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# COMBINED SYSTEM FOR PLANT DISEASE MONITORING USING UAVS, GROUND ROBOTIC PLATFORMS, AND NEURAL NETWORK-BASED IMAGE ANALYSIS

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*This paper addresses the problem of automated monitoring of agricultural crop diseases under field conditions using unmanned aerial vehicles. It is shown that most existing solutions are primarily focused on disease detection from individual images. In contrast, issues such as further diagnosis refinement, repeated inspection of problematic areas, and subsequent action determination after disease detection are considered much less frequently. Stem-type diseases, in particular sclerotinia, pose an additional challenge, as top-view imaging alone may not detect early infection signs promptly. On this basis, a proposed automated system combines a UAV for primary inspection, subsequent georeferencing of the point of interest, a ground module for additional follow-up inspection in the case of stem-type diseases, and a central computing module for data processing and decision-making regarding the treatment of infected areas. This approach enables combining rapid aerial inspection of large areas with more accurate follow-up inspection of plants from a side view, which is especially important for diagnosing lesions that are poorly visualized from above. As part of the experimental study, a prototype classifier based on the EfficientNetV2S convolutional neural network and the transfer learning approach was implemented. To improve training quality, image augmentation and a pseudo-negative sample generation method were applied. The obtained results confirmed the potential of convolutional neural networks for automated plant condition classification, as well as the feasibility of combining aerial imaging and ground-based follow-up inspection within a unified monitoring system. The proposed approach can serve as a basis for the further development of an intelligent system for the detection and localized treatment of disease foci under field conditions within the framework of precision agriculture.*

***Keywords:*** *UAV, computer vision, convolutional neural network, sclerotinia, automated monitoring, precision agriculture.*

**Statement of the Problem**

Agriculture plays a key role in ensuring sustainable development by contributing to both food and economic security. In modern agricultural production, various technical means are widely used to monitor plant condition; however, most of them perform clearly defined functions. For example, unmanned aerial vehicles are used to survey fields to identify problematic areas, whereas sprayers are mainly used to apply herbicides or other substances across the entire field. At the same time, decisions on the degree of plant infection, subsequent treatment, and the required application rate of the treatment agent are still largely based on an agronomist's subjective assessment. Such an approach is time-consuming and does not allow the problem to be detected early. As a result, interest in automated plant condition monitoring systems is increasing, as such systems are intended to ensure timely disease detection and minimize yield losses [1]. Accurate and rapid disease localization can contribute to increased productivity and reduced use of plant protection products [2].

The development of unmanned aerial vehicles and machine learning methods lays the groundwork for automated monitoring systems. Numerous studies [3 – 8] on plant disease detection and classification from images demonstrate the high effectiveness of approaches based on computer vision and machine learning. In the scientific literature, many studies use simplified datasets in which images typically show a single leaf or a stem with leaves [4, 8]. Under such conditions, the accuracy of plant condition identification may reach 95–98 % [5, 7, 8]. At the same time, fully automated systems that combine plant condition monitoring under field conditions with subsequent decision-making regarding plant protection measures are much less represented [9, 10].

Various types of drones equipped with multispectral [9], hyperspectral [11], thermal [9], and RGB [12, 13] cameras are currently being introduced for crop monitoring. Different sensors are appropriate for different crops and types of pathologies, including foliar, stem-related, and temperature-related ones [9, 11 – 13]. The main advantage of UAVs lies in their ability to inspect large areas at high spatial resolution rapidly and to obtain detailed data on plant condition at relatively low financial and labor costs [9, 13].

However, for such specific diseases as sclerotinia

(Sclerotinia sclerotiorum) in soybean and sunflower, the conventional UAV-based approach may be insufficiently effective [8, 14]. These diseases affect the stem, and top-view drone images can identify such foci only when the disease is already well developed [14]. This is of fundamental importance for stem-type diseases, since early visual symptoms are often localized not in the upper part of the plant, but on the stem or in the lower zone. Therefore, using only a top-view perspective does not always allow reliable, possible detection of infection. In this context, the optimal image acquisition perspective, namely the side view, becomes increasingly important. Such a perspective can be achieved by using ground-based equipment, such as a camera mounted on a tractor or an automated inter-row sprayer, which can detect disease foci at early stages and enable more localized application of plant protection products. Another important advantage of this approach is the ability to use more powerful computing modules than those available on UAVs, enabling closer alignment with real-time implementation [15].

