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ORIGINAL

Microclimate condition monitoring system for the prevention of methane contamination in the methane contamination in compost production in Microfarms

Sistema de Control de condiciones del microclima para la prevención de contaminación por metano en la producción de compost en Microfarms

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ABSTRACT

This work focuses on the development and implementation of a microclimate variable control system to prevent microbial contaminants in compost production, with the objective of investigating composting methods and how they can help reduce the production of methane, a greenhouse gas, and thus contribute to environmental care. The Action-Research methodology is used with the use of sensors that monitor data on environmental variables of ambient temperature, relative humidity and soil moisture, which are sent to an IoT platform where the necessary data are processed and generated. A specific infrastructure is designed for compost production, which includes a closed box lined with greenhouse plastic, a container for the compost, a piping system to maintain humidity, a heater to raise the temperature and a protective box for the sensors. Also included is the development and training of a neural network model that predicts methane production based on the above variables. The data show that composting at temperatures between 55-65 degrees Celsius, using aerobic biological methods, significantly reduces methane production by eliminating bacteria responsible for methane generation. The data collected and model predictions can be monitored remotely through the IoT platform. At the conclusion of the work, the compost generated was found to be suitable for micronization.

Keywords: Microclimate; Methane; Microfarms; Compost; Composting; IoT.

RESUMEN

Este trabajo se enfoca en el desarrollo e implementación de un sistema de control de variables de microclima para prevenir contaminantes microbianos en la producción de compost, con el objetivo de investigar métodos de compostaje y cómo estos pueden ayudar a reducir la producción de metano, un gas de efecto invernadero y por ende contribuir al cuidado del medio ambiente. Se utiliza la metodología Action-Research con el uso de sensores que monitorean datos de variables ambientales de temperatura ambiente, humedad relativa y humedad del suelo, que se envían a una plataforma IoT en donde se procesan y generan los datos necesarios. Se diseña una infraestructura específica para la producción de compost, que incluye una caja cerrada forrada con plástico de invernadero, un contenedor para el compost, un sistema de tuberías para mantener la humedad, un calefactor para elevar la temperatura y una caja protectora para los sensores. También se incluye el desarrollo y entrenamiento de un modelo de red neuronal que predice la producción de metano basado en las variables mencionadas. Los datos muestran que el compostaje a temperaturas entre 55-65 grados centígrados, utilizando métodos biológicos aeróbicos, reduce significativamente la producción de metano al eliminar bacterias responsables de su generación. Los datos recopilados y las predicciones del modelo se pueden monitorear remotamente a través de la plataforma IoT. Al concluir el trabajo, se comprobó que el compost generado es adecuado para microfarms, pues cumple con los requisitos de calidad y nutrientes necesarios según el método de compostaje de Berkeley y contribuye al cuidado del medioambiente.

Palabras clave: Microclima; Metano; Microfarms; Compost; Compostaje; IoT.

INTRODUCTION

Global warming is a growing concern due to the greenhouse effect, caused in part by inadequate treatment of organic and inorganic wastes that release large amounts of CO2. Anaerobic decomposition of these wastes produces methane, a gas that intensifies the greenhouse effect and contributes to climate change, affecting photosynthesis and plant development, and disrupting agricultural production[1] as well as threatening the balance of the planet.[2]

In Ecuador, agriculture is fundamental to the economy and food supply, accounting for 8 % of annual production and helping to reduce poverty. However, this sector also contributes 0,15 % of global greenhouse gas emissions,[3] which, although small, is detrimental to the country due to its impact on forests and the natural balance.[4] To mitigate this problem, proper waste management is crucial, using waste for composting. Composting converts waste into humus rich in nutrients such as carbon, hydrogen, oxygen and others that favor plant growth.[5] This process can be optimized through a network of sensors that monitor parameters such as humidity and temperature, using machine learning algorithms to create a suitable environment for the production of effective and sustainable compost,[6,7] as a fundamental benefit for a microfarm system or urban home gardens, through the application of the Berkeley method, with the hot composting technique, which consists of producing high quality compost at controlled temperatures in reduced times (18 days),[2] the production of greenhouse gases such as methane, which contribute to environmental pollution, is avoided; this environmentally polluting gas is produced when waste is decomposed without using an adequate method.

The use of sensors and IoT technology allows for intelligent management of waste decomposition, ensuring that conditions are optimal for compost production. This approach not only reduces environmental impact by reducing methane production,[8] but also contributes to quality and quantity in agricultural production, benefiting farmers by enabling them to produce their own compost.[9]

The objective of this work is to develop an IoT system with neural networks as a suitable scenario to produce quality compost avoiding the emission of polluting gases and empowering agriculture.

METHOD

This work uses the "Action Research" methodology as a method of systematic inquiry where the practical stage is initiated, leading to the execution of a cyclical process according to the diagnosis of the problems. The phases accomplished within this methodology are: identify, plan, implement and evaluate applied in order to improve specific practices from data collected to achieve relevant improvements in the practices carried out.[10]

The first phase presents the study of requirements and requirements that are important for system design, implementation elements, flowcharts, block diagrams and data analysis. These requirements are raised from the ISO/IEC/IEEE 29148: 2018 standard,[11] some of the important requirements defined are: the ambient temperatures of the container must be between 55°C and 65°C, ambient humidity of 18°C, soil humidity of 62°C, methane 20 ppm, and the system must operate 24 hours a day and have a permanent wireless connection to send data to a storage database and a processing platform,[10] the analysis of this information was performed using a convolutional neural network, CNN, since the data has a spatial and/or temporal structure, generating correlational patterns and extracting the necessary features at any stage of training, and it does not require too much CPU and GPU processing.[12]

DEVELOPMENT

The hardware used was selected and calibrated based on the datasheets considering their appropriate thresholds, scenarios according to the nature of the project, costs and market availability. Once the devices have been calibrated, each stage of the system is started. The development stage of the system starts with the block diagram, each one with its respective characteristics to give proper operation to the whole system, see figure 1.

