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OVERVIEW OF METHODS AND MEANS OF AUTOMATED DETERMINATION OF THE CURRENT STATE OF BIOLOGICAL OBJECTS

The beginning of the fourth industrial revolution and the rapid development of technologies – in particular artificial intelligence, cloud computing and the Internet of Things – have given rise to a new era in agriculture, which has been called "smart" or "digital" agriculture. Modern agriculture faces numerous challenges that prevent it from obtaining the desired harvest. This paper overviews scientific works related to cultivated plants grown around the world. It is shown that climate change, which causes droughts, floods, frosts or other adverse weather conditions, soil depletion, water shortages and increased costs for fertilizers and pesticides, plant diseases and the spread of pests – all these factors lead to significant crop losses. Traditional methods of monitoring the condition of cultivated plants and soils do not allow for quick results and forecasting changes. On the other hand, modern automated diagnostic systems provide farmers with the opportunity to quickly obtain a wide range of necessary information about the current condition of cultivated plants. The rapid development of digital technologies leads to the need to carry out a comprehensive review of existing methods and means of determining the current state of biological objects, analyze their advantages and disadvantages, degree of automation, accuracy, adaptability to different types of crops and growing conditions. The results of this analysis will allow us to form substantiated recommendations for improving existing or developing new automated systems for monitoring cultivated plants that will meet modern requirements for accuracy, speed and scalability. Agriculture plays a key role in the production of food, fodder and industrial crops. However, traditional farming methods are largely dependent on the workforce, which can seriously affect the efficiency and sustainability of field production. In this regard, the introduction of field robots that can replace humans in performing routine and labor-intensive tasks such as plowing, sowing, spraying, fertilizing, harvesting and transportation is becoming extremely relevant. This will contribute to increasing the level of automation of agricultural processes and help combat global food shortages. Modern agricultural robots combine innovative technologies, including advanced robotics, sensors, artificial intelligence and big data analytics. Due to this, they provide high-precision observation, autonomous decision-making, intelligent process management and efficient task execution, which opens the way to a fully autonomous agriculture of the future. That is why, to solve the existing problems of agriculture, it is necessary to create a comprehensive automated system that would include modern solutions in the field of robotics and artificial intelligence.

Key words: *automated collection and processing, artificial intelligence, neural networks, unmanned aerial vehicles, biological objects.*

Formulation of the problem. In the current conditions of rapid development of biotechnology and growing challenges associated with climate change, monitoring of biological objects is becoming particularly relevant. Biological objects are all forms of living organisms, covering a wide range: from microorganisms to highly organized animals and plants. Their systematic study, observation and analysis allow for timely detection of violations in the functioning of biosystems and prevent potential threats to both individual species and entire ecosystems [1].

Among the diversity of biological objects, plants occupy a special place, which are the basis of life on Earth. They not only form the basis of food chains, but also provide oxygen, stabilize the soil, and regulate climatic conditions. In agriculture, plants are the main sources of food, fodder and raw materials, and that is why effective management of their condition is a strategic task for the agricultural sector.

However, plants, like all biological organisms, are susceptible to harmful factors, including diseases, pests, and adverse weather conditions. These factors can significantly reduce yields, degrade product quality, and cause economic losses. That is why systematic monitoring of plant health and early diagnosis of pathologies are becoming key elements of modern crop production. Early detection of signs of diseases or pest infestation [2] allows for timely preventive or curative measures, avoiding large-scale spread of the problem, and maintaining the productivity of agricultural systems.

The application of innovative technologies in this area, such as remote sensing, computer modeling, machine learning, and automated pathology detection systems, opens new opportunities for increasing the accuracy and efficiency of diagnostics. Thus, the transition from a general understanding of biological objects to a targeted study of the state of plants as key elements of agrobiosystems is not only logical, but also an extremely important step in ensuring food security and sustainable development of agriculture.

