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Smart Biodigester System for Bioenergy Production Using Artificial Neural Network

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Biogas Production, Internet of Things (IoT), Artificial Neural Network (ANN), methane gas prediction, household organic waste

Abstract

This study proposes an Internet of Things (IoT)-based smart biodigester system integrated with an Artificial Neural Network (ANN) for methane gas prediction and automatic control in household-scale biogas production. Conventional household biodigesters generally lack real-time monitoring and intelligent control mechanisms, resulting in unstable methane quality and inefficient gas utilization. The proposed system employs an ESP32 microcontroller and multiple sensors to monitor fermentation parameters, including temperature, gas pressure, pH value, substrate volume, and methane concentration. Sensor data collected during a 29-day anaerobic fermentation process were transmitted to a mobile-based monitoring platform and processed using an ANN model to predict methane gas concentration. A total of 870 valid data samples were used for model training and evaluation. To improve gas quality, the produced biogas was purified using a three-stage filtration system consisting of water, steel wool, and silica gel filters. The ANN prediction output was integrated with a servo-based automatic control mechanism to regulate methane gas flow into the storage tank according to predefined quality thresholds. Experimental results demonstrate that the proposed ANN model achieved a Mean Absolute Error (MAE) of 27.8 ppm, Root Mean Square Error (RMSE) of 34.6 ppm, Mean Absolute Percentage Error (MAPE) of 3.21%, and coefficient of determination (R^2) of 0.94, indicating high prediction accuracy and strong agreement with actual methane measurements. The integration of IoT monitoring, ANN-based prediction, and automatic gas flow control improves the safety, efficiency, and reliability of household-scale biogas systems.

1. Introduction

The issue of household waste in Indonesia is becoming increasingly critical due to population growth and changes in consumption patterns. According to data from the National Waste Management Information System (SIPSN), the total national waste volume exceeded 21 million tons in 2022, with over 30% comprising organic household waste such as food scraps, fruits, and vegetables [1]. Without proper management, these wastes accumulate at

Final Processing Sites (Tempat Pemrosesan Akhir – TPA), causing soil, water, and air pollution through anaerobic decomposition that produces methane (CH_4) and carbon dioxide (CO_2)—two major greenhouse gases contributing to global warming [2]. Kitchen waste, as a significant part of household organic waste, possesses highly favorable characteristics for energy recovery. Its moist, easily degradable composition and daily availability in nearly every household make it a promising feedstock for renewable energy conversion in the form of biogas. However, its potential remains underutilized due to its small-scale nature and the common practice of indiscriminate disposal with other types of waste.

Biogas production through anaerobic fermentation offers a sustainable and environmentally friendly solution for addressing kitchen waste while simultaneously generating alternative energy. An integrated waste management approach that combines anaerobic bioreactor systems with real-time monitoring has been shown to improve the effectiveness and scalability of organic waste conversion, particularly in community-based implementations[3]. Typically consisting of 55–65% methane and CO_2, biogas can serve as a viable fuel source for household applications, such as cooking and replacing liquefied petroleum gas (LPG) [4]. Nevertheless, many small-scale household biogas systems still operate manually, lacking automation and adequate monitoring. This results in unstable fermentation conditions, suboptimal gas output, and potential safety hazards due to uncontrolled pressure levels. The integration of microcontroller-based real-time monitoring, automatic gas flow control, and gas purification mechanisms has been demonstrated to improve both the efficiency and operational safety of biogas production systems[5]. Therefore, the implementation of an intelligent control system is essential to automate the monitoring and regulation of fermentation processes. The Internet of Things (IoT) technology enables real-time sensor data collection and remote access, allowing users to observe digester conditions without being physically present.

Furthermore, the proposed system integrates Artificial Neural Network (ANN) technology as a predictive model capable of learning historical data patterns and estimating gas production potential[6]. In this study, the ANN algorithm is utilized to model the relationship between the volume and condition of organic waste with the expected biogas output. By processing input parameters such as temperature, humidity, gas pressure, methane concentration, and waste volume, the ANN provides accurate predictions regarding the volume of gas to be produced [7]. Previous studies on biogas systems have primarily focused on real-time monitoring of fermentation parameters using IoT technology without integrating intelligent prediction and automatic control mechanisms [14], [16]. Several IoT-based biodigester systems provide remote monitoring capabilities; however, they generally lack predictive analysis for methane quality assessment and adaptive gas flow regulation [8]. Meanwhile, ANN-based methane prediction studies are mostly implemented in large-scale or industrial anaerobic digestion systems and are rarely integrated into low-cost household biodigesters [9]. In addition, limited studies combine IoT-based monitoring, ANN-driven methane prediction, gas purification, and automatic actuator control within a single integrated platform [10]. Therefore, there remains a need for an integrated intelligent biodigester system capable of combining real-time monitoring, methane prediction, gas purification, and automatic control for household-scale applications.

This research aims to design an intelligent control and monitoring system based on IoT and ANN to evaluate and predict the performance of the biogas fermentation process using household kitchen waste. The system is expected to improve efficiency, safety, and sustainability in converting domestic waste into clean, renewable energy through an integrated and automated approach.

2. Literature Review

The application of biogas technology using organic waste, particularly kitchen waste, continues to gain attention due to its environmental benefits and potential as a renewable energy source. Kitchen waste offers several advantages as a biogas substrate, including its abundance, continuous availability, and high biodegradability, making it more suitable compared to lignocellulosic agricultural residues. However, conventional biogas systems are generally operated manually with limited monitoring, resulting in unstable fermentation processes and inefficient gas production [11]. To overcome these limitations, researchers have developed intelligent monitoring systems based on the Internet of Things (IoT). These systems enable real-time monitoring of critical parameters within the biodigester, including temperature, pH, gas pressure, substrate volume, and methane concentration. Sensor data are transmitted wirelessly to cloud-based platforms for remote analysis, visualization, and control, enhancing system responsiveness and operational flexibility.

Beyond monitoring, the implementation of machine learning algorithms such as Artificial Neural Networks (ANN) has been utilized to predict methane gas production based on fermentation parameters[12]. ANN identifies patterns within the input data—such as temperature, pH, and pressure—and maps them to output values representing the volume of biogas produced. Through a training process, the network adjusts its internal weights to improve predictive accuracy, which can be used to support automated decision-making, including adjusting mixing speed or regulating fermentation temperature [7].

Moreover, gas purification is a crucial stage to improve biogas quality. Biogas production to increase methane concentration can be carried out through three purification stages[13]. Raw biogas contains impurities such as CO_2 and H_2S, which reduce combustion efficiency and can damage appliances. Low-cost purification methods using media such as water scrubbers, silica gel, and steel wool are commonly applied in small-scale or household biodigesters. Each medium serves a specific function: water absorbs CO_2, silica gel removes moisture, and steel wool neutralizes H_2S, resulting in cleaner biogas that is more suitable for domestic applications [14][15].