The project includes the following blocks: sensors, data acquisition, processing and automation, actuators, energy and visualization. The sensor block consists of a DTH22 temperature and humidity sensor, a capacitive soil humidity sensor, and an MQ2 methane gas sensor, which are responsible for receiving data from the controlled environment during the compost production time (18 days).

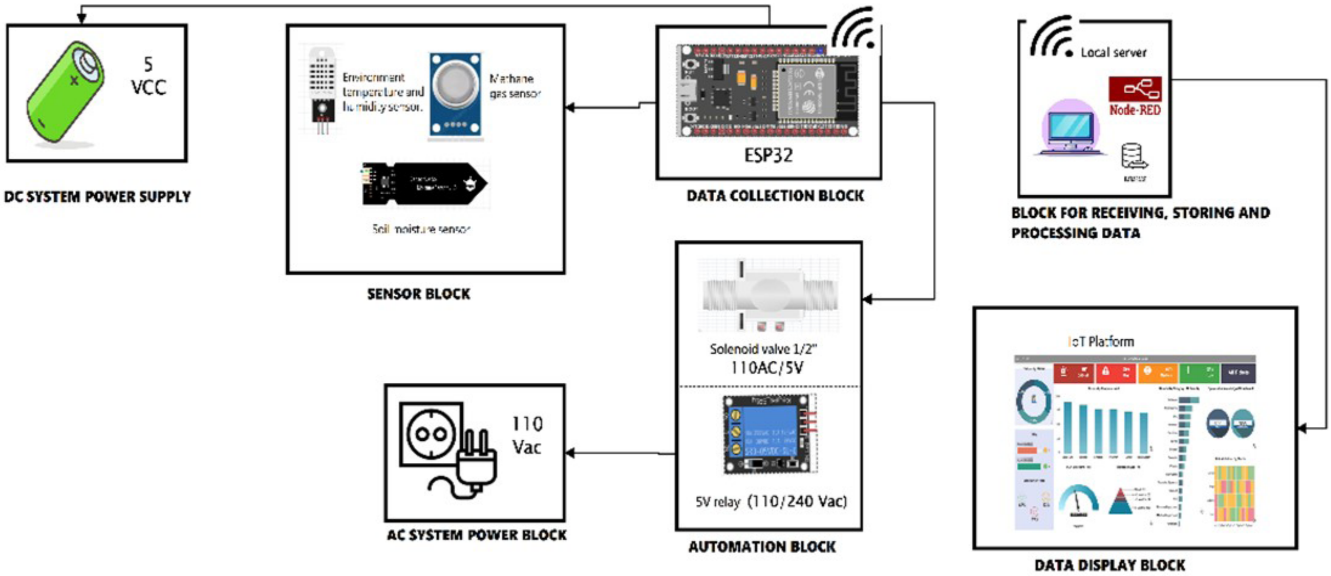

Figure 1. System Block Diagram

Then there is the data acquisition block for both analog and digital values, then the automation block manages the parameters obtained for soil moisture, temperature and ambient humidity and methane gas. The actuator block consists of a solenoid valve that is automatically activated by an ESP32 microcontroller when the controlled environment has a low humidity level, providing the proper environment within the controlled system. To power the system, two power supplies are provided, the first in DC through 5-volt batteries for the sensors, the controller board and the processing board, both ESP32. The second power source of the system is AC, which supplies 110 V to the solenoid valve that is activated when necessary. The next block is for data reception, storage and processing, which by means of a convolutional neural network determines that the automated environment reduces methane levels compared to a traditional environment that meets the characteristics of the Berkeley method that allows achieving an optimal compost for its use: brown color, without aromas, compact, totally decomposed, with a grayish surface color. Finally, the visualization block allows the data taken and processed from the different variables in real time. These training values will allow the neural network to predict the methane value at the end of the compost production process, as well as to provide the administrator with the possibility of constant monitoring of the system.

Design of the container structure: the prototype is based on the Berkeley technique of home composting, its structure includes a wooden skeleton lined with a special greenhouse plastic to retain heat, its dimensions are 1,25 m high, 90 cm wide and 60 cm deep; it has a division at 25 cm from the ground to support the essential elements for the decomposition of waste in the production of compost, as shown in figure 2.

Figure 2. Compost box dimensions

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Microfarms optimize small spaces and use a composting box of less than 1 cubic meter.[11] The box is lined with greenhouse plastic to maintain the internal heat; on the inside, a ribbed base supports a heater connected to an adapted outlet, which also allows the attachment of a 1/8" hose connected to a micro-sprinkler to irrigate the compost with water. The hose is connected to one end of the solenoid valve with an adapter, at the other end the solenoid valve is connected to a water stopcock that regulates the flow of liquid, see figure 3.

