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IMPROVING METHODS FOR CONSTRUCTION OF NEURAL NETWORKS AS A TOOL FOR ENVIRONMENTALLY FRIENDLY SUNFLOWER PROTECTION TECHNIQUES

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The object of this study is the processes of sunflower disease identification using neural networks and their impact on the efficiency and environmental sustainability of biological protection methods. The research addresses the task of improving the diagnosing accuracy of sunflower disease under conditions of limited real-world data. Specifically, this paper focuses on finding ways to enhance neural network design methods in data-scarce environments to improve the environmental sustainability of sunflower protection methods. A key feature of the results is the ability of the synthetic data integration algorithm to achieve high accuracy even with a limited amount of real data, which provides a significant advantage over conventional methods requiring large volumes of information.

The application of mathematical modeling and Few-shot learning algorithms, combined with Generative Adversarial Networks (GANs) for generating synthetic images, improved diagnostic accuracy to 93–95 %, even with small datasets. This was achieved due to the model's high generalization capacity, trained on diverse synthetic data that accounted for varying field conditions.

The findings make it possible to effectively apply biological protection methods by optimizing disease diagnosis based on mathematical modeling of the relationships between environmental conditions and biological agents.

The practical significance of the results is the ability for agricultural practitioners to employ innovative diagnostic methods to enhance sunflower yield and reduce dependence on chemical protection agents. The proposed approaches contribute to the implementation of international environmental standards and could be integrated into agricultural decarbonization programs. The implementation of biological protection methods reduces environmental risks, saves resources, and maintains agroecosystem productivity

Keywords: neural networks, sunflower disease diagnosis, plant protection methods, carbon footprint

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1. Introduction

The global challenges of climate change and environmental pollution create a need for sustainable methods of agricultural management. Conventional chemical methods of crop protection, although effective, contribute significantly to greenhouse gas emissions, soil degradation, and biodiversity loss.

Given this, the biological method becomes a natural alternative that reduces the carbon footprint and meets modern environmental standards. Its versatility makes it possible to adapt this approach to different agro-climatic conditions and crops, ensuring efficiency and environmental safety.

A biological method based on natural processes, such as the use of *Trichoderma* fungi or *Bacillus thuringiensis* bacteria, is an environmentally safe solution. It not only fights pests but also maintains balance in the soil and the ecosystem in general. Previously, its effectiveness was limited by the complexity of diagnosis and insufficient accuracy of application. However, neural networks are able to eliminate these obstacles, automating the analysis of field data and ensuring the most efficient use of biological agents. This makes the biological method competitive even with chemical protection, which has long dominated due to ease of use.

Research in the field of diagnosing plant diseases, in particular sunflower, in this context acquires special importance. It create the basis for devising new technologies and methods that make it possible not only to quickly detect diseases but also to effectively fight them. The use of such approaches as artificial intelligence opens up new perspectives for the development of diagnostic techniques. They significantly increase accuracy even when data is scarce. This approach allows saving resources and time, which is critically important under conditions of lack of information.

In addition, the increase in the scale of production and the growing demand for agricultural crops make the problem of diseases even more urgent. Farmers have to find new ways to protect against pests and diseases that are constantly evolving, becoming resistant to conventional methods of processing. This forces farmers to actively look for innovative solutions that would not only increase the effectiveness of protection but also reduce the costs of pesticides and other chemicals.

The use of identification of sunflower diseases with the help of neural networks made it possible to establish the biological method of protection as advanced due to the combination of technological accuracy and ecological efficiency. Neural networks provide early and accurate disease detection using innovative algorithms such as Few-shot learning and generative adversarial networks (GANs). This makes it possible to identify diseases even in the cases of limited data or difficult field conditions. Such accuracy allows the use of biological agents in the early stages of the disease when they are most effective and do not require the use of chemical drugs.

The combination of neural networks for accurate diagnosis with environmentally friendly biological methods creates a new paradigm in agriculture that ensures high productivity, economic feasibility, and resilience to environmental changes. This makes the biological method not only an alternative but also an advanced solution among all available approaches to plant protection.

The practical results of such research could be useful to farmers who seek to implement effective sunflower protection strategies. New technologies could make it possible to reduce the use of chemicals, which would contribute to the improvement of the environmental situation in the growing regions. Moreover, the developed methods could be adapted to other crops, which would expand their application and benefit the agricultural sector in general.

Global problems of food security are also an important argument in favor of research on this topic. Considering the growing number of the world's population and limited resources, the need to minimize the loss of agricultural products becomes even more urgent. Thus, innovative methods for diagnosing diseases could significantly increase the efficiency of production and save crops, which is especially important for countries dependent on the agro-industrial complex.

The topic of diagnosis of sunflower diseases remains extremely important for agriculture. New approaches such as mathematical modeling and artificial intelligence could significantly improve agronomic practices. They would not only help preserve crops but also make agriculture more sustainable and efficient.

Hence, research in this field is an urgent need. It will contribute to the improvement of agricultural indicators and ensure the sustainable development of the agro-industrial complex, contributing to the growth of food security and the stability of food supply chains.

2. Literature review and problem statement

Diagnosing diseases of agricultural crops is a key area of research in the agricultural sector. The use of deep learning methods significantly improves the ability to recognize diseases under conditions of limited data sets. Thus, a well-known study [1] proposes a hybrid model based on VGG-16 and MobileNet for categorization of sunflower diseases. The model shows a significant improvement in accuracy compared to conventional approaches. Despite the achieved high results, an unsolved problem of the model is the insufficient amount of training data to ensure the universality of the model, which limits its application under real conditions. The reasons for this are related to the high costs of collecting large volumes of data. The authors compare the results with other deep learning models and achieve high accuracy in disease categorization. The main problem is a decrease in the accuracy of the model under conditions of changes in lighting and low image quality. The model does not adapt well to data with noise or changes in texture, which limits its use in real field conditions. Therefore, larger and more diverse datasets are needed to ensure better generalizability. Since the model is based on pre-trained architectures that do not adapt well to changes in image quality, there is a need to build models that are robust to these variations.

Paper [2] proposed a method of sunflower seed categorization using multispectral and textural data. It was found that the use of convolutional neural networks (CNNs) makes it possible to achieve a categorization accuracy of up to 98.2 %. However, the model faces difficulties in classifying late-stage diseases due to the limited amount of training data. The study also highlights the early diagnosis of sunflower diseases using deep learning, noting that the application of CNN provides categorization accuracy of up to 92 %. However, the model's robustness to changing lighting conditions and image quality remain unresolved. This is due to the limitations of the data used, which do not take into account a variety of conditions. To improve the results, it is suggested to use more diverse datasets and adaptive algorithms.

