Electronics and Information Technologies, 2026, 35, 175–184
http://publications.lnu.edu.ua/collections/index.php/electronics/index

UDC: 681.5, 004.93

INTEGRATION OF GRAPHENE-SENSOR-BASED ELECTRONIC NOSE TECHNOLOGY INTO MOBILE MICROCONTROLLER PLATFORM

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Olenych, I., Boyko, Y., Kukharska, B., Yaremyk, R., Sinkevych, O., Pavlyk, R., & Karbovnyk, I. (2026). Integration of Graphene-Sensor-Based Electronic Nose Technology into Mobile Microcontroller Platform. *Electronics and Information Technologies*, 35, 175–184. https://doi.org/10.30970/eli.35.13

ABSTRACT

Background. The integration of sensors, in particular electronic nose technology, into mobile platforms is a fundamental element in the development of modern robotics and autonomous intelligent systems. This combination opens up new possibilities for automated air quality monitoring, detection of pollution sources, and the execution of rescue operations in hazardous conditions. An important aspect in this context is the use of artificial intelligence and machine learning algorithms to analyze sensor data and predict environmental changes. Consequently, particular attention was focused on implementing the microcontroller architecture of the intelligent sensor system.

Materials and methods. The developed mobile sensor platform architecture comprises a graphene FET-based sensor module, an impedance analyzer module, and a control module based on the ESP32 microcontroller. Normalized graphene channel resistance profiles and normalized gate resistance measured in atmospheres of acetone, ammonia, ethanol, and toluene vapor were used to develop a neural network-based machine learning model and test the intelligent sensor system.

Results. The developed model provided 90.9 % sensor data classification accuracy. The weighted average values for Precision, Recall, and F1-score are 0.94, 0.91, and 0.92, respectively, confirming the high quality of the classification and the model balance across the different classes of the target gases. The machine learning model deployed on the ESP32 microcontroller uses about 26% of flash memory and 6% of RAM for target gas recognition. The gas identification time, which does not exceed 1 ms, is small enough for the real-time intelligent sensor system.

Conclusions. The distributed architecture for the mobile sensor system based on the ESP32 microcontroller, combining control, sensor data measurement and acquisition, and data analysis functions, was proposed. It is demonstrated that the developed machine learning model provides high accuracy of target gas identification. The obtained results confirm the feasibility of implementing the proposed solutions on real-time platforms with limited computing resources.

Keywords: Graphene field-effect transistor, sensor platform, measuring system, microcontroller, machine learning model, gas recognition.

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INTRODUCTION

Mobile robotic platforms represent a significant step toward operational efficiency and autonomy in various industries, the security sector, logistics, agriculture, and everyday life [1-3]. Central to this evolution is the integration of robotics, sensor systems, and artificial intelligence technologies, which are set to enhance robot adaptability to changing operating conditions and to ensure informed decision-making. Increasing demands for robot autonomy necessitate the use of a wide range of sensors to gather reliable information about the surrounding environment, enabling the localization and navigation of mobile platforms, as well as the real-time execution of specialized tasks. As robotic platforms perform increasingly complex tasks, their ability to understand their environment becomes crucial [4].

Sensor integration is a fundamental element of Industry 4.0, IoT, and unmanned technology development. In modern technological systems, mobile robots are part of a unified information space, exchanging data with other devices and information systems. An important aspect in this context is the implementation of multisensor data fusion methods, which enable the processing of information from various sources and the creation of a comprehensive picture of the environment [5, 6]. The use of artificial intelligence and machine learning algorithms makes it possible not only to analyze vast amounts of sensor data but also to predict changes in the state of objects or the environment. As a result, navigation reliability and operational robustness of mobile robots under conditions of uncertainty are increased.

The integration of electronic nose (e-nose) technology into mobile robotic platforms is of particular scientific and practical interest. The e-nose refers to an intelligent sensor system consisting of an array of gas sensors and pattern recognition algorithms for analyzing volatile organic compounds and gas mixtures [7-9]. Combining this technology with mobile robots opens up new possibilities for automated gas leak detection, air quality monitoring, pollution source localization, process diagnostics, and rescue operations in hazardous environments. At the same time, the platform mobility enables spatial mapping of gas concentrations and increases the informational value of the obtained data.

