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Predicting Biogas Quality for Renewable Energy System: An Implementation of Gaussian Naïve Bayes Classifier

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Abstract — **The utilization of organic household waste for biogas production presents a promising alternative energy solution; however, it is often limited by the lack of intelligent monitoring and control systems. This study proposes the design and implementation of an Internet of Things (IoT)-based monitoring and control system integrated with a Gaussian Naïve Bayes (GNB) algorithm to classify biogas quality in real time. The system employs an ESP32 microcontroller combined with a K-Type thermocouple sensor, MQ-4 and MQ-135 gas sensors, and an MPX5700 pressure sensor to collect environmental data during the biogas production process. A dataset consisting of 120 samples was collected and divided into training (80%) and testing (20%) sets. The GNB model classifies biogas into three categories: Good, Moderate, and Poor. Experimental results show that the model achieved an accuracy of 95.83%, with high precision and recall across all classes. The system also demonstrated an energy conversion efficiency of 33.3% when converting biogas into electrical energy to power a fan. These results indicate that the proposed system effectively integrates IoT and machine learning to automate and optimize biogas utilization, providing a scalable and cost-effective solution for renewable energy applications in community-based waste management systems.**

Keywords: Alternative Energy, Biogas Classification, Household Waste, Internet of Things (IoT), Gaussian Naïve Bayes.

I. INTRODUCTION

Human life is fundamentally dependent on energy, particularly when it comes to electricity for running domestic appliances. However, a major contributing factor to environmental degradation, particularly greenhouse gas emissions, is the strong reliance on fossil-based energy [1]. Because of this problem, a number of renewable energy sources have been created, including biogas, which is created by the anaerobic breakdown of organic waste [2][3]. Biogas's capacity to transform waste into clean, useable energy makes it a promising answer. The composition of waste based on its source is illustrated in Fig. 1, showing that household waste contributes the largest portion of total waste generation.

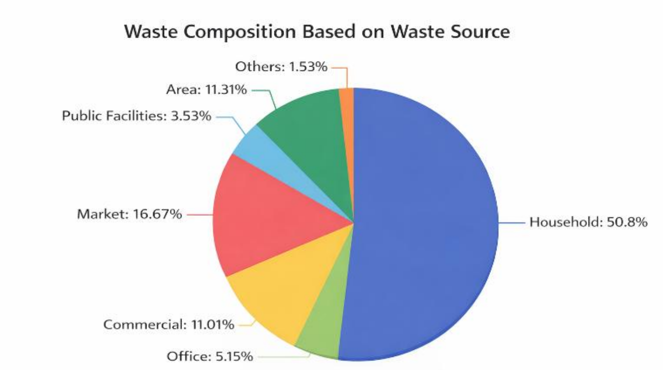

Fig. 1. Waste Composition Based on Waste Source

The composition of waste based on its source is illustrated in Fig. 1, showing that household waste contributes the largest portion of total waste generation. According to the Ministry of Environment and Forestry's 2024 report, Indonesia generated approximately 33.7 million tons of waste, with 50.8% originating from households. A significant portion 40.06% remains unmanaged, contributing to environmental degradation and public health issues [4]. Most of this waste consists of biodegradable materials that can be converted into biogas [5]. Recent studies have highlighted the effectiveness of machine learning approaches in improving biogas production prediction and quality assessment [6][7]. However, the integration of real-time monitoring with intelligent classification systems remains limited. Notwithstanding this promise, domestic biogas utilization is still in its infancy. The absence of systems capable of intelligently monitoring and evaluating the usability of biogas prior to its distribution to end-use devices is a significant restriction.

Due to its active involvement in community-based waste management, the TPST 3R Mulyoagung in Malang Regency was chosen as the research's pilot site. Even though the facility hasn't developed or used biogas usage before, it offers a perfect setting for investigating the conversion of organic waste from homes into sustainable energy. By starting the design, construction, and testing of an on-site biogas system, this study presents a novel strategy for the TPST. The goal of this project is to show a workable and replicable strategy for small-scale waste-to-energy conversion in comparable community facilities by integrating biogas processing into the TPST's operational framework [8].