Overall, the integration of IoT technologies and ANN-based prediction models in biodigester systems offers a smart, cost-effective, and scalable solution to convert household kitchen waste into clean energy. This approach enhances system responsiveness, ensures consistency in gas production, and reduces dependency on manual supervision. It aligns with the broader goals of sustainability in energy and waste management, particularly in rural communities.

3. Methodology

This study adopts an experimental research approach to develop a smart monitoring and control system for household waste–based biogas production. The methodology covers the complete research workflow, including system design, sensor installation, real-time data acquisition, and intelligent data processing using an Artificial Neural Network (ANN). The ANN algorithm is implemented to model the nonlinear relationship between fermentation parameters and biogas production, as well as to predict and optimize methane gas output based on historical and real-time sensor data[16]. The final stage of the methodology involves evaluating the performance of the monitoring, prediction, and control system in terms of accuracy, stability, and reliability during the biogas fermentation process.

3.1 Research Design

This study adopts an experimental research design to develop and evaluate a smart biodigester system for household-scale biogas production. The research focuses on integrating Internet of Things (IoT) technology with an Artificial Neural Network (ANN) to enable real-time monitoring, intelligent prediction of methane gas concentration, and automatic control of gas flow. The experimental approach allows direct observation of system performance under real operating conditions and facilitates validation of the proposed prediction and control strategy. The research is divided into several main stages. The first stage involves the design and construction of the smart biodigester system, including selection and integration of sensors, ESP32 microcontroller, communication modules, and actuator components. The second stage focuses on the development of an IoT-based monitoring platform that enables continuous acquisition, transmission, and visualization of fermentation parameters. The third stage involves the development of an ANN-based prediction model using historical sensor data to estimate methane gas concentration. The final stage consists of integrating the ANN prediction results with the automatic control mechanism and evaluating overall system performance.

The overall workflow of the research begins with continuous data acquisition from the biodigester system. Sensor data are transmitted wirelessly to a cloud-based database and then processed through data preprocessing and normalization. The processed data are used to train and validate the ANN model. Once trained, the ANN model generates methane concentration predictions based on real-time sensor inputs. These predictions are compared against predefined quality thresholds to determine control actions for the gas outlet valve. The system operates in a closed-loop manner, combining monitoring, prediction, and control to ensure safe and efficient biogas production. This research design enables systematic evaluation of both the monitoring infrastructure and the ANN-based prediction model, providing a comprehensive framework for intelligent household-scale biogas management.

3.2 Monitoring and Control System Design

The monitoring and control system is designed using an ESP32 microcontroller as the central processing unit due to its low power consumption, wireless communication capability, and suitability for IoT-based applications[17]. The system integrates multiple sensors to monitor critical fermentation parameters, including temperature, substrate volume, gas pressure, and methane gas concentration. Sensor data is transmitted wirelessly via a Wi-Fi connection to a mobile-based application for real-time visualization and remote monitoring. Figure 1 illustrates a 3D model of the intelligent monitoring and control system, presenting the physical layout of the main components. These components include the ESP32 microcontroller, a temperature and humidity sensor (DHT22), a gas pressure sensor (MPX5700AP), a methane gas sensor (MQ-4), a substrate volume sensor (JSN-SR04T), and a servo motor (MG996R). The servo motor is utilized to actuate the methane gas outlet pipe sleeve, enabling controlled gas flow within the biodigester system. This integrated design enables reliable long-term monitoring of the anaerobic digestion process while supporting remote supervision and control. Figure 2 shows the arrangement of the hardware components of the system. The sensors are connected to the ESP32 as the main controlling unit, while the servo motors are operated through digital outputs. The system is designed with low power consumption and wireless connectivity to achieve energy efficiency and ease of installation, especially in remote locations. The design is made to be easily reproducible and stable in monitoring the biogas fermentation process continuously.

Fig. 1 *Design 3D*

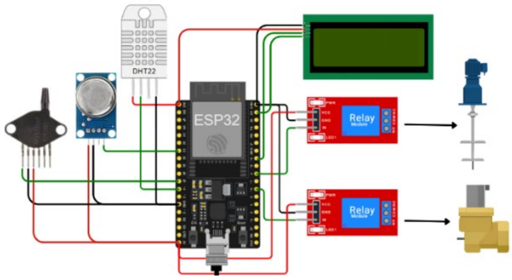

Fig. 2 *Hardware circuit*

In addition to the monitoring function, the system is also equipped with a control mechanism for regulating methane gas flow. An MG996R servo motor is employed to actuate the gas outlet pipe sleeve once the methane gas quality meets the predefined standards after the filtration process[18]. The servo motor can be operated in both manual and automatic modes through the mobile-based application. A virtual control interface allows users to adjust the servo position, enabling the gas outlet to be opened or closed remotely. This functionality ensures that methane gas is released only when appropriate quality conditions are achieved, thereby enhancing operational safety, system efficiency, and reliability in household-scale biogas utilization.

3.3 Data Collection and Storage Process

Data collection in this study was conducted through continuous monitoring of the smart biodigester system during the anaerobic digestion of household organic waste. The biodigester was operated under real household-scale conditions to obtain representative fermentation data. Sensor nodes integrated with the ESP32 microcontroller measured key fermentation parameters, including temperature (°C), gas pressure (kPa), pH value, substrate volume (L), and methane gas concentration (ppm). The fermentation experiment was conducted over a period of 29 days, from October 3 to October 31, 2025. The experimental duration was selected based on the typical Hydraulic Retention Time (HRT) commonly applied in household-scale anaerobic digestion systems, which generally ranges from 20 to 30 days depending on substrate characteristics and operational conditions [11]. Previous studies have reported that methane production tends to increase significantly during the second to fourth week of the fermentation process, when microbial activity becomes more stable and methanogenic bacteria enter their active growth phase [19]. Therefore, the selected duration was considered sufficient to capture the major phases of anaerobic digestion, including the startup phase, active methane production phase, and stabilization phase.

During the experimental period, sensor readings were acquired automatically at regular intervals of approximately 5 minutes. All sensor data were transmitted wirelessly via Wi-Fi and stored in a cloud-based database using Firebase, enabling real-time data synchronization and secure storage. Prior to storage, the received data packets were validated to ensure data completeness and integrity. Incomplete or corrupted records caused by temporary communication interruptions were discarded during the filtering process. After preprocessing and validation, a total of 870 valid data samples were obtained and used for ANN model development and evaluation.