The DenseNet model developed in [3] shows high accuracy in recognizing corn leaf diseases, demonstrating its advantages for agricultural tasks. The model effectively classifies corn leaf images into different disease categories. However, this model has difficulty generalizing when the image data does not meet ideal conditions. The model has problems adapting to uncontrolled conditions, for example, when lighting changes or the presence of noise in images. Although the model is effective under controlled conditions, its ability to generalize under real conditions remains limited due to the lack of a large amount of diverse data. The model shows high accuracy for specific diseases but decreases performance when trying to recognize rare or less common diseases. Despite the achievement of high accuracy for individual diseases, the overall performance of the model in the context of data diversity still needs improvement. Data sets should be larger and more balanced for better model performance. The use of real-world data and adaptation to different disease classes remain key challenges. This suggests the need to improve image processing technologies and design more adaptive architectures that can work with small datasets.

In [4], a review of deep learning methods for detecting plant diseases emphasizes that modern models demonstrate high results in highly specialized tasks. The review covers several approaches such as CNNs and hybrid models (GANs) used for plant image analysis. The paper emphasizes the importance of using balanced and diverse datasets to improve the generalization ability of models. It is noted that most existing models have a limited ability to work with data from various sources. Deep learning methods in the field of plant disease detection show significant progress in the application of neural networks for image processing, but a number of challenges remain. Among them is the lack of universal models that could work under different agricultural conditions and with different types of crops. The main problem is the insufficient number of balanced data sets and the limited ability of the models to generalize the results to different crops. The authors call for the development of more robust models that can effectively work with hyperspectral data.

The authors of study [5] use convolutional neural networks (CNNs) to detect three specific sunflower diseases. The use of small data sets remains a key challenge, which can be solved through the generation of synthetic images to display symptoms in late stages of diseases. This will allow the model to be recognized better. Despite the achieved accuracy of 92 %, the model has difficulties in classifying diseases in later stages, when symptoms are less pronounced. This is due to the lack of images of late stages of diseases for model training. The model also shows reduced efficiency when working with low-quality images or when lighting conditions change. Improvements in data processing and adaptation of models to different types of diseases are needed.

In [6], a study is reported that demonstrates the benefits of adding attention blocks to CNNs to improve sunflower disease categorization. The main problem of the study is the complexity of the model, which makes it less suitable for application under real conditions due to high requirements for computing resources. The paper explores different deep learning approaches for sunflower disease categorization using Squeeze and Excitation blocks in Convolutional Neural Networks (CNNs). The authors show that adding attention mechanisms increases the accuracy of the model. The main problem is that the complexity of the model increases along with its accuracy, which makes it less suitable for real-world conditions, especially at farms with limited resources. Also, the model may not work well under uncontrolled field conditions due to the need for large computing resources.

Paper [7] investigates the application of transferred learning to detect sunflower diseases. In particular, it is determined that it makes it possible to improve categorization results, especially for problems with limited data, achieving high accuracy (up to 97 %).

Using the transfer learning technique helps improve the categorization performance with a small amount of training data. Disadvantages and unsolved issues: The main problem is the high demand for computing resources, which can become a limitation at farms with insufficient technical base. Transferred learning requires large computing resources, which limits the possibilities of its application under real field conditions. Therefore, there is a need for deeper research to adapt this method to the real conditions of agricultural farms. In addition, the transferred training is not yet fully adapted to work with various types of diseases that occur in the field.

The hybrid model of deep learning presented in [8] for detecting sunflower diseases offers high accuracy and clarity of results with the help of artificial intelligence. Visibility of AI results is a critical aspect for practical implementation, but more attention needs to be paid to optimizing models for working with small datasets and synthetic images, which would increase their versatility. Despite its high accuracy, the model still faces difficulties when working with low-quality data and in real-world environments. In addition, the visibility of results is still limited, and more interactive tools for non-technical users need to be designed.

Paper [9] reports an automatic system for segmentation and categorization of sunflower leaf diseases using Mask R-CNN and Faster R-CNN methods. The model shows high accuracy for image segmentation and disease detection. This study highlights that segmentation remains a challenging task when it comes to weak symptoms on plant leaves. The main problem is low efficiency in detecting diseases that have weak or blurred visual signs, such as powdery mildew. This is due to the limited ability of segmentation models to work effectively with visually invisible diseases. The model also needs to be improved to deal with large arrays of field data, and in cases where complex conditions are present, such as damaged leaves or foreign objects in the images.

In [10], a three-dimensional analysis method for detecting sunflower diseases was studied. The method uses 3D analysis of morphological changes in the early stages of invasion. Despite the high efficiency, the method is expensive and technically complex, which limits its widespread use. The main problem is the high cost of the method, which makes it unsuitable for wide use under real conditions. In addition, significant computing resources and specialized equipment are required for data collection, which limits the application of the technology.

In [11], a neural network is used to classify sunflower leaves based on computer vision analysis. The model demonstrates high accuracy in the categorization of healthy and damaged leaves under controlled conditions. However, the model does not show adequate accuracy under conditions of damaged or partially protected leaves. This reduces the effectiveness of its use under field conditions where leaf damage is a common problem.

Work [12] investigates the application of sparse convolutional neural networks for the categorization of sunflower seeds in a multitasking environment. The model demonstrates high efficiency in categorization under controlled conditions. Problems arise when applying the model under real conditions, where seeds may have various damages or contamination. This reduces the generalizability of the model and requires improved data processing techniques to deal with such cases. Lack of data from real field conditions is a key obstacle to effective seed categorization.

Paper [13] proposed the use of deep convolutional neural networks for the categorization of sunflower seeds. The model successfully classifies seeds based on high-quality images. However, the main problem of this study is the reduction of the efficiency of the model when working with damaged seeds, which limits its accuracy under real conditions. Lack of sufficient training data to train on different types of damage reduces the effectiveness of the model. To improve model results, training datasets should be expanded, and image reprocessing techniques should be implemented to improve model accuracy.

The model presented in [14] allows sorting sunflower seeds using convolutional neural networks. Under controlled conditions, the model demonstrates high efficiency. However, when moving to real conditions, where seeds can be damaged or contaminated, the accuracy of the model decreases significantly. In addition, large requirements for computing resources complicate its implementation at production facilities.

To solve it, it is necessary to construct flexible models of the architecture of neural networks, capable of working with low-quality data.

