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Electronic device for automatic individualized monitoring of enteric methane emissions in dairy cows

Dispositivo electrónico para el monitoreo automático e individualizado de emisiones entéricas de metano en vacas lecheras

Dispositivo eletrônico para o monitoramento automático e individualizado das emissões entéricas de metano em vacas leiteiras

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Abstract

Background: Monitoring enteric methane (CH_4) emissions is essential for identifying animals with lower emissions in selection programs and for assessing the effectiveness of emission reduction strategies. Current methods are often expensive and complex, limiting their widespread application. **Objective:** This study aimed to develop and evaluate a low-cost, automated system for individual monitoring of CH_4 emissions in dairy cows. **Methods:** The system consisted of an MQ-4 gas sensor complemented by a 2 L/min airflow system, and an animal identification module utilizing artificial intelligence. The CH_4 data were wirelessly transmitted via an ESP8266 Wi-Fi module to a laptop computer for storage. CH_4 concentrations were recorded three times per second, and precise timestamps were used to document cow entry and exit at the milking stall. For the animal identification module, video frames of 26 cows during milking were extracted and organized into individual folders for each animal. Four versions (s, n, m, and l) of the YOLOv8 and YOLOv10 models were fine-tuned and evaluated with a dataset divided into training, validation, and testing sets. Performance metrics included Precision, Recall, F1-Score, and Accuracy. The CH_4 measurement system was tested on 10 Holstein cows during their milking sessions. **Results:** The prototypes successfully measured and recorded CH_4 emissions from individual cows. Continuous recording allowed the generation of detailed time-series graphs, revealing fluctuations in emissions. Some cows showed higher average CH_4 emission levels, demonstrating the device's ability to identify high-emitting individuals. Baseline CH_4 concentrations in the feeder area were stable across cows, ensuring accurate emission measurements. The comparative analysis of the identification module highlighted the YOLOv8n model as the most suitable option, due to its balance between low latency (24 ms) and high performance, achieving perfect scores across all metrics. **Conclusions:** The system enables effective monitoring of CH_4 emissions in dairy cows, providing a practical and economical alternative to traditional methods. The integration of low-cost sensors with advanced artificial intelligence enhances its applicability in genetic improvement programs and sustainable livestock management practices.

Keywords: *artificial intelligence; automatic monitoring; CH_4 emissions; computer vision; dairy cows; enteric methane; livestock management; MQ-4 gas sensor; YOLO model.*

Resumen

Antecedentes: El monitoreo de las emisiones de metano entérico (CH_4) es fundamental para identificar animales con menores emisiones en programas de selección y para evaluar la efectividad de las estrategias de mitigación. Sin embargo, los métodos actuales suelen ser costosos y complejos, lo que limita su aplicación generalizada. **Objetivo:** Desarrollar y evaluar un sistema automatizado y de bajo costo para el monitoreo individual de emisiones de CH_4 en vacas lecheras. **Métodos:** Desarrollamos un dispositivo de medición de la concentración de CH_4 basado en el sensor de gas MQ-4, complementado con un sistema de flujo de aire de 2 L/min, y un módulo de identificación de animales que utiliza inteligencia artificial. Los datos de CH_4 se transmitieron de forma inalámbrica, a través de un módulo ESP8266 Wi-Fi, a un computador portatil para su almacenamiento. Las concentraciones de CH_4 se registraron tres veces por segundo, y se utilizaron marcas de tiempo precisas para documentar la entrada y salida de las vacas del puesto de ordeño. Para el módulo de identificación de los animales se extrajeron fotogramas de video de 26 vacas durante el ordeño, los cuales se organizaron en carpetas individuales por animal. Se ajustaron y evaluaron cuatro versiones (s, n, m y l) de los modelos YOLOv8 y YOLOv10 con un conjunto de datos dividido en entrenamiento, validación y prueba. Las métricas de rendimiento incluyeron Precisión, Recall, F1-Score y Exactitud. El sistema de medición se probó con 10 vacas Holstein durante sus sesiones de ordeño. **Resultados:** Los prototipos midieron y registraron exitosamente las emisiones de CH_4 de vacas individuales. El registro continuo permitió generar gráficos detallados de series temporales, evidenciando fluctuaciones en las emisiones. Algunas vacas presentaron mayores niveles promedio de CH_4, lo que demostró la capacidad del dispositivo para identificar individuos con altas emisiones. Las concentraciones basales de CH_4 en el área de alimentación fueron estables entre las vacas, garantizando mediciones precisas. El análisis comparativo del módulo de identificación destacó el modelo YOLOv8n como la mejor opción, por su equilibrio entre baja latencia (24 ms) y alto rendimiento, alcanzando puntuaciones perfectas en todas las métricas (precisión, recall, F1-Score y exactitud). **Conclusion:** El sistema desarrollado permite monitorear eficazmente las emisiones de CH_4 en vacas lecheras y constituye una alternativa práctica y económica a los métodos tradicionales. El uso de sensores de bajo costo y la inteligencia artificial avanzada potencia su aplicación en programas de mejora genética y en prácticas sostenibles de manejo ganadero.

