Model	Accuracy	Macro F1-score
Random Forest	1.00	1.00
XGBoost	0.96	0.96
SVM	0.58	0.60
Logistic Regression	1.00	1.00

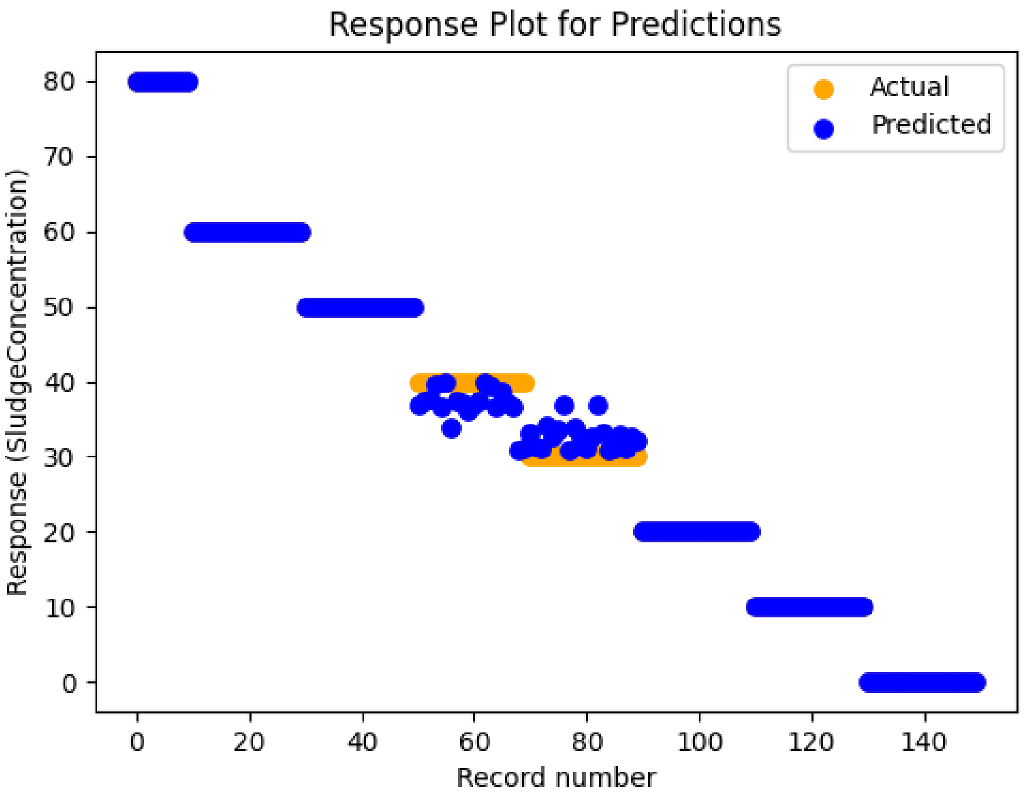
RESULT & DISCUSSION





- DFRobot turbidity sensor works using a photoelectric method (higher sludge = lower voltage)
- Sensor can measure up to 3000 NTU only.
- Voltage readings converted to NTU using the datasheet formula.
- Distilled water used to calibrate 0 NTU.
- From the graphs, turbidity exceeds 3000 NTU when sludge concentration is above 20%.
- Readings beyond this point may not be reliable.