**The purpose of this study** is to analyze methods and tools for plant disease detection and to present the concept of an automated system to improve monitoring efficiency. In addition, the study presents results from training a neural network module for plant condition classification within the proposed system.

**Analysis of Existing Research**

The development of disease monitoring technologies is characterized by a transition from traditional diagnostic methods based on the assessment of characteristic disease symptoms and visible signs of pathogens, such as symptomatology, microscopy, and the incubation method [16], to next-generation methods, including drone-based technologies [17]. The above-mentioned methods depend heavily on the individual expertise of specific specialists and become accurate and reliable only when evaluation criteria and standards are properly followed. Therefore, these methods are often economically inefficient and require considerable time to identify disease foci.

The results of individual studies show that the use of drones and spectral monitoring can improve the speed and accuracy of phytopathogen detection compared with conventional molecular, serological, and microbiological methods in certain applied scenarios [17, 18].

Study [11] reports the advantages of hyperspectral cameras, which enable the detection of diseases even before visible symptoms appear, at the stage of changes in the biochemical composition of plant tissue. However, the high cost of such equipment and the large volume of data requiring complex post-processing make these solutions poorly accessible for large-scale implementation in medium-sized farms. In contrast, studies [7, 19] demonstrate that modern deep learning algorithms make it possible to achieve high accuracy, exceeding 90 %, even when using conventional RGB sensors, provided that proper imaging conditions and a high-quality dataset are ensured.

The technical complexity of spectral sensing, sensitivity to lighting, wind, and humidity, and the need to maintain a stable flight altitude and trajectory impose significant limitations on implementing such solutions on a large scale in agricultural practice. This is especially relevant in the early stages of disease development, when symptoms appear on the lower or side parts of the plant and are inaccessible for direct top-view imaging.

At the same time, studies are increasingly emerging that implement automated solutions for specific crops with their own features, such as inter-row spacing and the need to analyze the plant from a side view. Combined agricultural systems have already been described in the scientific literature; however, in most cases, they implement a different logic of platform interaction than the one proposed in this study. In particular, UAV+UGV systems are primarily focused on joint data collection, field condition assessment, route coordination, and improved monitoring completeness [10]. In contrast, ground robotic platforms often implement a computer vision-based local targeted treatment loop without UAV involvement, including approaches based on neural network object detection and mobile agrorobot control [20]. Review publications also indicate that a considerable portion of current research is focused on either disease detection and classification tasks or UAV-oriented monitoring [9, 13].

On this basis, the concept of a hybrid automated system combining aerial and ground platforms was formed (Fig. 1).

In such a system, the drone performs rapid top-view field inspections, collecting primary data on plant condition and identifying suspicious areas based on changes in spectral indicators, leaf temperature, soil moisture, and other parameters [9, 12, 13]. Next, an autonomous ground module, for example, a self-propelled tractor or an automated sprayer equipped with a camera, performs a detailed inspection of the selected areas from a side view or from within the inter-row space [10]. In this case, the ground platform does not inspect the entire field, but only the risk zones previously identified by the UAV as potentially problematic. This approach enables reducing the time required for follow-up inspection and improving the practical efficiency of the system. Data from the two viewpoints are combined to improve the reliability of identifying disease foci and reduce the risk of missing symptoms. If this solution is integrated directly into a sprayer, localized treatment of the disease focus is carried out; if a tractor is used, the coordinates of the detected focus are recorded for subsequent treatment.

A key element of the proposed system is a unified centralized control subsystem that analyzes data and coordinates the actions of different modules, from sensors to protection mechanisms. Computer vision algorithms process images by automatically recognizing characteristic signs of disease on the plant, after which the coordinates of infected plants are linked to GPS positions in the field. Based on this information, the system controls the targeted spraying module in real time. In particular, an autonomous sprayer may receive a command to increase the fungicide application rate for specific infected plants and, conversely, to reduce or switch off application in healthy areas.