The combined analysis of data from different sensors, which form a unique multidimensional profile of the gaseous environment, is the basis of artificial olfaction. Recognition accuracy depends heavily on sensor stability, as drift in the characteristics of a large number of sensors creates a complex dependence of response on operating conditions [10]. The use of monosensor e-nose technology, on the one hand, simplifies the sensor system and reduces power consumption – factors important for mobile platforms and IoT – and on the other hand, increases the efficiency of gas identification over a long period of time. However, typical monosensor gas analyzers require additional thermal or ultrasonic influence on the sensing element [11, 12], which complicates the sensor system structure.

A promising solution to this problem could be the implementation of sensors based on the field-effect in graphene. The high sensitivity of graphene conductivity to local changes in the electric field induced by adsorbed gas molecules offers great potential for graphene-based materials in gas detection. Target gases are identified by analyzing the conductivity profiles of graphene field-effect transistors (FETs) measured in the studied environment using machine learning methods [13, 14]. Unlike thermal and ultrasonic effects on the sensor, measuring the dependence of the graphene FET channel resistance on the gate voltage is a relatively simple task using microprocessor technology [15]. This approach enables the integration of graphene sensors into microelectronic technology and the implementation of a portable gas analyzer based on a microcontroller-based measurement system architecture that meets the requirements of the IoT paradigm. Therefore, the work focused on investigating the feasibility of integrating

graphene FET-based e-nose technology into mobile microcontroller platforms and on developing tiny machine learning models capable of reliably identifying target gases.

MATERIALS AND METHODS

Sensor platform architecture

The developed mobile sensor platform architecture is a highly integrated system based on the ESP32 microcontroller (DD3), comprising a sensor module, an impedance analyzer module, and a control module (**Fig. 1**). The sensor module contains, as a sensing element, a FET based on a reduced graphene oxide (RGO) film deposited on the surface of porous silicon (PS) on a silicon substrate [14], as well as an analog interface. To obtain conductivity profiles of the graphene FET that are independent of the polarity of the voltage between the source and drain, the capability for AC measurements was provided.

The impedance analyzer module enables the software-controlled generation of a harmonic probe voltage V_{out} within a specified frequency range and with a set quantization step by the AD5933 impedance meter integrated circuit (DD2) from Analog Devices, as well as real-time impedance measurement using the Discrete Fourier