In the context of modern technologies, the use of unmanned aerial vehicles (UAVs) is of particular importance for automated monitoring of the condition of plants, as they are an effective source of data for analysis and diagnostics. Data obtained from UAVs can be processed using automated diagnostic systems based on artificial intelligence, computer vision, and machine learning. Such systems can detect signs of diseases, pest infestation, nutrient deficiencies, or environmental stress factors in real time [2]. This significantly increases the speed and accuracy of agronomic decision-making, helps optimize the use of plant protection products, and minimizes costs. The use of UAVs in combination with analytical platforms creates intelligent decision-making support systems that are able not only to identify problems but also to predict their development. As a result, the integration of UAVs into the agricultural monitoring system ensures the transition to precision agriculture, which is based on the operational analysis of large amounts of data and allows achieving high efficiency with minimal environmental impact.

Analysis of recent research and publications. Crop problems caused by diseases, pests and adverse weather conditions are key challenges for modern agriculture. Climate change and rising global temperatures, these factors tend to intensify, which negatively affects the productivity of agricultural systems. Foreign researchers are actively working to study these problems and develop effective approaches to solving them.

In particular, the authors of work [3] note that climate change significantly affects the spread and intensity of plant diseases. Changing temperature regimes and uneven distribution of precipitation create favorable conditions for the development of new pathogens. The authors emphasize the need to integrate modern methods of monitoring and forecasting plant diseases for timely detection and control.

In work [4], the relationship between climate change and the spread of crop pests is examined. The authors note that an increase in average temperature contributes to the expansion of the ranges of some pests that were previously distributed only in warm regions. Researchers recommend, in addition to traditional methods and remote sensing technologies, to implement adaptive plant protection strategies, in particular, breeding varieties resistant to specific pests.

Another approach to solving the problem of climate change and pests is presented in [5]. Climate change significantly affects the biological characteristics, distribution and probability of pest outbreaks in various crops and on all types of land and agricultural landscapes. Already now, up to 40% of the world's food resources are lost due to the activity of pests. In this regard, reducing their negative impact is an extremely important task for ensuring global food security, reducing the use of agricultural resources and reducing greenhouse gas emissions. That is why the authors proposed a climate-smart plant protection system – an integrated interdisciplinary approach aimed at reducing crop losses from pests, improving ecosystem functions, reducing the intensity of emissions per unit of output and increasing the resilience of agricultural systems to climate challenges.

The issue of the impact of weather conditions on crop yields is considered in the study [6]. The authors note that to counteract existing problems, it is necessary to implement adaptation and mitigation strategies. These include both traditional and agroecological practices that contribute to improving soil health, efficient water use and carbon sequestration. Climate-smart technologies and improved irrigation systems will increase the resilience of agricultural systems to change. Educational programs for farmers and local initiatives play an important role. Therefore, to ensure food security in the face of climate change, it is necessary to implement holistic approaches to adaptation and sustainable development of agriculture.

Plant diseases seriously threaten food security and biodiversity, so timely and accurate diagnostics are critically important. As the authors of [7] argue, CRISPR/Cas systems have proven themselves as effective tools for detecting pathogens due to their high accuracy and speed. However, there is a lack of a comprehensive overview of their application in phytopathology, which limits their practical implementation. In the article, the authors considered the principles of CRISPR/Cas biosensors, examples of detecting viruses, bacteria and fungi in plants, as well as the prospects for the development of these technologies for precision agriculture and effective crop protection.

Climate change also contributes to the spread of new diseases. In the study [8], an analysis of the spread of wheat diseases under conditions of increasing temperature was conducted. The authors found that certain types of fungal diseases, such as powdery mildew, become more aggressive under increased humidity and warm weather. They recommend the use of combined protection methods, including biological preparations and monitoring using UAVs.

In the modern scientific community, much attention is paid to the application of **artificial neural networks and machine learning** algorithms for the classification of biological objects. Due to the ability to automatically learn from large amounts of data and detect hidden patterns, these methods demonstrate high efficiency in recognizing biological samples, such as cells, tissues, or plant and animal species.

Recent advances in the use of convolutional (CNN) and graph convolutional networks have significantly improved the classification of hyperspectral images. However, the limited amount of data, noise, high spectral variability, and complex spatial structures remain serious obstacles, especially in agriculture. To overcome these problems, the authors of [9] proposed a new model – DRFG (dimensionality reduction fuzzy graph network), which combines the advantages of other networks. The system works in two stages: first, pre-classification is performed using CNN, after which the data is refined using lightweight graph convolutional networks and clustering. The authors argue that DRFG provides effective dimensionality reduction and high classification accuracy of hyperspectral images, making it a promising technology for precision agriculture.