Although the dataset size is relatively modest compared to large-scale machine learning datasets, it is considered sufficient for this study due to the low-dimensional input space consisting of four fermentation parameters and the use of a compact feedforward ANN architecture. In addition, the dataset was collected continuously under varying fermentation conditions, enabling the model to capture the dynamic characteristics of methane generation during anaerobic digestion. Previous studies have demonstrated that ANN-based regression models can achieve stable prediction performance using datasets of comparable size when the process dynamics are adequately represented [20][9]. Furthermore, the prediction performance obtained in this study, indicated by low prediction error and a high coefficient of determination, confirms the adequacy of the collected dataset for methane concentration prediction. Furthermore, the prediction performance obtained in this study, indicated by low prediction error and a high coefficient of determination (R^2), confirms the adequacy of the collected dataset for methane concentration prediction. Each data sample consists of four input parameters, namely temperature, gas pressure, pH value, and substrate volume, along with one output parameter representing methane gas concentration. These parameters were selected because they significantly influence microbial activity and methane formation during anaerobic digestion.

Based on the collected dataset, temperature values ranged from 27 to 35 °C, gas pressure ranged from 98 to 110 kPa, pH values ranged from 6.5 to 7.2, substrate volume was maintained at approximately 50 L, and methane gas concentration ranged from 500 to 1900 ppm. These ranges indicate that the dataset successfully captures both suboptimal and near-optimal fermentation conditions. Table 1 presents representative samples of fermentation sensor data obtained from the smart biodigester system. The table illustrates examples of temperature, pressure, pH, substrate volume, and corresponding methane gas concentration values used in ANN model development.

Table 1 *Sample fermentation sensor data*

Temperature (°C)	Pressure (kPa)	pH	Substrate Volume (L)	Actual CH_4 (ppm)
30	101	6.8	5	900
32	105	6.9	52	1100
35	110	7.0	55	1400

All stored data were exported in comma-separated values (CSV) format and used in subsequent preprocessing, ANN training, and performance evaluation stages. The cloud-based storage system ensures data availability for offline analysis and supports reproducibility of the proposed method.

3.4 Data Preprocessing

Prior to training the Artificial Neural Network (ANN), a data preprocessing stage was conducted to improve model performance and training stability. The raw sensor data obtained from the smart biodigester system consists of parameters with different units and numerical ranges, including temperature (°C), gas pressure (kPa), pH value, and substrate volume (L). If directly used, these differences in scale may cause certain variables with larger numerical values to dominate the learning process, leading to slow convergence and suboptimal model performance. To address this issue, Min–Max normalization was applied to all input features and output data. This method linearly transforms each variable into a normalized range between 0 and 1 using the following Eq. (1):

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x represents the original data value, x_{min} and x_{max} denote the minimum and maximum values of each parameter, respectively, and x_{norm} is the normalized value. Min–Max normalization was selected because it preserves the original distribution of the data while ensuring uniform scaling across all input variables. This approach is particularly suitable for neural network training, as it accelerates convergence, improves numerical stability, and enhances the effectiveness of gradient-based optimization algorithms.

Based on the experimental dataset, the temperature values ranged from 27 to 35 °C, gas pressure ranged from 98 to 110 kPa, pH values ranged from 6.5 to 7.2, substrate volume was maintained at approximately 50 L, and methane gas concentration ranged from 500 to 1900 ppm. After normalization, all parameters were mapped into the range [0,1] before being fed into the ANN model. This preprocessing step ensures that all features contribute proportionally to the learning process, enabling the ANN to effectively model the nonlinear relationship between fermentation parameters and methane gas concentration.

3.5 Artificial Neural Network Model Architecture

The Artificial Neural Network (ANN) model in this study was developed to predict methane gas concentration based on key fermentation parameters obtained from the smart biodigester system. A feedforward multilayer perceptron (MLP) architecture was selected due to its capability to model complex and nonlinear relationships between multiple input variables and output targets commonly found in anaerobic digestion processes [20] [21]. The ANN consists of three main layers: an input layer, one hidden layer, and an output layer. The input layer comprises four neurons representing the primary fermentation parameters, namely temperature (°C), gas pressure (kPa), pH value, and substrate volume (L). These parameters were selected because they significantly influence microbial activity and methane formation during anaerobic digestion processes [8].

The hidden layer configuration was determined through a series of preliminary experiments involving multiple ANN architectures with different neuron configurations. Several single hidden-layer models, including 4–4–1, 4–6–1, 4–8–1, 4–10–1, and 4–12–1, were evaluated to identify the optimal number of hidden neurons. In addition, deeper architectures containing two hidden layers, such as 4–8–4–1 and 4–12–6–1, were also tested to compare prediction performance, convergence behavior, and computational efficiency. The performance of each architecture was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), coefficient of determination (R^2), and validation loss. Experimental results indicated that the 4–10–1 architecture achieved the best overall prediction performance, producing the lowest prediction error and the highest coefficient of determination while maintaining stable convergence behavior. Although deeper architectures were capable of learning more complex nonlinear relationships, they did not provide significant performance improvement and exhibited higher computational complexity as well as a greater tendency toward overfitting. Therefore, the 4–10–1 architecture was selected as the optimal ANN configuration for methane concentration prediction in this study. Furthermore, the selected architecture provides lower computational cost and faster convergence, making it suitable for implementation in resource-constrained IoT-based embedded systems.

Table 2 *Comparison of ANN architectures*

Architecture	MAE	RMSE	R^2	Validation Loss
4–4–1	52.4	68.1	0.81	0.024
4–6–1	41.7	54.3	0.87	0.019
4–8–1	33.2	42.5	0.91	0.013
4–10–1	27.8	34.6	0.94	0.008
4–12–1	29.4	37.8	0.93	0.012
4–8–4–1	30.1	39.5	0.92	0.015
4–12–6–1	31.6	41.2	0.91	0.017

Each neuron in the hidden layer employs the Rectified Linear Unit (ReLU) activation function, which is defined as:
$f(x) = \max(0, x)$

ReLU was selected because it accelerates convergence during training and reduces the risk of vanishing gradient problems [22]. The output layer consists of one neuron representing the predicted methane gas concentration (ppm). A linear activation function was applied in the output layer to produce continuous numerical outputs suitable for regression tasks. Before the training process, all input features were normalized using Min–Max scaling to map the data into the range [0,1]. This normalization process ensures that each variable contributes proportionally to the learning process and improves overall model stability. The proposed ANN architecture enables the system to effectively learn the nonlinear relationship between fermentation parameters and methane gas concentration, thereby providing reliable predictions that support intelligent decision-making in the automatic control of the smart biodigester system.

3.6 ANN Training Process

The Artificial Neural Network (ANN) model was trained using 870 validated sensor data samples collected from the smart biodigester system during a 29-day anaerobic digestion process. Each sample consists of four input parameters, namely temperature, gas pressure, pH value, and substrate volume, with methane gas concentration as the output parameter. Prior to training, the dataset was randomly shuffled to reduce ordering bias and improve model generalization. The dataset was divided into 70% training data, 15% validation data, and 15% testing data. The training dataset was used to optimize network weights, while the validation dataset was employed to monitor model performance and reduce overfitting. The testing dataset was reserved for final model evaluation.