Palabras clave: *emisiones de CH_4; inteligencia artificial; manejo ganadero; metano entérico; modelo YOLO; monitoreo automático; sensor de gas MQ-4; vacas lecheras; visión por computadora.*

Resumo

Antecedentes: O monitoramento das emissões de metano entérico (CH_4) é fundamental para identificar animais com menores emissões em programas de seleção e para avaliar a eficácia das estratégias de mitigação. No entanto, os métodos atuais costumam ser caros e complexos, o que limita sua aplicação em larga escala. **Objetivo:** Desenvolver e avaliar um sistema automatizado e de baixo custo para o monitoramento individualizado das emissões de CH_4 em vacas leiteiras. **Métodos:** O sistema foi composto por um dispositivo de medição da concentração de CH_4 baseado no sensor de gás MQ-4, complementado por um sistema de fluxo de ar de 2 L/min, e um módulo de identificação de animais utilizando inteligência artificial. Os dados de CH_4 foram transmitidos sem fio por meio de um módulo ESP8266 Wi-Fi para um computador portátil para armazenamento. As concentrações de CH_4 foram registradas três vezes por segundo, e foram utilizados carimbos de tempo precisos para documentar a entrada e saída das vacas na estação de ordenha. Para o módulo de identificação animal, foram extraídos quadros de vídeo de 26 vacas durante a ordenha, os quais foram organizados em pastas individuais por animal. Quatro versões (s, n, m e l) dos modelos YOLOv8 e YOLOv10 foram ajustadas e avaliadas com um conjunto de dados dividido em treinamento, validação e teste. As métricas de desempenho incluíram Precisão, Recall, F1-Score e Acurácia. O sistema de medição da concentração de CH_4 foi testado com 10 vacas Holstein durante suas sessões de ordenha. **Resultados:**

Os protótipos mediram e registraram com êxito as emissões de CH_4 de vacas individuais. O registro contínuo permitiu gerar séries temporais detalhadas, evidenciando flutuações nas emissões. Algumas vacas apresentaram níveis médios mais elevados de CH_4, demonstrando a capacidade do dispositivo de identificar indivíduos com altas emissões. As concentrações basais de CH_4 na área de alimentação foram estáveis entre as vacas, garantindo medições precisas. A análise comparativa do módulo de identificação ressaltou o modelo YOLOv8n como a melhor opção, pelo equilíbrio entre baixa latência (24 ms) e alto desempenho, alcançando pontuações perfeitas em todas as métricas. **Conclusões:** O sistema desenvolvido permite o monitoramento eficaz das emissões de CH_4 em vacas leiteiras, constituindo uma alternativa prática e econômica aos métodos tradicionais. A integração de sensores de baixo custo com inteligência artificial avançada amplia seu potencial para programas de melhoramento genético e práticas sustentáveis de manejo do gado.

Palavras-chave: *emissões de CH_4; inteligência artificial; manejo de gado; metano entérico; modelo YOLO; monitoramento automático; sensor de gás MQ-4; vacas leiteiras; visão computacional.*

Introduction

Climate change is a global concern driven by greenhouse gas (GHG) emissions from human activities, among which methane (CH_4) plays a significant role due to its global warming potential, which is 28.5-fold higher than that of carbon dioxide (CO_2) over a 100-year period (Bäck et al., 2024). Enteric CH_4 emissions constitute a major component of agricultural GHG emissions. Ruminants contribute approximately 16% of CH_4 emissions via enteric fermentation and an additional 5% from animal waste (Devine and Devine, 2024). Therefore, the accurate quantification of these emissions is essential for identifying low-emission animals in genetic selection programs and for evaluating the effectiveness of mitigation strategies.

Current methods for measuring enteric CH_4 emissions, such as open-circuit respiration chambers (Pinares and Waghorn, 2014), the GreenFeed system (Zimmerman and Zimmerman, 2012), the SF_6 method (Johnson et al., 2007), and laser-based methane detectors (Chagunda et al., 2009) are effective but expensive and technically demanding, which limits their widespread adoption in livestock production (Tedeschi et al., 2022). As an alternative, the CH_4-to-CO_2 ratio in cow breath samples measured with systems such as the Gasmet DX-4000 (Gasmet Technologies Oy, Helsinki, Finland) has emerged as a practical option. However, this approach still faces implementation challenges, especially in developing countries. This highlights the need for more accessible and practical methods for monitoring CH_4 emissions in livestock production. Additionally, it is essential to develop reliable identification systems that accurately assign emission readings to specific individuals.

Traditional identification methods include radio frequency identification (RFID) devices (Kampers et al., 1999). While RFID devices are widely used and effective for individual animal identification, they require installing a passive tag on each animal, representing a significant investment. Costs further increase when accounting for infrastructure needed, such as readers and data management systems, particularly in large-scale operations. Recent advances in Precision Livestock Farming have highlighted the potential of integrating RFID with other technologies, such as computer vision (CV). CV is a field of artificial intelligence that enables computers and systems to interpret visual information from their environment (de Oliveira et al., 2024). Using advanced algorithms and image processing techniques, CV can rapidly and accurately identify and classify objects in images or videos (Wang et al., 2023). CV can serve as a complementary or alternative method, allowing the identification of multiple animals simultaneously without the need for individual devices. This approach reduces costs and is less invasive, making it particularly suitable for large herds (Li et al., 2021).

The objective of this work was to develop and test a low-cost system for the individualized monitoring of CH_4 emissions in dairy cows, using artificial intelligence for animal identification and low-cost sensors for measuring CH_4 concentrations in breath samples. This system aims to provide a practical and economical alternative to traditional methods, facilitating its application in genetic selection programs and emission mitigation strategies in livestock production.

Materials and Methods

Ethical approval

The work was conducted following ethical approval from the Technical Committee for Animal Experimentation at the Universidad de Antioquia, Colombia. This approval is documented in Act No. 151, dated April 11, 2023.

Device integration

Figure 1 illustrates the integration of a low-cost, wireless CH_4 measurement device with a computer vision-based cow identification system. The CH_4 sensor transmits data wirelessly via the ESP8266 Wi-Fi module to a central laptop for storage and analysis. Simultaneously, a camera captures video, which is processed by a computer vision system to identify individual cows. By linking CH_4 measurements with the identification system, the device ensures accurate assignment of emissions to specific cows, supporting individualized monitoring.