The intensive modernization of agriculture requires effective solutions for accurate and operational monitoring of pests. Traditional observation methods are inferior in efficiency, and existing deep learning models are often unstable in complex conditions. In response to these challenges, the authors of [10] proposed an innovative monitoring system that combines an advanced convolutional neural network (SAO-CNN) with swarm intelligence for controlling drones. The system uses adaptive convolutional layers, self-supervised learning, and ConvLSTM for effective video data analysis, and the ACO and PSO algorithms optimize UAV trajectories and task distribution. As a result, a classification accuracy of 91.2% was achieved, flight time was reduced by 29.2%, and energy consumption was reduced by 32%. The solution outperforms popular models (YOLO, ResNet, etc.) and provides high real-time performance, making it an effective tool for precision agriculture and sustainable crop management.

In the study [11], a forest image segmentation model based on CNN with U-Net architecture was implemented and evaluated. The algorithm involved preprocessing satellite images and corresponding masks: resizing, normalization, and division into training and test sets. The model consisted of an encoder, decoder, and pass-through connections, and was trained using the binary cross-entropy loss function and the Adam optimizer, with early stopping and checkpoint retention mechanisms. To assess the quality of segmentation, the authors used IoU, Dice, accuracy, completeness, specificity, and F1-score metrics. The study confirmed the effectiveness of U-Net in segmenting forest areas and the importance of high-quality data selection for training.

In the study [12], deep learning models VGG16, Inception v3, ResNet50 and a specially designed CNN were compared for the detection of cauliflower diseases common in countries such as Bangladesh and India. The models were trained using transfer learning on the VegNet dataset and evaluated using the following metrics: accuracy, loss and F1 score. ResNet50 showed the highest accuracy of 90.85%, while the special model achieved 89.04%. Based on the results, the authors conclude that deep learning, in particular ResNet50, is an effective tool for automatic disease detection, which can improve crop yields and strengthen food security.

Pine wilt disease threatens ecosystems and causes economic losses, so its early detection is critically important. The authors of [13] proposed a PWDViTNet model for detecting early signs of infection. It is based on ShuffleNetV2 (as an efficient CNN architecture) and Vision Transformer, which combine local and global feature modeling. The model also uses multi-scale feature fusion to more accurately focus on infected areas. The authors tested the model on images collected by UAVs in Laoshan National Park. It achieved an accuracy rate of 72.6%, which is 4.1% higher than the baseline ShuffleNetV2 model, with a slight increase in computational cost and size. The authors claim that PWDViTNet demonstrates effectiveness in early detection of pine wilt disease and can potentially be used for broader monitoring in agriculture.

Weeds significantly reduce crop yields, and the emergence of herbicide-resistant species complicates their control. Effective weed management requires targeted, species-specific strategies that can be implemented using machine learning technologies. However, due to the biological diversity of weeds and changing environmental conditions, their accurate detection remains challenging. The aim of the study [14] was to create an annotated image database of five weed species (common nettle, dandelion, water hemp, Palmer's amaranth, lamb's quarter) and evaluate the performance of the YOLOv8–YOLOv11 models and fast R-CNN. For this purpose, 2348 field images were collected, which underwent pre-processing and annotation. As a result, the authors concluded that the YOLO models demonstrate better suitability for accurate and fast real-time weed detection in agriculture.

The use of UAVs in agriculture is one of the key tools of modern precision agriculture, which allows to significantly increase the efficiency of agricultural land management. However, despite numerous advantages, the use of UAVs in this area is accompanied by several problems that need to be solved. This overview considers only the main challenges described in modern scientific works.

