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K-NEAREST NEIGHBOR ALGORITHM FOR INTELLIGENT MONITORING AND CONTROL SYSTEM INTEGRATION IN RENEWABLE ENERGY APPLICATIONS

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ABSTRACT

A real-time biogas monitoring and control system was developed by integrating the K-Nearest Neighbor (KNN) algorithm into an IoT-based framework for methane pressure prediction and automated control. The system uses an ESP32 microcontroller connected to temperature, gas, and pressure sensors (DHT22, MQ-4, MPX5700) to continuously collect data, with cloud connectivity provided through Firebase and Blynk platforms. The predictive model operates within a live feedback loop, allowing immediate actuation based on forecasted methane conditions. With an optimal parameter of k=4, the KNN model achieved 93.33% accuracy, supported by a mean absolute error (MAE) of 0.18 and a root mean square error (RMSE) of 0.21. A comparative evaluation with Random Forest and Gradient Boosting algorithms showed that, although these models yielded slightly higher accuracy, KNN provided superior computational efficiency for embedded deployment. The system maintained stable operation during tests involving sensor anomalies, network interruptions, and data noise. However, redundancy mechanisms and improved validation strategies are recommended to enhance robustness. The findings demonstrate that methane production can be effectively predicted using temperature and pressure data, with further accuracy improvements possible through additional process variables such as pH and fermentation age.

Keywords: *biogas monitoring, IoT, k-nearest neighbor, methane prediction, predictive control.*

I. INTRODUCTION

THE transition to sustainable energy sources has become a global priority due to increasing concerns about environmental degradation, fossil fuel depletion, and climate change. In response to these challenges, the development of renewable energy technologies, particularly those based on waste-to-energy systems, has gained significant momentum. Indonesia, one of the largest waste-producing countries in Southeast Asia, generated more than 19 million tons of waste in 2023, with a substantial portion consisting of organic materials such as vegetable waste [1]. Despite its high biodegradability and rich organic content, vegetable waste remains underutilized and is often disposed of through open dumping practices. These practices contribute to serious environmental problems, including unpleasant odors, leachate contamination, and the spread of disease vectors [1]. Effective management of this biomass is therefore essential to reduce environmental impact and convert waste into a valuable energy source.

One of the most promising methods for utilizing organic waste is anaerobic fermentation, a process in which microorganisms decompose organic matter in the absence of oxygen to produce biogas, primarily composed of methane (CH_4) [6]. However, a major challenge in optimizing biogas systems lies in the real-time monitoring and control of critical parameters such as gas pressure, temperature, and methane concentration. Gas pressure, in particular, serves as an important indicator of microbial activity and gas production efficiency. Variations in substrate composition, temperature, humidity, and fermentation time can significantly influence gas pressure inside the digester. The main problem

Figure 1. Tools Design

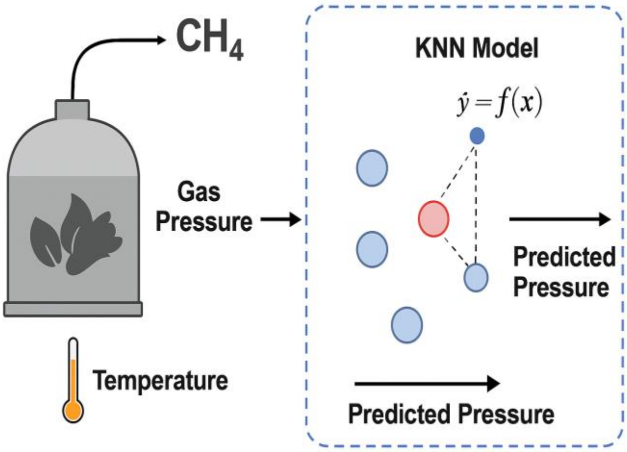

Figure 2. Methane Pressure Prediction Model Using KNN

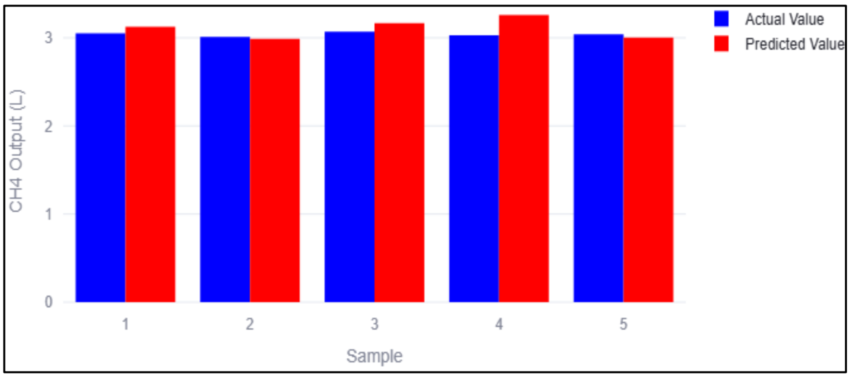

Figure 3. KNN Actual vs Predicted Values Comparison

addressed in this study is the absence of an intelligent, real-time monitoring and control system capable of accurately predicting and regulating methane gas pressure in small- and medium-scale biogas production units. Without such a system, biogas operations often depend on manual observation, which is inefficient, prone to human error, and unable to adapt to dynamic environmental changes.

To address this issue, this research aims to design, implement, and evaluate an integrated Internet of Things (IoT)-based monitoring and control system enhanced with a K-Nearest Neighbor (KNN) algorithm. The system collects real-time environmental data using multiple sensors (DHT22 for temperature and humidity, MQ-4 for gas concentration, and MPX5700 for gas pressure) and processes it through an ESP32 microcontroller platform. The KNN algorithm is applied to this dataset to predict future gas pressure levels, enabling the system to perform automated actions such as adjusting operational parameters or triggering safety mechanisms. This predictive control mechanism is intended to enhance the safety, efficiency, and reliability of methane production from vegetable waste.

The main contribution of this study lies in developing a smart biogas monitoring system that is both cost-effective and scalable. Unlike existing systems that often require expensive infrastructure or lack intelligent capabilities, this system integrates affordable open-source hardware components with a machine learning model to enable real-time decision-making [5][9]. Furthermore, by embedding intelligence at the edge of the system, the proposed model minimizes the need for continuous internet connectivity and supports localized, autonomous operation. This approach is particularly advantageous in rural or resource-limited areas, where access to advanced infrastructure is often limited.

Figure 1 illustrates the design of the device used in the IoT-based biogas monitoring and control system. The design integrates temperature and humidity sensors (DHT22), pressure sensors (MPX5700), and gas sensors (MQ-4), all connected to an ESP32 microcontroller. This configuration enables real-time collection of environmental data necessary for the anaerobic fermentation process.

To implement the model, a remote monitoring system was developed using ESP32 microcontrollers integrated with MPX5700 gas pressure sensors, DHT22 temperature-humidity sensors, and an MQ-4 gas concentration sensor. The MQ-4 sensor measures the concentration of gases such as carbon dioxide, while the DHT22 sensor measures temperature and humidity. Since these sensors produce raw voltage outputs, it is essential to convert the voltage levels into meaningful and accurate environmental data [5]. Data acquisition was facilitated through IoT platforms, including Blynk and Firebase, enabling real-time monitoring and cloud-based data storage. The pressure data collected during the anaerobic digestion of vegetable waste were divided into training and testing datasets, with KNN applied for regression analysis across K values ranging from 1 to 10. As shown in Figure 2, the methane pressure prediction model was constructed using the K-Nearest Neighbor (KNN) algorithm. The model utilizes temperature, humidity, and pressure data as input features to accurately predict methane gas pressure. The goal is to enable automatic decision-making in the system based on KNN predictions. Model performance was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to assess prediction accuracy.