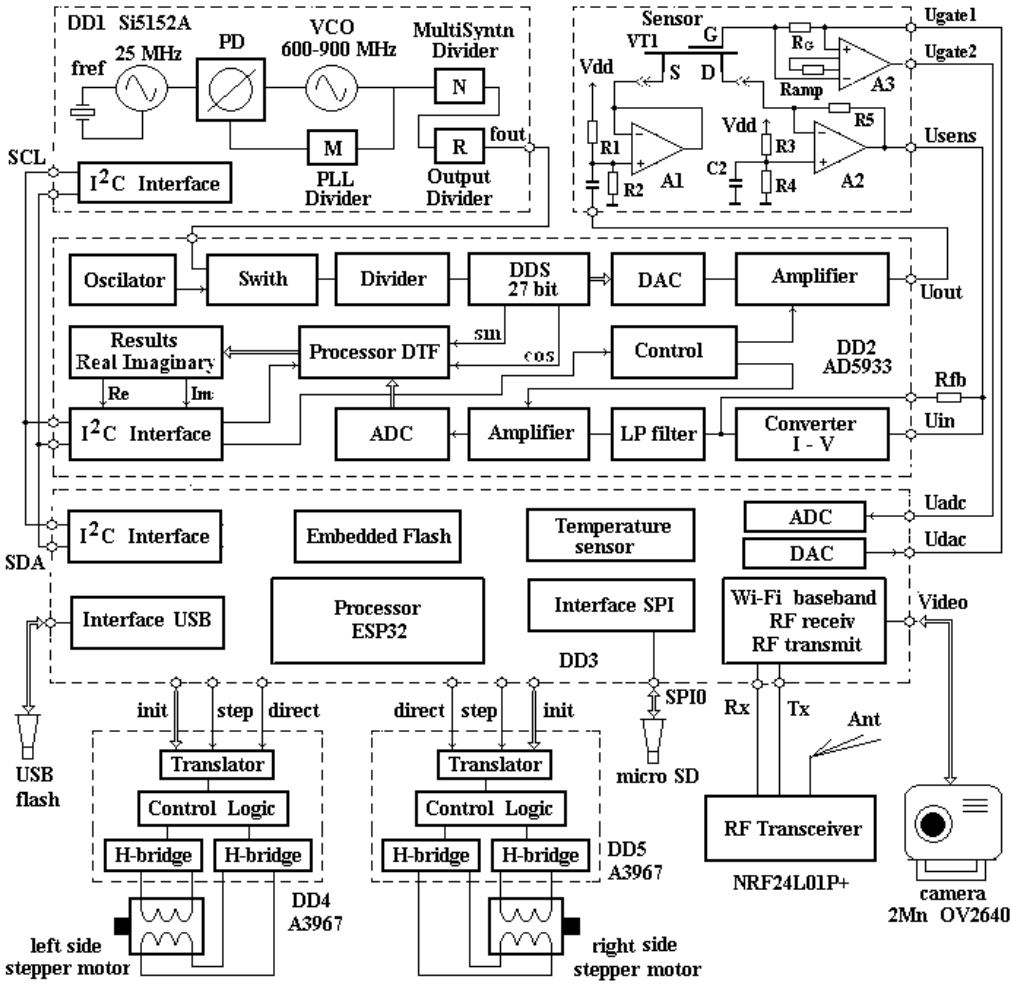


Fig. 1. Block diagram of a mobile sensor platform based on the ESP32 microcontroller

Transform [16]. According to the datasheet, the AD5933 can measure impedance in the 1–100 kHz range without any external components. The lower limit of the frequency range can be decreased using an external clock generator. The probe voltage induces a current through the graphene FET channel, the magnitude of which depends on both the gate voltage V_G and the gas type and concentration. The conversion of the measured information into a voltage V_{in} is implemented using an analog interface based on operational amplifiers A1 and A2. The real and imaginary parts of the impedance are determined by the discrete Fourier transform processor integrated into the AD5933 impedance meter chip for each gate voltage value within the programmed range at a specified frequency. The resulting internal resistance profiles of the graphene FET channel are stored in non-volatile memory.

Software control of the external clock generator Si5152A (DD1) and the frequency generator integrated into the DD2 chip is performed by an ESP32 microcontroller via the I^2C serial data bus. In addition to initializing the input registers and reading the output registers of the AD5933 impedance meter chip, the ESP32-based control module controls the FET gate voltage and the mobile platform motors, implements machine learning models, and transmits the video stream and control signals using an external RF transceiver NRF24L01P+. Installing the external transceiver enables motion control and video monitoring over greater distances (up to 100 m with the built-in antenna and 1 km in open space with an external antenna).

Drivers in the chips DD4 and DD5 of the A3967 type from Allegro MicroSystems Inc. are used to control the stepper motors of the mobile platform. Each microchip incorporates a ready-made electronic module for stepper motor control. A distinctive feature of the control scheme implementation is the use of an integrated translator that autonomously generates complex phase sequences for current in microstepping mode, while receiving only two logic pulse signals (step and direction) from the ESP32 microcontroller. This implementation of stepper motor control significantly reduces the load on the processor's computing resources. The translator A3967 automatically determines the current motion phase and switches the internal circuitry (H-bridges) to the next microstep. To control a standard bipolar stepper motor, two independent H-bridges in each driver are used, the current of which is regulated by a pulse-width modulated control circuit.

Data preparation

Experimental data measured in atmospheres of acetone, ammonia, ethanol, and toluene vapor within the 0–10 % concentration range were used to test the intelligent sensor system. The measured dataset consisted of the dependencies of the RGO–PS–Si-based FET resistance on the gate voltage for various concentrations of the target gases. **Fig. 2** illustrates the normalized resistance profiles of the RGO channel in the absence of target gases and in an atmosphere of acetone, ammonia, ethanol, and toluene.

Since the initial measurements form an irregular grid of gas concentration and gate-voltage values, their direct application in machine learning tasks is complicated by the lack of a consistent structure of input space. Therefore, multidimensional interpolation was applied to the experimental data to form a uniformly sampled feature space. In addition, the normalized resistance value of the sandwich structure – determined based on the gate leakage current for the corresponding target gas concentration – was added to the feature vector. The t-SNE dimensionality reduction method [17] was used to visualize the feature space (**Fig. 3**).