Due to the increase in the cost of labor, agricultural robots are becoming a key element of "smart" agricultural production, replacing people in complex tasks such as harvesting, weeding, pruning and pollination. An important component of such robots is hand-eye coordination, which allows them to act in real time based on visual data. Unlike industrial robots, agricultural robots operate in an unstable natural environment, which makes it difficult to accurately recognize targets and avoid obstacles. It is important to achieve a balance between accuracy and speed of task performance. Despite significant progress, robots still face challenges, especially in object recognition and adaptation to changing conditions. Therefore, the authors [15] concluded that further research should focus on imitating human movements and vision, improving self-learning capabilities, detecting errors in real-world environments, and improving systems with multiple sensors and manipulators.

In [16], an efficient method for accurate detection and localization of banana clusters in natural environments is proposed, aimed at applications in harvesting robots. Existing methods have the following limitations: many parameters and insufficient performance. To address these problems, a lightweight Slim-Banana model based on the improved YOLOv8l architecture is developed. For 3D banana localization, the model is combined with a RealSense depth sensor and TOF (time of flight) technology. It is deployed on an Nvidia Orin NX device. The model achieves 94.7% accuracy, 94.8% recall, and 98% mAP with an inference time of 113.6 ms. The average localization error is approximately 13 mm across all coordinates. The authors claim that this is the first known solution implemented on peripheral devices that demonstrates high accuracy and efficiency even in difficult horticultural conditions.

Remote control of multiple agricultural robots increases the efficiency of field work, but remains a challenging task due to the remoteness of the equipment and changing terrain conditions. Estimating the progress of work is complicated by the difference in task completion times, and the issue of synchronizing the speed of multiple robots in unstable field conditions are still insufficiently studied. In [17], a remote monitoring system is proposed that allows assessing the progress of work and managing field work. The key feature is the calculation of the remaining task completion time in real time and automatic adjustment of the robot speed depending on the current progress. The authors tested the system on real machines: in online simulation, the delay was ~100 ms (enough to safely control up to 50 robots), and in real conditions, it was about 2 s. Thanks to automatic speed adjustment, deviations from the schedule decreased from 26–33 s to only 4–13 s, which reduced the error in task performance.

The authors of the study [18] proposed an autonomous navigation method for agricultural robots designed to work on high beds. The method combines two approaches: movement along set route points and orientation along the beds themselves, which allows the robot to move efficiently without complex trajectory planning, even in environments with minimal landmarks. The robot uses LiDAR data for navigation. The method was tested in a virtual environment and on a real strawberry farm, where the robot demonstrated stability with a deviation of no more than ±0.05 m and ±5° relative to the bed. The results confirm the high accuracy and reliability of the proposed system. The authors of the study also emphasize the importance of preliminary modeling, which allows optimizing the characteristics of the robots and navigation algorithms before real implementation. It was shown that even parameters such as the LiDAR range significantly affect the stability of movement. The authors' future research will focus on modeling more complex conditions–with uneven surfaces and variability of farm landscapes–to improve the accuracy and practical use of field robots.

With the development of autonomous navigation, agricultural robots are increasingly being used in the agricultural sector. One of the key challenges is dynamic obstacle avoidance in complex field conditions. The popular DWA (Dynamic Window Approach) algorithm allows local obstacle avoidance, but its effectiveness is limited by fixed weight coefficients, which reduces adaptability to environmental changes. To solve this problem, the authors of [19] integrated the TD3 (Twin Delayed Deep Deterministic Policy Gradient) deep learning method into DWA. Thanks to this, the weights of the evaluation function adapt to the situation in real time, improving the flexibility and accuracy of navigation. Simulations and field tests have shown that the new TD3-DWA approach successfully avoids obstacles in more than 90% of cases, outperforming the classic DWA. This makes it a promising solution for safe and efficient navigation of agricultural robots.

Agricultural multi-robot task assignment (AMRTA) is a key direction for improving the efficiency of robotic agriculture. In the study [20], the AMRTA task was first presented as a traveling salesman problem with workload constraints (NWC-MTSP), which allows to minimize the maximum working time of individual robots and evenly distribute the load. The authors proposed a new method NWC-APONet, which combines graph neural networks and reinforcement learning for optimal task assignment. Experimental verification on real and synthetic agricultural data showed high efficiency of the model, confirming its practical value for multi-robot control systems in the agricultural sector.