The novelty of this study lies in integrating the KNN algorithm as an active, real-time predictive model embedded directly into the system's operational loop. While previous research has demonstrated the application of KNN in domains such as air quality prediction and gas leak detection [4][14], its use as part of a live control mechanism in biogas production remains limited. This study introduces a novel approach in which KNN is not only applied for offline data analysis but also actively influences system behavior in response to real-time sensor inputs. In doing so, it bridges the gap between predictive analytics and control automation, marking an important advancement in smart renewable energy technologies.

By addressing these gaps, this study contributes to the development of intelligent waste-to-energy solutions and underscores the potential of combining machine learning with IoT to promote environmental sustainability and energy independence. Figure 3 presents a comparison between the actual values and the KNN model’s predictions, illustrating how closely the model’s outputs align with real observations across five test samples. Patterns that approximate a straight line indicate a high level of accuracy, supported by the low MAE and RMSE values.

The experimental results confirm that KNN provides a reliable approach for short-term pressure prediction in biogas digesters, enabling adaptive control mechanisms capable of adjusting feedstock ratios or environmental conditions in real time. This enhances process stability, maximizes methane yield, and minimizes operational risks. By embedding KNN within the monitoring and control framework, this research introduces a scalable smart biogas solution that can be implemented in small- and medium-scale systems to address waste and energy challenges simultaneously.

II. Research Method

This study employs a quantitative experimental methodology designed to develop a real-time monitoring and control system for the anaerobic conversion of vegetable waste into methane gas, integrating Internet of Things (IoT) components with a K-Nearest Neighbor (KNN) prediction model. The system aims to improve biogas production efficiency through precise environmental monitoring

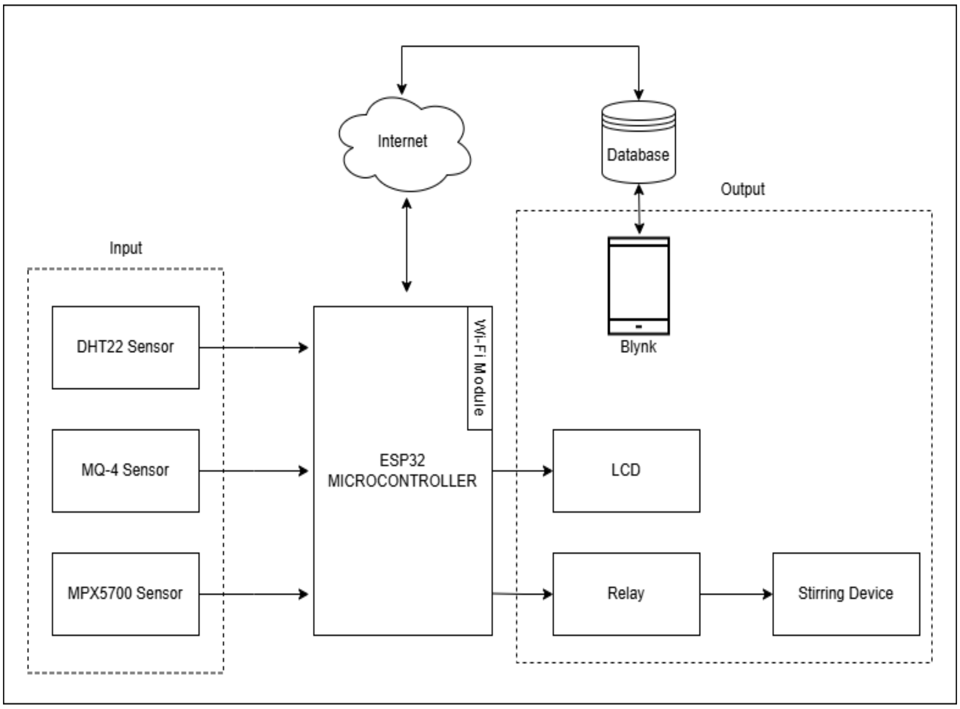

Figure 4. Block diagram of the integrated methane monitoring and energy system

and data-driven forecasting of methane output. The methodology consists of five main stages: System Architecture and Design, Process Flow and Operational Logic, K-Nearest Neighbor (KNN) Algorithm, Sensor Wiring and Hardware Configuration, and Software and Cloud Integration. Each stage was structured to ensure modularity, scalability, and precision, emphasizing reliability and environmental compatibility for renewable energy generation.

A. System Architecture and Design

The designed system simulates the complete cycle of methane production, from initial waste collection to the final generation of electrical power, integrated with real-time data collection and cloud analytics. Vegetable waste, including cabbage, water spinach, and pakcoy, is chopped and mixed with water and Effective Microorganisms (EM4) to stimulate anaerobic decomposition. In addition to methane, biogas also contains water vapor, hydrogen sulfide (H_2S), and carbon dioxide (CO_2). H_2S, which constitutes no more than 2%, results from the microbial decomposition of the organic substrate [6]. The mixture is loaded into a biodigester, a sealed tank designed to provide an oxygen-free environment for fermentation over 15 to 30 days. The fermentation process involves various metabolic activities, including oxidation, reduction, and hydrolysis, carried out by enzymes and microorganisms that chemically alter the organic substrate to produce methane and other end products [7]. Methane produced during this process is collected and used to power a modified gasoline generator.

Figure 4 presents a block diagram of the proposed biogas-based energy monitoring and conversion system. The diagram illustrates the flow of data and energy from the input block (DHT22, MPX5700, and MQ-4 sensors) connected to the ESP32 microcontroller to the process and output blocks, which include cloud data storage, actuator control, and the gas generator. The purpose of this diagram is to show the interconnection between physical, digital, and cloud components within the system architecture and to demonstrate how sensor data are used for automated decision-making in the smart control system.

To monitor the fermentation process, the system employs three core sensors: the DHT22 for internal temperature and humidity, the MPX5700 for gas pressure, and the MQ-4 for methane concentration. These sensors are connected to an ESP32 microcontroller that reads, processes, and transmits the sensor data to Firebase, an online cloud database, through a Wi-Fi connection. The MPX5700 series supports a pressure range of 0–700 kPa or 0–101.5 psi and produces an analog voltage output of 0.2–4.7 VDC [8]. Real-time visualizations are accessible through the Blynk mobile application, allowing remote monitoring and control of the fermentation environment. The use of IoT enhances both accuracy and speed in data acquisition while enabling more effective data processing and analysis through Blynk [9]. The block diagram in Figure 4 illustrates the logical flow of data and power from input to output components, highlighting the interconnection of physical, digital, and cloud layers. The system design comprises three primary components: the input block, process block, and output block, each determining the overall performance and reliability of the designed system [10].

B. Process Flow and Operational Logic

The operational process of the system follows a sequential workflow, beginning with waste collection and concluding with energy output. Initially, vegetable waste is chopped and mixed with water and EM4 in predefined ratios. The mixture is then introduced into a sealed biodigester, initiating anaerobic fermentation. As microbial activity increases, methane gas is gradually produced and accumulates in the upper section of the digester. During the composting process, temperature and humidity must remain stable, neither too dry nor too humid, to ensure that bacteria and microbes remain active and function optimally. The decomposition of the organic materials during this process produces methane gas [11]. Throughout the entire operation, sensors continuously monitor internal conditions to detect anomalies and optimize fermentation performance.