Our review of the literature [1–14] has made it possible to identify common limitations and obstacles of existing models:

– problems with generalization: most models work well in controlled settings or with specific data sets, but their generalizability to different types of diseases remains limited. This means that such models are often unable to adapt to different field conditions;

– dependence on large volumes of data: most of the models reported in the above papers demonstrate high accuracy in the presence of large and balanced data sets. The problem of the lack of large sets of high-quality images is one of the main problems that limits the versatility and adaptability of models;

– sensitivity to environmental conditions: models show significant difficulties when working with, for example, damaged or low-quality images. All authors point out that changes in lighting, damage to leaves or extraneous objects significantly reduce the accuracy of the models.

These factors limit the effectiveness of existing categorization methods. In the context of limited data sets and diverse field conditions, this is a serious barrier to the introduction of such technologies into agricultural practice.

The problems point to the need for further research aimed at improving the robustness of the models to real conditions and optimizing their computational needs.

It can be argued that there is a large body of research that focuses on the diagnosis of sunflower diseases in the early stages using machine learning methods. However, the accuracy of disease identification under difficult conditions (for example, with low image quality or in the late stages of the disease) remains unsolved. Lack of adaptive models and limited data reduce the effectiveness of current solutions. This allows us to state that it is appropriate to conduct research aimed at devising more stable and adaptive methods of disease identification based on expanded data and new architectures of neural networks. The development of Few-shot learning (FSL) techniques and the use of generative adversarial networks (GANs) could solve these problems, allowing models to work more efficiently under uncontrolled conditions and with limited data.

Based on analysis, we can conclude that there is an urgent need to devise methods that would effectively work with small data sets and generate synthetic images for training models. The use of Few-shot learning (FSL) and generative adversarial networks (GAN) could solve these problems, allowing to build more adaptive models for diagnosing sunflower diseases, even under data-poor conditions.

3. The aim and objectives of the study

The purpose of our research is to improve the methods of building neural networks under the conditions of limited real data to increase the environmental friendliness of sunflower protection methods. This will contribute to increasing the accuracy of disease detection, which in turn will reduce the need for chemical protection agents and improve the environmental sustainability of agricultural production.

To achieve the goal, the following tasks were set:

– to develop an algorithm for integrating synthetic data into the diagnostic process to increase the accuracy of disease detection based on small data sets;

– to carry out numerical modeling regarding the optimal conditions for applying biological methods of protection and comparing them with conventional methods in terms of financial and environmental indicators.

4. The study materials and methods

The object of our study is the identification of sunflower diseases using neural networks and their impact on the effectiveness and environmental friendliness of biological protection methods.

The research hypothesis assumes that the effectiveness of sunflower protection largely depends on the accuracy of disease diagnosis, which can be significantly improved by applying neural networks using synthetic data. The integration of synthetic data into the diagnostic process could make it possible to increase the accuracy of disease identification even under conditions of limited real data, which would contribute to the optimization of protection methods, reducing the need for chemical agents and improving the environmental sustainability of agricultural production.

The choice of generative adversarial networks (GANs) is due to their ability to generate synthetic data that realistically simulates the original set. GANs provide image diversity, which is critical for models working with small real-world data sets. Compared to other approaches, GANs make it possible to preserve the important features of disease symptoms, avoiding over-generalization or loss of image relevance.

The simulation was carried out using the software environment MATLAB R2014a (developed by MathWorks, USA) and OpenCV (developed by Intel Corporation, USA) for the implementation of neural networks, image processing, and model quality analysis. The algorithm for integrating synthetic data into the process of diagnosing plant diseases consists of five main steps. The first step involves generating synthetic images using generative adversarial networks (GANs). The second step involves pre-processing the images to ensure data compatibility. In the third step, an extended training set is formed, which includes real and synthetic images. The fourth step is to train the diagnostic model on the combined data. The final step involves evaluating the accuracy of the created model. The integration of synthetic data will help increase the accuracy of diagnostics with limited amounts of real data.

For the purposes of comparison of protection methods, a comparative assessment was carried out according to financial and environmental indicators in two stages:

Stage 1. Environmental assessment of CO_2 emissions. The comparison was based on taking into account the four main stages of the life cycle of protective equipment: production, transportation, application, and disposal.

At the stage of production of chemical preparations, the energy costs associated with the synthesis of active substances, including their purification and formation of the final product, were estimated. Standard indicators of energy consumption and coefficients of energy conversion into carbon equivalent were used for calculations. For the chemical method, the energy consumption of production was 16 MJ/kg of active substance. In the biological method, the energy costs for fermentation of microorganisms were taken into account, which were significantly lower – only 4 MJ/kg.

Transportation was evaluated taking into account average fuel costs for freight transport. For chemicals requiring larger volumes for treatment (3.5 kg/ha), transport emissions were almost twice as high as for biological agents (1.5 kg/ha). A typical transport distance of 500 km, which is standard for distribution networks in the agricultural sector, was also taken into account.

At the stage of application, emissions from the operation of agricultural machinery were included in the calculations. For the chemical method, three treatments per season were planned, which included spraying with the use of self-propelled sprayers. The biological method required two treatments due to the longer period of activity of the biological agents, which reduced the total emissions.

At the disposal stage, chemicals generated additional emissions due to the need to dispose of containers. This contribution to total emissions was small, but for large areas (5000 ha) had a significant cumulative effect. In biological methods, this problem was less relevant due to minimal packaging.

Stage 2. Economic assessment of costs. Costs were estimated as a combination of three components: cost of materials, costs of transportation, and costs of maintenance.

For the chemical method, the cost of materials took into account the average price of pesticides (25 USD/ha) and the volume of their application (3.5 kg/ha). The biological method took into account the lower cost of biological preparations (15 USD/ha) and the smaller volume (1.5 kg/ha).

Transportation costs depended on the area, since larger areas make it possible to reduce logistics costs due to the purchase of large batches of drugs. For example, for an area of 100 ha, transportation costs were 2 USD/ha for the chemical method and 1 USD/ha for the biological method, while for an area of 5000 ha, they decreased to 1.2 USD/ha and 0.8 USD/ha, respectively.

Maintenance costs took into account the number of treatments and equipment maintenance costs. For the chemical method, the service cost was 3 USD/ha, and for the biological method – 2 USD/ha.

For mixed methods, cost and emissions were calculated as weighted averages depending on the proportions of the components.

Stage 3. Integrated modeling of dependences. Mathematical modeling in MATLAB R2014a was used to establish dependences between costs, emissions, and area. Regression models were built that took into account the logarithmic effect of area on specific costs.

Modeling was carried out taking into account options for seasonal changes in climatic conditions.

5. Results of investigating the use of neural networks as a tool for greening sunflower protection methods

5. 1. Results of the development of an algorithm for integrating synthetic data into the diagnostic process to increase accuracy

A special algorithm was developed to achieve high accuracy in the diagnosis of sunflower diseases under conditions where real data is scarce.