Task statement. Due to the urgency of the problem of ensuring the stable development of the agro-industrial complex and the growing risks associated with diseases of cultivated plants, the impact of pests and adverse weather conditions, there is an objective need to develop effective means of monitoring biological objects, in particular plants. Timely diagnostics of changes in the physiological state of plants is the key to preserving the harvest, increasing the efficiency of agrotechnical measures and minimizing financial losses.

The rapid development of digital technologies leads to the need to carry out a comprehensive overview of existing methods and means of determining the current state of biological objects, analyze their advantages and disadvantages, the degree of automation, accuracy, adaptability to different types of crops and growing conditions. The results of this analysis will allow us to form substantiated recommendations for improving existing or developing new automated systems for monitoring cultivated plants that will meet modern requirements for accuracy, speed and scalability.

Outline of the main material of the study. Determining the current state of biological objects, in particular plants, is critically important for increasing the efficiency and sustainability of agricultural production. Modern agricultural production requires operational and accurate monitoring, which allows for timely detection of problems, optimization of resource use and increase in yield.

Although traditional monitoring methods, in particular visual inspection of fields, remain widespread, they are not effective in large areas due to the high time consumption, the need for significant labor resources and low accuracy. In contrast, automated solutions, based on UAVs, sensor systems and artificial intelligence tools, open new opportunities for farmers.

Today, machine learning and neural networks play a key role in improving the analysis of plant health. The overview showed that one of the most widespread is the convolutional neural network and its variations. Thanks to their ability to process large amounts of data, these mathematical models can accurately (from 70% to 99% depending on the specific type of neural network, the training data set and environmental conditions) recognize disease symptoms, detect pests, analyze vegetation changes and assess stress factors (such as lack of water or nutrients). Combining these technologies with UAV images allows you to create detailed field maps with precise positioning of problem areas. This allows for localized applications of fertilizers, water or plant protection products, which reduces costs and minimizes damage to the environment.

However, despite significant advantages, an overview of scientific works showed that there are several technical barriers that complicate the effective use of UAVs for precise plant monitoring. Among the main problems are navigation limitations. In particular, drones can lose GPS signal in areas with poor coverage or in conditions of obstacles (dense plantings, buildings, complex terrain). In such situations, alternative navigation methods are needed, such as visual SLAM navigation or inertial systems, which are complex and expensive to implement. In addition, the limited flight time due to battery capacity limits the size of the area that can be covered in a single flight, which creates difficulties when covering large areas.

Among the existing problems, a significant challenge is the delay in data transmission between the UAV and the base station, especially when performing complex tasks in real time. Even small delays in receiving or processing commands can lead to inaccuracies in the flight path, missed target areas, or errors in image collection. The problem is exacerbated when using wireless communication channels in conditions of interference or over long distances, which reduces the responsiveness of the control system. This limits the ability of the drone to effectively operate in the online correction mode, which is critical for precision agricultural operations.

In addition, the accuracy of plant classification depends largely on the quality of image collection. Factors such as lighting variations, shadows, leaf movement due to wind, weather conditions (fog, dust), as well as differences in crop growth phases can complicate recognition. Even modern neural networks can make mistakes in conditions of excessive visual similarity between species or when training samples were limited.

Another major challenge remains the accessibility of modern solutions for small and medium-sized farms. The high cost of equipment (in particular, UAVs, sensors and software) and the need for specialized skills to operate them hinder widespread implementation. This highlights the need for government support, subsidies and training programs that will help farmers integrate innovations into their operations.

Thus, the combination of high technology, UAVs or ground robots, artificial intelligence and automated monitoring systems has the potential to significantly transform modern agriculture, making it more accurate, environmentally sustainable and economically profitable. The development of such automated system is an urgent task today, therefore, in further work, the design and development of an automated system for determining the current state of biological objects will be carried out.

Conclusions. Agriculture is the basis of the production of food, fodder and industrial crops. However, traditional approaches to its management largely depend on the workforce, and its shortage can negatively affect the efficiency and stability of agricultural production. An overview of scientific works has shown that traditional methods of monitoring cultivated plants and soil quality do not provide the necessary information in a short period of time, which can be critical for the survival of the crop.