To further evaluate the robustness and generalization capability of the proposed ANN model, a 5-fold cross-validation procedure was additionally performed. In this approach, the dataset was divided into five subsets, where four subsets were used for training and one subset was used for validation iteratively. The process was repeated five times until each subset had been used once as the validation dataset. The average values of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2) were calculated to evaluate prediction consistency and model stability.

Table 3 *Results of 5-fold cross validation*

Fold	MAE	RMSE	R^2
1	28.1	35.0	0.93
2	27.4	34.2	0.94
3	28.7	35.5	0.93
4	27.9	34.8	0.94
5	28.3	35.1	0.93
Mean	28.1	34.9	0.93
Std. Dev	0.43	0.47	0.005

The selected ANN architecture was the 4–10–1 configuration obtained from preliminary architecture evaluation experiments discussed in the previous subsection. The model was trained using the backpropagation learning algorithm with the Adam optimizer and a learning rate of 0.001. Mean Squared Error (MSE) was used as the loss function for prediction error evaluation as in Eq. (2).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

The training process was conducted for a maximum of 500 epochs with a batch size of 32. The number of epochs was determined based on preliminary convergence analysis, which showed that both training loss and validation loss stabilized before reaching the maximum epoch limit. Experimental observations indicated that model performance improvement became insignificant after approximately 450 epochs, while extending the training beyond 500 epochs did not provide noticeable reduction in validation loss. To reduce the risk of overfitting, an early stopping mechanism with a patience value of 20 epochs was implemented. The training process was automatically terminated when no significant improvement in validation loss was observed over consecutive epochs. Figure X illustrates the convergence behavior of the ANN model during the training process. The proposed training configuration enables the ANN model to effectively learn the nonlinear relationship between fermentation parameters and methane gas concentration, resulting in stable and reliable methane prediction performance suitable for intelligent biodigester control applications.

3.7 ANN Implementation Platform

The Artificial Neural Network (ANN) model in this study was implemented using the Python programming language due to its flexibility and extensive support for machine learning applications. Model development, training, and evaluation were performed using the TensorFlow framework with the Keras high-level API, which provides efficient and reliable tools for constructing feedforward neural network architectures and optimizing learning processes. The ANN model was designed as a fully connected feedforward network consisting of an input layer, one hidden layer, and an output layer. The input layer receives four fermentation parameters, namely temperature, gas pressure, pH value, and substrate volume, while the output layer produces a single value representing methane gas concentration. This architecture was selected to capture nonlinear relationships between fermentation conditions and methane production.

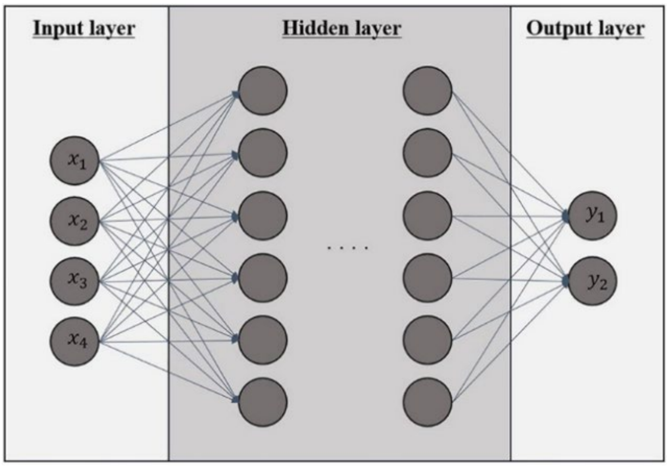

Fig. 3 *Shows the architecture of the ANN model used for methane gas prediction*

Data preprocessing, model training, and performance evaluation were conducted on a standard personal computer environment. Sensor data stored in the cloud database were exported in comma-separated values (CSV) format and processed offline using Python. The Keras library was utilized to define the network structure, configure training parameters, and monitor training performance, including training and validation loss during the learning process. The overall workflow of ANN training and deployment begins with data acquisition from the smart biodigester sensors, followed by preprocessing and dataset splitting. The processed data are then used to train and validate the ANN model. After the model achieves satisfactory performance, it is employed to generate methane concentration predictions using real-time sensor inputs. These prediction results are subsequently integrated into the system logic to support automatic control of the gas outlet valve in the smart biodigester system. The use of TensorFlow and Keras ensures reproducibility and scalability of the proposed approach, allowing the ANN model to be retrained or further optimized as additional fermentation data become available.

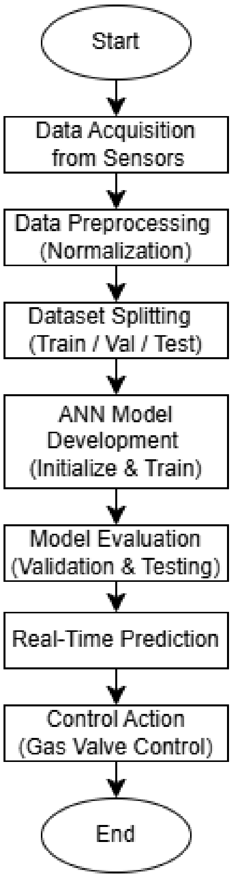

Fig. 4 *Illustrates the flowchart of the ANN training and prediction process*

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3.8 Automatic Control System Integration

The automatic control system is integrated by linking the ANN-based methane gas prediction to the actuator control logic within the mobile application. The predicted methane concentration serves as the primary decision parameter for regulating gas flow through the outlet sleeve. The biogas produced in the digester is first passed through a three-stage gas filtration system to improve gas quality[23]. After completing the filtration process, the ANN model evaluates the methane concentration based on real-time sensor data. If the predicted methane level exceeds the predefined quality threshold, an automatic control signal is sent to the servo motor to open the gas outlet sleeve, allowing methane to flow into the storage tank. Conversely, if the predicted methane concentration does not meet the required standard, the sleeve remains closed, preventing low-quality gas from entering the storage system. In addition to automatic operation, the system also supports manual control through the mobile application interface. Users can manually open or close the sleeve using virtual control buttons when required. This dual-mode operation provides flexibility between intelligent data-driven automation and user intervention, ensuring safe, efficient, and reliable biogas management.

3.9 Research Flowchart

To illustrate the overall system operation, a research flowchart is developed to describe the complete workflow from system initialization to automatic control execution. The process begins with system design and sensor installation, followed by continuous data acquisition of fermentation parameters. The collected data are then transmitted to the cloud database and processed by the ANN model to predict methane gas concentration. The flowchart also depicts the integration of the three-stage gas filtration process, after which the ANN prediction is evaluated against predefined methane quality thresholds. Based on this evaluation, control decisions are generated to either open or keep the gas outlet sleeve closed. The flowchart further includes monitoring, evaluation, and feedback paths that allow system performance to be assessed and improved over time. This comprehensive representation highlights the interaction between monitoring, prediction, filtration, and control components, forming an intelligent and adaptive biogas monitoring and control system.