Figure 3. Elements that make up the composting box

Design of the composter: the assembly of the container consists of a bottle of 20 liters capacity, with several holes to ensure aeration of the compost, which rests on a wooden box that supports up to 44 pounds of content, the composter is filled with organic waste and soil in the same proportion (22 pounds), to make this compost the following elements are needed: potato peel waste which is easy and quick to decompose, banana peels which provide potassium and strengthen the formation of flowers or fruits, as green waste grass which allows the detoxification of the soil, finally, all compost must have an element that provides calcium in this case crushed eggshells are added. The 22 pounds of organic waste should be cut into small pieces to facilitate decomposition, each layer should be evenly dispersed in the container until the container is full as shown in figure 4.

Figure 4. Structuring layers of compost in the container

Sensors structure: internally, the sensor node is protected by a protective housing to avoid contact with possible debris such as soil and substances that may affect normal operation, see figure 5.

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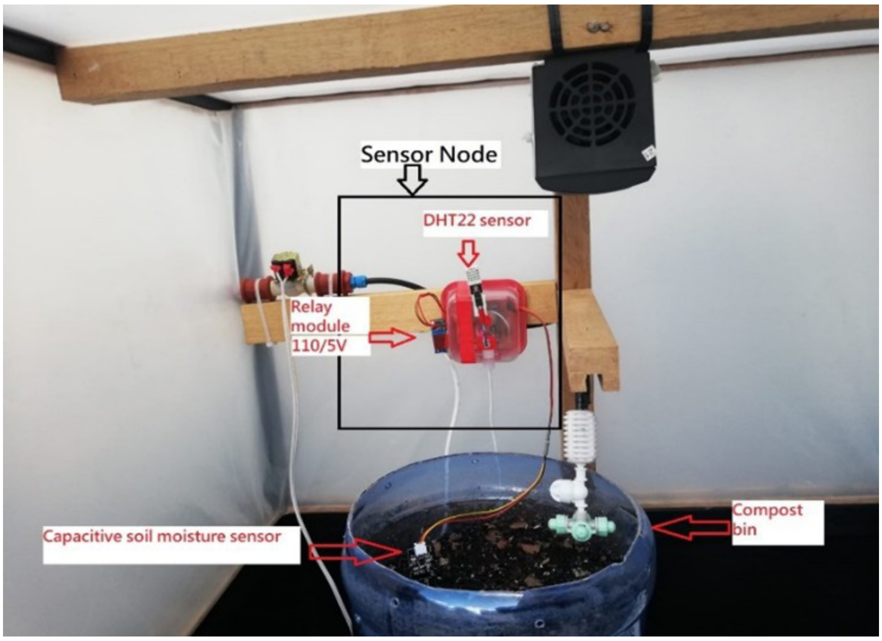


Figure 5. Sensor node structuring

Hardware connection diagram: in the first phase, the soil moisture sensor and the ambient temperature and humidity sensor are integrated as inputs and data from the MQ2 gas sensor as output, for processing and learning of the neural network, as shown in figure 6.

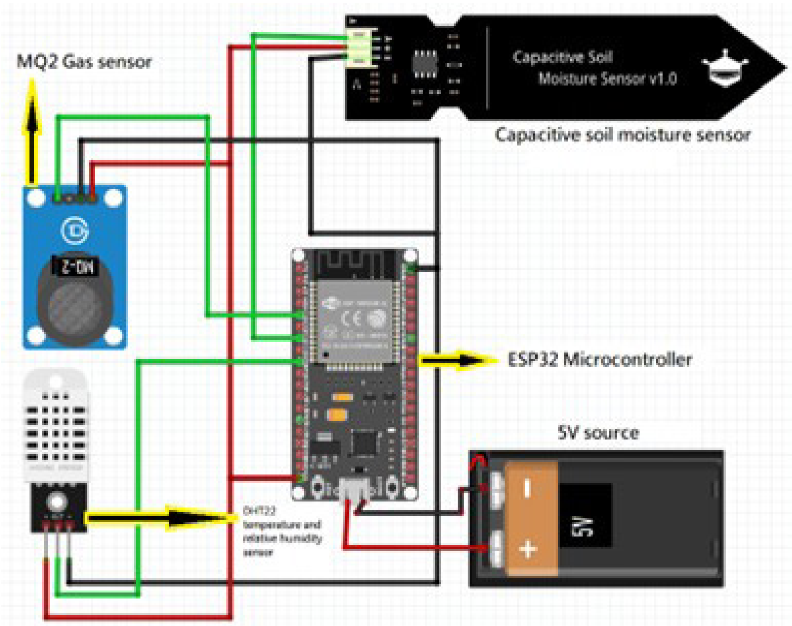


Figure 6. Hardware connection diagram for the training phase

In phase two, the soil moisture sensor and the ambient temperature and humidity sensor are integrated, in addition to a relay module that activates the solenoid valve to irrigate the soil of the composting bin with water flow. Based on the learning of the neural network with the previous training data, methane values are determined from these sensory variables, see figure 7.

Control System Design: the choice of the implements that make up the design is made, which are consolidated in the software block diagram, which allows visualizing the operation of the system. Each block fulfills the following functions: collection of information through the ESP32 microcontroller using the Arduino development IDE as software, data is sent to the local server through the MQTT protocol. The data received are stored in a database designed in the MariaDB manager and processed in a local server through NodeRED where the neural network is designed.[12] As the project is focused on the Internet of Things, the data visualization is achieved through graphs in the ThingSpeak software, this is shown in figure 8.

