Design and implementation of an IoT-based system for intelligent crop health monitoring

Volodymyr Lavrik[a], Hanna Alieksieieva[b], Oksana Kovalska[c], Yuri Lebedenko[a], Maksym Sukalo[a], Mykola Kudinov[d], Vitaliy Mezhuyev[*e]

[a]Department of Information and Computer Technologies, Kyiv National University of Technologies and Design, Kyiv, Ukraine

[b]Department of Computer Technologies and Informatics, Berdyansk State Pedagogical University, Berdyansk, Ukraine

[c]Department of Architectural Design of Civil Buildings and Structures, Kyiv National University of Construction and Architecture, Kyiv, Ukraine

[d]Department of Physics, Mathematics and Teaching Methods, Berdyansk State Pedagogical University, Berdyansk, Ukraine

[e]FH JOANNEUM University of Applied Sciences, Institute of Industrial Management, Kapfenberg, Austria

[*]Corresponding author: vitaliy.mezhuyev@fh-joanneum.at

ABSTRACT

This paper presents the development of an intelligent IoT device for automated, real-time monitoring of crop conditions in agriculture. The proposed solution involves Raspberry Pi Zero 2 W hardware, multi-sensor modules for environmental data collection, NB-IoT for long-range wireless communication, and the YOLOv8 convolutional neural network for plant image analysis. The objective is to create a compact, low-cost, and energy-efficient solution that enables early detection of plant diseases and environmental stress in remote or infrastructure-poor agricultural areas. The developed system enables accurate identification of disease symptoms and damage on crop leaves based on visual and environmental input, facilitating timely intervention and reducing yield loss. The YOLOv8 model was adapted for resource-constrained edge deployment, trained on a custom dataset of strawberry leaf diseases, and integrated into the embedded device with high accuracy and low latency. System testing confirmed reliable performance under field conditions, with successful image classification and robust NB-IoT communication. The proposed solution is scalable and applicable to various crops and contributes to the practical implementation of precision agriculture and intelligent farming systems.

Keywords: Internet of Things (IoT), precision agriculture, deep learning, neural networks, YOLOv8, plant disease detection, edge computing, environmental monitoring.

1. INTRODUCTION

Modern agriculture faces global challenges such as climate change, population growth, scarcity of natural resources, particularly water and fertile land, and the unstable socio-economic situation in many regions. These factors highlight the need for innovative approaches to agricultural management, specifically the use of digital technologies to enhance efficiency and environmental sustainability in farming processes [1,2].

Traditional methods for monitoring plant conditions are characterised by low accuracy, high labour intensity, and limited ability to quickly respond to negative changes. They do not effectively detect signs of disease, pests, or nutrient deficiencies at early plant development stages, which reduces both yield and product quality [3].

This underscores the need for automated and scalable systems for collecting and processing agricultural data. Internet of Things (IoT) technologies provide the opportunity to create intelligent monitoring systems that utilise networks of sensors, controllers, and data transmission modules to capture environmental parameters in real time. Applying IoT technology in agriculture can significantly improve monitoring accuracy and efficiency through continuous data collection and adaptive solutions [2,4]. For instance, IoT device with sensors for temperature, humidity, soil pH, light levels, and video surveillance modules enable highly precise diagnostics of plant conditions in field settings [4].

Second International Conference on Communication, Information, and Digital Technologies (CIDT 2025),
edited by Sos S. Agaian, Xiangjie Kong, Proc. of SPIE Vol. 14064, 140641E
 · doi: 10.1117/12.3090104

Integrating such IoT systems with artificial intelligence (AI) algorithms, particularly deep learning, opens possibilities for automatic analysis of collected images and other type of data. Neural network models like YOLOv8 and YOLOv9 can detect pathological changes in leaves or signs of pest activity with high accuracy, even in complex visual conditions [5].

Despite the potential of IoT and AI for the agricultural sector, significant barriers to their practical implementation remain, including lack of ready-to-use solutions, weak digital infrastructure in rural areas, and insufficient expertise of farmers caused by the lack of practice-oriented training programs [6,7].

This study presents the design and implementation of an intelligent IoT-based system for real-time crop health monitoring. By integrating environmental sensors, NB-IoT communication, and the YOLOv8 deep learning model on a low-power Raspberry Pi Zero 2 W platform [8], the system enables early detection of plant diseases with high accuracy. The proposed solution demonstrates practical significance for precision agriculture, especially in remote areas with limited infrastructure.