It is important to note that the focus of this paper is on design and system integration rather than exhaustive calibration or validation. Future work will refine calibration procedures and evaluate the device's performance under diverse field conditions to validate its effectiveness and reliability in real-world applications.

Figure 1. Schematic representation of the integrated methane measurement and identification system installed in a milking stall: A) Air pump, B) Protection box housing electronics, C) Air sampler, D) Camera for cow identification, and E) Central laptop for receiving information via Wi-Fi from the device.

CH_4 emissions detection module

A low-cost system was developed for detecting changes in the concentration of CH_4 in the air exhaled by cows during milking, based on the integration of various electronic and mechanical components (Figure 2), detailed as follows:

1. MQ-4 gas sensor: Its sensitivity and specificity allow it to measure CH_4 concentrations within the range required for this type of sample (200 to 10,000 ppm; Fakra et al., 2020). We used the MQ-4 sensor manufactured by Winsen Electronics Technology Co., Ltd.

2. Air pump: This was used to generate a constant flow of 2 L/min, ensuring that air from the feed trough, where cows eat concentrate during milking, was consistently directed toward the gas sensor inside the device box.

3. Plastic tubing: Channeled the air from the collection point (feed trough) to the gas sensor, minimizing CH_4 loss and ensuring a representative sample of the exhaled air.

4. ESP8266 Wi-Fi module: Responsible for collecting and transmitting the data generated by the gas sensor. It uses a Wi-Fi connection to send the data to a laptop for further analysis. The ESP8266 module used in our study was manufactured by Espressif Systems. This module integrates a 32-bit Tensilica processor and offers Wi-Fi connectivity, making it suitable for IoT applications.

5. Protection box: All electronic and mechanical components were placed inside a protection box to ensure their optimal functioning and to protect against physical and environmental damage.

6. Power source (5V): Provides the necessary voltage to power the MQ-4 gas sensor, ESP8266 Wi-Fi module, and air pump.

7. Laptop computer: Used for data storage.

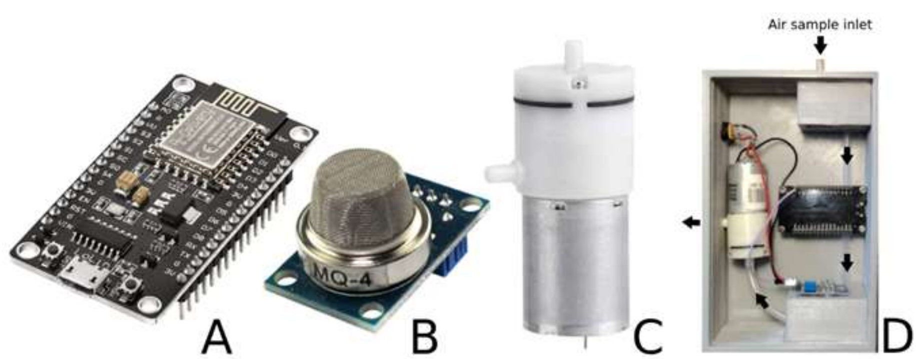

Figure 2. Components of the methane emissions recording device. ESP8266 Wi-Fi module (A), MQ-4 gas sensor (B), air pump (C), and plastic box containing the electronic and mechanical components (D). The arrows indicate the airflow direction.

For the mechanical operation of the system, the air pump generates a constant airflow of 2 L/min, which is directed through a plastic tube from the feed trough to the MQ-4 gas sensor. This continuous flow allows uninterrupted measurement of CH_4 concentrations in the air exhaled by the cows during milking. For the electronic operation, the CH_4 concentration data detected by the MQ-4 sensor were processed by the ESP8266 Wi-Fi module, which wirelessly transmits them (via Wi-Fi) to a laptop for storage and further analysis.

The Arduino code for data transmission (Appendix 1) allows the ESP8266 Wi-Fi module to connect to a Wi-Fi network and send the sensor readings. Initially, the device is configured to operate in station mode (Wi-Fi client) and connects to the specified network. Once the connection is established, the code enters a continuous loop where the sensor values are read and sent to the local server via an HTTP POST request. This mechanism ensures the continuous and real-time transmission of CH_4 data detected during device operation. On the laptop, the Python code for receiving and storing the data sent by the ESP8266 Wi-Fi module (Appendix 2) is based on the Flask framework (https://flask.palletsprojects.com/). The Flask server is configured to accept GET and POST requests at the "/data" route. When a POST request is received, the server extracts the device ID and sensor readings, records the date and time, and saves these data in a text file on the laptop.

To test the CH_4 emissions recording device, the emissions of 10 dairy cows were monitored with two prototypes (anticipating a possible malfunction of one device) during milking (05:00 h and 14:00 h) at the dairy unit of La Montaña farm, Universidad de Antioquia, located in the municipality of San Pedro de Los Milagros, Antioquia (Colombia), at an altitude of 2350 masl, with an average temperature of 15 °C and 83% relative humidity. Variations in CH_4 concentration were recorded three times per second in a text file for each prototype during milking. An observer noted the exact time of entry and exit of each cow from the milking stall, and this information was used to organize the detections by cow and milking session.

During the trials, cows entered the milking stall and feeding area at their usual milking times, as part of their daily routine. Each cow remained at the feeder for several minutes, depending on milk production, which determined the overall milking duration. This allowed the device to record CH_4 emissions continuously during their stay. Between consecutive cows, there was a natural pause in visits to the milking stall. During this interval, the continuous airflow maintained by the air pump helped to remove any residual CH_4 from the sampling system, ensuring that emissions from a previous cow did not persist in the measurement area. Although some residual methane could potentially influence the baseline concentration, this aspect was not the focus of the current study. As mentioned, the primary purpose at this stage was to demonstrate the device's design and integration, rather than to provide fully corrected emission data.