The growth of the Internet of Things (IoT) makes it possible to use a variety of sensors coupled with microcontrollers like the ESP32 to monitor the environment in real time. Continuous data collection on gas properties, such as temperature, pressure, carbon dioxide content, and methane concentration, is made possible by these technologies. IoT offers a basis for monitoring, but for it to be fully successful, it needs to be combined with an intelligent decision-making system. The Gaussian Naïve Bayes (GNB) classification algorithm, in particular, is a key component of machine learning in this situation. Based on Bayes' Theorem, GNB is a probabilistic classifier that works well with datasets that have continuously distributed, normally distributed characteristics [9][10]. Based on sensor data, GNB is employed in this study to categorize biogas quality into three groups, namely Good, Moderate, and Poor. The classification outcome establishes whether biogas should be restricted to avoid wasteful use or permitted to flow to a generator for energy conversion. The gas is directed to a generator that runs a fan system if it is deemed "Good" or "Moderate". The mechanism immediately closes the gas valve if it is deemed "Poor."

The system has been connected with the Blynk IoT platform to enable remote monitoring and user engagement. Through a mobile application, users may monitor biogas metrics and categorization status. By increasing total energy efficiency and decreasing reliance on fossil fuels, this intelligent control system seeks to make biogas a more reliable domestic energy source [11][12].

By integrating IoT-based sensing, AI-powered classification, and automated actuator control for sustainable energy use, this research offers a novel paradigm. The suggested method is inexpensive, scalable, and simple to put into practice, especially in rural and semi-urban areas where access to energy may be erratic or limited. Additionally, it encourages community members to actively participate in trash management and increases household awareness of the adoption of renewable energy [13].

II. METHODS

This study employed an experimental research design aimed at developing and testing a smart monitoring and controlling system for utilizing household waste-derived biogas as an alternative energy source for a water heater. The system integrates multiple sensors, an ESP32 microcontroller, and machine learning (Naïve Bayes algorithm) to classify biogas quality and automate energy conversion through a biogas-powered generator.

A. Type of Research

Using a quantitative methodology, this research is an applied experimental investigation. The accumulation of organic waste in the home and the demand for reasonably priced, renewable energy sources for domestic use more especially, supporting a fan system were the real-world problems it was intended to solve. The designed system converts garbage to biogas, using the Gaussian Naïve Bayes algorithm to classify the gas quality, and determines whether the biogas is suitable for powering a fan-connected generator.

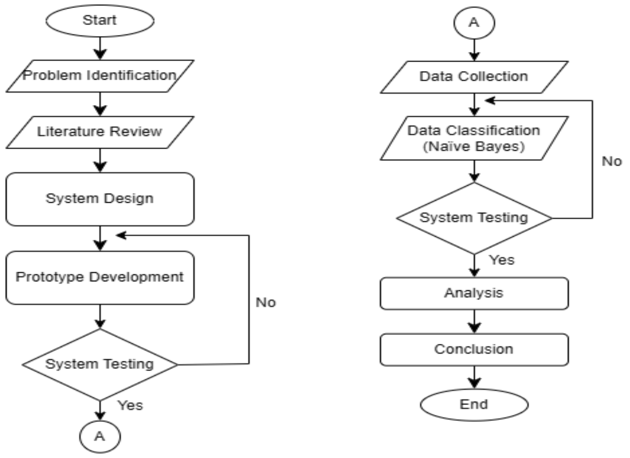

Fig. 2. Research Framework and Workflow

Using an experimental approach, the research measures and analyzes sensor data in real-time, including temperature, pressure, and CO_2 and methane levels. The analysis's findings dictate system actions, like whether to permit the flow of biogas. At TPST 3R Mulyoagung, biogas produced on-site from a blend of cow dung and food waste was used for testing.