RESULT & DISCUSSION



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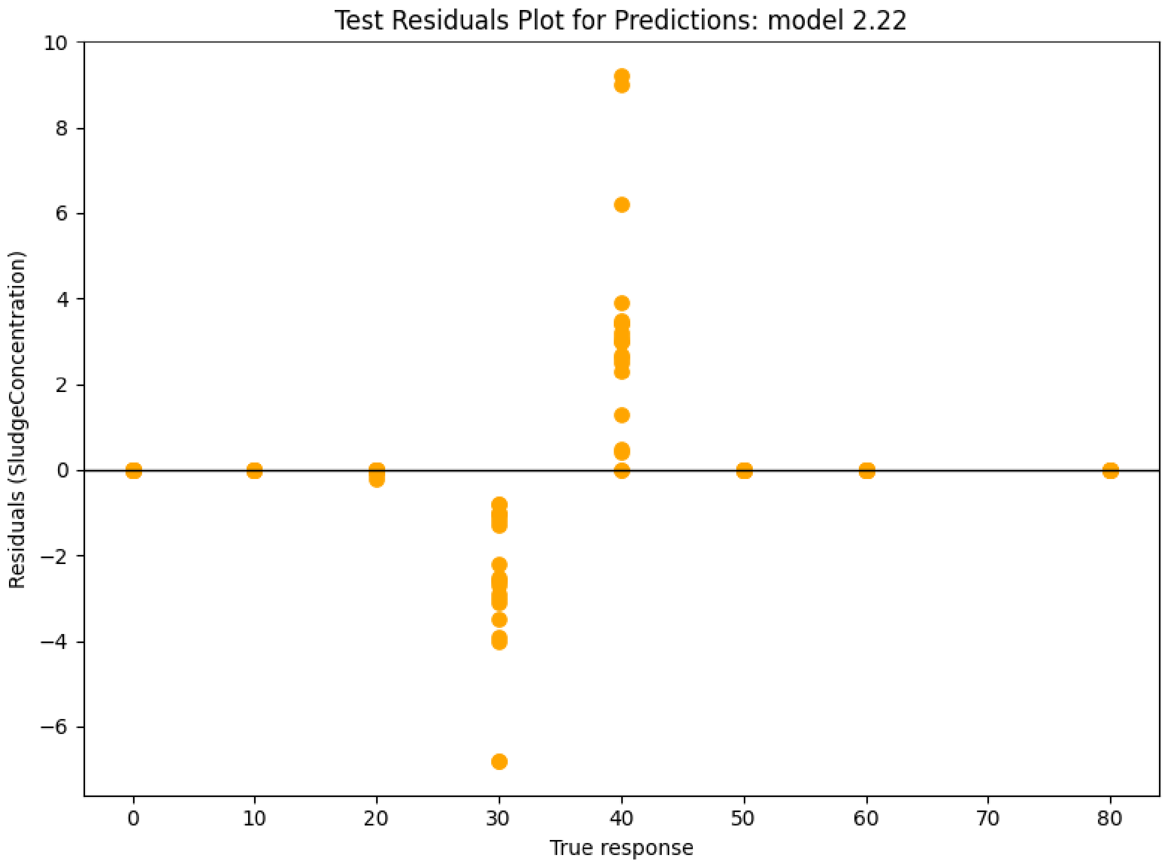
RESULT & DISCUSSION



- Positive residuals mean the model under-predicted (actual > predicted).
- Negative residuals mean the model over-predicted (actual < predicted).