As a result, a unified labeled dataset containing consistent values for gas concentration, gate voltage, and the corresponding electrical characteristics of the sensor element was formed, enabling its direct application in classification algorithms. A dataset containing over 400 records was split into training and testing sets at an 80/20 ratio.

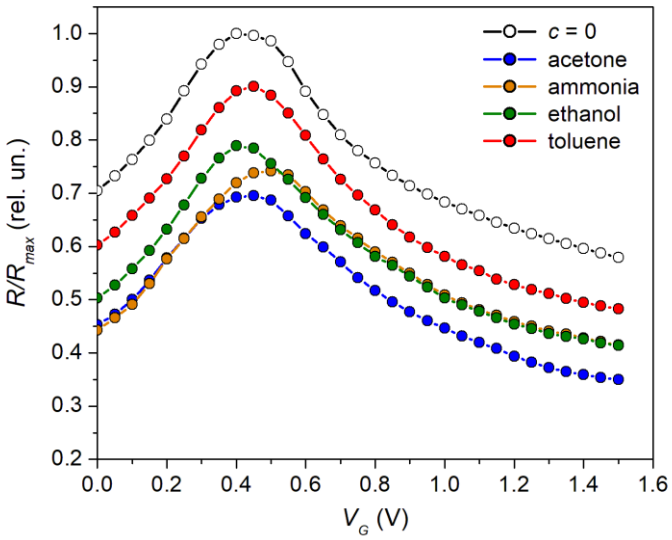


Fig. 2. The normalized resistance profiles of the RGO channel in the absence of target gases (c = 0) and in an atmosphere of acetone, ammonia, ethanol, and toluene at c = 6 % concentration

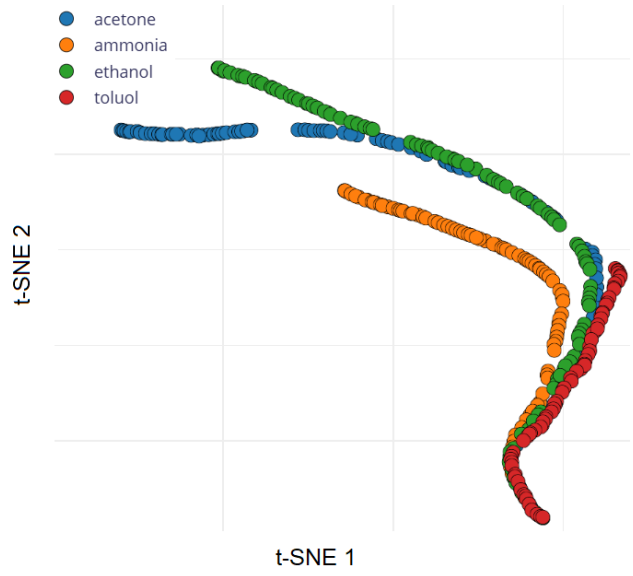


Fig. 3. Visualization of feature space

Model design

The classification model was based on a multilayer feedforward neural network. The input layer comprised 32 neurons, corresponding to the dimensionality of the feature vector. The input signal was then processed by two fully connected (dense) hidden layers with 20 and 10 neurons, respectively, using the ReLU activation function. The output layer contained four neurons, corresponding to the four target gas classes: acetone, ammonia, ethanol, and toluene. A Softmax activation function was applied to the output layer to convert the model outputs into a probability distribution over the

target classes. The learning rate was set to 0.0005. This value was selected empirically and, when used with the Adam optimizer during training, provided a stable learning process with a gradual improvement in classification accuracy.

RESULTS AND DISCUSSION

The trained neural network was tested on the validation set to evaluate the quality of the constructed model. The report on the effectiveness of the developed model is shown in **Fig. 4**. According to the confusion matrix, the "toluene" class demonstrated the highest recognition accuracy, with a correct classification rate of 100 %. For the "acetone", "ammonia", and "ethanol" classes, the proportion of correctly classified sensor data was 95.7, 88.2, and 83.3 %, respectively. Errors are related to the assignment of individual results measured in the atmosphere of other gases, probably at low concentrations, to the toluene class, since the accuracy of the classification depends on the concentration of the target gases [18].