2. LITERATURE REVIEW

As emphasized by Rajak et al. [1], one of the key advantages of using IoT systems in agriculture is their ability to continuously collect diverse parameters such as soil moisture, ambient temperature, lighting levels, and pest presence. These data are transmitted to central processing systems or cloud platforms for real-time analysis and decision-making support.

The implementation of the IoT technologies in agriculture has gained significant momentum in recent years, as researchers and practitioners strive to optimize productivity while reducing resource consumption. Smart agriculture, often referred to as “Agriculture 4.0,” involves the integration of sensor systems, wireless networks, and cloud computing to monitor and manage agricultural operations in real time [1,2].

Several studies have emphasized the transformative role of IoT-based monitoring systems in crop management. For instance, Shahab et al. [2] highlight how IoT sensors can be used to track soil moisture, nutrient levels, and microclimatic conditions, thereby improving irrigation efficiency and reducing water waste. Similar findings are supported by Rajak et al. [1], who demonstrate that real-time environmental monitoring enhances decision-making regarding fertilization, pest control, and harvesting schedules.

Table 1 gives a short overview of the most common IoT applications in agriculture, which highlights key directions such as soil monitoring, precision irrigation, smart greenhouses, remote farm management systems etc.

Table 1. Overview of modern IoT technologies in agriculture

IoT Application in Agriculture	Description	Use Cases
Soil condition monitoring	Sensors measure soil moisture, temperature, pH, and nutrient levels	Watering control, pre-planting soil analysis
Precision irrigation systems	Automated watering based on sensor data and weather forecasts	Smart irrigation that activates only when needed
Smart greenhouses	Automated microclimate management using environmental sensors	Optimizing conditions for crops, automatic lighting and watering control
Environmental monitoring	IoT sensors collect data on air temperature, humidity, wind, solar radiation	Weather prediction for planning agricultural activities
Machinery management	GPS and IoT for automation of tractors and harvesting machines	Autonomous seeding, harvesting, and crop treatment
Remote farm control	Sensor and camera data accessible via apps or web interfaces	Real-time monitoring of greenhouses and animal farms
Inventory management systems	Monitoring of storage levels for fertilizers, feed, water, and fuel	Shortage detection and automated ordering
Livestock health monitoring	Sensors and RFID for animal activity and health tracking	Early disease detection via temperature and activity monitoring

Note, that edge-deployed models can be trained for quality detection in other types of industrial surface analysis tasks [9]. Time series-based forecasts are crucial for managing connectivity reliability in production systems in general [10].

Multimodal IoT systems integrating various sensors and machine learning models have demonstrated significant potential in field applications, as shown by Garg et al. [11] Recent developments in multimodal systems demonstrate how combinations of IoT sensors and ML models can significantly improve the accuracy of field data interpretation and automated agricultural decision-making. The standardization of environmental data collection in smart manufacturing was reviewed by Schlemitz and Mezhuyev [12].

To ensure continuous monitoring and data transmission, various wireless technologies were compared. The most optimal solution was found to be NB-IoT - a technology that operates on mobile networks and does not require additional infrastructure deployment, unlike Wi-Fi, LoRa, or Zigbee. As shown in Table 2, NB-IoT provides sufficient transmission speed, low energy consumption, and high signal stability, making it suitable for remote agricultural regions with minimal coverage.

Table 2. Comparative characteristics of wireless data transmission technologies

Technology	Range	Data Transmission Speed	Energy Consumption	Equipment Cost	Characteristics
LoRa	Up to 15–20 km (open space)	0.3–50 Kbps	Very low	Low	Suitable for a large number of sensors, operates in remote areas.
Zigbee	Up to 100 m	Up to 250 Kbps	Low	Low	Good for local networks, supports mesh structures.
NB-IoT	Up to 10 km (in urban areas)	Up to 250 Kbit/s	Very low	Medium	Uses mobile network infrastructure, stable connection.
Wi-Fi	Up to 100 m (indoors), up to 300 m (open space)	Up to 1 Gbps	Average	Low	High speed, but limited range and high energy consumption.
Bluetooth LE	Up to 50 m	Up to 2 Mbps	Very low	Low	Suitable for mobile devices, low latency.
4G LTE	Up to 10–15 km	Up to 150 Mbps	Average	Medium	Wide coverage, suitable for video or large data transmission.
5G	Up to 1–10 km	Up to 10 Gbps	High	High	Minimal latency, high throughput.
Satellite communication	Global coverage	Up to 100 Mbps	High	Very high	Used in remote regions where there is no mobile coverage.