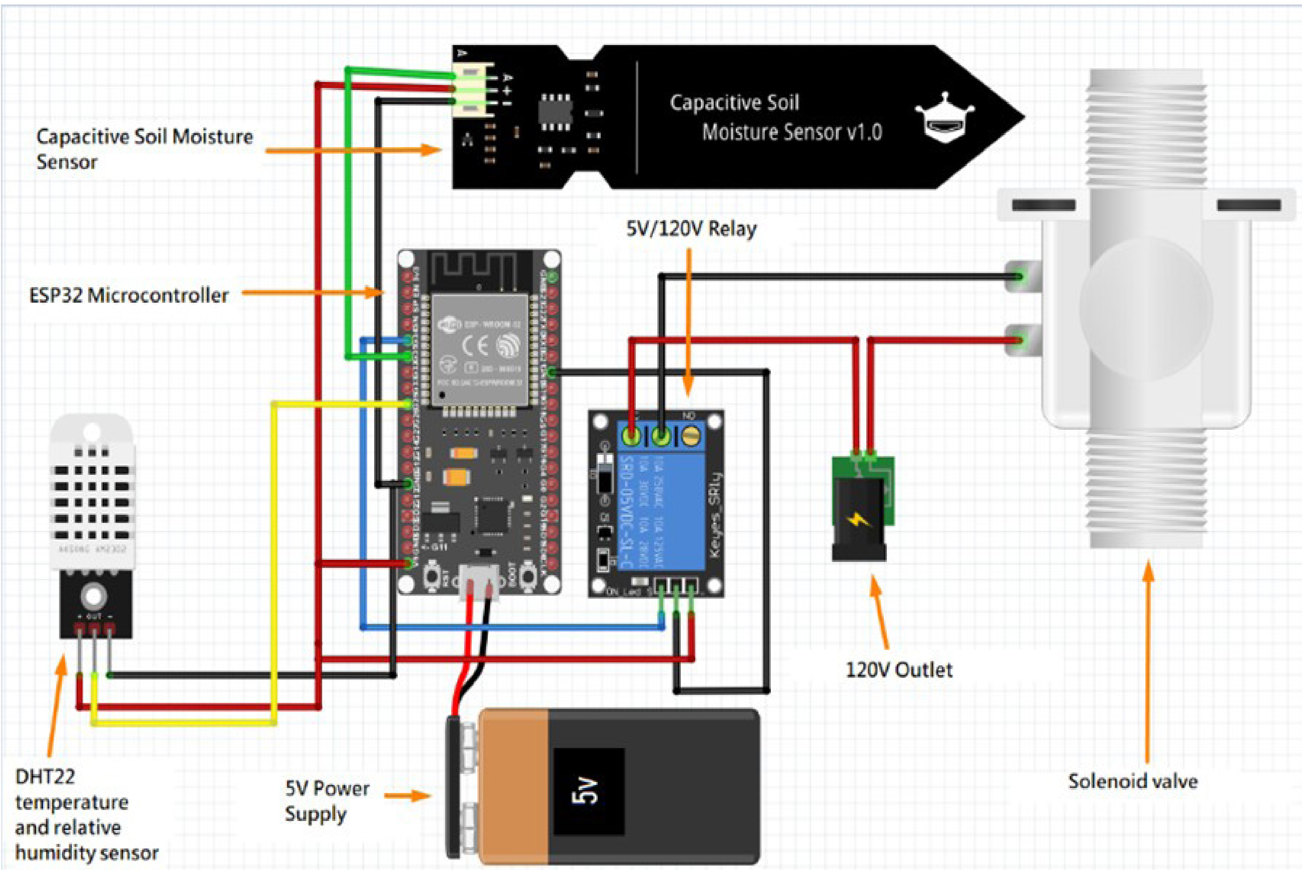


Figure 7. End connection diagram

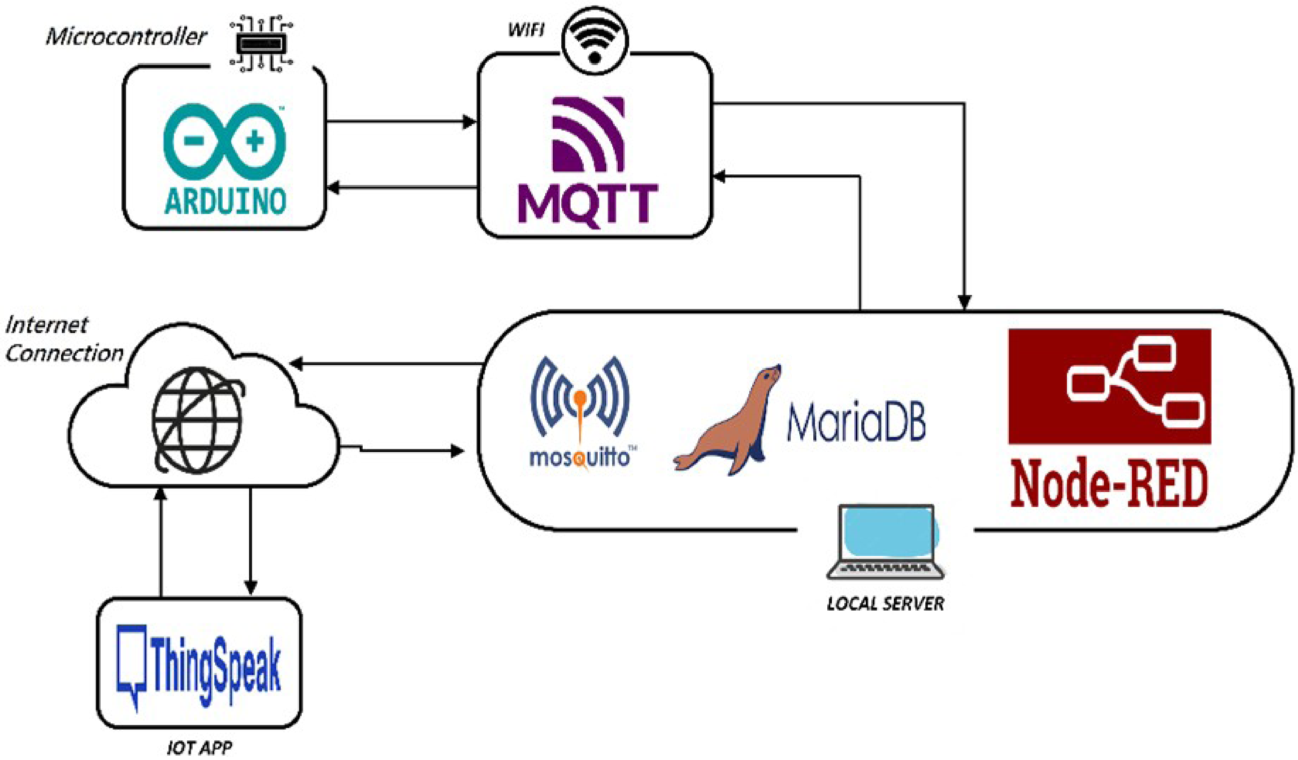


Figure 8. Software Block Diagram

The structure of the total system flow in the Node-Red is made up of several stages, the most relevant being the section that processes data for methane detection, see figure 9.