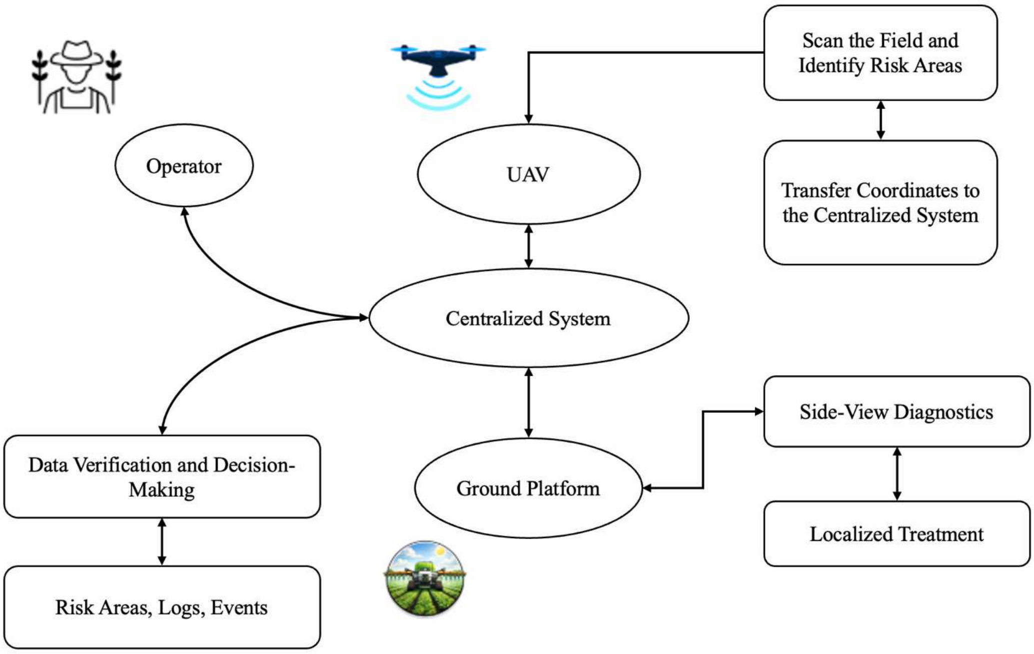


Fig. 1. Structural diagram of the automated system components and their functions

**Architecture of the Automated Plant Disease Monitoring System**

The proposed plant monitoring and protection system implements a two-level architecture that combines aerial and ground robotic platforms under the control of a unified centralized subsystem. This approach allows separating the functions of global inspection and local diagnostics, which is especially important for diseases with complex spatial manifestation patterns, particularly stem and root-zone pathologies.

At the macro level, the system performs rapid inspection of large areas using UAVs, enabling the prompt generation of a map of potential risk zones. These may include factors such as increased leaf temperature, detected by a thermal imaging sensor and indicating disturbed water exchange; changes in soil moisture, where lower areas are associated with higher risk; or irregular plant density, manifested as reduced stand density. This level is not intended for the precise identification of individual plants but rather serves as a spatial filter that narrows the area for further analysis.

At the micro level, an autonomous ground platform, such as a robotic sprayer or a tractor equipped with a computer vision system, performs proximal sensing in the selected areas using side-view imaging, which provides higher informativeness for detecting stem-type pathologies.

The coordination between both levels is ensured by a centralized control subsystem that aggregates data from various sources, synchronizes them in space and time, and generates control signals for the plant protection system's executive mechanisms. After a computer algorithm confirms a disease, the system georeferences the affected object. It generates a control signal for the executive mechanism using the VRA (Variable Rate Application) concept [21]. This is intended to support the implementation of a targeted protection strategy, which involves the automated and balanced use of chemicals by increasing the dose at the center of infection while completely avoiding treatment of healthy areas, in accordance with the principles of sustainable agriculture.

**Macro Level: The Aerial Platform as a Risk Zone Assessment System**

The main task of the macro level of the system is the preliminary assessment of the spatial distribution of disease development risks in the field. At this stage, the UAV performs a rapid inspection to identify areas with a higher probability of infection. It should be noted that, depending on the type of disease, such an approach may be sufficient for identifying problematic areas and simultaneously activating countermeasures. However, it is insufficient for stem diseases, whose symptoms may be weakly expressed or completely invisible at early stages in nadir-view imaging.