In the current design phase, the baseline CH_4 concentration in the feeder area was treated as a conceptual reference point rather than a rigorously established measurement. The system's approach assumes that, under normal operating conditions, the feeder area maintains a relatively stable ambient CH_4 concentration that can serve as a starting level. While factors such as ventilation, proximity of other animals, and external emissions could influence this baseline, no separate measurements were taken during cow-absent periods to quantify these variations. Similarly, the airflow provided by the pump was assumed to be consistent with the manufacturer's nominal specifications (approximately 2 L/min) rather than independently measured or rigorously verified. At this stage, our priority was to integrate CH_4 detection, wireless data transmission, and computer vision-based identification into a single device, rather than ensuring fully characterized baseline conditions or meticulously controlled airflow. Consequently, we cannot confirm that the chosen airflow rate is adequate for reliably capturing subtle variations in CH_4 concentrations between individual animals. Future research will explore strategies to refine all these assumptions, including dedicated baseline measurements, improved flow-rate verification, and calibration steps.

Identification module

For the animal identification module, a computer vision system based on YOLO (You Only Look Once, Redmon et al., 2016) object detection model was used. The process began with capturing videos of 26 cows entering the milking stall. Due to the camera's position (above the feed trough), the videos contained exclusively images of a single cow, which facilitated the labeling process. Each video was labeled with the corresponding cow's name and stored on a laptop. From these videos, frames were

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extracted at a rate of three frames per second. These frames were saved in individual folders, each corresponding to a specific cow. This organization allowed for efficient management and easy access to each animal's data. The next step involved processing these frames using the YOLOv8m model, pre-trained by Ultralytics (https://www.ultralytics.com/). This model can detect cows, horses, and other animals, facilitating the precise identification of cows in the frames.

The YOLOv8m model was used to analyze each frame and provided the coordinates of the area where the cow was found. The information obtained from the YOLO analysis was saved in text files using the YOLO format. This format is widely used in computer vision applications and is characterized by its simplicity and efficiency. Each line in a YOLO annotation file represents an object detected in the image and follows the structure: 'class_id center_x center_y width height,' where 'class_id' is the identifier of the detected object's class (in this case, cow), 'center_x' and 'center_y' are the coordinates of the center of the bounding box around the object (normalized between 0 and 1) while 'width' and 'height' are the width and height of the bounding box (also normalized between 0 and 1). These annotations allow the location and size of each cow to be represented in the frames. The cows' names were alphabetically ordered and converted into numbers (between 0 and 25) to assign labels ('class_id') in the text files.

The fine-tuning process of the YOLO models began with the organization and division of the data (500 images) into three sets: 70% for training, 10% for validation, and 20% for testing. When fine-tuning a YOLO model, the training set of images is used by the model to learn object features and patterns. The model updates its parameters based on these images and their annotations. The validation set is used during training to monitor performance and prevent overfitting. The model does not learn from these images; instead, it uses them to fine-tune hyperparameters and decide when to stop training. The testing set is reserved for the final evaluation. These images are never seen during training or validation, ensuring an unbiased measure of the model's real-world performance.

In this study, the YOLO-based identification was tested using video frames containing only one cow at a time. This was due to the camera's placement directly above the feed trough, which naturally restricted the field of view to a single animal per image. However, YOLO is fundamentally designed for multi-object detection and, in principle, can identify several cows simultaneously. In real-world scenarios where multiple cows appear in the same frame, the visiting cow can be determined by selecting the largest bounding box detected, representing the animal closest to the camera and presumably the one currently at the milking stall.

The n, s, m, and l versions of the YOLOv8 and YOLOv10 models, pre-trained by Ultralytics and THU-MIG (https://github.com/THU-MIG), respectively, were selected to perform fine tuning with the images of the dairy cows. The training process involved the following steps: The model configuration specified the number of epochs (1000), image size (640 pixels), and batch size (8 images per iteration). During training, the model adjusted its parameters to optimize detection accuracy, using the training and validation datasets to evaluate its performance and avoid overfitting. A patience criterion was set, so if no significant improvements in model accuracy were observed during 50 consecutive epochs, the training would automatically stop to avoid overfitting and optimize the use of computational resources.

After completing the training process, the fine-tuned models were evaluated using the testing dataset. The performance metrics included Precision, Recall, F1-Score, and Accuracy. Each of these metrics offers a distinct and complementary perspective on the model's ability to make accurate predictions. Precision is the proportion of true positive examples out of all examples predicted as positive, focusing on the correctness of the model's positive predictions. Recall, also known as sensitivity or the true positive rate, measures the proportion of actual positive examples that were correctly identified by the model, emphasizing the model's ability to capture all relevant positive instances. The F1-Score is the harmonic mean of Precision and Recall, providing a single metric that balances the trade-off between these two aspects, especially in scenarios where both are equally important. Accuracy is the proportion of all correctly classified examples, both positive and negative, out of the total number of evaluated examples (Sokolova and Lapalme, 2009).

Results

CH_4 emissions detection module

The CH_4 detection module successfully generated continuous data on the CH_4 concentration in the air exhaled by dairy cows during milking. The data were recorded in text files, capturing CH_4 concentration values three times per second for each cow throughout the milking session. By combining these data with precise timestamps of each cow's entry and exit from the milking stall, it was possible to create detailed time-series graphs illustrating the fluctuations in CH_4 emissions for each animal.