Smart greenhouses represent one of the most advanced implementations of IoT in agriculture. As noted by Udutalapally et al. [4], automated greenhouse systems that rely on wireless sensor networks can regulate temperature, humidity, and CO_2 levels, maintaining optimal growing conditions while minimizing manual intervention.

In recent years, attention has turned to the application of AI, particularly deep learning, in conjunction with IoT systems. CNNs, such as the YOLO (You Only Look Once) architecture, have proven effective in detecting plant diseases from images. Optimising CNN pipelines enhances inference speed in constrained agricultural environments [13]. A growing body of literature emphasizes that deep learning models are rapidly transforming agricultural diagnostics, offering scalable solutions for real-time disease detection and yield forecasting [14]. Qin et al. [5] emphasize the speed and accuracy of YOLOv9 and SIS-YOLOv8 in identifying visual symptoms of crop stress, such as leaf discoloration, spotting, and structural deformation. These findings align with broader research trends highlighting the growing role of deep learning techniques in agricultural diagnostics and automation [15].

To support early-stage IoT planning, structured frameworks have recently been proposed using generative AI [16]. Recent work has explored interpretability in vision-based classification in industry, which is also important for agricultural images [17]. Furthermore, the deployment of wireless technologies with energy-harvesting capabilities is recommended to support IoT operations in environments with limited access to stable power sources [18].

Despite notable advances, challenges remain in deploying IoT and AI solutions in rural agricultural areas. These include the high cost of sensor equipment, lack of broadband internet access, data privacy concerns, and the need for user-friendly platforms tailored to farmers with limited technical expertise. The literature review allows us to select as the core processing unit for the monitoring system the Raspberry Pi Zero 2 W, considering its compact design and low energy consumption.

Moreover, there is a need for integrated systems that combine environmental data collection with automated analysis and feedback loops for adaptive crop management. The synergy between IoT devices and AI-driven analytics holds considerable potential for the future of precision agriculture, particularly in resource-constrained environments such as those found in parts of Eastern Europe and Ukraine. In this context, it is worth mentioning an intellectual control system for unmanned energy crop UAV and the method for planning the routes of harvesting equipment for crop monitoring [19,20].

Combining physical models with expert systems has proven effective in enhancing process control, both in manufacturing and scientific environments [21]. In the context of smart farming, these expert systems act as the decision-making backbone, supporting real-time analysis and autonomous responses. By embedding a structured logic model that reflects domain-specific knowledge, the system can evaluate sensor data not only quantitatively, but also qualitatively mimicking human expertise in assessing complex or ambiguous situations. This kind of knowledge-driven reasoning enables shopfloor or field-level decision support, allowing agricultural systems to detect inconsistencies, adapt to environmental changes, and optimize actions accordingly [22]. An abstract modelling layer can support modular design in mechanical systems, as shown in prior metamodeling research [23]. Also, pretrained models can dramatically reduce training data requirements while maintaining accuracy [24].

3. METHODOLOGY

The development of the intelligent crop health monitoring system followed a structured engineering process encompassing the design, integration, and validation of hardware and software components. The methodology consists of four primary stages: (1) system architecture design, (2) hardware integration, (3) software development and neural network training, and (4) field testing and evaluation.

3.1 System architecture design

The system architecture was designed to support continuous, real-time monitoring of crop health in remote agricultural environments. The core components include:

- **Environmental sensing module:** Sensors to measure temperature, humidity, light intensity, and soil pH.
- **Visual analysis module:** A camera module connected to the Raspberry Pi Zero 2 W for capturing leaf images.
- **Edge computing unit:** Raspberry Pi Zero 2 W selected for its compact size, low power consumption, and ability to run neural network models.
- **Communication unit:** NB-IoT modem integrated to transmit data over long distances without relying on local infrastructure.

This modular architecture ensures scalability and supports deployment in a variety of agricultural contexts with minimal setup.