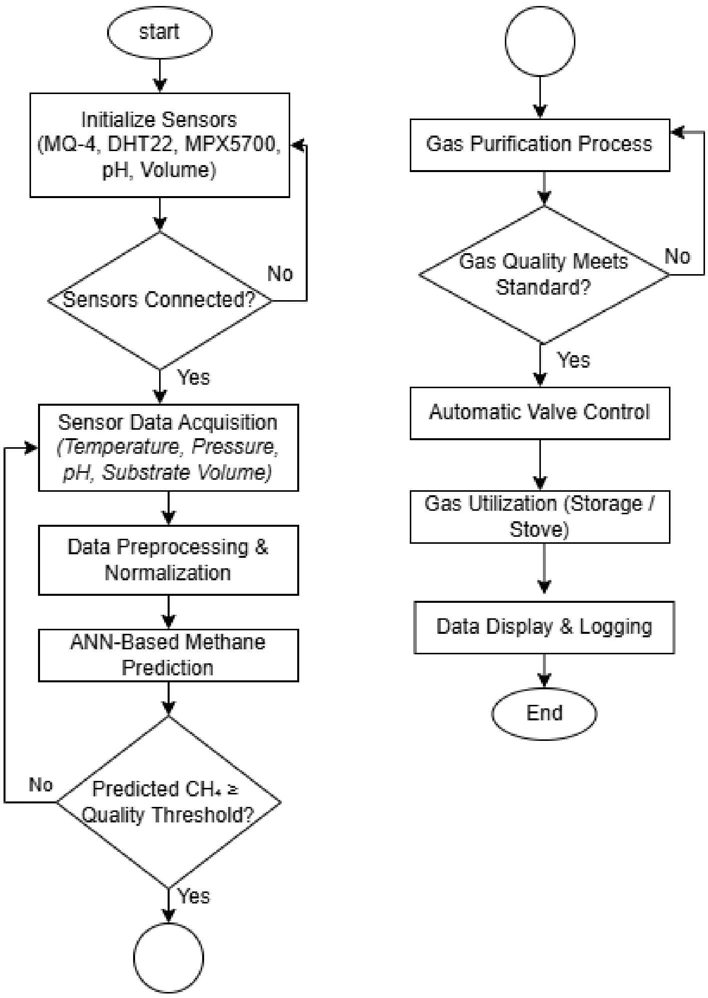

Fig. 5 *Flowchart*

3.10 Device Specifications and Operational Parameters

The selection of system components is based on considerations of energy efficiency, ease of integration, measurement reliability, and operational stability in household-scale biogas production. The ESP32 microcontroller is selected as the main processing unit due to its built-in Wi-Fi capability, low power consumption, and suitability for Internet of Things (IoT) applications[24]. Several sensors are integrated to monitor critical fermentation and gas quality parameters. Temperature and humidity measurements are obtained using the DHT22 sensor, while methane gas concentration is detected using the MQ-4 sensor. Gas pressure is measured using the MPX5700AP sensor, and substrate volume is monitored using the JSN-SR04T ultrasonic sensor. These sensors are chosen for their reliability and compatibility with anaerobic digestion environments. An MG996R servo motor is employed as the actuator to control the opening and closing of the gas outlet sleeve after the biogas passes through a three-stage filtration system. The servo motor provides sufficient torque and positional accuracy to ensure controlled gas flow toward the storage tank. The combination of these components enables stable system operation and supports real-time monitoring and intelligent control of biogas production.

4. Results and Discussion

This section presents the results of implementing a smart monitoring and control system for biogas production using household organic waste as the primary substrate. The system utilizes an ESP32 microcontroller connected to multiple sensors for real-time monitoring of fermentation conditions and methane gas quality. A mobile-based application serves as the main interface for monitoring sensor data and controlling the actuator. Sensor data collected from the biogas digester are transmitted to cloud storage and used as input for an Artificial Neural Network (ANN) model to predict methane gas concentration. The ANN model operates separately from the microcontroller and provides prediction results that support automated control decisions. When the predicted methane concentration meets the predefined quality threshold after passing through the three-stage filtration process, the system automatically activates the servo motor to open the gas outlet sleeve, allowing methane to flow into the storage tank. If the gas quality does not meet the required standard, the sleeve remains closed.

The system was tested over a fermentation period of several days under real operating conditions. All sensor data were monitored through the mobile application, allowing users to observe fermentation behavior and system responses in real time. In addition to automatic control, manual control is also available through the application interface, enabling users to directly operate the gas outlet sleeve when necessary. The results demonstrate that the proposed ANN-based monitoring and control system operates reliably and provides an effective solution for improving safety and efficiency in household-scale biogas utilization.

4.1 Fermentation Process Parameter Monitoring Results

This section presents the results of the implementation of an intelligent monitoring system for household-scale biogas production using organic waste as the fermentation substrate. The monitoring system was developed using an ESP32 microcontroller integrated with multiple sensors to continuously measure key fermentation parameters, including temperature, pressure, pH, and substrate volume. Methane concentration was measured using an MQ-4 gas sensor and used as a reference to evaluate biogas quality during the anaerobic digestion process.

The fermentation experiment was conducted over a period of 29 days, from October 3 to October 31, 2025, representing a complete observation cycle of biogas production under controlled conditions. During this period, methane concentration exhibited noticeable variations, with higher values observed under relatively optimal fermentation conditions characterized by temperatures in the range of 32–35 °C, stable pressure, and near-neutral pH levels, while lower methane concentrations occurred under less favorable conditions at lower temperatures and more acidic pH values. Sensor data was recorded periodically and transmitted in real time to a mobile-based monitoring application via a Wi-Fi connection, enabling continuous observation of fermentation dynamics without the need for complex cloud infrastructure. The collected sensor data was subsequently utilized as input parameters for the Artificial Neural Network (ANN) model to predict methane concentration. The predicted methane values were then compared with the actual measurements obtained from the MQ-4 sensor to assess the prediction performance of the proposed system. Table 3 summarizes the daily fermentation parameters and methane concentration results observed during the experimental period.

4.2 Performance Evaluation of ANN for Methane Gas Prediction

4.2.1 Prediction Accuracy

The prediction performance of the proposed Artificial Neural Network (ANN) model was evaluated to determine its capability in estimating methane gas concentration based on fermentation parameters. Several statistical performance metrics were employed, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). These metrics provide quantitative measures of prediction error magnitude and the agreement between predicted and actual methane concentration values.

Table 5 shows that the proposed ANN model achieved relatively low MAE and RMSE values, indicating small prediction errors between estimated and actual methane concentrations. In addition, the high coefficient of determination ($R^2 = 0.94$) demonstrates a strong correlation between predicted and measured methane values, confirming that the ANN model successfully captures the nonlinear relationship between fermentation parameters and methane production behavior.