As the project involves the design and construction of a functional prototype, complete with sensors, a microcontroller, a valve, a generator, a fan, and mobile monitoring through the Internet of Things, it is also classified as developmental research. The system combines aspects of environmental sustainability, machine learning, and electronics to provide a workable, community-based solution.

B. Data Collection and Analysis

The dataset used in this study consists of 120 samples collected from real-time sensor measurements. Each data instance includes methane concentration (CH_4), carbon dioxide (CO_2), temperature, and pressure, along with the corresponding class label (Good, Moderate, or Poor). The dataset is divided into 80% training data (96 samples) and 20% testing data (24 samples). Real-time data collection utilizing sensors coupled to an ESP32 microcontroller is the first step in the biogas classification process. The MQ-4 sensor measures the concentration of methane (CH_4), the MQ-135 measures the levels of carbon dioxide (CO_2), the MAX6675 thermocouple measures the temperature, and the MPX5700 sensor measures the gas pressure. Every ten seconds, these readings are gathered and processed by the ESP32 directly. Prior to categorization, the raw data is transformed into standard units and filtered to eliminate noise, guaranteeing that it accurately depicts the gas conditions.

The classification task is performed using the Gaussian Naïve Bayes (GNB) algorithm, which is embedded in the ESP32 firmware due to its computational efficiency and suitability for continuous sensor data. GNB assumes that each feature follows a Gaussian distribution, and calculates the likelihood of feature x_i given class C_k using:

$$P(x_i|C_k) = \frac{1}{\sqrt{2\pi\sigma_k^2}} \exp\left(-\frac{(x_i-\mu_k)^2}{2\sigma_k^2}\right) \qquad (1)$$

The overall class probability is then computed as:

$$\hat{C} = \arg\max_{C_k} P(C_k) \prod_{i=1}^{n} P(x_i|C_k) \qquad (2)$$

where μ_k and σ_k^2 represent the mean and variance of each sensor feature within class C_k, and $P(C_k)$ is the prior probability of the class [14][15]. The system classifies the biogas into Good, Moderate, or Poor, based on sensor input, and the resulting classification is used to control the solenoid valve. If classified as Good, the valve opens fully to allow gas flow to the generator powering the fan. For Moderate biogas, the valve opens partially, while Poor biogas results in the valve remaining closed.

From sensing to actuation, the complete process is carried out in real time. The Blynk IoT smartphone application shows the classification findings and sensor data, enabling users to remotely monitor the system and get notifications when biogas is judged unfit for consumption. The classification criteria for biogas quality are presented in Table I.

TABLE I
BIOGAS QUALITY CATEGORY PER VARIABLE

Variable	**Range**	**Category**
CH_4 (ppm)	> 500	Good
	300 - 500	Moderate
	< 300	Poor
CO_2 (ppm)	< 400	Good
	400 - 700	Moderate
	> 700	Poor
Temperature (°C)	30 - 40	Optimal
	< 30 or > 40	Poor
Pressure (kPa)	10 – 30	Optimal
	< 10 or > 30	Poor

Sample training data used for model development is shown in Table II.

TABLE II
SAMPLE TRAINING DATA

CH_4 (ppm)	**CO_2 (PPM)**	**Temp (°C)**	**Pressure (kPa)**	**Class**
5500	12513	28.1	93.3	Poor
17500	22560	29.7	97.0	Poor
21700	25132	30.1	98.3	Moderate
39700	37078	31.8	103.9	Moderate
65500	48965	33.4	112.0	Good
72700	55604	34.3	114.2	Good

An example of testing data used for classification is presented in Table III.

TABLE III
DATA TESTING EXAMPLE

CH_4 (ppm)	CO_2 (PPM)	Temp (°C)	Pressure (kPa)	Class
500000	200000	33.5	115	?