3.2 Hardware integration and device construction

The hardware design focused on building a compact, energy-efficient, and weather-resistant device. Key components included:

- **Microcontroller and control logic:** The Raspberry Pi Zero 2 W manages data acquisition and neural inference.
- **Sensor modules:** BME280 for temperature and humidity, analog-to-digital converters for soil pH, and ambient light sensors.
- **Communication hardware:** NB-IoT modem integrated with custom firmware to ensure reliable long-range wireless transmission.
- **Power management:** Efficient power circuitry with energy-saving modes was implemented to support autonomous operation over long durations.
- **Protective casing:** The assembled hardware was enclosed in a waterproof and UV-resistant shell suitable for field deployment.

3.3 Software development and YOLOv8 integration

The system software was developed to manage sensor data acquisition, image processing, neural inference, and data transmission. A central element of the system is the YOLOv8 convolutional neural network, responsible for detecting disease symptoms from leaf images.

- **Dataset preparation:** A custom dataset of strawberry leaf images showing various disease symptoms was annotated and used to train the model.

- **Model training:** Training was performed in Google Colab using a Tesla L4 GPU. The model was optimized for execution on edge devices by pruning and quantizing the network.

- **Deployment:** The trained YOLOv8 model was deployed on the Raspberry Pi with minimal latency using ONNX runtime and lightweight Python scripts for inference.

3.4 Field testing and validation

To validate the system's effectiveness, it was deployed under field conditions where it performed automated environmental monitoring and leaf image analysis. Key validation steps included:

- **Functionality tests:** Ensuring sensor accuracy, stable data transmission via NB-IoT, and correct operation of all hardware modules.

- **Image inference tests:** Evaluating detection accuracy of the neural network under varying lighting and background conditions.

- **Performance metrics:** Monitoring power consumption, communication reliability, and system response times.

4. DESIGN, DEVELOPMENT, VALIDATION AND APPLICATION

4.1 Logical framework for intelligent plant monitoring

To ensure the reliability and adaptability of smart agricultural systems, it is essential to implement not only physical sensors and AI algorithms but also a structured logic framework that can support reasoning, conflict resolution, and learning from evolving data. The proposed intelligent monitoring model incorporates such a framework, distinguishing between verified knowledge and uncertain observations, and using this structure to continuously refine system decisions based on both sensor data and neural network outputs.

This approach enables the system to function semi-autonomously, validating new data against its internal knowledge base, detecting contradictions, and updating its interpretation of plant conditions accordingly. By structuring information in this way, the system is not only responsive but also self-adaptive, progressively improving decision-making quality over time — even in unstructured, real-world agricultural environments.

Let's describe this intelligent activity model in detail, highlighting how data is categorized, processed, and integrated into system logic for plant condition monitoring.

To implement intelligent plant monitoring systems, a specific logic of information processing must be established. This model evaluates data received from IoT devices, sensor systems, or image processing results using neural networks.

If new information does not contradict the system's existing knowledge, it is integrated into the structure of existing models. In the case of contradictions, a reassessment process is initiated, potentially leading to a revision of the current understanding of the plant's condition or its environment.

Within this model, knowledge is conditionally divided into two main categories (Figure 1):

- DBF (Database of Verified Facts) – This is confirmed information obtained from reliable sources, such as scientific databases, long-term observations, or authoritative sensor data.

- DUDF (Database of Unverified Facts) – This includes information that has not yet been fully validated, such as atypical sensor readings, preliminary machine analysis results with low confidence levels.

Both bases are structured as sets of interconnected groups:

- SVF (Set of Interconnected Facts in the DBF) – a set of groups of reliable facts that are logically or statistically related, for example: soil moisture + air temperature → risk of drought.

- SUF (Set of Interconnected Facts in the DUDF) – a set of potential but unconfirmed relationships, such as changes in leaf colour based on RGB image analysis that have yet to establish a confirmed correlation with chlorosis.