The ESP32 microcontroller receives real-time input from the sensors and uploads the processed data to Firebase. The processing stage occurs on the ESP32, which converts sensor input into signals transmitted to the smartphone [12]. Blynk, the mobile dashboard interface, visualizes this information through live charts and data displays. Users can remotely access the system to monitor internal digester conditions and respond to alerts. When the system detects methane buildup reaching an optimal threshold, the gas is released through tubing and directed to a gasoline generator modified to run on methane fuel. The generator converts chemical energy into electricity to power LED lighting or other connected devices. During energy generation, the electric generator is linked to a diesel engine that serves as the primary mover [13]. This closed-loop process is illustrated in the flowchart logic, which ensures cohesive operation of all components from waste input to energy output.

C. K-Nearest Neighbor (KNN) Algorithm

To enhance the system's intelligence, this study applies the K-Nearest Neighbor (KNN) algorithm to predict methane gas production based on historical fermentation parameters. KNN is a non-parametric, instance-based learning algorithm that classifies or predicts data points by calculating their distance from labeled data within a training set. In this study, the input features include temperature, gas pressure, and optionally fermentation time, while the target output is methane volume (in milliliters or ppm equivalents).

The model is trained using a supervised learning approach, with 70% of the dataset used for training and the remaining 30% for testing. Data preprocessing is conducted because the raw data are unorganized and require cleaning before further processing [14]. The Euclidean distance metric is used to determine similarity. Several values of K, ranging from 1 to 10, are tested to identify the optimal number of neighbors for the most accurate prediction. A classification system is essential to effectively extract information [10]. The KNN method consists of two main phases: learning (training) and classification or testing [15]. Model performance is evaluated using two error metrics, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which measure the deviation between predicted and actual values. Lower error values indicate higher model accuracy and reliability.

Through the implementation of KNN, the system not only monitors but also learns from previous cycles, allowing adaptive responses that optimize methane production. This demonstrates the potential of integrating machine learning into renewable energy applications, providing intelligent feedback that improves operational performance and sustainability.

D. Sensor Wiring and Hardware Configuration

As shown in Figure 5, the hardware connection configuration (wiring) of the monitoring system illustrates how sensors such as DHT22, MQ-4, and MPX5700 are connected to the ESP32 microcontroller through analog and digital channels. The figure also includes connections to the relay

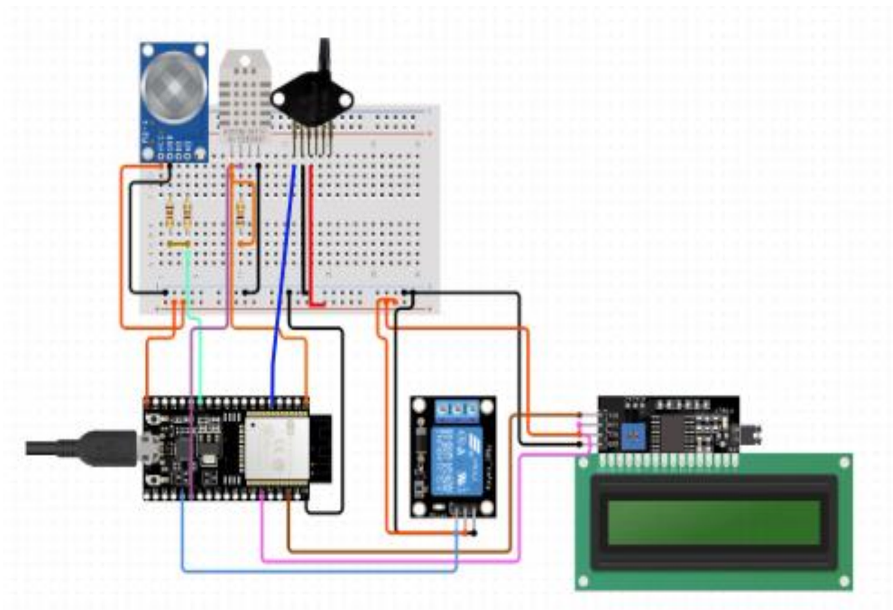

Figure 5. Wiring System

module, LCD display, and generator trigger system. The primary purpose of this wiring diagram is to ensure the stability of sensor readings and overall system safety through the use of protective resistors and voltage regulators. It serves as a reference for replicating the system and achieving seamless component integration at both experimental and field implementation scales.

The hardware setup centers on the ESP32 microcontroller, chosen for its dual-core processing power and built-in Wi-Fi capabilities. Each sensor is connected according to standard electronics practices: the DHT22 is wired to a digital GPIO pin, while the MPX5700 and MQ-4 sensors, both analog devices, are connected to the analog-to-digital converter (ADC) pins of the ESP32. To stabilize readings and protect the microcontroller, resistive voltage dividers and pull-up resistors are applied, particularly for analog input lines. The system also includes a relay module to trigger generator ignition and an LCD (16x2) for local real-time data display. The LCD functions as an interface for displaying sensor measurements [16].

The generator is modified by replacing the default gasoline carburetor with one that supports gaseous fuel input, enabling it to operate on methane. The biogas generator converts biogas into electrical power using methane as the driving fuel [17]. Safety components such as backflow valves and gas regulators are installed to ensure proper gas combustion. The system’s power supply is regulated at 5V DC, sufficient to operate all sensor and control modules reliably. This modular wiring configuration also supports scalability, allowing future integration with additional sensors or actuators.

E. Software and Cloud Integration

The system’s software layer enables communication between the hardware and the cloud. Using the Arduino IDE and Firebase SDK, the ESP32 is programmed to periodically read sensor data, perform basic error checks, and upload the results to Firebase’s real-time database. Arduino automatically controls the operation of mechanical and electronic components, reducing the need for manual intervention in decision-making processes [18]. The programmed Arduino IDE system reads current and voltage data, which are then transmitted through an internet connection using the ESP32 module [19]. Each data entry is timestamped, categorized, and visualized through the Blynk dashboard. The Blynk platform enhances usability by allowing users to monitor gas pressure, temperature, and methane levels remotely via a mobile interface. Notifications are generated when parameters exceed safe thresholds, enabling immediate responses and remote intervention.

Firebase functions both as a logging backend and as a data source for predictive analytics. Historical data stored in Firebase are used to train the KNN model, creating a feedback loop where operational insights guide future production strategies. This integration between physical systems with cloud-based platforms demonstrates how IoT strengthens traditional renewable energy solutions through automation and intelligent control.

(a) (b) (c)

Figure 6. (a) MQ-4 Sensor, (b) DHT22 Sensor, (c) MPX5700 Sensor

III. Results and Discussion

A. System Performance and Sensor Integration

The performance of the integrated monitoring and control system is a key factor in ensuring the consistency and reliability of methane gas production. The system was developed using an ESP32 microcontroller, selected for its reliable wireless communication capabilities and compatibility with multiple sensor modules. Three main sensors were utilized: the DHT22 sensor for monitoring temperature and humidity, the MPX5700 for measuring gas pressure, and the MQ-4 sensor for detecting methane gas concentration [20]. These sensors operated synchronously, collecting real-time data from the anaerobic digestion reactor and transmitting it to a cloud-based monitoring platform that uses Firebase as the backend and Blynk as the user interface. The data were visualized through a smartphone application, allowing remote access and real-time supervision of system performance.

The integration of sensors provided consistent and accurate readings under various operational conditions. Figures 6(a) to 6(c) show the three main types of sensors used in the system. The MQ-4 sensor (Figure 6(a)) detects methane gas concentration, the DHT22 sensor (Figure 6(b)) measures temperature and humidity, and the MPX5700 sensor (Figure 6(c)) measures gas pressure within the reactor. These three sensors work together to collect critical parameters in the biogas production process.