Figure 3 presents an illustrative example of the type of data generated by the CH_4 emissions recording device. The graph displays the CH_4 concentration (in parts per million, ppm) over time for three cows, identified as Cow 1, Cow 2, and Cow 3. The data reveal a clear pattern: the CH_4 concentration rapidly increases from the baseline level—measured as the concentration in the feeder area—once the cows begin concentrate intake in the milking station. This baseline concentration represents the average CH_4 level in the feeder area when no cows are present in the milking station.

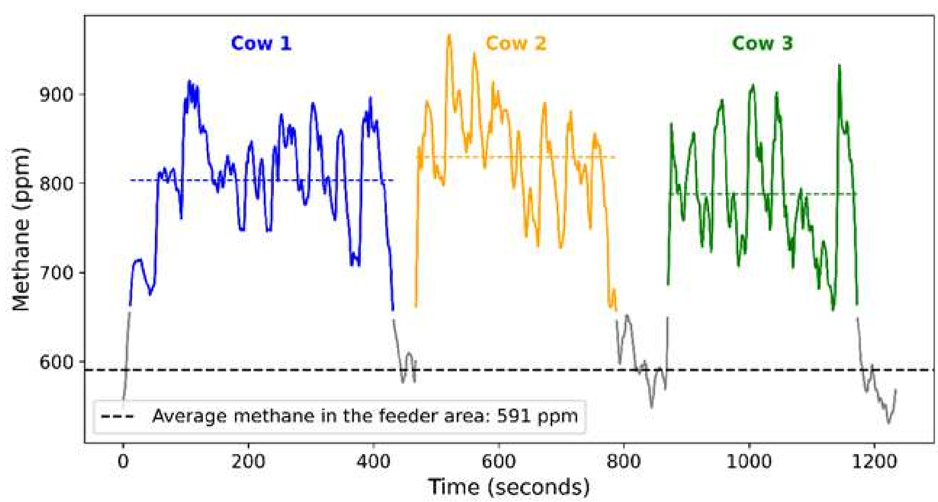

Figure 3. Methane concentration over time for three cows (Cow 1, Cow 2, and Cow 3), identified by colors (blue, orange, and green, respectively). The gray segments represent periods when the CH_4 concentration was within the feeder area range (500-655 ppm). The colored dashed lines indicate the average CH_4 concentration for each cow.

The colored dashed lines in Figure 3 indicate the average CH_4 concentration for each cow during the milking session. Notably, these lines show that Cow 2 exhibited the highest average CH_4 emission level compared to the other cows. This observation is important as it suggests that Cow 2 may be a higher emitter of CH_4 under the conditions of this test. In addition to identifying the highest emitter, the data also allow for a comparison of emission patterns between the cows. For example, Cow 1 and Cow 3 demonstrated different emission profiles, with variations in both the amplitude and frequency of their CH_4 concentration peaks. The CH_4 concentration in the feeder area, represented by the black dashed line in Figure 3, serves as a crucial reference point for understanding the emission dynamics. This baseline provides a consistent metric against which CH_4 concentration increases during active feeding can be measured. However, ensuring measurement reliability and consistency involves several critical steps, including comparison with validated reference methods, evaluation of systematic and random errors, repeatability under identical conditions, and consistency across different individuals (Bartlett and Frost, 2008). In the present study, our primary focus was on the design and integration of the CH_4 measurement device. While we have successfully demonstrated the device's capability to detect and record CH_4 concentrations, a comprehensive evaluation of its reliability and consistency is beyond the scope of this paper.

The results demonstrate the effectiveness of the CH_4 emissions detection device in monitoring CH_4 emissions from dairy cows during milking. The device captured detailed emission profiles for individual cows, highlighting differences in CH_4 output that could be important for understanding and managing CH_4 emissions in dairy farming. The ability to identify high-emitting cows, like Cow 2 in this example, offers valuable insights that could inform targeted interventions to reduce overall CH_4 emissions in dairy herds.

Identification module

Table 1 provides a comparative analysis of the YOLO models, evaluating their performance based on the number of training epochs required to achieve optimal results, latency, precision, recall, F1-Score, and accuracy. All evaluations were conducted on an x86_64 machine equipped with an Intel® Xeon® CPU (2.00 GHz, 2 threads) and a single NVIDIA Tesla T4 GPU with 15 GB of memory. The YOLOv8n model achieved maximum performance with perfect values in Precision, Recall, F1-Score, and Accuracy (1.00) on both the validation and testing datasets, with a low latency of 24 ms. This indicates that YOLOv8n offers both excellent accuracy and speed. The YOLOv8s, YOLOv8m, and YOLOv8l models also performed well but had slightly lower performance metrics compared to YOLOv8n. Specifically, the YOLOv8s model achieved Precision, Recall, F1-Score, and Accuracy values ranging from 0.98 to 0.99, with the same latency of 24 ms as YOLOv8n. YOLOv8m and YOLOv8l had marginally higher latencies (36 ms and 39 ms, respectively) without significant improvements in performance metrics. The YOLOv10 series models also demonstrated high performance. For instance, YOLOv10l achieved perfect scores in all metrics (1.00) on both validation and testing datasets but had a higher latency of 37 ms. Other YOLOv10 models showed near-perfect performance with slightly varied latencies. Considering both performance and latency, the fine-tuned YOLOv8n model emerges as the best option. It offers perfect performance metrics with the lowest latency among the models tested, making it highly suitable for the identification of individual cows within the images used in this study.

Table 1. Performance and latency comparison of fine-tuned YOLOv8 and YOLOv10 models on validation and testing datasets.