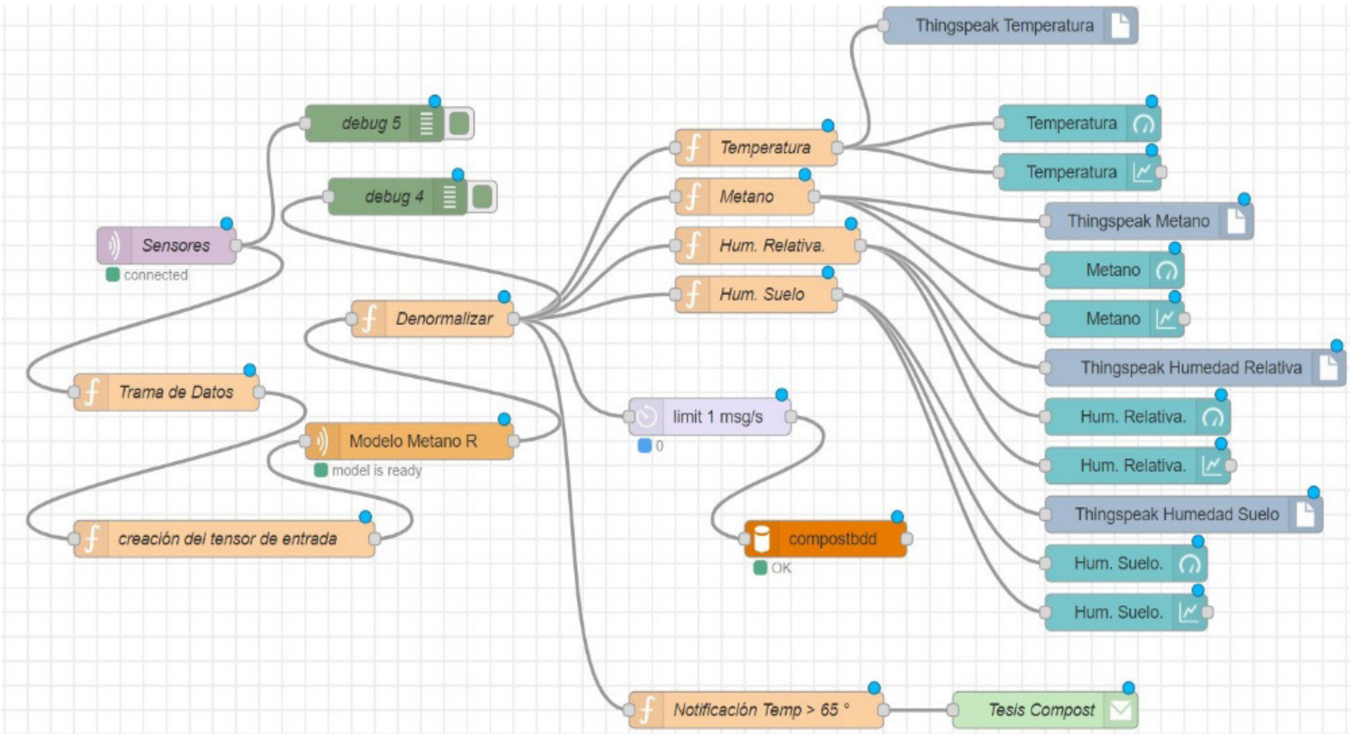


Figure 9. Total flow in Node-Red

This section allows feeding the database and using Tensor Flow models to make inferences,[13] that with training data from the methane sensor MQ2 (ppm), ambient temperature and humidity sensor DHT22 in (°C), a capacitive sensor for soil moisture in (%), during a 14-day composting process according to the Berkeley method, which lasts 18 days in total. During the first 4 days, the compost is kept without aeration, at temperatures between 55 and 65 °C. Starting on day 5, data collection and turning every two days begins to aerate the waste and provide oxygen, eliminating gases generated during decomposition. The data collected is stored in a database and divided into input data (ambient temperature and humidity, soil moisture) and output data (methane). This training data allows the neural network to predict the methane concentration and then compare the values obtained with the MQ2 sensor. Data is collected under various humidity and temperature conditions to obtain a wide variation of methane values. The development of the neural network model is carried out in Google Colab using Python, ensuring compatibility with Node-Red for data formatting. To create a neural network for predicting methane in composting, a data set in .csv format is used as shown in table 1. These data, taken by sensors during the composting process, are divided into inputs (ambient temperature, ambient humidity, soil moisture) and expected outputs (methane). The neural network is structured using the Keras library, designing a dense network with complete connections between neurons of 3 successive layers. Since the problem does not require a deep network, two hidden layers with 7 neurons each are defined. The first hidden layer receives the three inputs from the .csv file, and the output layer has a single neuron that predicts the methane level. The sequential Keras model connects the hidden layers and the output layer, suitable for predicting values over a time interval. After defining the structure, the model is prepared for training using the collected data, see figure 10.