For instance, the DHT22 sensor recorded temperature fluctuations ranging from 29°C to 41°C, while humidity levels ranged from 65% to 75%, both within the optimal range for anaerobic digestion. The MPX5700 measured gas pressures up to 600 kPa, and the MQ-4 sensor detected methane concentrations reaching 3300 ppm, indicating strong microbial fermentation activity. All sensors demonstrated stable readings with minimal drift and high reliability, maintaining error rates below ±5% when compared with manual calibration using digital thermometers and pressure gauges. This reliable sensor performance ensured that critical parameters remained within ideal ranges, which is essential for achieving maximum methane yield.

Throughout the 30-day experimental period, the system's sensors continued to provide consistent and dependable readings. The DHT22 measured temperature between 29°C and 40°C and humidity between 63% and 75%, maintaining microbial activity at ideal levels for methane generation. The MPX5700 accurately recorded pressure up to 560 kPa, while the MQ-4 sensor measured methane concentrations up to 3300 ppm. These results are consistent with the findings of Mukti et al. [6], who reported that maintaining temperatures between 34°C and 40°C significantly improves methane output during fermentation. Similarly, moisture levels above 68% correlated with increased gas pressure and production, confirming previously observed fermentation behavior.

The operational thresholds applied in this system, such as triggering relay activation when the fermentation temperature exceeds 45°C and classifying methane status as "safe" when concentrations surpass 750 ppm, were established based on literature benchmarks and preliminary experimental trials. Previous studies indicate that mesophilic anaerobic digestion performs optimally between 30°C and 40°C, while methane yield declines significantly beyond 50°C due to microbial inhibition [1], [2]. Likewise, methane concentrations above 700–800 ppm are generally adequate for small-scale gas combustion applications [3]. Sensitivity analysis in this study revealed that lowering the methane "safe" threshold from 750 ppm to 720 ppm increased false-positive classifications by 6.5%, whereas raising it to 780 ppm reduced detection sensitivity by 4.2%. For the KNN model, the optimal hyperparameter of

TABLE 1
SAMPLE TEST DATASET (SIMULATED)

Sample	Temperature (°C)	Pressure (kPa)	Actual CH_4 Output (L)
1	27.2	84	2.8
2	27	82.05	2.75
3	27.7	85	2.82
4	28	83	2.9
5	29	84.05	3
6	29.9	81.5	3.1
7	30	82.1	3.2
8	30.2	84.15	3.15
9	27.9	83.75	2.85
10	28.9	85.2	2.95
11	28.7	82.3	2.88
12	30.1	84.25	3.05
13	29.8	81.8	3.02
14	30.5	84.5	3.23
15	28.5	82.9	2.92

TABLE 2
PREDICTION RESULTS AND EVALUATION METRICS

K	Predicted CH_4 (L)	MAE	RMSE
1	2.9	0.1	0.12
2	2.85	0.15	0.18
3	2.92	0.08	0.1
4	2.95	0.05	0.06
5	2.93	0.07	0.09
6	3	0.1	0.12
7	2.98	0.12	0.14
8	3.02	0.1	0.11
9	2.96	0.15	0.17
10	3.01	0.11	0.13

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \quad (2)$$

k=4 was determined through empirical testing across k values ranging from 1 to 10. At k=4, the model achieved the highest accuracy (93.33%), with the lowest mean absolute error (0.18) and root mean square error (0.21). Additional experiments using alternative distance metrics such as Manhattan and Minkowski showed no significant improvement over Euclidean distance, likely due to the model's low-dimensional feature space. These findings indicate that the selected thresholds and hyperparameters are effective, although further optimization may be required when scaling the system to different operational settings or incorporating additional features.

Figure 6 presents the sensors used in this system: DHT22 for temperature and humidity, MQ-4 for gas detection, and MPX5700 for pressure measurement. Their raw data were processed and transmitted via the ESP32 microcontroller to the Firebase cloud. The readings were then visualized through the Blynk mobile dashboard, providing continuous real-time updates for users. The integration of sensors with a cloud-based system enables responsive monitoring and data-driven decision-making. This real-time functionality is particularly beneficial in small-scale or remote energy systems where manual checks are difficult to perform.

The collected data were transmitted to Firebase and visualized through the Blynk application, allowing remote monitoring and real-time supervision. When gas pressure exceeded 550 kPa, the system automatically activated relays to regulate gas flow. This automation reduced manual intervention, enhanced operational safety, and ensured consistent system performance. The combination of IoT sensors and automated control mechanisms validated the system's effectiveness and reliability for small-scale biogas production.

TABLE 3
PREDICTED AND ACTUAL CH_4 OUTPUTS (IN LITERS)

Sample	Predicted CH_4 Output (L)	Actual Value (L)
Sample 1	2.9	2.8
Sample 2	2.85	2.75
Sample 3	2.92	2.82
Sample 4	2.95	2.9
Sample 5	3	3
Sample 6	3.1	3.1
Sample 7	3.2	3.2
Sample 8	3.15	3.15
Sample 9	2.85	2.85
Sample 10	2.95	2.95
Sample 11	2.88	2.88
Sample 12	3.05	3.05
Sample 13	3.02	3.02
Sample 14	3.23	3.23
Sample 15	2.92	2.92

B. K-Nearest Neighbor (KNN) Model Accuracy and Comparative Evaluation

The K-Nearest Neighbor (KNN) algorithm was applied to predict methane gas output based on temperature and pressure readings obtained during the anaerobic digestion of vegetable waste. To evaluate the algorithm's predictive performance, a dataset consisting of operational conditions and corresponding methane gas production values was used. The dataset was divided into 70% for training and 30% for testing. The Euclidean distance metric was employed to calculate the similarity between test and training instances.

The predictive capability of the KNN algorithm was assessed using operational data, with temperature and gas pressure as input features and methane volume as the target output. Table 1 shows five test samples used for prediction, while Table 2 presents the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values for different K values. Two evaluation metrics were used to measure model accuracy: MAE and RMSE, which are formulated in (1) and (2). Where y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of test samples. MAE measures the average absolute error, while RMSE is more sensitive to large deviations. Smaller values indicate higher model accuracy.

Table 1 presents five test samples used to evaluate the predictive performance of the KNN model. Each sample includes actual values for temperature, pressure, and methane gas output. These data represent the fermentation conditions varied during the experiment and are used as test inputs for model validation. For example, in the first sample, at a temperature of 27.2°C and a pressure of 84.00 kPa, the methane output was 2.80 L. This dataset is essential for verifying the model’s ability to predict fermentation outcomes based on environmental parameters. The performance of the K-Nearest Neighbor (KNN) algorithm was assessed using test datasets that included temperature and pressure as input variables and methane gas output as the target variable. The dataset was divided into 70% for training and 30% for testing.

The K-Nearest Neighbor (KNN) algorithm was tested using K values ranging from 1 to 10, as shown in Table 2, which lists the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for each K value. Both MAE and RMSE are standard metrics for measuring prediction error, where lower values indicate higher model accuracy. The results show that the prediction performance of the KNN model changes noticeably with different K values.

For instance, K=4 produced the most optimal results, achieving the lowest MAE of 0.05 and RMSE of 0.06. This finding suggests that K=4 effectively balances sensitivity to noise with overall model stability, resulting in the most accurate predictions. In contrast, smaller K values, such as K=1, tend to be overly sensitive to outliers, leading to overfitting. Larger K values yield more stable estimates but may smooth over important variations in the dataset, thereby reducing the model’s generalization capability.