Model	Epochs[1]	Latency[2]	Precision		Recall		F1-Score		Accuracy	
	Training	Testing	Validation	Testing	Validation	Testing	Validation	Testing	Validation	Testing
YOLOv8n	116	*24*	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
YOLOv8s	35	*24*	0.99	0.99	0.99	0.98	0.99	0.99	0.99	0.99
YOLOv8m	156	*36*	0.99	0.98	0.99	0.98	0.99	0.98	0.99	0.98
YOLOv8l	83	*39*	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
YOLOv10n	292	*25*	1.00	0.99	1.00	0.99	1.00	0.99	1.00	0.99
YOLOv10s	120	*26*	0.99	1.00	1.00	0.99	1.00	1.00	1.00	1.00
YOLOv10m	131	35	0.99	1.00	0.99	1.00	0.99	1.00	0.99	1.00
YOLOv10l	164	37	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

[1] Epochs refer to the total number of training iterations completed. Training was stopped early as no improvement was observed in the last 50 epochs.
[2] Latency indicates the time (in milliseconds) taken by the fine-tuned models to process a single image from the testing dataset.

Figure 4 presents examples of dairy cow identification results using the YOLOv8n model. All images from the validation and testing sets achieved high identification performance, each with a high probability score (≥ 0.98). This consistency demonstrates that the model effectively identifies each individual cow without confusion or significant variability in performance across different animals. It can be seen that the models successfully identified the cows with high precision, highlighting the performance of YOLOv8n, which not only correctly identified the cows but also did so with low latency, which is crucial for real-time applications. The more advanced models, such as YOLOv8m and YOLOv8l, despite their slightly higher latency, maintained flawless detection performance, making them suitable for scenarios where latency is not critical, but maximum precision is required. On the other hand, the YOLOv10 series offers solid performance with acceptable latency, positioning themselves as a viable option when seeking a balance between latency and accuracy.

The analysis reveals that while all the evaluated models achieved remarkable performance, the choice of the optimal model will depend on the specific application requirements and the characteristics of the images used. For real-time applications where latency is a critical factor, YOLOv8n might be preferred despite its slight sacrifice in precision. However, for applications where precision is of utmost importance, YOLOv8n (Figure 4) emerges as the best choice, combining an ideal balance between performance and latency for the specific set of images used in this study.

Figure 4. Example of dairy cow identification results using a fine-tuned YOLOv8n model. This figure illustrates the detection and identification of individual cows as they pass through the milking station. Each cow is enclosed within a color-coded bounding box, labeled with the cow's name and the model's confidence score. These high confidence scores indicate the model's strong certainty in identifying each cow accurately.

Discussion

Monitoring enteric CH_4 emissions is essential for reducing the environmental impact of livestock. Traditional methods like open-circuit respiration chambers, the GreenFeed system, and the SF_6 tracer technique, while precise, are costly, complex, and difficult to implement on a large scale (Huhtanen et al., 2015; Bekele et al., 2022). Alternative methods, such as the sniffer technique (Garnsworthy et al., 2012), offer greater portability and less invasiveness but suffer from inconsistencies and lower accuracy. Our system attempts to address these challenges by providing a low-cost, practical, and scalable solution for measuring CH_4 emissions in dairy cows.

A low-cost, portable CH_4 quantification system using an MQ-4 sensor has been used for monitoring in biogas production and environmental studies (Nagahage et al., 2021; Tovar-Sánchez et al., 2023; Negara et al., 2024) and to study the daily dynamics of enteric CH_4 emissions in grazing ruminants (Ramirez-Agudelo et al., 2019).

The system developed in this study represents a significant innovation in this area, specifically applied to livestock. By utilizing an MQ-4 gas sensor and integrating it with an artificial intelligence-based identification module, the system offers a practical and economical alternative to traditional methods. However, like the sniffer method, our system could potentially face similar limitations related to sampling inconsistencies and environmental variations. The proximity of the sensor to the animal's mouth and nose may also introduce some variability in the measurements, especially if the sensor's position relative to the animal varies during data collection. Nevertheless, the developed system offers several key advantages that help mitigate these potential issues.

Cost-effectiveness: unlike the high costs associated with respiration chambers and the GreenFeed system, our system uses inexpensive sensors and components, making it accessible for widespread use, including in resource-limited settings. *Simplicity and ease of implementation:* the system is designed for easy integration into existing livestock management practices, particularly during milking sessions. The use of wireless data transmission and automated identification reduces the need for manual intervention and allows for seamless monitoring of multiple animals simultaneously. *Scalability:* the modular design of the system, combined with its low cost, makes it highly scalable. It can be easily adapted to monitor larger herds or implemented in different types of livestock production systems, expanding its applicability beyond dairy cows. *Non-invasive monitoring:* unlike the SF_6 tracer technique, our system does not require any invasive procedures, ensuring the well-being of the animals while still providing reliable CH_4 data.

Similar to the methods mentioned above, the baseline CH_4 concentration—or background CH_4 concentration—is crucial for accurate emissions monitoring. In controlled environments like respiration chambers, the background CH_4 levels are carefully measured and accounted for to ensure that only the CH_4 directly produced by the animal is recorded. The SF_6 technique also relies on establishing a clear background concentration to differentiate between the tracer gas and actual CH_4 emissions. The GreenFeed system similarly uses background measurements to calibrate its sensors and correct for any ambient CH_4 that might be present. In our system, the baseline CH_4 concentration in the feeder area serves as a critical reference point, providing the necessary context for interpreting the CH_4 levels emitted by the cows during feeding and ensuring that the data reflects true enteric emissions rather than environmental noise. The accuracy of this baseline measurement is crucial because any fluctuations or inaccuracies could lead to misinterpretations of the subsequent data. For instance, if the baseline is inaccurately high due to residual CH_4 from previous feeding sessions, the system might underestimate the actual increase in emissions during feeding.