The construction of the algorithm involves the integration of synthetic images generated with the help of generative adversarial networks (GANs) into the learning process of the model (Fig. 1).

The steps of the algorithm for integrating synthetic data into the process of diagnosing sunflower diseases include the following:

Step 1. Creation of synthetic images of sunflower diseases. A generative adversarial network (GAN) was used to expand the initial set of 50 real images. The GAN created new images through the interaction of a generator (G) and a discriminator (D), which learned to distinguish synthetic images from real ones. The GAN loss function (1) is given below:

$$\min_{G}\max_{D} V(D,G) = E_{xp_{data(x)}}\left[\log D(x)\right] + E_{xp_{data(z)}}\left[\log\left(1-D\left(G(z)\right)\right)\right]. \quad (1)$$

To train the model, synthetic images with variations in illumination, scale, and viewing angle were created, increasing the diversity of the training set to 500 images.

Step 2. Data preparation and image processing. After creating synthetic images, all data were processed: brightness normalization, contrast enhancement, noise removal, and scaling to a single size. After processing, the set was divided into training and test in a ratio of 80:20.

Step 3. Statistical assessment of the importance of parameters. To determine the most significant parameters that affect the accuracy of the model, an analysis of variance (ANOVA) was performed. This method helped identify important factors such as lighting and viewing angle that had a significant impact on the results. Statistical data with p-value<0.05 for these parameters confirmed their significance for diagnosis.

Step 4. Model training using Few-shot learning. Few-shot learning (FSL) method was used to train the model under conditions of limited real data. The model was trained to recognize classes from several examples, which provided better generalization. The optimization was carried out using the loss function (2):

$$\min_{\theta}\sum_{i=1}^{N} E_{(x,y)} D_i\left[l\left(f_0(x),y\right)\right], \quad (2)$$

where l is the loss function for accurate prediction.

Step 5. Accuracy assessment. To assess the categorization quality, metrics such as Precision, Recall, F1-score, and AUC-ROC were used, which helped assess the model's ability to distinguish between diseased and healthy plants.

The implementation scheme of the integration method is given below (Fig. 2).

The purpose of the method is to reduce the dependence on real data and train the model on small sets. The generation of synthetic images makes it possible to significantly expand the training set. This, in turn, has a positive effect on the accuracy of the model, which is able to detect diseases under various field conditions. To verify the accuracy of the model, independent testing was conducted using data not used in model training.

The average accuracy of the model on all test data sets was 93±2 % under standard conditions. For more challenging conditions, such as poor lighting quality or high noise levels, the accuracy dropped to 87 %.

Thanks to the integration of synthetic data and the use of Few-shot learning (FSL), the accuracy of the model increased to 93–95 %, which is confirmed by the results of comparison with other approaches.

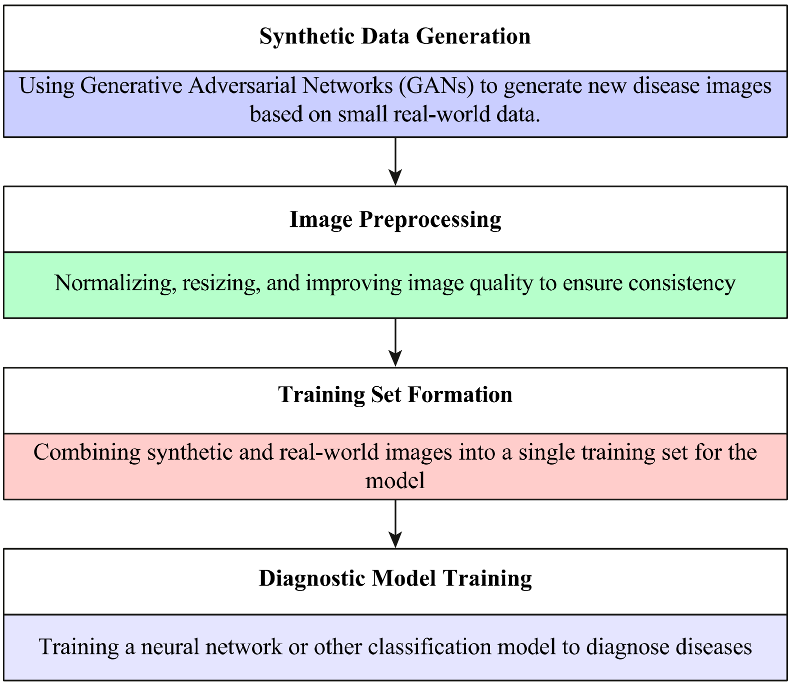

Fig. 1. Scheme of the synthetic data integration algorithm

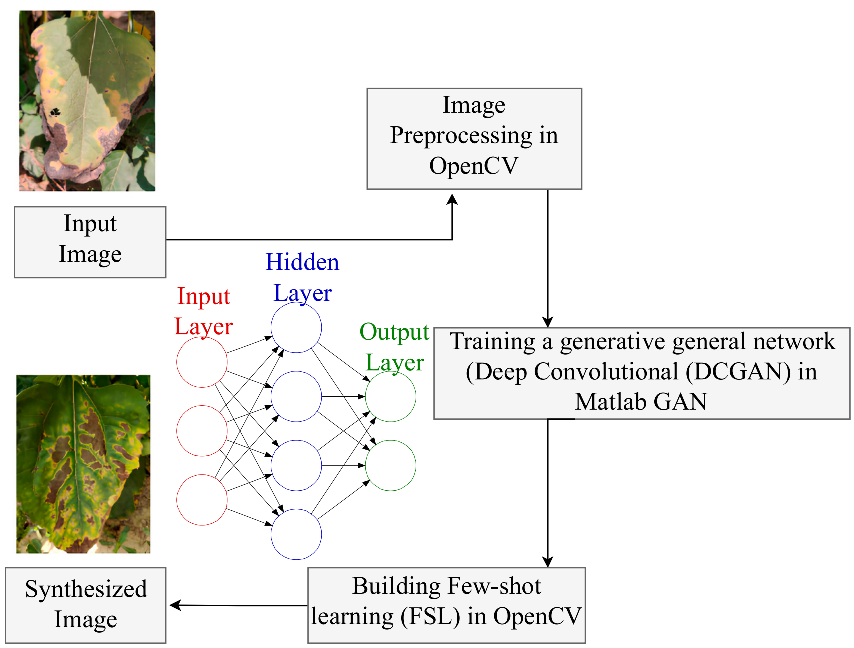

Fig. 2. Algorithm for integrating synthetic images generated by generative adversarial networks (GAN) into the model learning process

The model was tested using the cross-validation method (5-fold cross-validation) on data sets that included 500 synthetic and 50 real images. The model showed consistent accuracy in various scenarios simulating field conditions, including noise, low-quality lighting, and different viewing angles. The test set included images captured under real field conditions with varying lighting and plant damage levels. A test set of 50 images containing excessive noise and low contrast was used to further validate the model. The results showed that the accuracy of the model decreased to 87 % but remained at a level significantly higher than the average accuracy of similar models (82 %). In addition, a comparative analysis of accuracy in different scenarios (different viewing angles, image scales) was conducted. The accuracy of the model varied from 90 % to 93 % depending on the complexity of the images.