```
#ELABORACIÓN DE RED NEURONAL DENSA
oculta1 = tf.keras.layers.Dense(units=7, input_shape=[3], activation="relu")  #Capa1 de tipo densa
oculta2 = tf.keras.layers.Dense(units=7, activation="relu") #Capa2 de tipo densa
#oculta3 = tf.keras.layers.Dense(units=7, activation="relu")
capaSalida = tf.keras.layers.Dense(units=1) #Neurona de salida
modelo = tf.keras.Sequential([oculta1, oculta2, capaSalida]) #Modelo secuencial
```

Figure 10. Neural network model

To optimize the neural network, the ADAM optimizer is used, which efficiently adjusts the biases and weights to improve the accuracy of the predictions, allowing an optimal balance to achieve accurate methane prediction results, see figure 11.

```
modelo.compile(
    optimizer=tf.keras.optimizers.Adam(0.0001),  #valor de tasa de aprendizaje
    loss= 'mean_squared_error'  #Función de perdida
)
```

Figure 11. ADAM Optimizer

Prediction of the methane parameter from the neural network model: with the modeling of the neural network, it was possible to measure how well it models the training data, fulfilling the main objective of minimizing losses and improving the learning of the neural network in each iteration. Figure 12 shows that the loss magnitude is between 0,027 and 0,028, this value remains constant from iteration 500 of the neural network, which implies that the neural network stops learning.

```
import matplotlib.pyplot as plt
plt.xlabel = '#Epoca'
plt.ylabel = 'Magnitud de pérdida'
plt.plot(historial.history["loss"])  #resultado de la red en cada vuelta
```

```
[<matplotlib.lines.Line2D at 0x7f1bdb6c2bc0>]
```

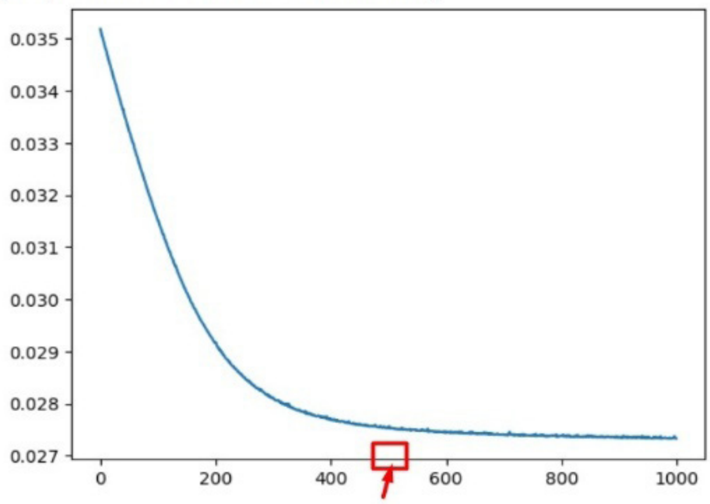


Figure 12. Graph of magnitude of data loss, with respect to neural network learning