RESULT & DISCUSSION

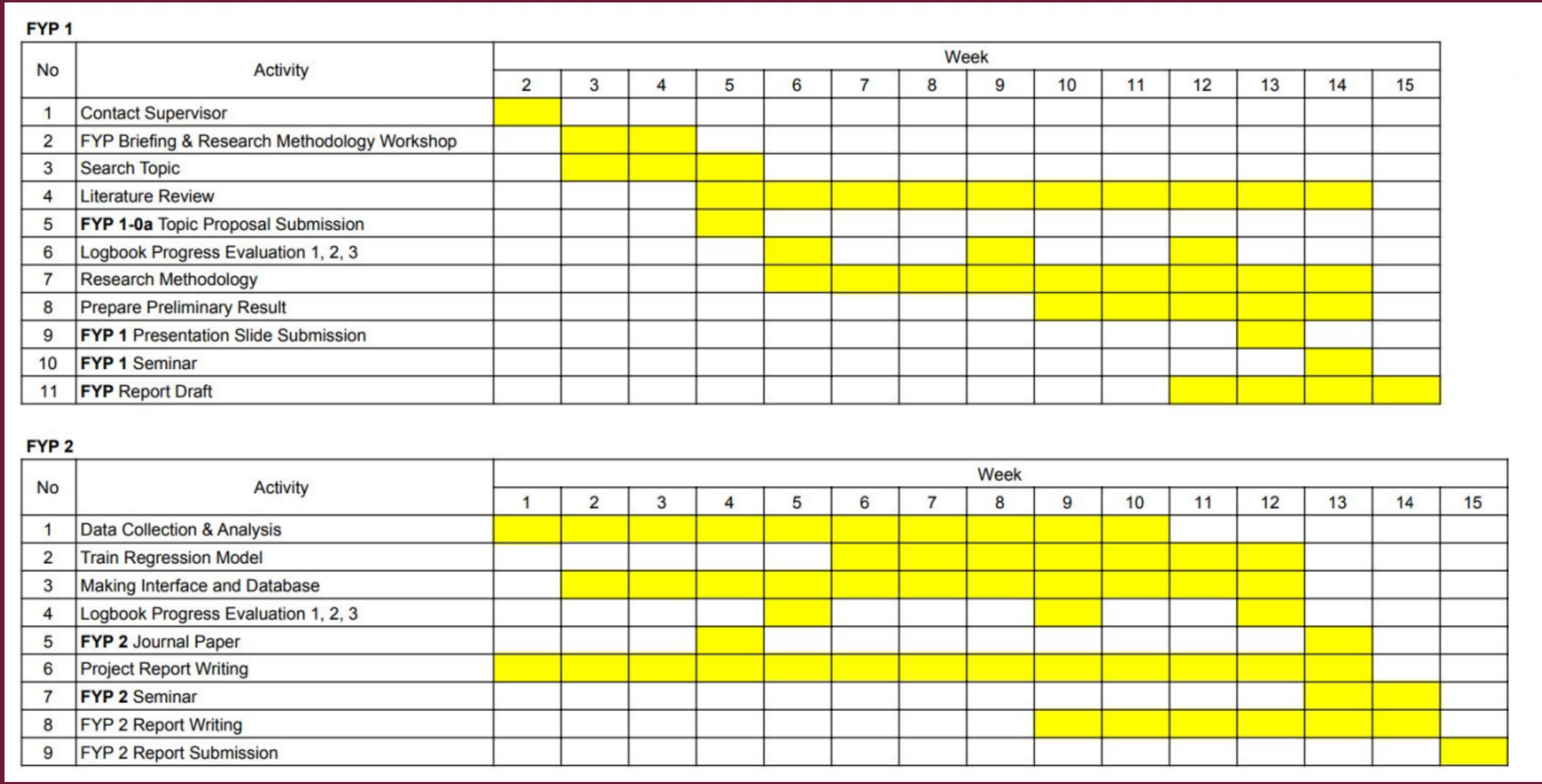
Limitations

- **Technical**
  - Only **turbidity sensor** was used; others (ultrasonic, temperature) were not functional.
  - **Intermediate concentrations** (e.g., 70%, 90%) caused unstable readings.
  - Conducted in **lab-scale setup** — results may differ in industrial environments.
  - Minor **light leakage** in black box may affect diluted sample readings.
  - **Room temperature (25–28°C)** used, while real digesters operate at higher temperatures (30–55°C).
- **Environmental**
  - **POME smell** is strong; it worsens after a few days of sludge formation.
  - **Poor ventilation** made long testing sessions uncomfortable.
  - **Time limits**: Samples couldn't be left exposed too long → reduced long-term data collection.

Key Observations

- Turbidity values increase as POME becomes denser → useful for early sludge detection.
- Averaging multiple readings helped reduce noise and improve model consistency.
- Data collection and logging system on Raspberry Pi functioned reliably for real-time use.

Gantt Chart



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Innovating Solutions

COSTING

No.	Item	Price,RM
1	Raspberry Pi 4 Model B	219.00
2	Gravity-Analog Turbidity Sensor For Arduino (DFRobot)	66.00
3	A/D Converter MCP3008	15.85
4	3D Printed Parts (PLA+)	80.00
Total		380.85

CONCLUSION

This project successfully developed a low-cost, sensor-based monitoring system for estimating sludge concentration in Palm Oil Mill Effluent (POME), simulating anaerobic conditions using a black enclosure and magnetic stirring:

- A clear correlation was observed between turbidity readings and sludge concentration.
- A PyQt5-based user interface was developed for real-time monitoring and data logging.
- Machine learning models (Random Forest, Logistic Regression) achieved 100% classification accuracy
- The Random Forest Regressor showed excellent predictive performance (R^2 = 0.984, RMSE = 2.89

Future Work

- Test the system using real industrial-scale POME to validate performance in field conditions.
- Reintegrate ultrasonic and temperature sensors to improve prediction reliability.
- Incorporate COD/BOD analysis for deeper sludge characterization and enhanced model accuracy.

THANK YOU

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