Figure 6 illustrates the comparison between actual methane concentration and ANN-predicted methane concentration during the fermentation process. The predicted values closely follow the trend of the measured methane concentration throughout the observation period, with only minor deviations at several measurement points. This result indicates that the ANN model is capable of providing stable and reliable methane concentration predictions under varying fermentation conditions.

Table 4 *Result of observations made over a 29-day period*

Date	Temperature (°C)	Pressure (kPa)	pH	Substrate Volume (L)	CH_4 Actual (ppm)	Predicted CH_4 (ppm)	Gas Production (L/day)
3 Oct 2025	30	101	6.8	50	1600	1585	12
4 Oct 2025	31	103	6.9	50	1450	1470	9
5 Oct 2025	29	100	6.7	50	1150	1135	6
6 Oct 2025	28	99	6.6	50	850	870	4
7 Oct 2025	27	98	6.5	50	600	620	2
8 Oct 2025	32	105	6.9	50	1750	1720	15
9 Oct 2025	31	104	6.9	50	1550	1530	11
10 Oct 2025	28	100	6.7	50	800	820	3
11 Oct 2025	30	102	6.8	50	1500	1485	10
12 Oct 2025	29	101	6.7	50	1200	1215	7
13 Oct 2025	33	107	7.0	50	1800	1770	17
14 Oct 2025	27	99	6.5	50	550	570	1
15 Oct 2025	32	106	6.9	50	1650	1630	13
16 Oct 2025	30	103	6.8	50	1400	1385	8
17 Oct 2025	28	100	6.6	50	750	770	3
18 Oct 2025	33	108	7.0	50	1700	1685	14
19 Oct 2025	31	104	6.9	50	1450	1430	9
20 Oct 2025	28	99	6.6	50	700	720	2
21 Oct 2025	31	105	6.9	50	1550	1570	11
22 Oct 2025	29	101	6.7	50	1100	1085	6
23 Oct 2025	34	109	7.1	50	1850	1820	18
24 Oct 2025	27	98	6.5	50	500	520	1
25 Oct 2025	32	106	7.0	50	1600	1580	12
26 Oct 2025	31	104	6.9	50	1500	1515	10
27 Oct 2025	28	100	6.7	50	800	820	3
28 Oct 2025	33	108	7.0	50	1700	1680	15
29 Oct 2025	30	102	6.8	50	1450	1435	9

Date	Temperature (°C)	Pressure (kPa)	pH	Substrate Volume (L)	CH_4 Actual (ppm)	Predicted CH_4 (ppm)	Gas Production (L/day)
30 Oct 2025	28	99	6.6	50	750	770	3
1 Nov 2025	35	110	7.2	50	1900	1870	20

Table 5 *Performance metrics of ANN model*

Metric	Value	Unit
MAE	27.8	Ppm
RMSE	34.6	Ppm
R^2	0.94	-
MAPE	3.21	%

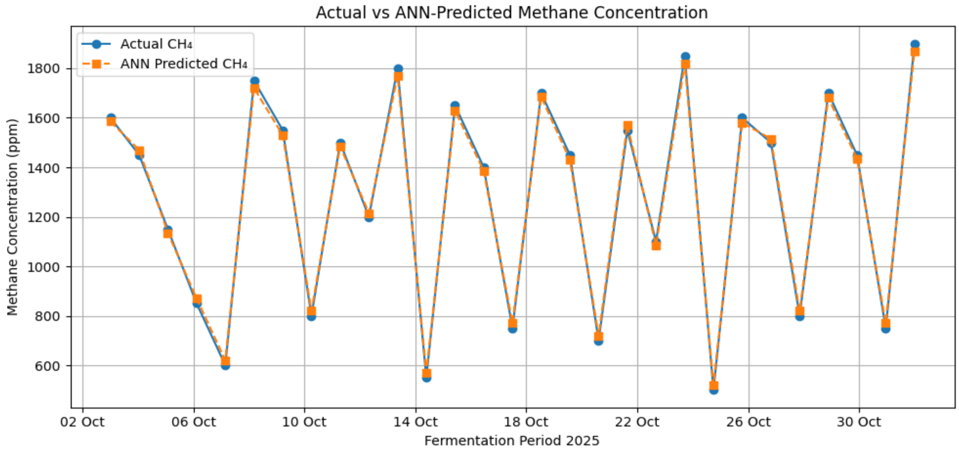

Fig. 6 *Actual vs ANN predicted methane concentration*

Figure 7 presents the daily biogas production trend during the 29-day anaerobic digestion process. Variations in gas production can be observed throughout the fermentation period, where methane generation tends to increase during the middle phase of digestion and becomes relatively stable toward the later stages. This behavior is consistent with the typical characteristics of anaerobic fermentation, in which microbial activity gradually intensifies before reaching stable methane production conditions. Overall, the prediction results demonstrate that the proposed ANN model provides reliable methane concentration estimation with high prediction accuracy and stable performance. These results indicate that the developed ANN-based prediction system is suitable for integration into real-time monitoring and intelligent control applications in household-scale smart biodigesters.

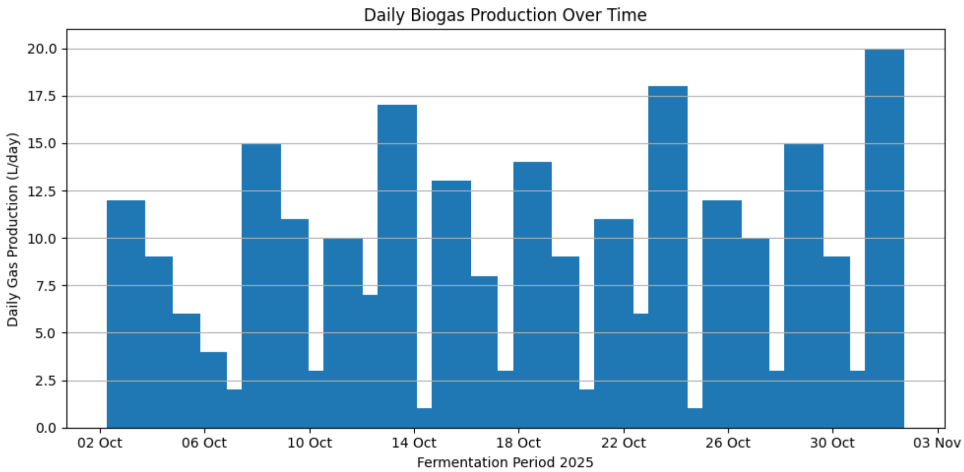

Fig. 7 *Biogas production over time*

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4.2.2 Training Convergence Analysis

The convergence behavior of the proposed Artificial Neural Network (ANN) model during the training process is illustrated in Figure 8. The graph presents the progression of training loss and validation loss over 500 training epochs using Mean Squared Error (MSE) as the loss metric.