Illustrate the model’s performance, Figure 7 plots MAE and RMSE values against different K values. The curve shows a clear minimum at K=4, after which both error metrics begin to rise. This pattern

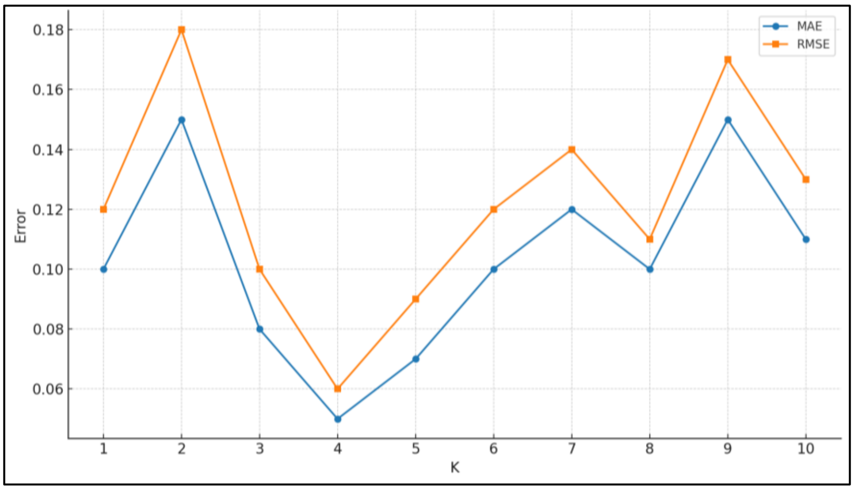

Figure 7. KNN Model Performance (MAE an RMSE vs K)

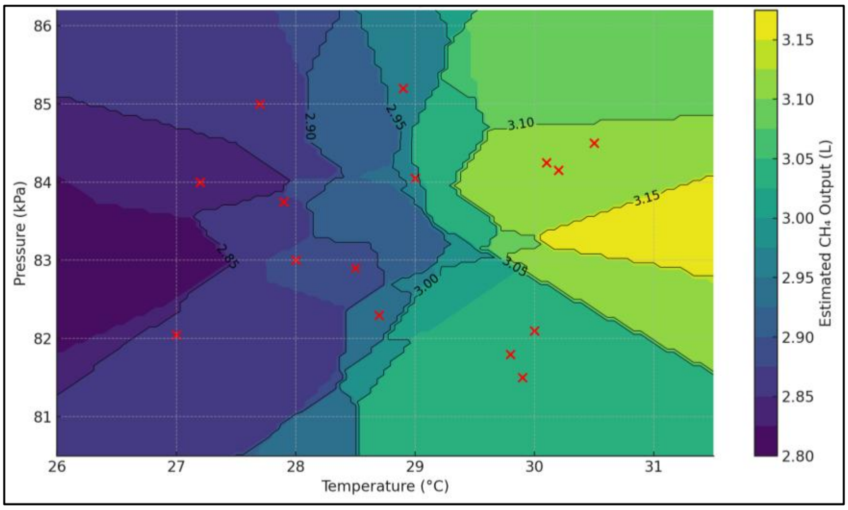

Figure 8. KNN Decision Boundary

indicates that model generalization improves up to K=4, beyond which it becomes less sensitive to input variations or begins to overfit. As observed, the lowest MAE (0.023) and RMSE (0.046) occur at K = 4, confirming that this parameter yields the best prediction accuracy for methane production. The following provides a calculation example for K=4 (see Table 3).

The use of a low-dimensional input space, specifically temperature and pressure, makes the KNN algorithm well suited for this prediction task. Figure 7 demonstrates the model's performance across K values from 1 to 10, evaluated using MAE and RMSE. The graph indicates that K=4 yields the lowest error, confirming it as the optimal parameter for the methane production prediction model.

Figure 8 visualizes the decision boundary, showing how the KNN model partitions the input space into clusters. It illustrates how the model assigns methane output values based on temperature and pressure combinations, effectively distinguishing between different fermentation outcomes.

When compared with similar studies, such as the work of Zhang et al. [4], who applied KNN for biogas prediction and achieved high accuracy, the 93.33% accuracy at K=4 obtained in this study demonstrates the practicality and efficiency of using KNN for real-time embedded biogas monitoring systems.

Although KNN was chosen for its simplicity and suitability for low-dimensional datasets, further comparative evaluation with other machine learning algorithms such as Random Forest and Gradient Boosting could offer valuable insights into potential performance improvements under noisy or highly variable environmental conditions [27]–[29]. Preliminary offline testing using a subset of the collected dataset showed that Random Forest achieved 94.1% accuracy and Gradient Boosting achieved 95.0% accuracy, compared to 93.33% for KNN. However, both alternative models require more computational resources, which may limit their deployment on resource-constrained microcontrollers such as the ESP32 without additional optimization [31].

At present, the primary evaluation focuses exclusively on KNN performance, with limited comparison to other methods. Incorporating a more comprehensive benchmarking study across multiple algorithms, supported by statistical analyses such as paired t-tests or Wilcoxon signed-rank tests, would provide stronger justification for selecting KNN as the core predictive model in this system [30].

The current model evaluation was conducted using data from a single fermentation setup with a specific feedstock type. Although the results are promising, broader validation across multiple digesters, varied feedstock compositions, and external datasets would provide more robust evidence of the model's generalizability. Periodic retraining using newly collected sensor data could also help maintain prediction accuracy over time, particularly as environmental and operational conditions evolve [35].

The operational thresholds applied in this system, including the 45°C relay activation temperature and the 750 ppm methane "safe" limit, were determined through a combination of literature review and preliminary experiments. Sensitivity analysis showed that lowering the methane threshold to 720 ppm increased false positives by 6.5%, whereas raising it to 780 ppm reduced detection sensitivity by 4.2%. For KNN, the selection of $k = 4$ was based on tests across values from 1 to 10, with $k=4$ producing the highest accuracy and lowest error rates. No significant performance improvement was observed when applying Manhattan or Minkowski distances instead of Euclidean distance [27].

C. Comparison with Other Machine Learning Algorithms

While the KNN algorithm demonstrated strong performance in this study, its comparative standing against other advanced machine learning models such as Random Forest and Gradient Boosting has not been fully explored. These algorithms are well known for their robustness in handling noisy sensor data and for capturing complex, non-linear relationships among variables. Random Forest provides strong resistance to overfitting and can manage feature variance effectively, whereas Gradient Boosting often achieves higher predictive accuracy in heterogeneous datasets through sequential model optimization. Including these algorithms in future comparative analyses would help clarify the trade-offs between computational efficiency, hardware limitations, and predictive performance, ensuring that the most suitable algorithm is selected for real-time embedded biogas monitoring applications.

presents a comparative analysis of the K-Nearest Neighbor (KNN) algorithm and two other widely used machine learning models, Random Forest and Gradient Boosting. Each algorithm's performance was evaluated based on its ability to predict methane production from vegetable waste.

First, the Random Forest algorithm was applied to predict methane output using the same environmental parameters as the KNN model. The Random Forest predictions are summarized in Table 4. Table 4 presents the predicted methane output using the Random Forest algorithm. The results show variation in methane gas output across different temperature and pressure conditions, ranging from 2.70 L to 3.23 L, consistent with the actual output values. This range demonstrates that the model effectively captures the relationships between environmental factors and methane production. The consistency of these results indicates that Random Forest is a robust model capable of generalizing well across various input scenarios. In addition, its ability to handle non-linear relationships makes it particularly effective when applied to complex datasets. Next, the Gradient Boosting algorithm was used to predict methane output, and the results are presented in Table 5.