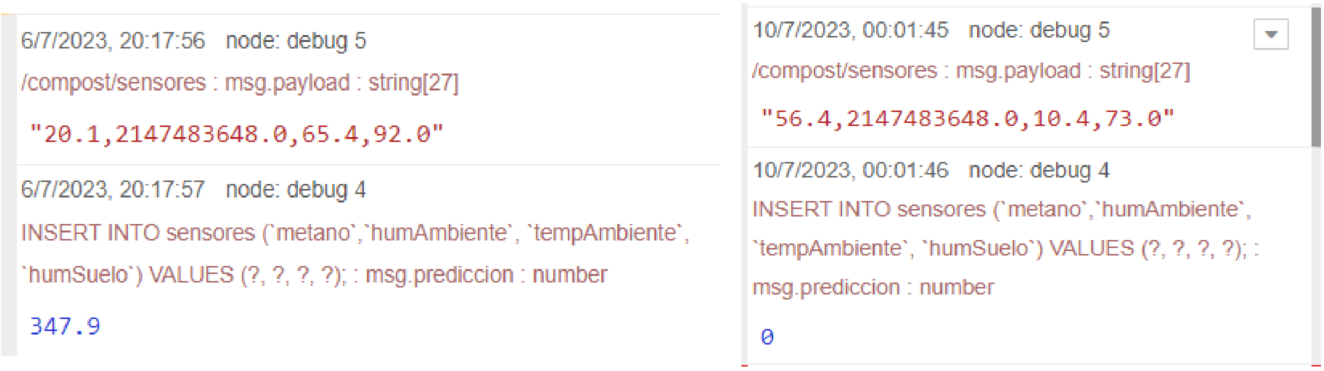
```
[9] print ("Variables internas del modelo")
    print (oculta1.get_weights())
    print (oculta2.get_weights())
    print (capaSalida.get_weights())
```

```
Variables internas del modelo
[array([[-0.13873038,  0.09021348,  0.674419  ,  0.6111994 ,  0.31822416,
         0.51126266, -0.14647695],
       [ 0.46569562, -0.28957087,  0.14286338,  0.33885697, -0.7699072 ,
         0.07776602,  0.06493299],
       [-0.83378804, -0.64298224, -0.63374996, -0.23530382,  0.45532754,
         1.1161711 ,  0.01884802]], dtype=float32), array([-0.06656337,  0.        ,  0.00724743,  0.03087181,  0.07015984,
       -0.2006568 , -0.04931099], dtype=float32)]
[array([[-0.6411693 , -0.19675483,  0.28230262, -1.3089389 , -0.10966901,
        -0.08152368,  0.09877738],
       [ 0.6411613 ,  0.5136602 , -0.63643473, -0.18132624,  0.63010013,
        -0.0069589 ,  0.0399527 ],
       [-0.0315522 , -1.0894376 , -0.23564434,  0.41406068,  0.41119593,
         0.04936398,  0.15508167],
       [-0.33994368,  0.08936635, -0.2449412 ,  0.39929512,  0.3878358 ,
         0.40750998,  0.43017417],
       [-0.01074886,  0.69159317,  0.3645128 , -0.48304605,  0.17077254,
        -0.7791084 ,  0.70985264],
       [-0.07103723,  0.30133384, -0.28580758, -0.58996147,  0.1432845 ,
         0.56988114,  0.53230226],
       [-0.08857208,  0.49476582, -0.4070558 , -0.2402317 , -0.04711419,
        -0.4362068 , -0.21706298]], dtype=float32), array([ 0.        , -0.09775046,  0.        ,  0.15962698, -0.02225383,
        0.02435706, -0.02408063], dtype=float32)]
[array([[ 0.7942304 ],
       [ 0.70493674],
       [-0.18523693],
       [ 1.2946019 ],
       [ 0.39554682],
       [-0.36351085],
       [ 0.05689753]], dtype=float32), array([-0.02225179], dtype=float32)]
```

Figure 13. Verification of neural network weights and biases

In each hidden layer, we check how the weights and biases of the network are structured. The arrays marked with yellow represent the weights assigned to each neuron of the hidden layer while the arrays marked in green represent the biases of the model. With this it is possible to verify the best combination found by the neural network optimization process to reach the result in the most accurate way, as can be seen in figure 13.

Comparison of training data and neural network prediction: with the model running through Node-Red, the sensor data is validated, the neural network technique is applied, and the methane gas emission is predicted over a period of 14 days. In figure 14 a) the controlled microfarm conditions show the following data: ambient temperature of 20,1°, ambient relative humidity of 65,4 % and soil moisture percentage of 92 %, resulting in a methane prediction value of 347,9 ppm. For the second case, figure 14 b) shows values of ambient temperature 56,4°, ambient relative humidity 10,4 % and soil moisture percentage of 73 %, which generates a methane gas production prediction of 0 ppm. This means that the higher the temperature in the controlled system, the lower the emission of pollutant methane gas, reaffirming the optimal conditions required in the Berkeley method, which suggests an optimal environment between 55-65 degrees Celsius as the ideal temperature to reduce the generation of methane pollutant gases, with these optimal conditions the compost is suitable for its use.



a) b)

Figure 14. comparative methane levels at NodRed

Table 1 shows two situations to be analyzed regarding the prediction of methane gas presence in the compost production; the data taken from an extract of the training data obtained from the last compost production shows a similarity with the data obtained in the training and visualization platform Node-Red of 347,9ppm, which agrees with the data taken by the MQ2 sensor of 346ppm, showing that the values predicted by the neural network do not differ significantly from the values taken by the methane sensor. Likewise, it is evident that in a temperature environment between 55-65 degrees Celsius the methane gas emission presents 2 ppm, which compared with the values obtained by the training of 0ppm do not differ significantly, concluding that the composting process ends successfully in the predicted time and contributing to the non-contamination by methane gas emission.

Table 1. Extract from training database, different temperatures

Data No.	Methane	enviromentHum	enviromentTemp	groundHum
576	346	64	20	92
998	2	9	57	73

RESULTS AND DISCUSSION

Each composting period takes eighteen days approximately of which the first four days do not require any action; therefore, from day 5 to day 18 the data reception was performed having a period of fourteen days, after several tests performed, from the last composting process its results were analyzed, where the methane level is predicted with the neural network instead of measuring it with a sensor. The Berkeley method is used, keeping the compost at temperatures between 55 and 65 degrees to carry out an aerobic process that minimizes methane production.[14] The compost is aerated and stirred after the fifth day, every two days, to maintain oxygenation and avoid the activation of microbes that generate methane.