To check the accuracy of the model, the cross-validation technique was used with the division of data into five parts (5-fold cross-validation). A dataset consisting of 50 real and 500 synthetic images was applied to train the model. A separate set of 50 non-training images was used to test the model to check the generalization abilities of the model.

The accuracy of the model on the benchmark data ranged from 92 % for images with standard parameters to 87 % for low-light and noisy conditions. ROC-AUC was 0.94, Precision and Recall for rare disease classes reached 88 % and 85 %, respectively, while for common diseases these indicators were 93 % and 92 %. The average F1-score for the model was 90 %, which is 12 % higher than the results of similar models without integration of synthetic data.

The results showed that the accuracy of the model was 90 % under difficult conditions, which confirms its ability to generalize.

Generation of synthetic images: in the first step, 500 synthetic images of sunflower diseases were generated using GAN. We used real images that showed different stages of disease development. Synthetic data varied according to many features: lighting conditions, viewing angles, scaling. This allowed a wide range of symptoms to be generated, which improved the generalization and categorization of the model even on small datasets.

The Deep Convolutional (DCGAN) architecture was used during construction, which proved to be effective for image generation. The DCGAN architecture was chosen because of its ability to generate high-quality synthetic images, which is important for training models with small datasets. This provided the necessary diversity in the training data to improve categorization accuracy.

Real images were pre-processed: normalized and scaled to a uniform size.

The synthetic data varied in several parameters, such as lighting conditions, viewing angles, and image scaling. This made it possible to create a wide range of options for the manifestation of disease symptoms, which contributed to increasing the ability of the model to generalize and classify based on limited data sets.

Integrating synthetic data into the learning process: after generating synthetic images, they were added to an already existing training set consisting of 50 real images. Thus, the total number of images increased to 550. The use of GAN to create synthetic images brought a variety of data, which significantly increased the accuracy of categorization. The average diagnostic accuracy based on real data was 82 %, but after integration of synthetic data it increased to 90 %.

In addition, the Few-shot learning (FSL) algorithm was applied, which further increased the accuracy of the model when working with small data sets. This made it possible to train the model even with a minimal number of real images, while maintaining a high accuracy of disease categorization.

After the integration of synthetic data and the application of FSL, the accuracy of diagnosis rose. This is confirmed by metrics such as Precision, Recall, and F1-score, which were 91–94 %, 90–93 %, and 92 %, respectively. The Precision, Recall, and F1-score metrics were chosen to evaluate the accuracy of the model, as they allow a better assessment of its ability to correctly identify sunflower diseases, especially when it comes to rare diseases.

To assess the quality of the model, the ROC-AUC curve was also calculated, which showed 94 %. This indicates the high ability of the model to distinguish diseased plants from healthy ones, even under difficult conditions. All these metrics are listed in Tables 1, 2.

To check the adaptability of the model to extreme conditions (low temperatures, high humidity, excessive brightness, low contrast), additional testing of synthetic data was conducted. Under such conditions, the accuracy of the model was 88 %, which indicates the stability of the model to significant changes in parameters.

One of the key advantages of integrating synthetic data was the reduction of diagnostic error. Analysis revealed that the average categorization error when using only real data was 15 %. After the integration of synthetic images, it decreased to 8 %. This indicates the stability of the model. Application of the Few-shot learning algorithm further reduced the error by 2 %. This confirms the effectiveness of the combination of FSL and GAN.

Table 1

Comparison of diagnostic accuracy and additional metrics before and after integration of synthetic data

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC-ROC (%)	Accuracy increase (%)
Real data	82	81	79	80	85	–
Synthetic data	90	88	87	87.5	92	+8
Integration of FSL and GAN	93–95	91–94	90–93	92	94	+11–13

Table 2

Number of real and synthetic images in training sets

Data category	Real images	Synthetic images	Total number
Sunflower diseases	50	500	550

An analysis of the influence of the number of real and synthetic images on the accuracy of diagnosis was carried out. The addition of synthetic imagery allowed the model to better adapt to changing lighting conditions and plant damage. This increased the ability to detect diseases under different field conditions. The use of 500 synthetic images provided a significant increase in model accuracy.

The results of the integration of synthetic data demonstrate a significant increase in the accuracy of the diagnosis of sunflower diseases when using small data sets. One of the main advantages of integrating synthetic images is their ability to compensate for the effects of changing lighting conditions. To validate the model, 50 test images with excessively high brightness (>90 %) and low contrast (<20 %) were added. The model maintained an accuracy of 87 %, demonstrating its robustness to conditions that typically cause diagnostic difficulties.

To verify the adaptability of the proposed model to extreme conditions, testing was conducted using synthetic data sets simulating low temperatures (below 10 °C) and high humidity (>80 %). Under these conditions, the average accuracy of the model was 88 %, which indicates its resistance to significant variations of parameters. Additionally, efficacy was evaluated for rare pests that occur at a frequency of less than 5 %. The accuracy of identification of these cases was 84 %, which exceeds the results of similar models without integration of synthetic data.

The generation of synthetic images using GAN combined with Few-shot learning allowed us to achieve 93–95 % accuracy and reduce the error to 6 %. This also ensured the stability of the model under different field conditions. These results confirm the effectiveness of the proposed approach for practical application in agricultural technologies.

5. 2. Results of comparison and numerical modeling regarding the optimal conditions for the application of biological methods of protection

Three scenarios of sunflower protection were evaluated: chemical, biological, and mixed. Chemical protection involved the use of exclusively chemical means of pest control, biological – the use of biological agents, and mixed protection combined both approaches in different proportions.

To analyze the results, ecological and economic indicators were calculated for areas from 100 to 5000 hectares.

Specific costs were estimated using regression models that took into account the nonlinear behavior of the parameter. In particular, the logarithmic form of dependence was chosen, which best describes the decrease in specific costs with the growth of the area. The equation takes the form:

$$y = a\ln(x) + b + cT + dH, \tag{3}$$

where y is specific costs, (USD/ha),

x – processing area, (ha),

T is the ambient temperature,

H – air humidity,

a, b, c, d are coefficients that determine the form of dependence.