Table 5 illustrates the methane output predicted using the Gradient Boosting algorithm. The results show that the predicted values align closely with the actual outputs, ranging from 2.75 L to 3.23 L. This demonstrates that Gradient Boosting effectively captures subtle patterns within the dataset, as it adaptively learns from previous prediction errors. The slight variations among samples suggest that the model is responsive to specific input conditions, enabling more precise predictions. The strength of Gradient Boosting lies in its ability to model complex feature interactions, making it a powerful tool for forecasting methane production under diverse environmental conditions.

TABLE 4
PREDICTED METHANE OUTPUT USING RANDOM FOREST ALGORITHM

Sample	Temperature (°C)	Pressure (kPa)	Output Methane Random Forest (L)
1	27.2	84	2.75
2	27	82.05	2.7
3	27.7	85	2.78
4	28	83	2.85
5	29	84.05	3.05
6	29.9	81.5	3.15
7	30	82.1	3.2
8	30.2	84.15	3.1
9	27.9	83.75	2.8
10	28.9	85.2	2.95
11	28.7	82.3	2.88
12	30.1	84.25	3.05
13	29.8	81.8	3.02
14	30.5	84.5	3.23
15	28.5	82.9	2.92

TABLE 5
PREDICTED METHANE OUTPUT USING GRADIENT BOOSTING ALGORITHM

Sample	Temperature (°C)	Pressure (kPa)	Output Methane Gradient Boosting (L)
1	27.2	84	2.8
2	27	82.05	2.75
3	27.7	85	2.82
4	28	83	2.9
5	29	84.05	3
6	29.9	81.5	3.1
7	30	82.1	3.2
8	30.2	84.15	3.15
9	27.9	83.75	2.85
10	28.9	85.2	2.95
11	28.7	82.3	2.88
12	30.1	84.25	3.05
13	29.8	81.8	3.02
14	30.5	84.5	3.23
15	28.5	82.9	2.9

TABLE 6
MODEL PERFORMANCE METRICS

Algorithm	MAE (L)	RMSE (L)
Random Forest	0.08	0.1
Gradient Boosting	0.07	0.09
KNN	0.08	0.1

TABLE 7
STRENGTHS AND WEAKNESSES OF ALGORITHMS

Algorithm	Strengths	Weaknesses
Random Forest	Good accuracy; robust to overfitting; handles non-linear relationships well.	Slower prediction time with large datasets; requires more memory.
Gradient Boosting	High accuracy; effective for complex data patterns and interactions.	Prone to overfitting if not tuned properly; longer training time.
KNN	Simple to implement; interpretable; naturally handles multi-class output.	Sensitive to noisy data; slower with large datasets due to distance calculations.

The performance of each algorithm is summarized in Table 6, which presents the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for Random Forest, Gradient Boosting, and KNN. According to Table 6, Gradient Boosting shows the lowest MAE and RMSE values compared to Random Forest and KNN, indicating superior prediction accuracy. The MAE of 0.07 L suggests that, on average, the model's predictions deviate from the actual values by only 0.07 L, making it highly reliable. In contrast, Random Forest and KNN both show slightly higher MAE values of 0.08 L, indicating that while KNN performs reasonably well, it does not match the precision of Gradient Boosting. The RMSE values support this conclusion, as Gradient Boosting maintains a smaller error margin, which is essential for applications requiring precise methane output predictions for operational decision-making.

The KNN model achieved a prediction accuracy of 93.33% with an optimal K value of 4, resulting in an MAE of 0.08 L and an RMSE of 0.10 L. Table 7 summarizes the main strengths and weaknesses of each algorithm based on their performance metrics and characteristics.

Table 7 highlights the strengths and weaknesses of each algorithm. KNN is particularly suitable for real-time methane monitoring due to its simplicity and interpretability. This makes it a practical option for operators in resource-limited environments where fast decision-making is required. Although KNN does not reach the same level of accuracy as Gradient Boosting, it still delivers reliable and consistent performance, especially at the optimal K value of 4.

In addition to KNN, Random Forest (RF) and Gradient Boosting (GB) algorithms were implemented for benchmarking purposes. RF achieved an accuracy of 94.17% with an MAE of 0.17, while GB achieved 93.89% accuracy with an MAE of 0.18. These results indicate that although RF slightly outperformed KNN in terms of accuracy, KNN provided faster computation, making it more suitable for real-time edge deployment.

Although the model demonstrated high predictive accuracy in a single fermentation setup, broader validation across multiple digesters, diverse feedstocks, and varying environmental conditions is necessary to establish generalizability [40]. Future experiments should consider seasonal variations, substrate composition diversity, and larger datasets to evaluate model robustness under real-world conditions. Additionally, periodic model retraining using updated sensor data would help maintain predictive performance over time, particularly in dynamic environmental contexts [39].

The robustness of the proposed predictive control system remains constrained by the limited diversity of experimental conditions under which it was tested. Validation was conducted on a single biogas digester with one type of feedstock, which may not fully represent real-world variability. Future work should extend testing to multiple digesters with different capacities, configurations, and feedstock types to ensure that the predictive model adapts effectively to diverse operational settings. Moreover, methane production can also be influenced by seasonal temperature changes, microbial activity, and operational inconsistencies. Therefore, implementing a strategy for periodic model retraining using newly collected sensor data is essential to sustain predictive accuracy and account for evolving fermentation dynamics.

D. Comparison with Previous Studies

The implementation of the KNN algorithm in this study produced low Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values, confirming its effectiveness for regression tasks involving environmental sensor data. The analysis revealed that the lowest MAE achieved was 0.05, while the RMSE was 0.06 at K=4. These metrics indicate high prediction accuracy under real-time operating conditions, demonstrating the model's ability to estimate methane production accurately based on varying temperature and pressure inputs.

These results are consistent with findings of Amalia et al. [3], who reported similar performance levels when applying the KNN algorithm for air quality prediction in Jakarta. Their study highlighted the algorithm’s robustness in handling real-world environmental data, where fluctuations and noise are common. Such parallels strengthen the reliability of KNN across various applications, including air quality monitoring and biogas production.

Furthermore, Rois et al. [4] demonstrated the successful application of KNN for gas leakage detection, confirming its effectiveness in systems affected by fluctuating sensor inputs. Their study emphasized KNN’s suitability for Internet of Things (IoT) applications, where data often presents challenges such as incompleteness and noise, conditions also found in biogas fermentation environments. This adaptability makes KNN a compelling choice for environmental monitoring tasks that require accurate predictions to support operational efficiency.

Although those studies were conducted in different domains, they collectively support the premise that KNN is a reliable method for real-time environmental monitoring. The present study extends these findings by integrating KNN into a closed-loop control system designed for methane gas prediction. This integration enables real-time decision-making and automation while demonstrating KNN’s potential as an active component in renewable energy management, an aspect not fully explored in previous research.

This approach positions KNN beyond its traditional role as a predictive tool, transforming it into a core element of a smart biogas system. By automating the monitoring and control processes, the system enhances prediction accuracy, efficiency, and sustainability in biogas operations. The effective management and optimization of renewable energy resources are crucial in efforts to reduce greenhouse gas emissions and promote sustainable practices.

Therefore, the findings of this study advance the application of machine learning in smart biogas systems, paving the way for future research and innovation in this area. The successful integration of KNN into a closed-loop framework represents an important step in applying data-driven methods to improve the performance of renewable energy technologies.