The assessment of risk zones is based on the analysis of indirect indicators correlated with the development of pathological processes in plants. Such indicators include temperature anomalies in the leaf canopy associated with disturbances in water exchange, changes in vegetation spectral characteristics, irregular plant stand density, and spatial features of terrain and soil moisture. In the case of sclerotinia, in particular, a special role is played by low-lying areas of the field with increased moisture, where favorable conditions for infection development are formed.

The macro level generates a generalized map of crop heterogeneity, which serves as input for more detailed analysis at the ground level. To implement macro-level functions, the UAV must be equipped with a set of sensors capable of measuring spatial and biophysiological parameters of crops. The basic element is an RGB camera, which provides a visual assessment of plant cover structure and plant stand density. To increase the system's sensitivity to plant stress conditions, it is advisable to use a thermal imaging sensor capable of detecting local changes in leaf temperature associated with transpiration disturbances.

If appropriate equipment is available, the system may be supplemented with multispectral sensors that enable the calculation of spectral indices sensitive to plant physiological conditions. Another important requirement is the presence of a navigation module, such as GPS or RTK, which ensures accurate georeferencing of the collected data and enables the further use of coordinates within the control system.

Imaging parameters, in particular flight altitude and UAV speed, should be selected to achieve a balance between coverage area and spatial resolution. Flight speed should be coordinated with the sensor capture frequency to ensure continuous thermal or spectral maps without temporal discretization artifacts. The intermediate macro-level result should be a generalized risk zone map that reflects the spatial distribution of potentially problematic areas in the field. This map may be represented as a set of georeferenced polygons or points of interest with corresponding anomaly indices that characterize the degree of deviation from the “normal” state of plants.

**Micro Level: Detailed Sensing and Side-View Diagnostics**

The task of the autonomous ground platform is to provide more detailed plant diagnoses within the macro-level risk zones. The ground module uses a side-view observation perspective, which provides significantly higher informativeness for detecting stem and root-zone pathologies.

Side-view imaging enables visualization of features that are barely noticeable or completely hidden when viewed from above. Such features include changes in stem color and texture, the appearance of characteristic deposits such as white mold, deformation of the root zone, or local necrotic lesions. These manifestations are crucial for the reliable diagnosis of stem diseases, in particular sclerotinia.

The ground platform navigates to the coordinates of the risk zones using satellite navigation systems and/or internal odometry sensors. After reaching the corresponding area, the system switches to an active sensing mode, where the camera's video stream is analyzed in real time. This mode enables diagnostics without stopping movement, which is critical for the practical implementation of the system under field production conditions.

The movement speed of the ground platform is determined by a set of technical parameters, including the computational power of the onboard device, image resolution, frame rate, and the latency of the computer vision model. These constraints are especially important when edge devices are used, where processing resources are limited. From a practical perspective, the platform's movement speed must be coordinated with the ability to analyze the image promptly and generate the control action required for localized plant treatment.

**Centralized Control Subsystem and Diagnosis Verification**

The coordination between the aerial and ground levels is carried out by a centralized control subsystem that performs data aggregation, logical interpretation of results, and generation of control actions. The centralized subsystem receives two types of input: spatially generalized macro-level data in the form of risk zone coordinates, and detailed results of proximal diagnostics obtained from the ground platform. Based on these data, a verification procedure is implemented, reducing the probability of false positives and improving the overall reliability of the system.

Diagnosis verification is based on the combination of spatial context and computer vision results. A zone identified as risky at the macro level is considered an area with an increased a priori probability of infection; however, the final decision is made only after the analysis of side-view images. This approach helps avoid situations in which indirect indicators, such as local humidity, are misinterpreted as a disease.

After the presence of a disease has been confirmed, the centralized subsystem georeferences the affected object and generates a control command for the plant protection system's executive mechanism. If the confidence level of the computer vision algorithms is insufficient, the information may only be recorded and passed to the operator for further analysis, without initiating active actions.

The final stage of the micro-level operation is the transformation of computer vision results into a deterministic control action aimed at localized plant protection. For this purpose, the Variable Rate Application (VRA) concept is used, which involves changing the application rate of plant protection products depending on the spatial distribution of infection.