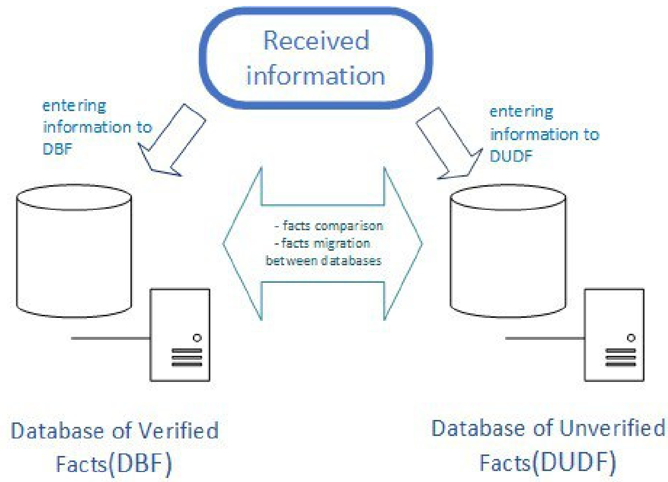

Figure 1. Model of intelligent reasoning in plant condition monitoring

The model operates based on the following logic:

1. Fact Confirmation:

– new information received from sensors (e.g., decreased moisture levels), if it matches verified data in DBF, is integrated into the system as an additional fact;

– if it contradicts information from DUDF (e.g., abnormal leaf color changes detected by multiple sensors), the source is evaluated. If confirmed, the fact is transferred to DBF.

2. Fact Refutation: if new data contradict established facts in DBF (e.g., typical temperatures did not cause expected changes in the plant), the fact is moved to DUDF for further analysis or verification.

3. Integration of new information: data that is not linked to existing groups (e.g., a new type of sensor or a new health indicator) may be classified under DBF or DUDF depending on the reliability of the source.

At the initial stages of NN training and adaptation to a specific environment, the model exhibits subjectivity since the number of verified facts is limited. Over time, the system accumulates knowledge, automates reliability assessments, and refines internal logical connections. For example, in the early stages, the model may interpret leaf darkening as a sign of moisture deficiency. However, after receiving additional confirmation (such as low nitrogen levels), the system will eventually reclassify this fact, linking it to a nutrient deficiency rather than water scarcity.

Thus, the intelligent reasoning model for plant condition monitoring is a dynamic, self-learning system that adapts to new knowledge and improves the accuracy of its decisions as data accumulates.

4.2 Device design and hardware implementation.

To build the system, a Raspberry Pi Zero 2W board was selected [8], combining high energy efficiency, compactness, and sufficient computational power for running neural networks.

Figure 2 illustrates the key components of the device's hardware architecture: a power supply module, sensors, an NB-IoT modem, and a microcontroller that handles signal processing and data transmission control. A drawback of this board is the lack of a hardware support for machine learning and a limited amount of RAM. However, for monitoring tasks that involve processing a single image every few hours, these limitations are not critical.

Figure 3 illustrates a prototype board that integrates all necessary components: a BME280 temperature and humidity sensor [25], ESP-M3 8285 power controller, TIP122 transistor, power management chips, and communication connectors. This level of integration minimizes the device's size and weight, which is essential for field deployment. Figure 4 presents the completed device in a protective enclosure, designed for real-world outdoor use. Its construction allows for easy mounting on greenhouses, poles, or agricultural drones.