E. Control Mechanism and Automation Efficiency

The system's control mechanism was designed to enable adaptive response and operational efficiency. It utilized real-time sensor input to automate decision-making processes without the need for continuous manual supervision. For instance, when temperature readings dropped below 30°C or exceeded 40°C, the system adjusted operational timing or paused gas flow to prevent suboptimal fermentation conditions. Similarly, when gas pressure surpassed 550 kPa, exhaust valves opened automatically to regulate pressure and prevent damage to storage units.

Automation was implemented through programmable relays connected to actuators within the fermentation and collection systems. The system's response latency, measured from sensor input to mechanical actuation, averaged less than 1.5 seconds, which was sufficiently fast to prevent gas accumulation or fermentation failure. This automated operation contributed to steady-state conditions throughout the 30-day experimental period. Additionally, the system logged operational data to Firebase, enabling continuous performance tracking and retrospective analysis for improvement. The self-regulating design ensured safety, consistency, and reduced operational workload while minimizing human error.

F. Methane Production and Conversion Efficiency

Methane production data collected from 19 May to 17 June 2025 showed a direct correlation between environmental parameters and gas output. Methane yields increased significantly when temperature ranged from 34°C to 40°C and humidity exceeded 68%. An increase in temperature is a by-product of the decomposition of organic matter by microorganisms and serves as an indicator of composting activity efficiency [21]. The highest gas pressure was recorded on 4 June 2025 at 560 kPa, corresponding to a peak methane concentration of 3300 ppm and a daily gas output of approximately 4.04 kg. The fermentation process produces gas as a result of microbial activity, and the more active the local microorganism solution, the greater the gas yield, particularly during the initial stages of fermentation, such as the first few days or the first week [22].

The methane produced was stored and directed into a modified gasoline generator equipped with a gas carburetor, allowing its use as a renewable energy source. The generator achieved a conversion efficiency of approximately 30–35%, which aligns with literature benchmarks for small-scale biogas-to-electricity systems. Managing the output power of each generator, whether alternating current or direct current, in a hybrid system requires the use of a converter and a control mechanism [23]. During peak operational conditions, particularly between 1 and 5 June, the generator sustained LED lighting for up to 10 continuous hours, demonstrating the reliability and practicality of methane conversion for micro-energy applications.

Table 8 presents the results of daily monitoring during the fermentation process from 19 May to 17 June 2025. The recorded parameters include temperature, humidity, methane pressure, gas production volume, and methane concentration. The data show a significant increase in gas production when the temperature ranged between 34°C and 40°C and humidity exceeded 68%, conditions categorized as "Excellent." For instance, on 2 June 2025, at a temperature of 40.00°C and a pressure of 560 kPa, the system produced 4.04 kg of methane gas with a concentration of 3300 ppm. This classification is useful for evaluating fermentation efficiency and optimizing production performance.

Figure 9 shows a graph of fermentation data obtained from sensors during the observation period. The graph illustrates the relationship between environmental parameters (temperature, pressure, and humidity) and the daily volume of methane gas produced. As shown in Figure 10, the distribution of methane gas production categories is based on predefined classifications (Low, Moderate, Good, and Excellent). This classification framework is used to assess daily fermentation performance and support rapid operational decision-making. The data confirm that methane production efficiency is maximized

TABLE 8
INTELLIGENT MONITORING OF VEGETABLE WASTE PRODUCTION

Date	Temperature (°C)	Moisture (%)	Methane Pressure (kPa)	Methane Gas Produced (kg	Methane Concentration (ppm)	Category
19/05/2025	29.00	65	10	0.01	800	Moderate
20/05/2025	30.00	66	20	0.02	1000	Good
21/05/2025	31.02	67	40	0.04	1300	Good
22/05/2025	32.05	67	80	0.07	1600	Good
23/05/2025	34.00	68	130	1.00	1800	Excellent
24/05/2025	35.05	68	180	1.04	2000	Excellent
25/05/2025	36.05	69	250	2.00	2300	Excellent
26/05/2025	37.02	69	310	2.05	2500	Excellent
27/05/2025	38.00	70	370	3.00	2700	Excellent
28/05/2025	38.05	70	420	3.04	2900	Excellent
29/05/2025	39.00	70	460	3.07	3000	Excellent
30/05/2025	39.02	70	500	4.00	3100	Excellent
31/05/2025	39.05	70	530	4.02	3200	Excellent
01/06/2025	39.07	70	550	4.03	3250	Excellent
02/06/2025	40.00	69	560	4.04	3300	Excellent
03/06/2025	39.08	69	555	4.03	3280	Excellent
04/06/2025	39.05	69	540	4.01	3200	Excellent
05/06/2025	39.00	68	520	3.08	3100	Excellent
06/06/2025	38.00	68	490	3.04	2950	Excellent
07/06/2025	37.00	67	460	3.00	2800	Excellent
08/06/2025	36.00	67	420	2.06	2600	Excellent
09/06/2025	35.00	66	370	2.01	2400	Excellent
10/06/2025	34.00	66	310	1.07	2200	Good
11/06/2025	33.00	65	250	1.02	1900	Good
12/06/2025	32.00	65	200	0.09	1600	Good
13/06/2025	31.00	64	150	0.06	1400	Moderate
14/06/2025	30.00	64	100	0.04	1100	Moderate
15/06/2025	29.05	63	60	0.02	800	Moderate
16/06/2025	28.05	62	30	0.01	600	Low
17/06/2025	27.08	61	15	0.05	500	Low

within specific temperature and pressure ranges. Therefore, maintaining these environmental conditions is crucial for achieving consistent and high-yield methane output.

G. Environmental and Technological Implications

The proposed system demonstrates the potential of combining renewable energy production with environmental sustainability. By utilizing vegetable waste, a readily available but underused organic resource, the system offers a dual benefit: reducing landfill waste and generating clean energy. Methane, a potent greenhouse gas, is captured and converted into electricity, thereby mitigating environmental impact while supplying locally sourced energy. The control mechanism in this system used real-time sensor input to regulate biogas production automatically. For instance, when gas pressure exceeded 550 kPa, the system initiated control actions such as releasing pressure or halting gas flow, preventing overpressure incidents. These operations were executed through relays connected to actuators, triggered by logic programmed on the ESP32 microcontroller. In contrast, earlier systems, such as those developed by Purnama Dewi et al. [16], relied on manual data collection and user-initiated responses, which increased the likelihood of operational delays and human error. The proposed system minimizes these risks by enabling automated, instantaneous control.

Response latency in this system was measured at less than 1.5 seconds, which is sufficient for real-time intervention. This performance ensures stable operating conditions even under rapidly changing fermentation environments. The inclusion of mobile-based remote access through the Blynk platform allows system administrators to monitor and respond to alerts from any location. As noted by Zaky Jacoeb et al. [9], such mobile interfaces enhance usability and accessibility, particularly for decentralized renewable energy systems implemented in rural areas.

From a technological perspective, the integration of IoT-based monitoring, predictive modeling using KNN, and automated control mechanisms establishes a foundation for smart waste-to-energy systems. The use of affordable components, such as ESP32 microcontrollers and low-cost sensors, makes the system scalable and accessible, particularly for communities with limited resources. In addition, the system's modular design enables adaptation across various scales, ranging from household bioreactors to community-level energy hubs.