The neural network model, based on input from sensors such as an RGB camera, generates a probabilistic estimate of whether the object belongs to one of the classes, for example, "healthy," "sclerotinia," or "pest." Since the neural network's output is stochastic, the system implements a decision-making logic based on confidence thresholds (Fig. 2).

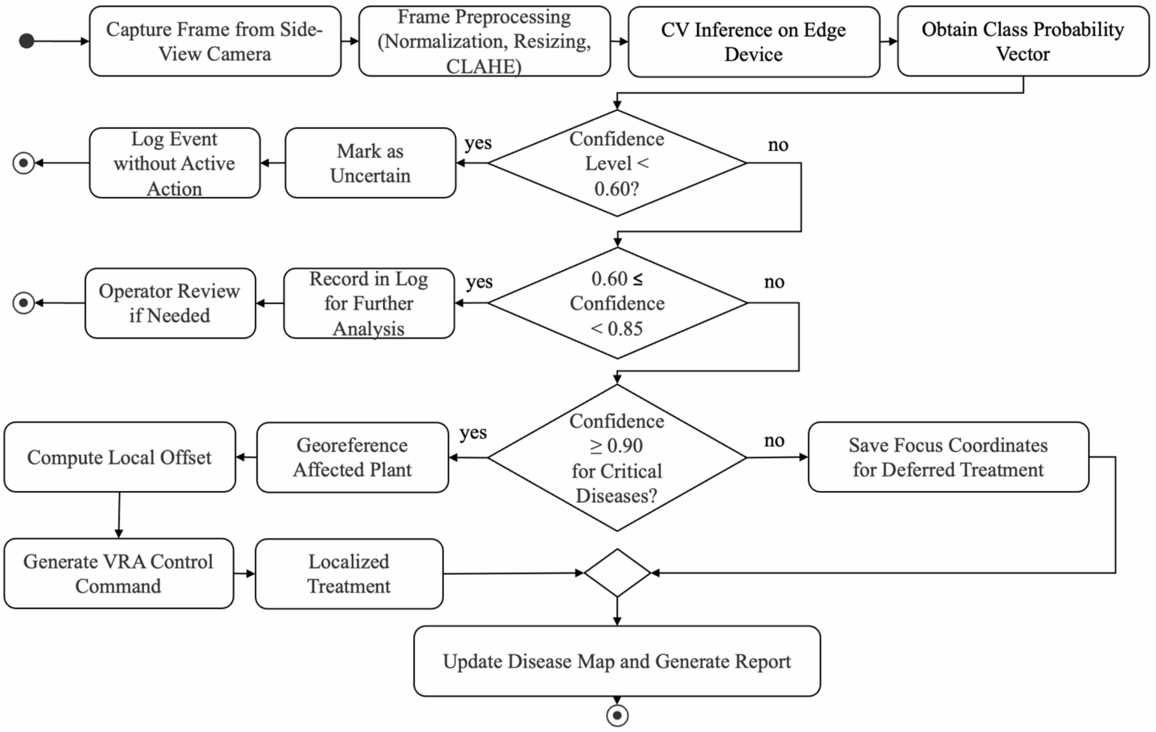


Fig. 2. Activity diagram of the data processing algorithm in the automated plant disease identification system

At a low confidence level, the classification result is ignored or marked as uncertain; at a medium confidence level, the coordinates are recorded for further analysis; and at a high confidence level, a direct control action is initiated. In the first two cases, additional verification of the results by an agronomist is advisable. If an appropriate software interface is available, ambiguous areas may be passed to the operator for visual inspection and decision refinement. A detailed implementation of such a mechanism is beyond the scope of this study.

After a decision has been made, the system georeferences the affected plant. It calculates the local offset relative to the ground platform's axis of movement, enabling accurate determination of the sprayer section or treatment zone. The command for the executive mechanism is generated based on the platform's movement speed and delays in the actuation chain, ensuring synchronization of nozzle activation with the actual position of the affected plant.

**Results and Discussion**

The software for plant inspection and classification under field conditions was developed using the EfficientNetV2S convolutional neural network in Python. The main purpose of applying the model is to assess the feasibility of automatically analyzing plant images and assigning them to a particular class.