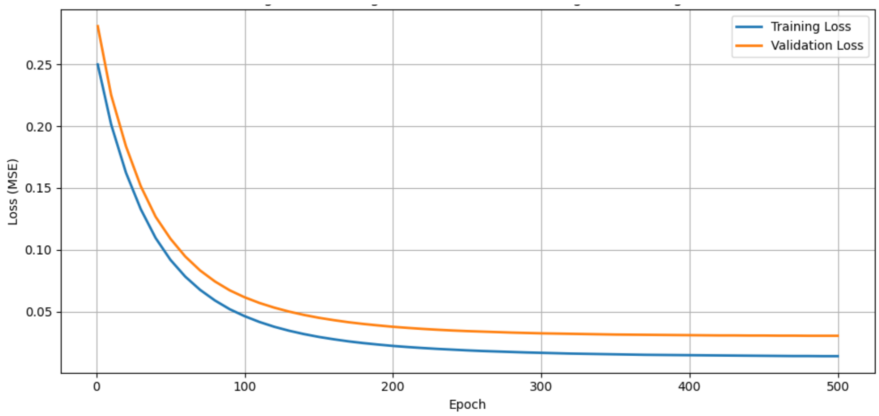

Fig. 8 *Training and validation loss during ANN training*

As shown in Figure 8, both training loss and validation loss decreased significantly during the early training stage, indicating that the ANN model successfully learned the nonlinear relationship between fermentation parameters and methane gas concentration. The loss curves continued to decrease gradually and became relatively stable after approximately 300–350 epochs, suggesting that the model had reached convergence. In addition, the validation loss curve follows a similar trend to the training loss curve without exhibiting significant divergence throughout the training process. The relatively small gap between the two curves indicates that the model achieved good generalization capability and did not experience severe overfitting. These results confirm that the implemented early stopping strategy and selected ANN architecture were effective in maintaining stable training behavior. Furthermore, no substantial improvement in validation loss was observed after the later training epochs, confirming that the selection of 500 epochs was sufficient for model optimization. Therefore, the proposed ANN model demonstrates stable convergence characteristics and reliable prediction performance for methane concentration estimation in the smart biodigester system.

4.2.3 Error Characteristics

The prediction performance of the proposed ANN model was evaluated using several statistical metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). These metrics were used to quantitatively assess the prediction capability of the ANN model in estimating methane gas concentration under varying fermentation conditions. The obtained MAE value indicates that the average prediction error between actual and predicted methane concentration values remained relatively low. Similarly, the RMSE result demonstrates that large prediction deviations occurred infrequently, indicating stable model performance throughout the testing process.

The coefficient of determination (R^2) of 0.94 indicates a strong correlation between predicted and actual methane concentration values. This result confirms that the ANN model successfully captured the nonlinear relationship between fermentation parameters and methane generation behavior during the anaerobic digestion process. Figure 9 illustrates the distribution of prediction residual errors generated by the ANN model. Most residual errors are concentrated near zero, indicating that the predicted methane concentrations closely match the actual measured values. In addition, the residual distribution does not exhibit extreme outliers, suggesting that the prediction errors are relatively stable and consistently distributed.

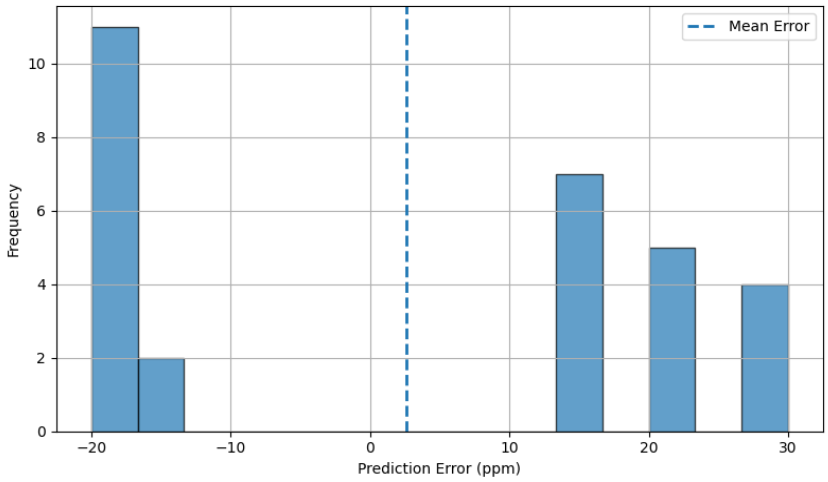

Fig. 9 *Prediction error distribution*

Furthermore, the relatively small difference between MAE and RMSE values indicates that large prediction errors occurred infrequently and that the model maintained consistent prediction accuracy across different operating conditions. The overall error analysis demonstrates that the proposed ANN model provides reliable methane concentration prediction performance and is suitable for integration into intelligent monitoring and automatic control systems for smart biodigesters.

4.2.4 Comparison with Baseline Model

To evaluate the effectiveness of the proposed Artificial Neural Network (ANN) model, a comparative analysis was conducted against a baseline regression model using Linear Regression (LR). Both models were evaluated using the same dataset and performance metrics to ensure a fair and consistent assessment. Table 6 presents the quantitative comparison results between the baseline Linear Regression model and the proposed ANN model.

Table 6 *Performance comparison between ANN and baseline model*

Model	MAE	RMSE	R^2	MAPE (%)
Linear Regression	58.3	71.5	0.76	8.94
Proposed ANN	27.8	34.6	0.94	3.21

The comparison results demonstrate that the proposed ANN model significantly outperformed the baseline Linear Regression model across all evaluation metrics. The ANN model achieved substantially lower MAE, RMSE, and MAPE values, indicating improved prediction accuracy and smaller prediction deviations. In addition, the higher coefficient of determination (R^2) confirms that the ANN model was more effective in capturing the nonlinear relationship between fermentation parameters and methane gas concentration. Figure 8 illustrates the graphical comparison between the proposed ANN model and the baseline Linear Regression model using the evaluated performance metrics.