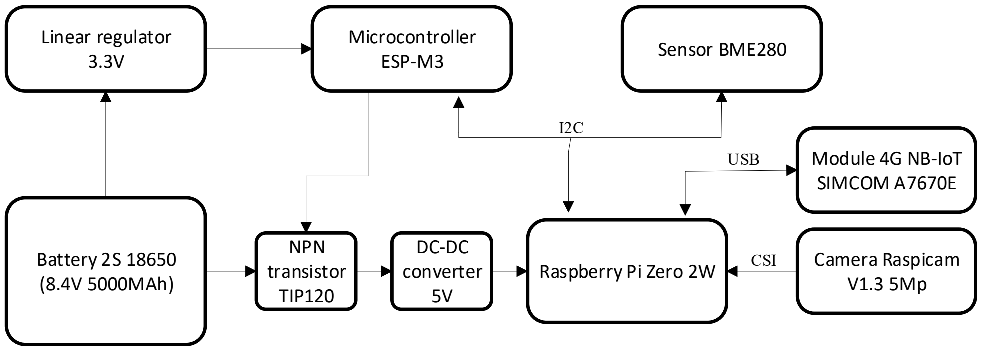

Figure 2. Structural diagram of the device's hardware

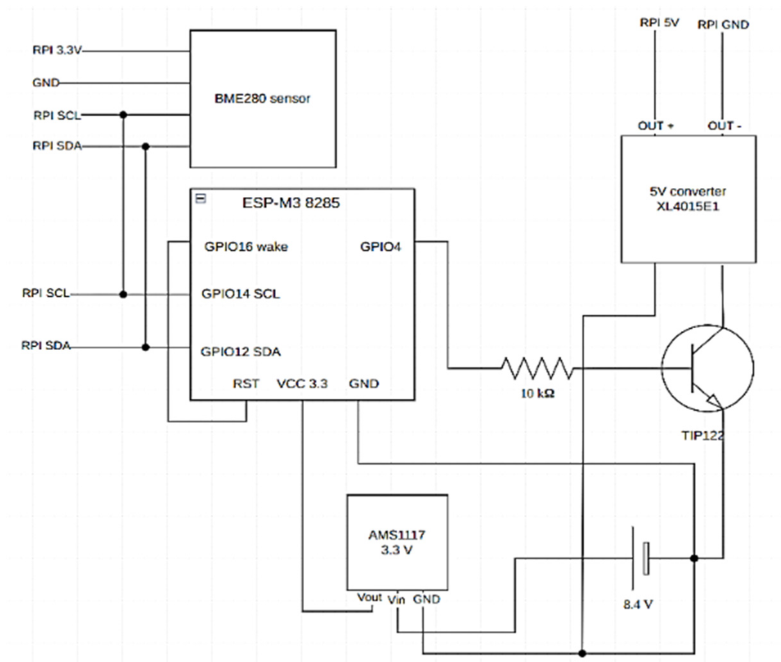

Figure 3. Schematic diagram of the device's main board

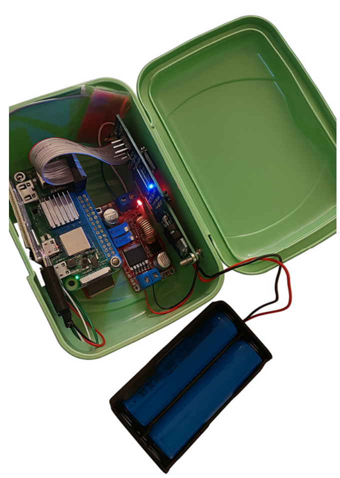

Figure 4. Internal view of the device in its enclosure

4.3 Neural network training results and device testing

The YOLOv8 model [5] was trained using the Google Colab environment with an Nvidia Tesla L4 GPU. It was adapted to a real dataset of strawberry leaf images exhibiting disease symptoms. Experimental results demonstrated high model accuracy in detecting leaf spots, discoloration, necrosis, and signs of fungal infections.

As shown in Figure 5, the model successfully identifies affected areas with a high level of confidence. This enables farmers to respond promptly to disease symptoms before they cause significant crop damage.

(a) Images of real objects (b) Corresponding objects predicted by the model

Figure 5. Data analysis objects

4.4 Analysis of the experimental results

The obtained results confirm the feasibility of implementing AI based IoT solutions in plant condition monitoring systems. The developed prototype demonstrates the effectiveness of the approach that combines sensor-based monitoring, IOT computing platforms, and NN models for visual data analysis.

The comparison of different data transmission technologies revealed that NB-IoT is the most balanced for the agricultural sector in terms of range, energy efficiency, and ease of integration. This significantly reduces implementation costs, which is a critical factor for small farming enterprises. The integration of energy-efficient wireless communication protocols is a critical factor for the deployment of IoT systems in remote agricultural areas [7].

The YOLOv8 neural network demonstrated high accuracy in detecting strawberry leaf diseases even under natural lighting and non-uniform backgrounds. This opens the door to expanding the system not only to other crops, but also to tasks such as predicting infection dynamics, assessing irrigation or fertilization needs, and generating agronomic recommendations. It is worth noting that despite the high detection accuracy, the large-scale implementation of such systems still requires addressing many technical and organizational challenges. These include improving user interfaces, reducing hardware costs, optimizing energy consumption, and enhancing autonomy for processing large volumes of images.

Compared to existing market solutions, our system demonstrates key advantages:

- low cost of hardware (Raspberry Pi Zero 2W combined with a custom-built board);
- minimal power requirements;
- autonomy and ability to operate in remote areas without relying on LAN;

– possible NN adaptation to a local dataset, increasing accuracy for region-specific threats.