To train the model, the transfer learning approach was used, which involves a conditional division into a base level and an upper level. In simplified terms, this can be described as follows: the base level, using algorithms embedded in the training library, extracts useful features such as shape, color gradients, and texture irregularities, whereas the upper level, based on the results of the base level, learns to classify images into the corresponding group. This approach enables the use of features already developed on large datasets and their adaptation to plant analysis.

The model was trained in two stages. At the first stage, the base part remained unchanged, and only the upper classification block was trained. At the second stage, partial fine-tuning of the upper layers of the base part was performed. Thus, the model was not trained from scratch, allowing it to adapt pre-existing features.

In the experiment, a dataset of 350 sunflower images was created, including 175 healthy plant images from different viewpoints and growth stages, as well as images of plants affected by sclerotinia at varying levels of severity. The dataset was divided into training, validation, and test subsets in the proportion of 70/15/15 %. Specifically, the training subset included 246 images, while the validation and test subsets each contained 52 images.

To improve the model's predictive performance, data augmentation was applied to the dataset. In particular, geometric transformations of images were used, namely changes in viewing angle, mirroring, and contrast variations. As a result, the number of training examples increased from 246 to 1230 images, thereby reducing the risk of model overfitting.

Another improvement applied in this work is the pseudo-negative sample generation method, which introduces noise or distortions into specific regions of the image to simulate the absence of characteristic disease features (Fig. 3).


Fig. 3. Examples of images belonging to the pseudo-negative class no_disease_pseudo.

Such images are assigned to a separate auxiliary class, “no_disease_pseudo,” which is characterized by the absence of pronounced disease features. The use of such examples reduces the likelihood that the model responds to random background elements and improves classification robustness.

Figure 4 presents the accuracy curves for the training and validation datasets. As shown in the graph, a rapid increase in model accuracy is observed during the initial stages of training, indicating the effectiveness of the transfer learning approach. Subsequently, the accuracy trend stabilizes, indicating that the model reaches a stable training regime.

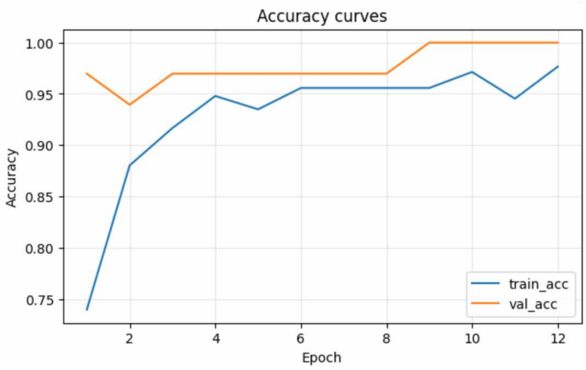


Fig. 4. Model accuracy curves for the training and validation datasets

The loss function, which describes how the model error changes during training, was analyzed separately (Fig. 5).

The graph shows that the gradual decrease in the loss values indicates a better fit of the model to the data in both datasets. The curves exhibit similar behavior, confirming that the model is not overfit and can form generalized feature patterns.

To evaluate the model’s confidence in its own predictions, the softmax function was used. This function is applied in the output layer and enables estimating the probability that an image belongs to a particular class.

In the implemented system, results can be divided into several categories based on confidence level.

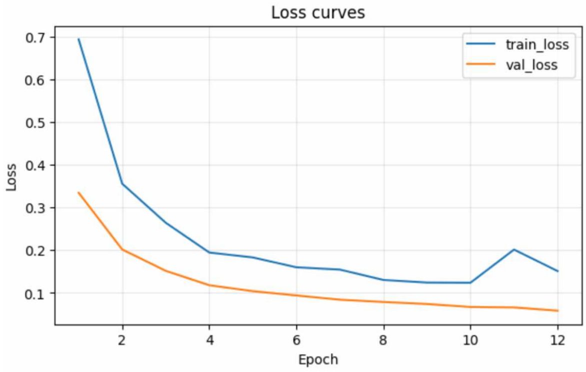


Fig. 5. Dynamics of the loss function during model training

At a low confidence level, the result may be rejected or sent for additional verification by the operator. At a medium confidence level, the obtained data may be used as auxiliary information. At a high probability value, the system can automatically register plant infection and transmit the information to the control unit.

Based on the indicators described above, it can be concluded that convolutional neural networks are fully suitable for automated plant condition diagnosis. Even under experimental conditions, the model demonstrated a stable ability to extract informative features on which infection classification is performed.