Confusion matrix

	acetone	ammonia	ethanol	toluene
acetone	95.7 %	0	0	4.3 %
ammonia	0	88.2 %	0	11.8 %
ethanol	0	0	83.3%	16.7 %
toluene	0	0	0	100 %
F1 SCORE	0.98	0.94	0.91	0.79

Metrics

Metric	Value
Area under ROC Curve	0.99
Weighted average Precision	0.94
Weighted average Recall	0.91
Weighted average F1 score	0.92

Fig. 4. Confusion matrix and the report on the model effectiveness for multiclass classification

The developed model achieved a classification accuracy of 90.9 % with a loss function value of 0.42. The obtained results indicate the ability of the model to correctly recognize the studied gases using data not included in the training set. The area under the ROC curve is 0.99, which serves as further evidence of the high class-discrimination capability. The weighted average values for Precision, Recall, and F1-score are 0.94, 0.91, and 0.92, respectively, confirming the high quality of the classification and the model balance across the different classes of the target gases. Dimensionality reduction was used to visualize the classification results. In **Fig. 5**, which illustrates the resulting diagram, correctly classified sensor data are marked with various shades of green, while incorrectly classified data are marked with shades of red. The majority of points belong to correctly classified data, confirming a high level of classification accuracy based on the derived sensory features.

The trained model was deployed on an ESP32 microcontroller to implement the developed sensor data analysis system. To verify the performance of the qualification model on the microcontroller, four test feature vectors corresponding to the target gases:

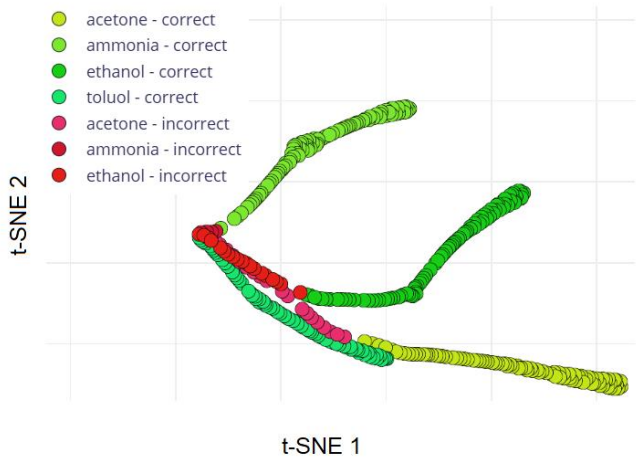


Fig. 5. Confusion matrix and the report on the model effectiveness for multiclass classification

acetone, ammonia, ethanol, and toluene were used. For these vectors, the model determined the probability of the sensor data belonging to each of the four classes and generated the classification results, which are presented in **Table 1**.

Analysis of the results in **Table 1** showed that the model deployed on the microcontroller correctly identified all target gases. The model identified ethanol with the highest confidence (almost 97.3 % probability). The probability of correctly identifying acetone and ammonia exceeded 80 %, indicating a sufficiently high classification quality. Even for the case of the lowest probability of toluene identification (54.3 %), the developed model successfully performed the classification. In addition, the gas identification time of the intelligent sensor system was evaluated. The time required to obtain a conclusion regarding the correspondence of each of the vectors to the target gases did not exceed 1 ms. Such performance confirms the feasibility of using the developed model for real-time sensor data analysis by the ESP32 microcontroller.

Table 1. **The probability of the test data belonging to "acetone", "ammonia", "ethanol", and "toluene" classes**

Actual	Predicted			
	acetone	ammonia	ethanol	toluene
acetone	0.84375	0.02734	0.01953	0.16406
ammonia	0.01172	0.81641	0.00781	0.07422
ethanol	0.08203	0.12500	0.97266	0.22266
toluene	0.05859	0.02734	0.00000	0.54297

Finally, the use of ESP32 microcontroller hardware resources was analyzed. The program code size, including the machine learning model, occupied 26 % of the available flash memory. And only 6 % of the microcontroller RAM was used to store global variables. Thus, the gas recognition model implementation leaves a significant amount of both flash memory and RAM free, which not only does not interfere with control of the mobile platform but also allows for the expansion of its functionality without the need to upgrade the hardware.