Thus, the development can be effectively integrated into a precision farming system as a component of intelligent agricultural management. The proposed approach is scalable to different crops, climate conditions, and production formats.

5. CONCLUSION

This research develops an intelligent IoT device for monitoring agricultural crop conditions. The project encompassed all key stages: hardware design, selection of the optimal wireless transmission technology (NB-IoT), software development, and integration of the YOLOv8 neural network to detect plant disease symptoms based on visual data.

Special attention was devoted to adapting the YOLOv8 model to operate under limited computational resources. The network was trained on a custom dataset of plant disease images and optimized for autonomous execution on the Raspberry Pi Zero 2W device without sacrificing accuracy. The results confirm the effectiveness of the proposed technical solution. The developed device provides:

– real-time automatic detection of leaf diseases;

– energy-efficient performance in field conditions;

– integration with cloud-based or local data systems.

The practical significance of the development lies in its potential for use by farms of various scales, particularly in remote regions having minimal infrastructure. The proposed system could serve as a foundation for scalable platforms in precision agriculture, automated phytosanitary monitoring, and yield analytics.

Future improvements include extending the device's functionality - such as implementing multispectral analysis, adapting to new crops, and generating automated recommendations for agronomic decisions.

REFERENCES

[1] Rajak, P., Ganguly, A., Adhikary, S., and Bhattacharya, S., "Internet of Things and smart sensors in agriculture: scopes and challenges," J. Agric. Food Res. 14, 100776 (2023). https://doi.org/10.1016/j.jafr.2023.100776

[2] Shahab, H., Naeem, M., Iqbal, M., Aqeel, M., and Ullah, S. S., "IoT-driven smart agricultural technology for real-time soil and crop optimization," Smart Agric. Technol. 10, 100847 (2025). https://doi.org/10.1016/j.atech.2025.100847

[3] Pacal, I., Kunduracioglu, I., Alma, M. H., et al. "A systematic review of deep learning techniques for plant disease detection", Knowledge-Based Systems, 256, 10944 (2024). https://doi.org/10.1007/s10462-024-10944-7

[4] Udutalapally, V., Mohanty, S. P., Pallagani, V., and Khandelwal, V., "sCrop: A novel device for sustainable automatic disease prediction, crop selection, and irrigation in Internet-of-Agro-Things for smart agriculture," IEEE Sensors J. 21(16), 17525–17538 (2021). https://doi.org/10.1109/JSEN.2020.3032438

[5] Qin, R., Wang, Y., Liu, X., and Yu, H., "Advancing precision agriculture with deep learning enhanced SIS-YOLOv8 for Solanaceae crop monitoring," Front. Plant Sci. 15, 1485903 (2025). https://doi.org/10.3389/fpls.2024.1485903

[6] Mezhuyev, V., Tschandl, M., and Mayr, M., "Converting manufacturing companies into data-driven enterprises: an evaluation of the transformation model," in Proc. 7th Int. Conf. on Computer Technology Applications (ICCTA 2021), ACM, 80–85 (2021). https://doi.org/10.1145/3477911.3477924

[7] Natraj, A. A., Lee, B., Castiblanco, F. A., Buckmaster, D. R., Wang, C. C., Love, D. J., Krogmeier, J. V., Butt, M. M., and Ghosh, A., "Ambient IoT: communications enabling precision agriculture," IEEE Commun. Mag. 63(4), 137–143 (2025). https://doi.org/10.1109/MCOM.003.2400508

[8] Raspberry Pi Foundation, "Raspberry Pi Zero 2 W." [Online]. Available: https://www.raspberrypi.com/products/raspberry-pi-zero-2-w/. [Accessed: July 18, 2025].