The calculation results from the training data table can be used to classify the quality of the media testing table which is described using Equations (3).

$$\mu_k = \frac{1}{N}\sum_{i=1}^{N} x_i, \quad \sigma_k^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i-\mu_k)^2 \qquad (3)$$

Where:

- μ_k is the mean of a feature in class C_k
- σ_k^2 is the variance of the same feature
- N is the number of sample in class C_k

a) Step 1: Calculate the Mean (μ) and Variance (σ^2) for Each Feature in Each Class

From the training data in Table II, we calculate the mean and variance for each class (Good, Moderate, Poor) as follows:

- Good Class (2 sample)
  - CH_4: $\mu = \frac{650+700}{2} = 675$, $\sigma^2 = \frac{(650-675)^2+(700-675)^2}{2} = 625$
  - CO_2: $\mu = \frac{380+350}{2} = 365, \sigma^2 = 225$
  - Temp: $\mu = \frac{33+34}{2} = 33.5, \sigma^2 = 0.25$
  - Pressure: $\mu = \frac{20+22}{2} = 21, \sigma^2 = 1$
- Moderate Class
  - CH_4: $\mu = \frac{400+320}{2} = 360, \sigma^2 = 1600$
  - CO_2: $\mu = \frac{500+650}{2} = 575, \sigma^2 = 5625$

- Temp: $\mu = \frac{32+35}{2} = 33.5$, $\sigma^2 = 2.25$
- Pressure: $\mu = \frac{18+19}{2} = 18.5$, $\sigma^2 = 0.25$

➢ Poor Class

- CH_4: $\mu = \frac{250+220}{2} = 235$, $\sigma^2 = 225$
- CO_2: $\mu = \frac{850+770}{2} = 810$, $\sigma^2 = 1600$
- Temp: $\mu = \frac{29+28}{2} = 28.5$, $\sigma^2 = 0.25$
- Pressure: $\mu = \frac{12+11}{2} = 11.5$, $\sigma^2 = 0.25$

b) Step 2: Calculate Prior Probability $P(C_k)$

$$P(C_k) = \frac{Number\ of\ sample\ in\ class\ C_k}{Total\ number\ of\ samples} \qquad (4)$$

Each class has 2 samples out of 6 total

$$P(Good) = P(Moderate) = P(Poor) = \frac{2}{6} = 0.33$$

c) Step 3: Compute Gaussian Likelihood per Feature

For each feature x_i, the likelihood given class C_k is calculated using the Gaussian pprobability density function:

$$P(x_i|C_k) = \frac{1}{\sqrt{2\pi\sigma_k^2}} \exp\left(-\frac{(x_i - \mu_k)^2}{2\sigma_k^2}\right) \qquad (1)$$

Example: For $CH_4 = 620$ on the Good class where $\mu = 675$, $\sigma^2 = 625$

$$P(620|Good) = \frac{1}{\sqrt{2\pi \cdot 625}} \exp\left(-\frac{(620 - 675)^2}{2 \cdot 625}\right)$$

$$= \frac{1}{62.5} \cdot e^{-2.42} \approx 0.016$$

Repeat the calculation for all feature and all classes.

d) Step 4: Compute Posterior Probability per Class

For each class, compute the full posterior probability

$$P(C_k|X) \propto P(C_k) \cdot \prod_{i=1}^{n} P(x_i|C_k) \qquad (5)$$

Where:

- $P(C_k)$ is prior probability
- $P(x_i|C_k)$ is likelihood of feature x_i given class C_k
- $X = (x_1, x_2, x_3, x_4)$ is the input vector

For Good class:

$$P(Good|X) = P(Good) \cdot P(CH_4 = 620|\text{Good}) \cdot$$

$$P(CO_2 = 390|\text{Good}) \cdot$$

$$P(\text{Temp} = 33|\text{Good}) \cdot$$

$$P(Pressure = 21|Good)$$

$$\approx 0.33 \cdot 0.016 \cdot 0.026 \cdot 0.48 \cdot 0.398$$

$$\approx 0.000026$$

Do the same for the Moderate and Poor classes.

e) Step 5: Predict the Class with Maximum Posterior Probability

$$\hat{C} = \arg\max_{C_k} P(C_k) \qquad (2)$$

The comparison of posterior probabilities for each class is presented in Table IV.