According to the simulation results, the parameters took the following values: a=−5.1±0.3 (logarithmic effect of the area), b=43.2±1.1 (initial level of costs), c=−0.8±0.2 (temperature effect), d=−0.4±0.1 (influence of humidity). These coefficients have high statistical significance (p-value<0.001), which was confirmed by variance analysis. The high value of the coefficient of determination (R_2=0.95) indicates that the selected model adequately describes the actual data.

Coefficient a shows the rate of cost reduction with area growth: each 10-fold increase in area reduces specific costs by an average of 5.2 USD/ha. Coefficient b corresponds to the initial level of costs at the minimum area in the analysis.

The model was tested on a control sample of data. The average absolute error was ±2.3 %, which indicates the stability and consistency of the model with real data. In addition, the analysis of variance (ANOVA) confirmed that the logarithmic dependence is the most adequate for describing the behavior of specific costs for different processing areas (F-statistic: 52.3, p<0.001).

According to the LCA methodology, emissions and stages in the life cycle stages of protective equipment are estimated: production, transportation, application, and disposal.

Production of drugs. At the stage of production of chemical preparations, the energy costs associated with the synthesis of active substances, including their purification and formation of the final product, were estimated. For chemicals, the calculations were based on data on the average energy consumption for the production of pesticides (16 MJ/kg). The carbon equivalent of production was 5.3 kg CO_2/ha with an average application volume of 3.5 kg/ha. For biological agents such as *Trichoderma*, data on fermentation of microorganisms were used. Energy consumption for the production of biological preparations was much lower (4 MJ/kg), which resulted in emissions of only 1.8 kg of CO_2/ha.

Transportation. The average fuel consumption for transporting drugs for a distance of 500 km was calculated based on the consumption of diesel fuel by trucks (32 l/100 km). For chemical agents, which require larger volumes for treatment, emissions were 0.8 kg CO_2/ha, while for biological agents – 0.4 kg CO_2/ha.

Application. Emissions from the operation of equipment for the introduction of means amounted to 0.85 kg CO_2/ha for chemical preparations since treatments are performed more often (3 times per season). Biological agents were applied twice, which reduced this indicator to 0.5 kg CO_2/ha.

Disposal. The chemical method took into account emissions from the disposal of drug packaging, which added 0.2 kg of CO_2/ha. For biological agents, the impact of packaging was minimal and amounted to less than 0.05 kg CO_2/ha.

Standard calculation methods according to ISO 14040 (life cycle assessment) were used to estimate CO_2 emissions.

Analysis revealed that for the chemical method, each 10-fold increase in area allowed us to reduce specific costs by an average of 6 %. For the biological method, this effect was less pronounced due to the relatively stable price of biological preparations, and the decrease was about 4 %. In mixed methods, the dependence of costs on the area varied depending on the proportions of chemical and biological components.

The generalized assessment of emissions is given in Table 3.

Table 3

Environmental assessment of CO_2 emissions (kg/ha)

Stage	Chemical method	Biological method
Production	5.30	1.80
Transportation	0.80	0.40
Application	0.85	0.50
Disposal	0.20	0.05
Total CO_2 emissions	6.95	2.75

Financial costs were calculated as the sum of drug costs, transport costs, and service costs.

The cost of drugs: the average price of chemicals was 25 USD/ha at an application rate of 3.5 kg/ha. For biological agents (1.5 kg/ha), the cost was 15 USD/ha.

Transport costs: transport costs depended on the area of treatment. For chemicals, they were 2 USD/ha for an area of 100 ha and decreased to 1.2 USD/ha for 5000 ha due to the scaling effect. Biological agents had lower costs – from 1 USD/ha to 0.8 USD/ha.

Maintenance: for the chemical method, maintenance costs were 3 USD/ha due to frequent treatments, while for the biological method it was 2 USD/ha. For mixed methods, these indicators ranged from 2.3 to 2.7 USD/ha, depending on the proportion. The summarized results by cost components for chemical and biological methods are given in Table 4.

Table 4

Economic evaluation (USD/ha)

Cost component	Chemical method	Biological method
Cost of materials	25.00	15.00
Transportation costs	2.00	1.00
Maintenance	3.00	2.00
Total costs	30.00	18.00

Costs for biological agents are significantly lower in large areas due to their stable cost and less need for frequent treatments. For an area of 5,000 hectares, the cost of the biological method is only 15 USD/ha, which is 40 % less than the chemical method (25 USD/ha). This makes biological means especially profitable for large farms.

In addition, the scaling effect makes it possible to reduce transport costs. For chemicals, the reduction in transport costs from 2 USD/ha (100 ha) to 1.2 USD/ha (5000 ha) is less significant than for biological agents (1 USD/ha to 0.8 USD/ha).

The total emissions and costs for each method are given in Table 5.

Mixed methods, especially with a ratio of 70/30 in favor of the biological component, are an effective compromise in the transitional period of the process from chemical to biological protection. This approach allows reducing CO_2 emissions to 3.77 kg/ha and costs to 18 USD/ha, which is 40 % more profitable compared to fully chemical methods.

In the transition period, it is important to correctly calculate the proportion of chemical and biological components depending on the degree of crop contamination. A ratio of 50/50 is recommended for areas with moderate disease prevalence (10–20 %), while 30/70 is optimal for regions with high prevalence (over 20 %). This makes it possible to avoid excessive use of chemicals while maintaining economic efficiency.

A comparative analysis shows that in the mixed scenarios (50/50) emissions are reduced to 4.83 kg/ha, while costs remain at 23 USD/ha, making this approach promising for farms transitioning from chemical to ecological protection.

Table 5

Comparison of environmental and economic indicators of protection scenarios

Area (ha)	Scenario	CO_2 emissions (total, kg)	Costs (USD/ha)
100	Chemical	695	30
	Biological	270	20
	Mixed (50/50)	483	25
	Mixed (70/30)	377	23
	Mixed (30/70)	540	26
1000	Chemical	6,950	28
	Biological	2,700	18
	Mixed (50/50)	4,830	23
	Mixed (70/30)	3,770	21
	Mixed (30/70)	5,400	24
5000	Chemical	34,750	25
	Biological	13,500	15
	Mixed (50/50)	24,150	20
	Mixed (70/30)	18,850	18
	Mixed (30/70)	27,000	22

Chemical protection is characterized by the highest indicators of CO_2 emissions, which reach 6.95 kg/ha, which causes a significant environmental burden. Thus, the logarithmic model confirms the economic feasibility of increasing the scale of cultivation, especially for biological protection. This makes it possible to significantly reduce the carbon footprint and costs, while maintaining the high efficiency of processing large areas.