[9] Teubl, M. S., Mezhuyev, V., and Tschandl, M., "Development of an ML model for the classification of surface quality in a milling process," in Proc. 2023 9th Int. Conf. on Computer Technology Applications (ICCTA '23), ACM, 214–219 (2023). https://doi.org/10.1145/3605423.3605449

[10] Hartner, R., and Mezhuyev, V., "Time series-based forecasting methods in production systems: a systematic literature review," Int. J. Ind. Eng. Manag. 13(2), 119–134 (2022). https://doi.org/10.24867/IJIEM-2022-2-306
[11] Garg, S., Pundir, P., Jindal, H., Saini, H., and Garg, S., "Towards a multimodal system for precision agriculture using IoT and machine learning," Proc. 12th ICCCNT 2021, IIT Kharagpur, India. https://doi.org/10.48550/arXiv.2107.04895
[12] Schlemitz, A., and Mezhuyev, V., "Approaches for data collection and process standardization in smart manufacturing: systematic literature review," J. Ind. Inf. Integr. 38, 100578 (2024). https://doi.org/10.1016/j.jii.2024.100578
[13] Hartner, R., Komar, J., and Mezhuyev, V., "An approach for increasing the throughput of CNN-based quality inspection systems in constrained environments," in 11th Int. Conf. on Software & Computer Applications (ICSCA 2022), ACM, 179–184 (2022). https://doi.org/10.1145/3524304.3524330
[14] Waqas, M., Naseem, A., Humphries, U. W., et al. "Applications of machine learning and deep learning in agriculture: a comprehensive review," Discover Artif. Intell. 3(1), Article 33 (2025). https://doi.org/10.1016/j.grets.2025.100199
[15] Wang, D. H., Cao, W. J., Zhang, F., et al. "A Review of Deep Learning in Multiscale Agricultural Sensing," Remote Sens. 14(3), 559 (2022). https://doi.org/10.3390/rs14030559
[16] Binder, M., and Mezhuyev, V., "A framework for creating an IoT system specification with ChatGPT," Internet of Things 27, 101218 (2024). https://doi.org/10.1016/j.iot.2024.101218
[17] Stadlhofer, A., and Mezhuyev, V., "Approach to provide interpretability in machine learning models for image classification," Ind. Artif. Intell. 1, 10 (2023). https://doi.org/10.1007/s44244-023-00009-z
[18] Sadowski, S., and Spachos, P., "Wireless technologies for smart agricultural monitoring using Internet of Things devices with energy harvesting capabilities," Comput. Electron. Agric. 172, 105338 (2020). https://doi.org/10.1016/j.compag.2020.105338
[19] Mezhuyev, V., Gunchenko, Y. O., Shvorov, S. A., and Chyrchenko, D. V., "A method for planning the routes of harvesting equipment," in Advanced ICT and IoT Technologies for the Fourth Industrial Revolution, Vol. 25 (2020). https://doi.org/10.31209/2019.100000133
[20] Gunchenko, Y., Shvorov, S., Lukin, V., and Mezhuyev, V., "Intellectual control system for unmanned energy crop combine," in Proc. 1st Int. Conf. on Intellectual Systems & Information Technologies (ISIT 2019), CEUR Workshops, Vol. 2683, 21–24 (2019).
[21] Mezhuyev, V., and Hofmann, P., "Expert system for bainite design: the approach to enrich physical models with information derived from knowledge models," in Proc. 2024 10th Int. Conf. on Computer Technology Applications (ICCTA '24), ACM, 270–275 (2024). https://doi.org/10.1145/3674558.3674597
[22] Mezhuyev, V., Sorko, S., Mayer, B., and Lackner, K., "Development of an expert system to support the decision-making process on the shop floor," in Gartner, W. C. (ed.), New Perspectives and Paradigms in Applied Economics and Business, Springer Proc. in Business and Economics, Springer, Cham, ch.14 (2023). https://doi.org/10.1007/978-3-031-23844-4_14
[23] Mezhuyev, V., Lavrik, V., and Alieksieieva, H., "Metamodelling architecture for computer-aided design of mechanical systems," in Proc. 2nd Int. Conf. on Computer Science & Software Engineering (CSSE 2019), 132–136 (2019). https://doi.org/10.1145/3339363.3339380
[24] Hofmann, P., Mezhuyev, V., and Panzitt, P., "Pretrained deep learning models to reduce data needed for quality assurance," in Proc. 2024 10th Int. Conf. on Computer Technology Applications (ICCTA '24), ACM, 76–85 (2024). https://doi.org/10.1145/3674558.3674569
[25] Bosch Sensortec, "BME280 combined humidity and pressure sensor." [Online]. Available: https://www.bosch-sensortec.com/products/environmental-sensors/humidity-sensors-bme280. [Accessed: May 12, 2025].