TABLE IV
COMPARISON OF CLASS PROBABILITIES

Class	Final Probability
Good	0.000026
Moderate	~0.000011
Poor	~0.000002

Since Good has the highest posterior probability, the input is classified as Good.

A confusion matrix is used to assess how well the Gaussian Naïve Bayes algorithm performs in dividing biogas quality into Good, Moderate, and Poor categories. The comparison between the algorithm's anticipated class and the actual class label derived from empirical observation such as flame tests or recognized quality ranges is represented by the confusion matrix. This matrix can be used to produce important performance metrics including accuracy, precision, and recall, which give information about how reliable the model is in practical settings [16]. The structure of the confusion matrix used for evaluation is shown in Table V.

TABLE V
CONFUSION MATRIX

		TRUE	FALSE
Prediction Value	TRUE	(TP)	(FP)
	FALSE	(FN)	(TN)

In the confusion matrix table there are True Positive (TP), False Negative (FN), False Positive (FP), and True Negative (TN). The four predictions have different meanings, where True Positive (TP) refers to instances where the predicted class matches the actual class. False Positive (FP) indicates instances where the predicted class is incorrect compared to the actual label. False Negative (FN) represents actual classes that were missed or wrongly predicted. True Negative (TN) is not explicitly shown in multi-class classification but is implicitly handled in per-class evaluation [16].

The model's performance was quantitatively evaluated on the testing set 20% of the data by comparing its predictions to actual labels using a confusion matrix. Performance was assessed using standard metrics derived from the matrix components True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The metrics used were Accuracy, Precision, Recall, and F1-Score, calculated as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\ Score = 2 \times \frac{Precision\ \times Recall}{Precision + Recall}$$

To evaluate the model performance comprehensively, several metrics were used, including accuracy, precision, recall, and F1-score. These metrics are derived from the confusion matrix and provide insights into the reliability of the classification model. Although cross-validation was not implemented due to real-time system constraints, the use of an 80:20 train-test split provides a reliable estimation of model performance.

C. System Architecture and Material

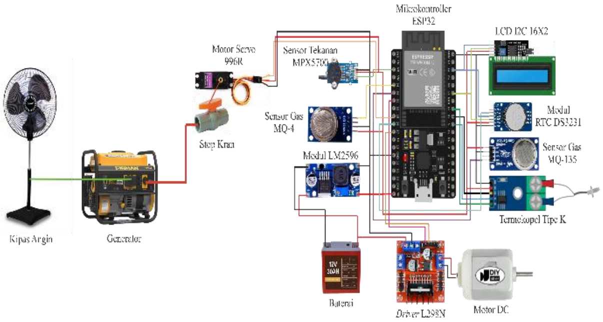

Fig. 3. Architecture System

The system architecture consists of several integrated hardware components including sensors, actuators, and a microcontroller. The ESP32 microcontroller is used as the main processing unit due to its capability in handling real-time data processing and wireless communication [17]. Temperature is measured using a K-Type thermocouple [18], while methane (CH_4) and carbon dioxide (CO_2) concentrations are detected using MQ-4 and MQ-135 gas sensors, respectively [19][20]. Gas pressure is monitored using the MPX5700 pressure sensor [21]. In addition, actuators such as a servo motor (MG996R) and DC motor are used to control the gas valve and mechanical processes within the system [22][23]. A Real-Time Clock (RTC) module is integrated to provide accurate timestamping for sensor data logging [24]. The system is powered using a LiFePO4 battery, ensuring stability and long operational life for off-grid applications [25]. Furthermore, the generated biogas is utilized to drive a generator which produces electrical energy to power a fan system [26][27]. All sensor data and system status are monitored in real-time through the Blynk IoT platform.