The behavior of the cows, including their movement during the milking session, can influence the concentration of CH_4 detected by our device. Additionally, the position of the cow relative to the sensor can result in variability in the measurements, as the detection of the concentration of CH_4 in the exhaled breath can diminish rapidly with distance. The position of the cow relative to the air sample inlet is particularly critical, as CH_4 concentration in the air sample can diminish rapidly with distance. To address this, our device incorporates an air pump system that generates constant airflow, ensuring that air from the feed trough, where the cows eat during milking, is consistently directed toward the gas sensor. This setup minimizes the impact of cow movement and environmental fluctuations by maintaining a steady flow of sampled air to the sensor, thereby enhancing the accuracy and reliability of the measurements. However, despite the advantages of the air pump system, careful positioning of the sampling inlet relative to the cow's nostrils or mouth remains crucial. If the inlet is not consistently aligned, variations in readings can still occur.

Despite the promising capabilities of our system, it is important to acknowledge certain limitations of the current study. One significant limitation is the inability to directly compare our CH_4 emission results with those obtained from studies using established reference methods, such as open-circuit respiration chambers, the GreenFeed system, or the SF_6 tracer technique. This limitation arises because our device is still in the prototype phase and has not yet undergone comprehensive calibration against these standard methods. Our primary focus was on the design, development, and initial testing of a low-cost CH_4 measurement device integrated with an artificial intelligence-based identification system. While we successfully demonstrated the device's potential for detecting CH_4 emissions and identifying individual cows, the absolute CH_4 concentration values recorded may not be directly comparable to those from validated methods. Without calibration and validation against these reference techniques, direct comparisons could be misleading or inaccurate. Therefore, our current results serve as a proof of concept rather than definitive quantitative measurements of CH_4 emissions. Future research will focus on calibrating the MQ-4 sensor against established reference methods and conducting controlled experiments to validate the device's accuracy.

The YOLO-based identification module demonstrated exceptional effectiveness in accurately identifying individual dairy cows during the milking process. The module's performance was thoroughly evaluated using various YOLO models, including the YOLOv8 and YOLOv10 series, each fine-tuned to optimize cow identification. The performance metrics used to assess these models—Precision, Recall, F1-Score, and Accuracy—indicate the module's high level of reliability and precision in a practical farm setting. In real-time applications, there is often a trade-off between the speed (latency) and accuracy of a model. Lower latency is crucial for applications requiring immediate response, such as real-time monitoring systems. However, achieving low latency can sometimes compromise the accuracy of the model. Among the various YOLO models evaluated, the YOLOv8n model emerged as the optimal choice for this study. The YOLOv8n's balance of low latency and high performance makes it particularly well-suited for applications where both real-time processing and high accuracy are required, such as monitoring and identifying cows during milking sessions.

In conclusion, we successfully developed a low-cost, effective system for monitoring enteric CH_4 emissions in dairy cows, combining the MQ-4 gas sensor with advanced artificial intelligence-based identification using YOLO models. The system demonstrated its capability to accurately detect and record CH_4 emissions during milking, providing detailed emission profiles for individual cows. The YOLOv8n model emerged as the optimal choice for cow identification, offering a perfect balance between accuracy and latency, crucial for real-time applications. The modular and scalable design of the system ensures its applicability across various livestock environments, promoting its potential use in genetic selection programs and emission mitigation strategies. Future enhancements, such as implementing rigorous calibration protocols, accurately establishing baseline CH_4 concentrations, and incorporating additional environmental sensors, will further improve the system's precision and reliability, reinforcing its potential as a practical, cost-effective alternative to traditional CH_4 monitoring methods in livestock management.

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Declarations

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Conflicts of interest

The authors declare that they have no conflicts of interest with regard to the work presented in this report.

Author contributions

John-Fredy Ramirez-Agudelo: was responsible for the design and conception of the study, contributed to the technical development, and participated in writing the manuscript. Sebastian Bedoya-Mazo: administered the project, collected data, performed data analysis, provided critical review and editing of the manuscript, and was involved in funding acquisition. Luisa-Fernanda Moreno-Pulgarín: contributed to data collection and technical development. Jose-Fernando Guarin-Montoya: was responsible for the study design and conception, oversaw general project administration, provided critical review and editing, and contributed to funding acquisition.

Use of artificial intelligence (AI)

During the preparation of this report, the authors used ChatGPT to enhance clarity and ensure grammatical accuracy. After using this tool, the authors reviewed and edited the document as needed and take full responsibility for its content.

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Appendices

Appendix 1: Arduino code for Real-Time Data Transmission using ESP8266 Wi-Fi module