CONCLUSION

The developed intelligent sensor system is proposed as a universal mobile platform based on the ESP32 microcontroller, combining control, sensor data measurement and acquisition, and data analysis functions. A distinctive feature of the hardware implementation of the developed sensor system is the ability to configure the measurement signal path and the measurement algorithm via software, taking into account the specific characteristics of the sensor response of the FETs based on the RGO–PS–Si structure. Local processing and analysis of the measured sensor data are performed directly by the microcontroller-based mobile platform. Sensor data classification is performed by the trained neural network deployed on an ESP32. The developed machine learning model demonstrates 90.9 % accuracy in recognizing gases (acetone, ammonia, ethanol, and toluene) and uses about 26 % of flash memory and 6 % of RAM for classification. The gas identification time does not exceed 1 ms. The obtained results confirm the feasibility of implementing the proposed solutions in real time on resource-constrained devices, particularly on mobile microcontroller platforms. The openness of the architecture to expansion at both hardware and software levels enables optimal configuration of the measurement parameters and enhances the functionality of the mobile platform.

ACKNOWLEDGMENTS AND FUNDING SOURCES

This work was supported by the Ministry of Education and Science of Ukraine [0124U000982].

COMPLIANCE WITH ETHICAL STANDARDS

The authors declare that the research was conducted in the absence of any conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization, [I.O., Y.B., I.K.]; methodology, [I.O., Y.B., B.K., O.S.]; investigation, [I.O., B.K., R.Y., M.P.]; writing – original draft preparation, [I.O., R.Y., O.S.]; writing – review and editing, [I.O., O.S.]; visualization, [I.O., B.K., R.Y.].

All authors have read and agreed to the published version of the manuscript.

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ІНТЕГРАЦІЯ ТЕХНОЛОГІЇ ЕЛЕКТРОННОГО НОСУ НА ОСНОВІ ГРАФЕНОВОГО СЕНСОРА У МОБІЛЬНУ МІКРОКОНТРОЛЕРНУ ПЛАТФОРМУ

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АНОТАЦІЯ

Вступ. Інтеграція сенсорів, зокрема технології електронного носа, у мобільні платформи є фундаментальним елементом розвитку сучасної робототехніки та автономних інтелектуальних систем. Таке поєднання відкриває нові можливості для автоматизованого моніторингу якості повітря, виявлення джерел забруднення і проведення рятувальних операцій у небезпечних умовах. Важливим аспектом у цьому контексті є використання штучного інтелекту та алгоритмів машинного навчання для аналізу сенсорних даних і прогнозування зміни навколишнього середовища. Відтак, особлива увага була зосереджена на реалізації мікроконтролерної архітектури інтелектуальної сенсорної системи.

Матеріали та методи. Розроблена архітектура мобільної сенсорної платформи містить сенсорний модуль на основі графенового польового транзистора, модуль аналізатора імпедансу та модуль керування на базі мікроконтролера ESP32. Нормовані профілі опору графенового каналу та нормований опір затвора, виміряні в атмосферах парів ацетону, аміаку, етанолу і толуолу, були використані для розробки моделі машинного навчання на основі нейронної мережі та тестування інтелектуальної сенсорної системи.

Результати. Розроблена модель забезпечила точність класифікації сенсорних даних 90,9 %. Середньозважені значення для влучності (англ. precision), повноти (англ. recall) і F1-міри (англ. F1-score) становлять 0,94, 0,91 і 0,92 відповідно, що підтверджує високу якість класифікації та збалансованість моделі для різних класів цільових газів. Модель машинного навчання, розгорнута на мікроконтролері ESP32, використовує близько 26 % флеш-пам'яті та 6 % оперативної пам'яті для розпізнавання цільового газу. Час ідентифікації газу, який не перевищує 1 мс, достатньо малий для функціонування інтелектуальної сенсорної системи в реальному масштабі часу.

Висновки. Запропоновано розподілену архітектуру мобільної сенсорної системи на основі мікроконтролера ESP32, що поєднує в собі функції керування, вимірювання та збору даних датчиків та аналізу даних. Продемонстровано, що розроблена модель машинного навчання забезпечує високу точність ідентифікації цільових газів. Отримані результати підтверджують можливість реалізації запропонованих рішень на платформах реального часу з обмеженими обчислювальними ресурсами.

Ключові слова: Графеновий польовий транзистор, сенсорна платформа, вимірювальна система, мікроконтролер, модель машинного навчання, розпізнавання газів.

Received / Одержано	Revised / Доопрацьовано	Accepted / Прийнято	Published / Опубліковано
10 September, 2026	18 September , 2026	21 September, 2026	28 September, 2026