D. Flowchart System

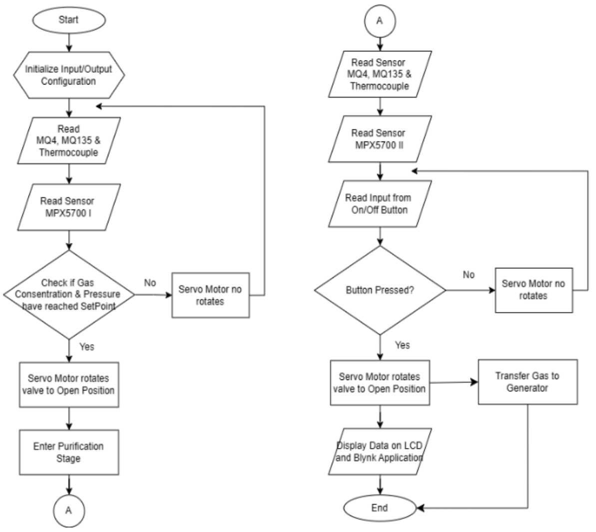

Fig. 4. Flowchart System

Fig. 4 shows the steps involved in the biogas-based fan control system's functioning, from input/output initialization to the valve's final actuation and data monitoring. Sensors and control pins are among the input/output components that are initialized at the start of the operation. After initialization, the system reads data from the MQ-4 and MQ-135 gas sensors to determine the CO2 and methane levels in real time and Thermocouple to determine temperature. Additionally, it uses the MPX5700 pressure sensor I to read pressure readings. A predetermined setpoint is then assessed by the system to determine whether the gas concentration and pressure have been reached. Otherwise, servo rotate the valve, which is ordinarily open or NO, stays closed to avoid purifying the gas too soon. When the setpoint is reached, the valve opens, letting biogas proceed to the purification phase. After verifying the manual ON/OFF button input, the system once more reads values from MQ-4, MQ-135, Thermocouple and MPX5700 sensor II. This button acts as an extra layer of control for manual override and safety. The mechanism maintains button ON/OFF Servo in valve to ON/OFF position, which stops the flow of gas, if the button is not touched. When the button is pressed, the purified biogas can enter the generator since the valve opens. In order to allow users to remotely monitor the system, sensor readings and system status (gas parameters, valve condition) are simultaneously transmitted to an LCD display and the Blynk mobile application. This flow gives users the flexibility to manually override the flow and guarantees that biogas is only used when it satisfies safety and performance requirements. Additionally, it permits transparent system operations and real-time tracking.

III.RESULTS AND DISCUSSION

Hardware validation was conducted to ensure data reliability. Sensor accuracy was evaluated by comparing device readings against calibrated reference instruments. The tests revealed a high degree of precision, with very low mean relative errors for all sensors. The mean relative error for the temperature sensor (Type-K Thermocouple) was 0.018% , the pressure sensor (MPX5700AP) was 0.018% , the CO_2 sensor (MQ-135) was 0.006% , and the CH_4 sensor (MQ-4) was 0.007%. Furthermore, functional testing of the control system confirmed that all actuators, including the stirrer motor and servo valves, responded correctly "Valid" to all predefined logical scenarios.

The extremely low error rates across all four sensors confirm that the selected hardware is highly reliable and accurate for the application of biogas monitoring. This level of precision is crucial as it validates the quality of the data collected, ensuring that the input for the machine learning model is trustworthy. The successful validation of the control system also demonstrates that the integration of hardware, software, and control logic was implemented correctly, resulting in a functional and responsive automated system. The energy conversion efficiency of the system is summarized in Table VI.