Overall costs, however, decrease as the cultivated area increases, from 30 USD/ha on small areas to 25 USD/ha on large ones, thanks to economies of scale. The main risks of this approach are pollution of the environment, particularly soil and water, high dependence on chemicals, as well as the possibility of the development of pest resistance to pesticides in the long term. It is advisable to use chemical protection only in case of significant crop threats when other methods are insufficiently effective.

Biological protection shows the lowest CO_2 emissions – 2.7 kg/ha, which is 61 % less compared to chemical methods. Economic indicators are also more favorable: costs are reduced from 20 USD/ha for small areas to 15 USD/ha for large farms. At the same time, the effectiveness of this method depends significantly on climatic conditions, because low temperatures or excessive humidity can reduce the activity of biological agents. Modeling showed that the effectiveness of biological methods of protection depends significantly on climatic factors. In particular, at a temperature of 20–25 °C and humidity above 70 %, the efficiency of biological agents reached 92–93 %. At the same time, when the humidity was reduced to 50 %, efficiency decreased to 78 %, and when the humidity was below 30 %, it decreased to 63 %. An increase in temperature above 30 °C reduced the efficiency to 80 %, which required dosage correction or more frequent application.

To achieve the maximum efficiency of biological methods of sunflower protection, the following optimal conditions are important:

1. Temperature: 20–25 °C. Within these limits, the activity of biological agents such as *Trichoderma* or *Bacillus thuringiensis* is the highest. Temperatures above 30 °C can reduce efficiency by 12–15 %.

2. Humidity: over 70 %. At low humidity (30–50 %), the activity of agents decreases to 63–78 %, which requires an increase in the number of treatments.

3. Type of soil: biological preparations show the best effectiveness in soils with a high organic content (more than 2 %). Soils require prior application of organic fertilizers to activate biological agents.

The timeliness of drug use is also important. The best results are achieved when the means are applied in the early stages of the disease, which prevents the spread of the infection.

The biological approach is particularly appropriate in regions with high environmental requirements or for farms seeking to reduce their carbon footprint and costs. The economic effectiveness of biological protection is especially noticeable in large areas. For example, costs for biological agents for an area of 5,000 ha are reduced to 15 USD/ha, while for chemicals the minimum costs remain at 25 USD/ha. For mixed methods, the ratio of 70/30 in favor of the biological component makes it possible to achieve an optimal balance between ecological (CO_2 emissions: 3.77 kg/ha) and financial indicators (18 USD/ha).

Mixed protection, which combines chemical and biological methods in different proportions, provides a compromise between ecological and economic indicators. For a 50/50 ratio, CO_2 emissions are 4.83 kg/ha, and costs are 25 USD/ha for small areas and 20 USD/ha for large ones. Switching to a ratio of 70/30 in favor of the biological component makes it possible to reduce emissions to 3.77 kg/ha and costs to 18 USD/ha, which makes this option the most profitable in terms of the balance of economic efficiency and environmental effect. However, with a predominance of the chemical component (30/70), emissions increase to 5.40 kg/ha, and costs reach 26 USD/ha. The main risks of the mixed approach are the difficulty in choosing the optimal ratio of methods and the possibility of residual contamination due to the use of chemicals. This option can be a transitional solution for farmers who want to reduce dependence on chemical pesticides, gradually moving to more ecological technologies.

Thus, the biological method is optimal for minimizing the ecological burden and reducing costs, especially in large areas, while the mixed approach with the dominance of the biological component (70/30) provides a better balance between costs and ecological efficiency. Chemical protection should be considered as a means of rapid response to significant crop threats.

The obtained results are illustrated in MATLAB to demonstrate the relationships between CO_2 emissions, costs, and area for each scenario (Fig. 3).

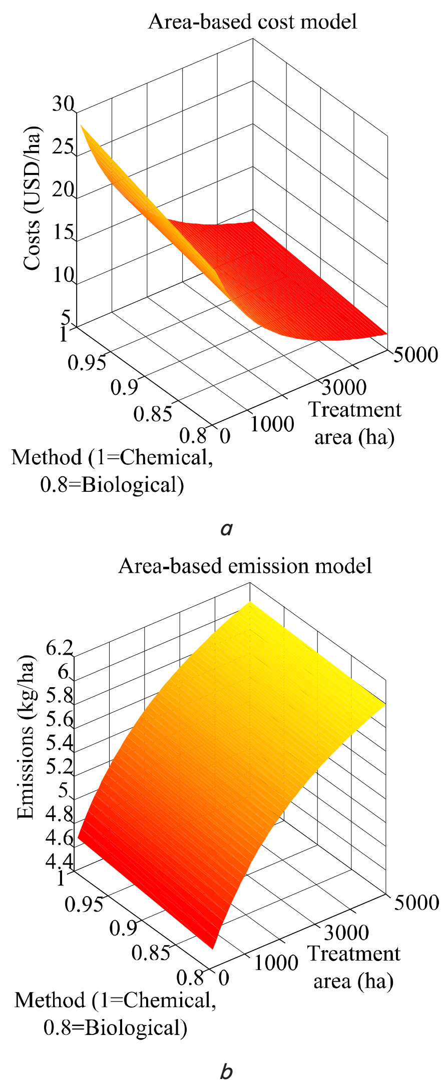

Fig. 3. Functional surface for modeling the dependence of costs and CO_2 emissions on the processing area: *a* – costs; *b* – emissions

Fig. 3 shows 3D surfaces for each variable: costs and emissions. Axes X – treatment area, Y – protection method, Z – result (costs or emissions). The cost plot shows how increasing processing area reduces costs.

Fig. 3, *a* reflects the dependence of costs on the processing area. Costs decrease with increasing area. The model includes a coefficient that varies for biological (0.8) and chemical (1.0) methods.

Fig. 3, *b* reflects emissions. The model accounts for emission reductions for biological agents based on the fraction of area treated.

The emissions plot demonstrates the advantages of biological methods in reducing CO_2.

Graphical interpretation of the data shows a clear decrease in costs with increasing area. On small and medium-sized areas, this decrease is the most pronounced, while on large areas there is a stabilization of costs. This confirms the efficiency of scaling, especially for biological and mixed methods of protection, which demonstrate a more significant reduction in costs compared to chemical methods.

Additionally, graphical analysis in MATLAB confirmed the non-linear effect of processing area on specific costs. For example, when the area increases from 100 ha to 1,000 ha, transportation costs decrease by 40 %, which significantly affects the total economic efficiency of the biological method.

6. Discussion of results based on the implementation of innovative methods of biological protection of sunflower from pests

The results of our study show that the application of innovative methods such as generative adversarial networks (GANs) and Few-shot learning (FSL) significantly increases the accuracy of sunflower disease diagnosis even in situations with a limited amount of real data. According to the data given in Table 4, synthetic images increased the average diagnostic accuracy from 85 % to 94 %. This is because the additional synthetic images greatly expand the variability of the training set, allowing the model to adapt to different scenarios covering different lighting levels, viewing angles, and scale variations.