Data analysis at temperatures between 55 - 65 degrees Celsius

Table 2 consolidates the analysis of the prediction data obtained from the operation of the neural network, which was conditioned at temperatures between 55 and 65 degrees Celsius. It is detailed that in intervals of ambient humidity percentage of 16-24 % with temperature variance between 56-59 degrees, soil humidity between 55-70 %, methane predictions represents between 10 ppm to 40 ppm, however, varying the relative humidity percentages of the environment decreases the methane emission value to 0 ppm.

Table 2. Results analysis table, temperatures between 55 and 65 degrees

Analysis Terms AmbientTemp	Percentage of Relative Humidity of the Environment	Soil Moisture Percentage	Neural Network Prediction Data
56° - 59°C	12 - 24	55 - 70	10 ppm – 40 ppm
59° - 63°C	9 - 10		0 ppm
	45 - 46		99 ppm -189 ppm

Methane, a greenhouse gas, is largely produced by improper composting and unattended waste decomposition. According to the Global Monitoring Laboratory, the methane trend in 2023 is 1920,74 ppm. This project, by composting at temperatures between 55 and 65 degrees to minimize methane production, results in an emission of 0,000189 % of air pollution, a minimal reduction compared to the annual levels reported by the institution.[15]

Data analysis, temperatures between 19 and 53 degrees Celsius

Table 3 shows the analysis of the prediction data obtained by means of the neural network taking into account temperatures below 53 degrees. This analysis was important because it allowed verifying that the decomposition of waste at temperatures lower than 55 degrees produces higher methane gas emissions and the quality of the compost does not guarantee compliance with the parameters of the Berkeley method. It is detailed that in intervals of ambient humidity percentage of 56-72 % with temperature variance between 19-26 degrees, soil humidity with percentages between 80-90 %, methane predictions represent a variation of 239-348ppm. Another scenario verified in these data is the variance of relative humidity percentages between 24-32 %, at temperatures of 41-48 degrees in which we have a methane prediction of 50-169ppm.

Table 3. Results analysis table, temperatures between 19 and 53 degrees

Analysis Terms Ambient Temp	Percentage of Relative Humidity of the Environment	Soil Moisture Percentage	Neural Network Prediction Data
19° - 26°C	56 - 72	80 - 90	239 ppm – 348 ppm
41° - 48°C	24 - 32		50 ppm – 169ppm

When compost is exposed to temperatures below 55 degrees Celsius, a variation in ambient relative humidity is observed, but not in soil moisture. This analysis shows that, at lower ambient temperatures in the controlled environment, methane gas production increases as waste decomposition is slower, which generates more emissions of this greenhouse gas.

Compost analysis

Figure 15. Compost content at the end of the process

In addition, the quality of the compost is in accordance with the Berkeley method technique, which recommends that the compost meet the following characteristics: dark brown color, without aromas, compact to the touch, without crumbling, totally decomposed, with whitish coloration on the surface, as can be seen in figure 16.

Figure 16. Characteristics of hot compost by the Berkeley method (hot compost)

At the end of the trials, it is feasible to apply this method in urban gardens or Microfarms without the need for chemicals, avoiding the proliferation of pathogens and bacteria that lead to the production of greenhouse gases and the consequent environmental pollution; in addition, the use of this type of composter allows the user to take advantage of all the nutrients to fertilize the soil and nourish it in a suitable way ready for the crops.

CONCLUSIONS

A microfarm system for compost production was implemented by modeling a convolutional neural network, which allowed real-time control and monitoring of the variables of the sensors that were finally implemented after the experimental development, which are the capacitive soil moisture sensor, the temperature and humidity sensor DHT22 and the methane sensor.

The graph of the loss function allowed the evaluation of the performance of the neural network, this graph is one of the most important to give veracity to a neural network model. Through this graph it was observed that a small amount of large errors is worse than a large amount of small errors, for which the result shows how bad are the results of the network in each lap it gave, noting that in the lap number 500 the loss value is minimal and is maintained in the following laps thus demonstrating that the network has already stopped learning.

As an important part is to avoid the greenhouse effect, which in the data analysis it was observed that when producing compost at temperatures between 55 and 65 degrees applying the Berkeley method, the emission of methane gas is 0 when achieving percentages of ambient humidity less than 11 %, so the composting method does allow avoiding the production of greenhouse gases and producing quality compost.

When inducing compost at temperatures between 55 and 65 degrees, it has been shown that ppm values vary by a minimum of 0 ppm to 189 ppm, representing 0,000189 % per 10000 ppm of this gas, which indicates a minimum percentage of affection and contribution to greenhouse gases.

With the implementation of a neural network, methane gas predictions were obtained in ppm units, based on the values of the data readings from the sensors. When performing the data validation, it was observed that, when the ambient temperature decreases, the percentage values of the relative humidity of the environment rise, which causes an increase in the production of methane gas, making it clear that one of the most important variables to control and monitor is the percentage of relative humidity of the environment.

In the data analysis, the variance of methane gas is made from 0ppm to 348 ppm, which indicates that this represents 0,000348 % of the production of methane gas for greenhouse effect of the overall functioning of the system exposed to different environmental conditions.

In this study, the reduction in methane gas emission in compost production was verified as metrics, that the compost is totally uniform, dissolved, adequate color, odorless according to the Berkeley method, it is suggested in future studies to perform the analysis of other types of metrics such as pH, nitrogen and others.

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