The system's ability to convert the chemical energy in biogas into electrical energy was tested. The results show that the system achieved an energy conversion efficiency of 33.3%. In a 10-minute test session, the generator consumed 0.1 m^3 of biogas (equivalent to 0.6 kWh of energy input) to produce 0.2 kWh of electrical energy, which was used to power a fan.

An efficiency of 33.3% is a reasonable and competitive figure for a small-scale biogas generator system. This result confirms that the system is effective and functional in converting organic waste into usable electrical power. The remaining 66.7% of potential energy is likely dissipated as waste heat from the engine and from imperfect combustion, which is typical for thermal conversion systems. Nevertheless, this achievement underscores the system's viability as an alternative energy solution at the community level.

TABLE VI
EFFICIENCY ENERGY

Parameter	Mark	Information
Testing Duration	10 minutes (≈0.167 hours)	
Volume of Biogas Used	0.1 m^3	$0.6\ m^3/hours \times 0.167\ hours$
Input Energy Potential (Biogas)	0.6 kWh	$0.1\ m^3 \times 6\ kWh/m^3$
Electrical Energy Output (Generator)	0.2 kWh	$Power\ 1.2\ kW \times 0.167\ hours$
Energy Conversion Efficiency	33.3%	$\left(\frac{0.2\ kWh}{0.6\ kWh}\right) \times 100\%$

The Gaussian Naïve Bayes (GNB) classification model was evaluated using 24 test samples. The model demonstrated excellent performance with an overall accuracy of 95.83%, correctly classifying 23 out of the 24 samples. The confusion matrix of the classification results is presented in Fig. 5, illustrating the comparison between predicted and actual classes. The detailed performance evaluation metrics are summarized in Table VII.

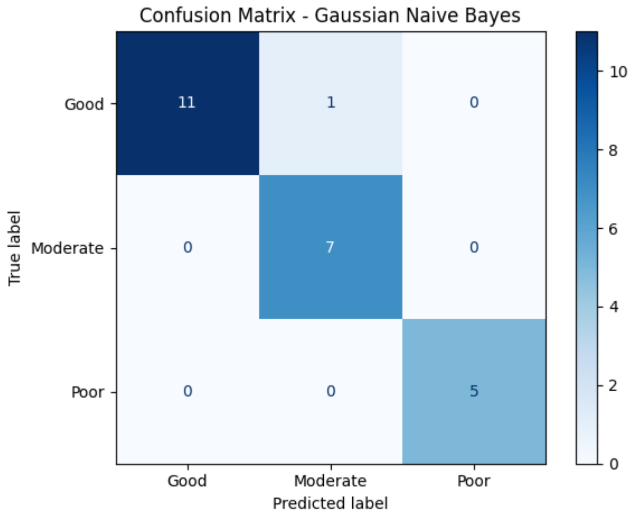

Fig. 5. Confusion Matrix of the GNB Classificcation Model

TABLE VII
PERFORMANCE EVALUATION MODEL

Evaluation Results of the 80:20 Split Data Model				
Class	**Precision**	**Recall**	**F1-Score**	**Support**
Good	1.00	0.92	0.96	12
Moderate	0.88	1.00	0.93	7
Poor	1.00	1.00	1.00	5
Accuracy			**0.96** **96%**	**24**

As shown in Table VII, the model achieved high precision, recall, and F1-score across all classes, indicating that the Gaussian Naïve Bayes algorithm is effective in classifying biogas quality based on sensor data. These results demonstrate that the selected features significantly contribute to classification performance.

These results are consistent with previous studies that applied machine learning techniques for biogas quality prediction, demonstrating that probabilistic models such as Gaussian Naïve Bayes can achieve high classification accuracy with relatively small datasets. This also confirms that the selected sensor features, including methane concentration, carbon dioxide levels, temperature, and pressure, are highly relevant indicators for determining biogas quality in real-time applications.