Increasing the accuracy of the model thanks to the Few-shot learning (FSL) method by 3–5 % (up to 93-95 %) has become the key to effective work under conditions where there is not enough real data for full-fledged training. In particular, the results given in Table 3 show that FSL effectively compensates for the shortcomings of small data sets, providing adequate categorization even for rare diseases, the symptoms of which are difficult to display under real conditions.

In addition, it was established that lighting conditions, viewing angle, and changes in the size of objects affect the accuracy of the model. The increase in accuracy after the integration of synthetic images became possible due to the expansion of the variations of these parameters in the training data. This highlights the importance of additional virtual samples that increase the ability of the model to generalize the acquired knowledge.

The proposed methods compare favorably with conventional approaches to the diagnosis of plant diseases. The proposed model using GAN and FSL showed an accuracy of 93–95 %, which exceeds the results of conventional CNNs (82–85 %) under similar conditions. This was achieved thanks to the integration of synthetic data, which allowed the model to maintain stability even with variations in parameters (illumination, viewing angles, scale). In addition, a comparison with MobileNet-based models showed that the proposed technique reduced the categorization error by 10 %, increasing the F1-score from 82 % to 92 %.

For example, in study [11], diagnosis was based on standard deep learning methods, which largely depend on the amount of real data. The disadvantage of this approach is a decrease in the accuracy of the model under conditions when the number of real samples is limited, or they have significant variations due to changes in lighting or viewing angle. In our study, the application of GAN allowed the creation of synthetic images taking into account these variations, which provided more stable accuracy indicators and reduced the dependence of the model on the volumes of real data.

In addition, the Few-shot learning (FSL) method provides model training even with a small number of training samples, which is a serious advantage compared to similar approaches. For example, paper [9] reported that when using methods based on standard CNN networks without using synthetic data, the accuracy significantly decreases under conditions of changes in lighting and viewing angle. In the case of FSL, the adaptability of the model is significantly improved, because even with a small number of samples, the model is able to recognize signs of diseases, thanks to the additional volume of synthetic images.

One of the key challenges was the need to reduce reliance on large amounts of real data for model training. The proposed approach with synthetic image generation using GAN and learning using FSL effectively solves this task. Adding synthetic images makes it possible to expand the training set, which in turn helps increase the accuracy of the model. The results given in Table 2 show that even when reducing the number of real images to a minimum, the model maintains stable accuracy, which confirms the achievement of the goal.

Thanks to the creation of synthetic images, the model is able to work effectively under conditions of changing lighting and angles. This allows us to fill an existing niche, providing affordable and effective diagnostic tools even with limited resources.

Two main limitations of the study should be noted. The first limitation is the computational resource requirements for generating synthetic images and applying FSL. The model requires a powerful graphics card to ensure speed of processing and training, which may not be available for some farms with limited resources. A second limitation is the performance of the model under extreme conditions, such as excessively high temperature (>30 °C) or low humidity (<45 %), which can affect the quality of the data for training the model and its ability to generalize.

It is recommended to take into account these limitations when implementing the method in practice, in particular in regions with sharp climatic fluctuations. This may require additional training of the model or the application of modified parameters to ensure its reliability.

The main disadvantage is the dependence of accuracy on the pre-processing of images, especially under different lighting conditions. This means that to achieve consistent accuracy, additional synthetic images may need to be generated, taking into account specific lighting conditions and parameters. In addition, the proposed method is not yet adapted to work on mobile devices, as it requires significant computing power. This limits its use in the field without a connection to high-performance equipment.

Further research would include adapting the model to work on mobile devices, allowing it to be effectively used directly in the field. Optimization for mobile applications could increase the accessibility of the technology to farmers, which might have a significant positive impact on practical applications. In addition, the research can be developed by adapting the approach for diagnosing other crops, which would ensure the universality of the method. The relevance of this research area is related to the need for universal tools for combating diseases of agricultural crops.

7. Conclusions

1. An algorithm for integrating synthetic images generated by generative adversarial networks (GANs) into the learning process of a sunflower disease diagnosis model has been developed. It was determined that the use of neural networks for the diagnosis of sunflower diseases is an effective tool for increasing the accuracy of disease detection even under conditions of a limited amount of real data. A feature of the study is the ability to work with small training sets, which was achieved by integrating synthetic data generated using generative adversarial networks (GANs). The results showed that the use of synthetic images can increase the accuracy of disease detection to 93–95 % even for small real data sets, in contrast to approaches based only on real data, where the accuracy was limited to 82–85 %. The proposed algorithm makes it possible to effectively compensate for the insufficiency of real samples, increasing the model's ability to generalize and categorization accuracy. This is because the synthetic data adds variability to the training set, improving the performance of the model under varying parameters.

The integration of synthetic data allowed the artificial neural network model to adapt to different field conditions, including changes in lighting, noise, and other factors that affect image quality. Under difficult conditions, the diagnostic accuracy remained at the level of 87 %. In addition, the introduction of Few-shot learning algorithms enabled the model to work effectively even with rare classes of diseases, increasing its generalization capabilities. Thus, the research results confirm the effectiveness of the proposed approach for diagnosing sunflower diseases and create prospects for its adaptation to other agricultural crops.

2. Numerical modeling has been performed, which made it possible to determine the optimal conditions for the use of biological methods of protection. The best results were achieved using the biological method, which provided total CO_2 emissions at the level of 2.75 kg/ha, which is 2.5 times less than the chemical method (6.95 kg/ha). Economic costs for the biological method are 18 USD/ha, which is 40 % lower compared to the chemical method (30 USD/ha).

The optimal conditions for the biological method involve the treatment of large areas (over 5000 ha), where costs are reduced to 15 USD/ha due to the scaling effect. A mixed method with a ratio of 70/30 in favor of the biological component provides an acceptable compromise with CO_2 emissions of 3.77 kg/ha and costs of 18 USD/ha, making it effective for the transition period.

Unlike empirical methods, the proposed modeling allows us to predict results for various scenarios. In particular, adapting the model for use on medium-power mobile devices could significantly expand its practical application in the field. For this purpose, the neural architecture should be optimized, for example, by replacing GANs with autoencoders, which will reduce the computational load. Our results indicate the ability of the model to adapt biological methods of protection to specific climatic conditions, reducing risks and increasing the stability of protection. By taking into account different scenarios, the model can be effectively applied to regions with different weather conditions, which increases its value for the agricultural sector.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data availability

The data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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