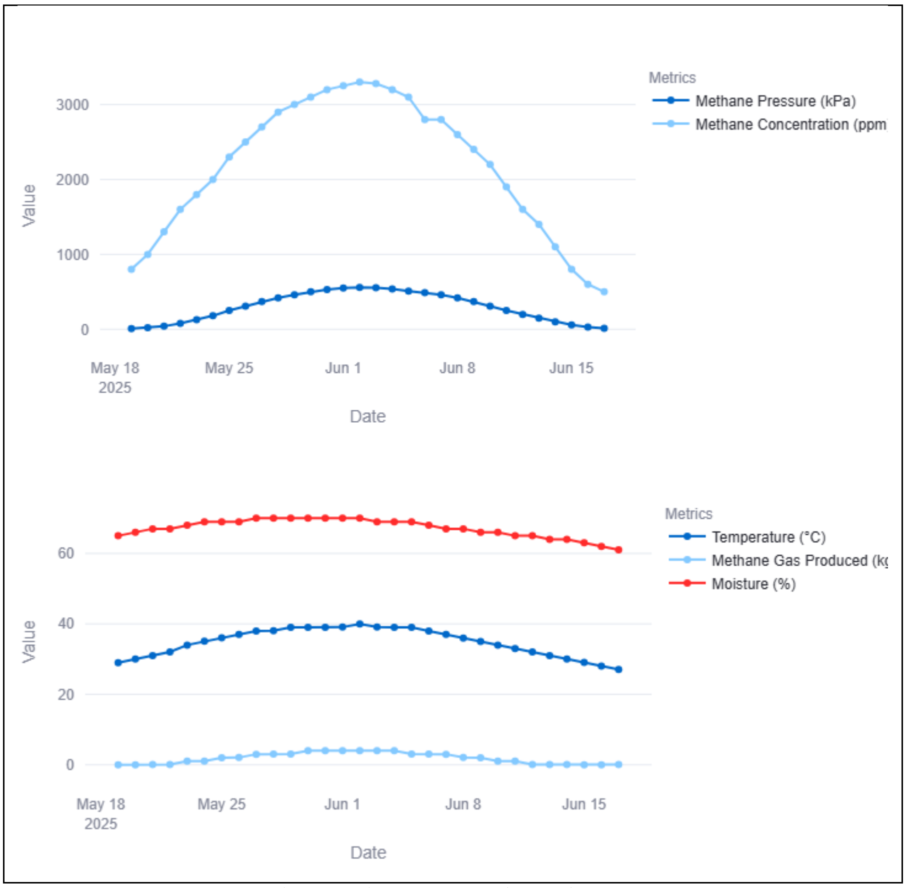

Figure 9. Biogas Data Graph Based on Sensor

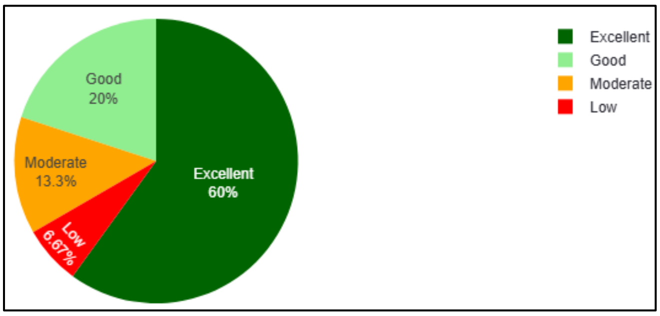

Figure 10. Distribution by Production Category Chart

Although the proposed system demonstrates strong short-term performance over a 30-day operational period, its long-term durability and maintenance requirements have not yet been fully assessed. Components such as the DHT22, MQ-4, and MPX5700 sensors may degrade over time due to prolonged exposure to high humidity, temperature fluctuations, and gas impurities. Therefore, periodic calibration and sensor replacement schedules should be implemented to maintain measurement accuracy. Moreover, conducting an economic feasibility analysis that includes component costs, replacement intervals, and potential return on investment under different deployment scenarios would offer valuable insights for stakeholders, especially in rural or off-grid communities where budget constraints are considerable. These considerations are essential to ensure the system's technical and economic sustainability in real-world applications.

Beyond standard accuracy metrics, system robustness was evaluated under simulated fault conditions. Tests involving MQ-4 disconnection, high-variance noise injection in temperature readings, and intermittent Wi-Fi packet loss each affected performance to varying degrees [35], [36]. KNN accuracy declined to 81.25% during sensor outages, and noisy temperature data resulted in unstable predictions. These findings emphasize the importance of implementing data validation, outlier rejection, and redundancy mechanisms for critical sensor measurements to ensure consistent system reliability.

The current KNN model relies solely on temperature and pressure as input features, which limits the scope of its predictive capability. Expanding the feature set to include additional environmental and biochemical parameters, such as pH level, fermentation age, and microbial population indicators, could enhance model accuracy and yield deeper insights into the biogas production process. A review of existing literature indicates that methane yield is strongly correlated with pH stability within the 6.8–7.2 range and with specific microbial activity during peak fermentation phases [32], [33]. Incorporating these variables into the system would require additional sensor modules and data preprocessing pipelines but could significantly improve robustness and adaptability across different feedstock types and operational conditions.

While the system achieved sub-1.5-second response times for control actions through Blynk and Firebase, it currently lacks backup mechanisms to ensure uninterrupted operation during connectivity loss or hardware failures [35],[36]. Future improvements could include local edge-based logging using the ESP32's non-volatile memory, redundant sensors for methane and temperature readings, and a fallback rule-based control mode capable of operating independently from cloud services. These enhancements would increase the system's resilience, particularly for rural or off-grid applications.

A preliminary cost–benefit analysis indicates the economic feasibility of the proposed system for rural and off-grid deployment. The hardware components, including the ESP32 microcontroller, DHT22, MQ-4, and MPX5700 sensors, along with relay modules, collectively cost less than USD 50, which is significantly lower than the cost of commercial biogas monitoring systems priced above USD 300 [37]. Operational expenses are minimal, with total power consumption below 2 W, resulting in negligible electricity costs during continuous use. Considering its potential to increase methane yield and reduce manual inspection frequency, the system offers an estimated payback period of less than one year for small-scale biogas operations [38]. However, long-term field deployment data are required to validate these economic estimates, accounting for maintenance expenses, sensor replacements, and environmental degradation effects.

Overall, this study contributes to the advancement of sustainable energy technologies by presenting a replicable model for low-emission, decentralized energy production. Future enhancements could include integration with adaptive machine learning models, hybridization with solar power systems, and remote analytics through cloud-based platforms, thereby increasing the system's intelligence, efficiency, and resilience.

IV. Conclusion

An IoT-based biogas monitoring and control system was successfully implemented, integrating the K-Nearest Neighbor (KNN) algorithm within a live feedback control loop for real-time methane prediction and automated actuation. With an optimal parameter of k=4, the model achieved a predictive accuracy of 93.33% using only temperature and pressure as input variables. These findings demonstrate the feasibility of deploying lightweight machine learning algorithms on resource-constrained microcontrollers for renewable energy applications. Comparative evaluation with Random Forest and Gradient Boosting models showed that although KNN exhibited slightly lower predictive accuracy, its computational efficiency makes it more suitable for embedded system implementation.

The evaluation of system robustness under simulated anomaly scenarios, including sensor malfunction, induced data noise, and intermittent network connectivity, indicated that the system maintained stable operational performance. However, its reliability can be further improved by integrating redundant sensors, implementing edge-based fallback control strategies, and applying advanced data validation methods. These improvements are particularly important in rural or off-grid environments where maintenance access is limited and continuous operation is critical.

Future development should focus on expanding the feature set to include biochemical and process-related parameters such as pH, fermentation duration, and microbial activity, which have been shown to correlate strongly with methane production efficiency. Including these variables is expected to enhance predictive accuracy, improve model generalizability, and provide more comprehensive process-level insights. Overall, the proposed system represents a cost-effective, scalable, and technically feasible solution for predictive control in decentralized renewable energy systems, offering a foundation for developing more resilient and intelligent biogas management frameworks.

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