Class “Good”:

$$Precision = \frac{11}{11+0} = 1.00$$

$$Recall = \frac{11}{11+1} = 0.92$$

$$F1\ Score = 2 \times \frac{1.00 \times 0.92}{1.00 \times 0.92} = 0.96$$

$$Accuracy = \frac{23}{24} \times 100\% = 95.83\%$$

The high accuracy of 95.83% indicates that the selected features (temperature, pressure, CO_2, and CH_4) are strong predictors of biogas quality and that the GNB algorithm is highly effective for this classification.

The 100% precision for the "Good" class is of high practical importance, as it means that every time the model predicted the biogas was suitable for use, it was correct. This ensures that the generator is only activated with optimal quality fuel, which enhances the system's operational safety and efficiency. Furthermore, the 100% recall for the "Moderate" and "Poor" classes shows the model's capability to correctly identify all instances of non-optimal gas. The only misclassification occurred when one "Good" sample was classified as "Moderate". Overall, this high level of performance confirms that the GNB model is a robust and reliable component for the system's decision-making process. The graphical representation of the model performance metrics is illustrated in Fig. 6, providing a visual comparison of precision, recall, and F1-score across all classes.

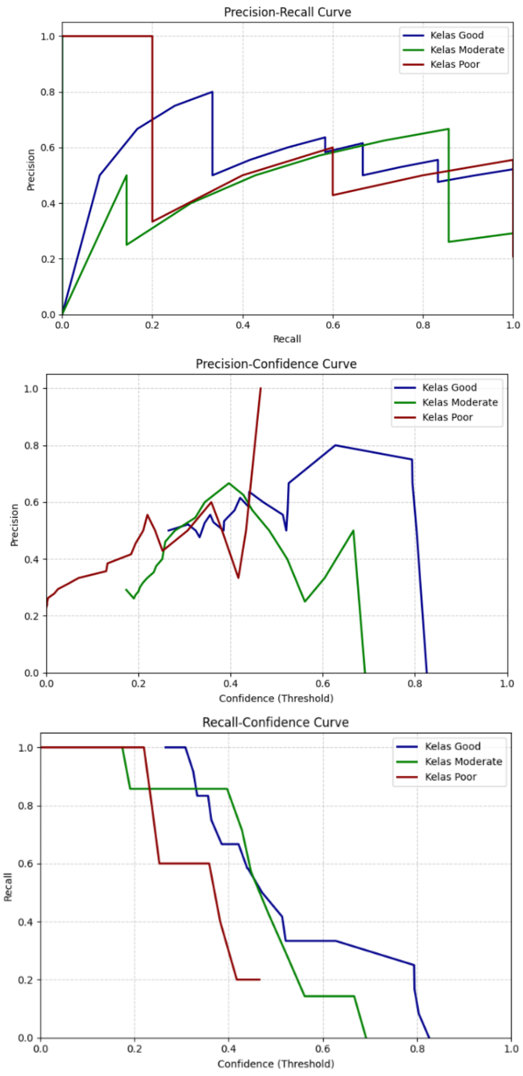

Fig. 6. Chart of Performance Evaluation Model

IV. CONCLUSION

This study successfully designed, implemented, and evaluated an intelligent IoT-based monitoring and control system for classifying the quality of biogas derived from household waste. The developed system proved to be reliable, with its integrated sensors demonstrating high accuracy; the mean relative errors for temperature and pressure were 0.018%, while for CO_2 and CH_4 they were 0.006% and 0.007%, respectively. The primary contribution of this research is the application of a Gaussian Naïve Bayes algorithm, which successfully classified biogas quality with an overall accuracy of 95.83%. Critically, the model achieved 100% precision for the "Good" quality class, ensuring high reliability in the automated decision-making for energy utilization. Functionally, the system was effective in converting waste into electricity, achieving an energy conversion efficiency of 33.3% when used to power a fan. For future development, a comparative study with other machine learning algorithms, such as Support Vector Machine (SVM) or Random Forest, is recommended, along with the integration of additional monitoring parameters like pH.

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