The use of robotic systems contributes to an increase in the level of automation of agricultural processes and is a promising tool for overcoming global challenges of food security. It has been shown that modern robots integrate sensors, artificial intelligence and data analytics, which allows achieving high accuracy in monitoring, autonomy in decision-making and efficiency in performing tasks. This creates prerequisites for the development of smart, fully autonomous agriculture.

An overview of scientific works has also shown that the use of UAVs is limited by technical and economic factors. Loss of GPS signal in dense vegetation, short flight time due to limited battery capacity, and communication delays with the base reduce the accuracy of data collection. Additionally, changing lighting, wind, and different phases of crop growth complicate image analysis, and the high cost of equipment and the need for specialized skills limit implementation for small farms. To overcome the existing challenges of the industry, it is advisable to develop an integrated automated system that combines advanced solutions in the field of artificial intelligence and robotics, ensuring adaptability, scalability, and efficient management of agricultural production.

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Цибульник С.О., Шелемаха В.В. ОГЛЯД МЕТОДІВ ТА ЗАСОБІВ АВТОМАТИЗОВАНОГО ВИЗНАЧЕННЯ ПОТОЧНОГО СТАНУ БІОЛОГІЧНИХ ОБ'ЄКТІВ

Початок четвертої промислової революції та стрімкий розвиток технологій – зокрема штучного інтелекту, хмарних обчислень і Інтернету речей – стали поштовхом до нової ери в сільському господарстві, що отримала назву «розумне» або «цифрове» землеробство. Сучасне сільське господарство стикається з численними викликами, які перешкоджають отриманню бажаного врожаю. У даній роботі проведено огляд наукових робіт, пов'язаних з культурними рослинами, які вирощують у всьому світі. Показано, що кліматичні зміни, які спричиняють засухи, повені, заморозки чи інші несприятливі погодні умови, виснаження ґрунтів, нестача водних ресурсів і зростання витрат на добрива та пестициди, рослинні хвороби та поширення шкідників – усі ці фактори призводять до значної втрати врожаю. Традиційні методи моніторингу стану культурних рослин та ґрунтів не дають змогу швидко отримати результати та прогнозувати зміни. З іншого боку, сучасні автоматизовані діагностичні системи надають аграріям можливість швидкого отримання *широкого кола необхідної інформації про поточний стан культурних рослин. З огляду на стрімкий розвиток цифрових технологій, необхідно здійснити комплексний огляд існуючих методів і засобів визначення поточного стану біологічних об'єктів, проаналізувати їх переваги та недоліки, ступінь автоматизації, точність, адаптивність до різних типів культур і умов вирощування. Результати цього аналізу дозволять сформувати обґрунтовані рекомендації щодо вдосконалення існуючих або розроблення нових автоматизованих систем моніторингу культурних рослин, що відповідатимуть сучасним вимогам до точності, швидкодії та масштабованості. Сільське господарство відіграє ключову роль у вирощуванні продуктів харчування, кормових та технічних культур. Проте традиційні методи ведення господарства значною мірою залежать від великої кількості робочої сили, нестача якої може серйозно вплинути на ефективність і стабільність польового виробництва. У зв'язку з цим надзвичайно актуальним стає впровадження польових роботів, здатних замінити людину у виконанні рутинних і трудомістких завдань, таких як оранка, сівба, обприскування, внесення добрив, збирання врожаю та транспортування. Це сприятиме підвищенню рівня автоматизації сільськогосподарських процесів та допоможе боротися з глобальним дефіцитом продовольства. Сучасні аграрні роботи поєднують інноваційні технології, включаючи передову робототехніку, сенсори, штучний інтелект і аналітику великих даних. Завдяки цьому вони забезпечують високоточне спостереження, автономне прийняття рішень, розумне управління процесами та ефективне виконання завдань, що відкриває шлях до повністю автономного сільського господарства майбутнього. Саме тому для вирішення наявних проблем сільського господарства необхідно створити комплексну автоматизовану систему, яка включала б в себе сучасні рішення в області робототехніки та штучного інтелекту.*

Ключові слова: *автоматизований збір та обробка, штучний інтелект, нейронні мережі, безпілотні літальні апарати, біологічний об'єкт.*