Despite the limited dataset size, the results indicate the potential of the EfficientNetV2S model for automated plant condition classification [22].

**Conclusions**

In this study, methods for plant disease monitoring were analyzed, along with their advantages and disadvantages. Owing to the development of UAVs and machine learning methods, traditional approaches based on subjective agronomist assessment can be significantly improved. Recent scientific publications support the prospects of this approach. There are many studies in the scientific literature showing that applying machine learning under laboratory conditions achieves high accuracy with minimal error. At the same time, the use of neural networks in field conditions remains limited, as input data may vary significantly across crop types and imaging conditions. Another important factor is the visual manifestation and progression pattern of the disease. A disease such as sclerotinia can spread from the stem, complicating its diagnosis with only a drone.

Thus, a fully automated system was proposed, consisting of a UAV, a central computing module, and a ground module, enabling more accurate disease detection, including stem-type diseases at an early stage. In the proposed system, the drone performs the initial inspection by identifying risk zones and transmitting the data to the central computing module. Next, the ground platform carries out additional inspection from a side view and transmits the data back to the central module. At the final stage, the central system determines the required application rate of the treatment agent.

As part of the experimental study, a neural network prototype was developed in Python, which may subsequently serve as the basis for an automatic classifier of drone images. In the prototype implementation, the transfer learning approach was used, the essence of which lies in dividing the neural network into two parts: a base part and an upper classification layer, which enables good results. To improve the model's learning capability, augmentation was applied, resulting in a fivefold increase in the dataset. The quality of model training was evaluated using the loss function and the accuracy curve, both of which confirm the feasibility of the proposed approach.

Therefore, the results of the study confirm the feasibility of combining a UAV and a ground-based module into a single system to improve versatility and the ability to detect various diseases, in particular sclerotinia. The proposed system has practical potential for further development as a solution that would automate plant treatment under field conditions and help reduce the negative environmental impact.

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## ІНТЕГРОВАНА СИСТЕМА МОНІТОРИНГУ ЗАХВОРЮВАНЬ РОСЛИН ІЗ ВИКОРИСТАННЯМ БПЛА, РОБОТИЗОВАНИХ ПЛАТФОРМ І НЕЙРОМЕРЕЖ

У статті розглянуто проблему автоматизованого моніторингу захворювань сільськогосподарських культур у польових умовах із використанням безпілотних літальних апаратів. Показано, що більшість існуючих рішень орієнтована насамперед на виявлення захворювання за окремими зображеннями, тоді як питання подальшого уточнення діагнозу, повторного огляду проблемної ділянки та визначення подальших дій після виявлення хвороби розглядаються значно рідше. Окрему складність становлять захворювання стеблового типу, зокрема склеротиніоз, для яких зйомка лише з верхнього ракурсу не завжди дозволяє своєчасно зафіксувати ранні ознаки ураження. На основі цього запропоновано структуру автоматизованої системи, що поєднує БПЛА для первинного огляду, з подальшою геоприв'язкою точки інтересу, наземний модуль для додаткового дообстеження у разі захворювань стеблового типу та центральний обчислювальний модуль для обробки даних і прийняття рішень щодо обробки уражених зон. Такий підхід дає змогу поєднати швидкий огляд великих площ із повітря та більш точне дообстеження рослин із бічного ракурсу, що особливо важливо для діагностики уражень, які погано візуалізуються зверху. У межах експериментального дослідження реалізовано прототип класифікатора на основі згорткової нейронної мережі EfficientNetV2S із використанням підходу transfer learning. Для підвищення якості навчання застосовано аугментацію зображень та метод генерації псевдонегативних прикладів. Отримані результати підтвердили перспективність використання згорткових нейронних мереж для автоматизованої класифікації стану рослин, а також доцільність поєднання аерозйомки та наземного дообстеження в межах єдиної системи моніторингу. Запропонований підхід може бути використаний як основа для подальшого створення інтелектуальної системи виявлення та локальної обробки осередків захворювань у польових умовах у межах задач точного землеробства.

**Ключові слова:** БПЛА, комп'ютерний зір, згорткова нейронна мережа, склеротиніоз, автоматизований моніторинг, точне землеробство.

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