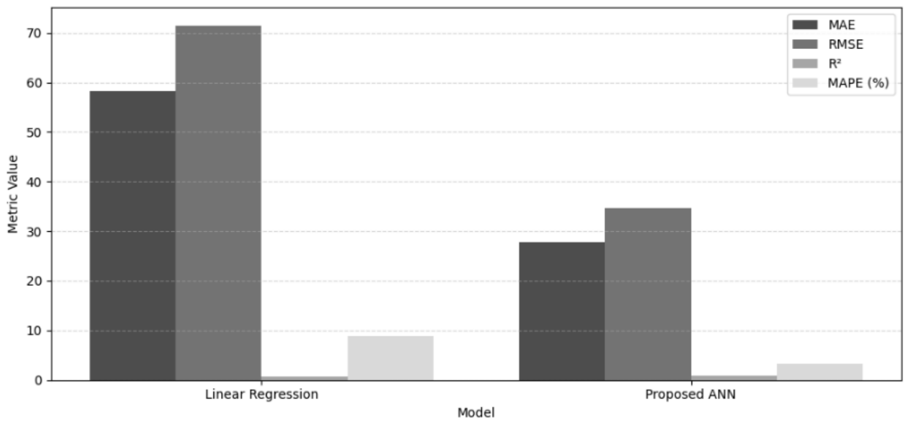

Fig. 10 *Comparison of ANN and baseline model*

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As shown in Figure 10, the ANN model consistently produced lower error values compared to the Linear Regression model. The reduction in MAE and RMSE indicates that the ANN model generated more accurate methane concentration predictions with fewer large deviations. Similarly, the lower MAPE value demonstrates that the ANN model maintained better relative prediction accuracy across varying methane concentration levels. Although the R^2 values of both models indicate acceptable prediction capability, the proposed ANN model achieved a substantially higher R^2 value of 0.94, demonstrating stronger agreement between predicted and actual methane concentration values. The superior performance of the ANN model can be attributed to its capability to learn complex nonlinear patterns inherent in anaerobic digestion processes. In contrast, the Linear Regression model is limited to linear relationships among variables, making it less effective for modeling dynamic fermentation behavior. These findings confirm that the proposed ANN-based approach provides a more reliable and accurate prediction framework for intelligent monitoring and automatic control systems in household-scale smart biodigesters.

4.3 Intelligent Methane Flow Control System

The proposed smart biodigester system successfully integrates IoT-based monitoring, ANN-based methane prediction, and automatic gas flow control for household-scale biogas applications. Fermentation parameters acquired by the ESP32 microcontroller were transmitted to the cloud database and processed by the ANN model to estimate methane gas concentration in real time.

The predicted methane concentration was used as the decision parameter for automatic valve control. When the predicted methane concentration exceeded the predefined threshold after passing through the filtration subsystem, the servo-actuated gas valve was automatically opened to allow methane gas to enter the storage tank. Otherwise, the valve remained closed to prevent low-quality biogas from being stored. The implemented filtration subsystem, consisting of water, steel wool, and silica gel filters, contributed to improving methane quality by reducing impurities and moisture content in the produced biogas. In addition, the developed mobile-based monitoring application enabled real-time observation of fermentation parameters, methane prediction results, and actuator status through Firebase cloud communication. The integration of ANN prediction, IoT communication, and automatic actuator control demonstrates that the proposed system can support intelligent, stable, and safer biodigester operation for renewable household energy applications.

4.4 Evaluation of Automatic Control System

The automatic control system was designed to regulate methane gas flow based on the ANN prediction results and predefined quality thresholds. Control of the gas outlet valve was performed using a servo motor operated through the ESP32 microcontroller. The system supports both manual and automatic control modes via the mobile-based application, allowing users to open or close the gas outlet remotely when required. In automatic mode, the servo motor is activated based on the predicted methane concentration generated by the ANN model after the gas passes through the three-stage filtration system. When the predicted methane concentration exceeds the quality threshold, the servo motor opens the gas outlet valve, allowing methane to flow into the storage tank. Conversely, when the predicted value falls below the threshold, the valve remains closed to prevent low-quality gas from being stored. The control system was tested continuously during the fermentation period and demonstrated stable and responsive performance. The servo motor responded to control commands with a short response time, indicating reliable communication between the mobile application, ESP32, and actuator. The availability of manual control also provides flexibility for users to intervene in special conditions or system maintenance, enhancing overall operational safety and usability.

4.5 Discussion of Results

The experimental results demonstrate that the proposed smart biodigester system, integrating IoT technology and Artificial Neural Network (ANN), operates effectively for monitoring and controlling household-scale biogas production. The ESP32-based monitoring system successfully captures fermentation parameters in real time and provides continuous access to system conditions through a mobile application, enabling remote supervision without direct physical presence. The ANN-based methane prediction model plays a crucial role in enhancing system intelligence by providing reliable estimates of methane concentration under varying fermentation conditions. The close agreement between predicted and actual methane values, supported by low MAE and RMSE results, confirms that the ANN model is suitable for representing the nonlinear behavior of the anaerobic digestion process. This predictive capability allows the system to make informed control decisions rather than relying solely on fixed sensor thresholds.

The integration of ANN predictions with the automatic control mechanism significantly improves operational safety and efficiency. By allowing methane gas to enter the storage tank only when quality requirements are met, the system reduces the risk associated with low-quality gas and uncontrolled pressure buildup. The three-stage gas filtration system further enhances gas purity, ensuring that the stored biogas is suitable for household utilization. In addition, the dual-mode control strategy, which combines automatic ANN-based control with manual user intervention, provides flexibility and reliability. Users can override the automatic system, when necessary, while still benefiting from intelligent data-driven automation under normal operating conditions. Overall, the proposed system demonstrates that combining low-cost IoT hardware with ANN-based prediction can result in a smart, efficient, and scalable solution for household biogas production and management.

4.6 Research Flowchart

The overall research workflow is summarized in the flowchart shown in Figure 6. The system operates in a closed-loop manner, starting from real-time data acquisition of fermentation parameters using IoT sensors, followed by wireless data transmission to the monitoring platform. The collected data are then processed by an Artificial Neural Network (ANN) to predict methane gas concentration. Based on the prediction results and predefined quality thresholds, the control unit automatically regulates the gas outlet valve using a servo motor. Manual control is also provided to allow user intervention when required. This flowchart highlights the integration of monitoring, prediction, and control processes in a unified intelligent biodigester system.

5. Conclusion

This study successfully developed an IoT-based smart biodigester system integrated with an Artificial Neural Network (ANN) to predict methane gas concentration and support automatic control. The ANN model demonstrated reliable prediction performance, as indicated by low error values, enabling intelligent regulation of gas flow based on predefined quality thresholds. The integration of monitoring, prediction, and control mechanisms improves operational efficiency, gas quality, and safety in household-scale biogas systems. Overall, the proposed system offers a practical and scalable solution for intelligent biogas management and can be further enhanced by incorporating additional parameters and adaptive learning strategies.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm their contributions to this paper as follows: ***study conception and system design:*** *Mochammad Junus, Rachmad Saptono, Mohd Noor, Agnes Medikawati P. E.;* ***system development and data collection:*** *Agnes Medikawati P. E.;* ***Data analysis and interpretation:*** *Mochammad Junus, Rachmad Saptono, Mohd Noor, Agnes Medikawati P. E.;* ***manuscript preparation:*** *Agnes Medikawati P. E., Mochammad Junus. All authors have reviewed and approved the final version of the manuscript.*

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