This appendix provides the Arduino code used for transmitting data from the ESP8266 module to a web server. The code initializes the ESP8266 Wi-Fi module in station mode to connect to a specified WiFi network, reads sensor data from an analog pin, and sends this data to a server using an HTTP POST request. The server response is then displayed in the serial monitor, allowing real-time monitoring of the sensor data transmission.

```
// Include the necessary libraries for the ESP8266 WiFi module and HTTP client functionality.
#include <ESP8266WiFi.h>
#include <ESP8266HTTPClient.h>

// Define the credentials for the WiFi network that the device will connect to.
// Replace the empty strings with your actual WiFi SSID and password.
const char* ssid     = "YOUR_SSID";
const char* password = "YOUR_PASSWORD";

// Initialize a WiFiClient object to manage network connections.
WiFiClient wifiClient;

// The setup function runs once when the device is powered on or reset.
void setup() {
 // Start serial communication at a baud rate of 115200 for debugging purposes.
 Serial.begin(115200);

 // Set the WiFi mode to station (client) mode.
 WiFi.mode(WIFI_STA);

 // Begin connecting to the specified WiFi network using the provided credentials.
 WiFi.begin(ssid, password);

 // Continuously check the WiFi connection status until connected.
 while (WiFi.status() != WL_CONNECTED) {
  delay(1000);          // Wait for one second before the next status check.
```

```
    Serial.print(".");      // Print a dot to the serial console to indicate ongoing connection attempts.
  }

  // Once connected, print a confirmation message to the serial console.
  Serial.println("\nWiFi connected");
  Serial.print("IP Address: ");
  Serial.println(WiFi.localIP());  // Display the assigned IP address.
}

// The loop function runs repeatedly after setup() has completed.
void loop() {
  // Verify that the device is currently connected to the WiFi network.
  if (WiFi.status() == WL_CONNECTED) {
    // Create an HTTPClient object to handle HTTP requests.
    HTTPClient http;

    // Define the server URL where the data will be sent.
    // Replace "192.XXX.XX.XXX" with the actual IP address of your Flask server.
    http.begin(wifiClient, "http://192.XXX.XX.XXX:8080/data");

    // Specify the content type of the HTTP request as form URL encoded.
    http.addHeader("Content-Type", "application/x-www-form-urlencoded");

    // Read the analog value from pin A0 where the MQ4 sensor is connected.
    int sensorValue = analogRead(A0);
    Serial.print("Sensor Value: ");
    Serial.println(sensorValue);  // Output the sensor value to the serial console for debugging.

    // Construct the POST data string with the device ID and sensor reading.
    // "ESP2" is used here as the device identifier; modify as needed for your setup.
    String postData = "device_id=ESP2&sensor_reading=" + String(sensorValue);

    // Send the POST request with the sensor data to the server and store the response code.
```

```
    int httpCode = http.POST(postData);

    // Print the HTTP response code to the serial console for debugging.
    Serial.print("HTTP Response Code: ");
    Serial.println(httpCode);

    // If the request was successful (response code > 0), process the server's response.
    if (httpCode > 0) {
      // Retrieve the response payload from the server.
      String payload = http.getString();
      // Display the server's response in the serial console.
      Serial.println("Server Response:");
      Serial.println(payload);
    } else {
      // If the request failed, print an error message with the response code.
      Serial.print("Error on sending POST: ");
      Serial.println(http.errorToString(httpCode).c_str());
    }

    // Close the HTTP connection to free resources.
    http.end();
  } else {
    // If the device is not connected to WiFi, print a warning message.
    Serial.println("WiFi not connected");
  }

  // Wait for 250 milliseconds before sending the next sensor reading.
  delay(250);
}
```

Appendix 2: Python code for Real-Time Data Reception and Storage using Flask

This appendix provides the Python code used for receiving and storing data sent by the ESP8266 module via HTTP POST requests. The code initializes a Flask application that listens for incoming data on a specified route (/data). Upon receiving the data, the server logs the methane readings along with a timestamp into a text file.

```
from flask import Flask, request
from datetime import datetime

# Initialize the Flask application
app = Flask(__name__)

# Global variable to store the name of the last file where data was saved
last_filename = None

# Define the route '/data' that handles both GET and POST HTTP methods
@app.route('/data', methods=['GET', 'POST'])
def data():
    global last_filename  # Allow modification of the global variable within this function

    if request.method == 'POST':
        # Extract 'device_id' and 'sensor_reading' from the incoming form data
        device_id = request.form.get('device_id')
        sensor_reading = request.form.get('sensor_reading')

        # Validate that both 'device_id' and 'sensor_reading' are provided
        if not device_id or not sensor_reading:
         return "Missing data in the POST request.", 400  # Return a 400 Bad Request if data is incomplete

        # Get the current date and time formatted as 'YYYY-MM-DD HH:MM:SS.ff'
        current_time = datetime.now().strftime('%Y-%m-%d %H:%M:%S.%f')[:-5]

        # Format the current time to 'YYYY-MM-DD_HH' for use in the filename
        filename_time = datetime.now().strftime('%Y-%m-%d_%H')
```

```
        # Prepare the content string to be written to the file
        content = f"{device_id},{current_time},{sensor_reading}\n"

        # Generate the filename using 'device_id' and the formatted current time
        filename = f"{device_id}_{filename_time}.txt"
        last_filename = filename  # Update the global variable with the new filename

        # Open the file in append mode and write the content
        with open(filename, 'a') as file:
            file.write(content)

        # Return an HTML response confirming successful data saving, displaying the filename
        return f"""
        <html>
            <body>
                <h1>Success</h1>
                <p>Data has been successfully saved to the file: <strong>{filename}</strong></p>
            </body>
        </html>
        """, 200

    elif request.method == 'GET':
        # Handle GET requests to provide status information about data logging
        if last_filename:
            # If data has been previously logged, inform the user
            return f"""
            <html>
                <body>
                    <h1>MQ4 Data Logging Status</h1>
                    <p>Data is currently being saved in the file: <strong>{last_filename}</strong></p>
                </body>
            </html>
```

```
        """, 200
    else:
        # If no data has been logged yet, inform the user accordingly
        return """
        <html>
            <body>
                <h1>MQ4 Data Logging Status</h1>
                <p>No data has been logged yet.</p>
            </body>
        </html>
        """, 200

# Entry point to run the Flask application
if __name__ == '__main__':
    # Start the Flask development server, accessible externally on port 8080
    app.run(host='0.0.0.0', port=8080)
```