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Technology for Blackcurrant Plantations Control Using Drones

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Abstract. This article presents a technology-based solution for monitoring blackcurrant vegetation using drones and artificial intelligence. The proposed system, implemented in a blackcurrant farm in Latvia, includes a three-stage process: mapping, identification and segmentation, and classification. Drones capture aerial images of the plantation, which are processed using tools like WebODM and deep learning algorithms to create accurate field maps. Neural networks are employed for identification, instance segmentation and classification of blackcurrant leaves into categories such as healthy, nutrient-deficient, or diseased. The system incorporates several AI model families—YOLO and ResNet —selected based on performance, accuracy, and resource efficiency. The methodology enables high-throughput analysis of large horticultural areas, supporting growers in decision-making by providing precise, visual insights into plant health. The approach demonstrates the viability of integrating drone technology and AI for precision agriculture, particularly in the specialized context of blackcurrant farming. The proposed technology, with appropriate adjustments, can also be applied to the vegetation monitoring of other horticultural crops.

Keywords: Drone Technologies, Machine Learning, Plant Vegetation Monitoring

1. Introduction

Unmanned Aerial Vehicle (UAV), hereinafter referred to as a drone in this article, is defined according to the Dictionary of Military and Associated Terms (Drone, 2005) as: "A powered, aerial vehicle that does not carry a human operator, uses aerodynamic forces to provide vehicle lift, can fly autonomously or be piloted remotely, can be expendable or recoverable, and can carry a lethal or nonlethal payload". The term "drone," commonly used in mass media, was introduced even before World War II, as the first unmanned aerial vehicles were named after bees and wasps.

Today, drone manufacturing costs and production volumes have reached a level that allows their application across various fields, including precision agriculture. Scientific reviews available in the literature analyse the latest advancements in drone technology used in precision farming. For example, Botta et al. (2022) compiled 184 publications using data from Google Scholar and SCOPUS, while Uzhinskiy (2023) reviewed 164 works focusing on the application of AI methods in agriculture.

The authors of these studies unanimously conclude that drones can be effectively used for crop vegetation monitoring, while agricultural operations should be performed using ground-based equipment. During a flight, a drone can capture images of designated field areas and transmit them for further analysis. Using machine learning methods, this enables the detection of vegetation conditions and issues that determine necessary agronomic actions. Thus, drones allow for rapid inspection of large agricultural areas and the collection of crucial data on crop health and required maintenance tasks.

This study is practically oriented, with the main objective being the development of a technology that integrates drones usage and artificial intelligence methods, described more in detail in (Oditis et al., 2025). The system is designed to alert farmers about plant diseases, pests, nutrient deficiencies, and other issues. The developed technology must be user-friendly and economically viable.

The following chapters provide a description of the technology designed to support blackcurrant cultivation using basic drones and imaging cameras. The proposed technology was tested on a blackcurrant farm in Latvia, confirming the validity of the chosen approach.

The structure of this study is as follows: Chapter 1 provides an overview of drone usage in precision agriculture worldwide. Chapter 2 focuses specifically on drone applications in horticulture. Chapter 3 presents the authors' proposed methodology for assessing blackcurrant plantations. Chapter 4 offers a visualization of blackcurrant plantation conditions. Chapter 5 discusses the obtained results and presents conclusions.

2. Drone application in horticulture

To feed the rapidly growing global population, agricultural enterprises must produce more food without increasing cultivated land areas. This can be achieved by applying advanced farming technologies. Some of these technologies are still in development, while others are already offered by commercial companies. Today, farms can utilize a range of advanced tools, such as satellite data, drones, autonomous platforms for agricultural operations, sensors, and robots, to obtain detailed information about crop and soil conditions and to perform specific agronomic tasks.

However, in many countries, including Latvia, the adoption of drone technology in agriculture is still in its early stages. Among various scientific and technological challenges being addressed to achieve sustainable development goals, the use of new technologies and methodologies in agriculture has attracted the interest of the engineering research community. The objective is to develop technologies suited for precision agriculture that enhance the long-term profitability and efficiency of agricultural production.

2.1. General overview of drone applications

According to (Botta et al, 2022) and (Uzhinskiy, 2023), data from the Food and Agriculture Organization (FAO) indicate that global food production must increase by 70% by 2050 to sustain the growing world population. However, in the European Union, the number of people employed in agriculture has decreased by 35% over the past decade, and the expansion of agricultural land is largely unfeasible.

These factors have driven increased interest in advanced agricultural technologies, including sensors, robots, drones, digitalization, and artificial intelligence (AI). AI and machine learning are considered highly promising for detecting agricultural issues, monitoring crop health, forecasting yields and prices, mapping harvests, and optimizing pesticide and fertilizer use.

There are various research directions that discuss the use of modern technologies in agriculture: Internet of Things (IoT) technologies in agriculture (Xu et al., 2022), bibliometric analysis of drone use in farming (Rejeb et al., 2022), deep learning methods for controlled-environment agriculture (Ojo et al., 2022), robotic harvesting technologies (Mail et al., 2023), machine vision applications in agricultural robot navigation (Wang et al., 2022), AI in agriculture (Oliveira et al., 2023), Agriculture 4.0 (Dayioglu et al., 2021), (Abbasi et al., 2022).

Depending on the specific task, drones can offer similar capabilities to satellite image analysis but with higher precision and flexibility. They can perform tasks such as soil analysis (Huuskonen et al., 2018), (Zhou et al., 2023), (Bertalan et al., 2022 monitoring sowing density and crop development (Wilke et al., 2021), (Koh et al., 2019), weed and pest detection and classification (Ong et al., 2023), (Ong et al., 2023), (Tetila et al., 2020), (Mohidem et al., 2021), and yield prediction and maturity assessment (Kumar et al., 2023), (Zeng et al., 2021), (Shahi et al., 2023).

In rare cases, drones can also be used for harvesting, precision fertilization (Chen et al., 2022), (Song et al. 2023), (Su et. al. 2022), pesticide spraying (Anand et al., 2019), (Ivič et al., 2019), (Sinha, 2020) and even mechanical pest eradication. IoT and sensor technologies provide farmers with real-time data on soil parameters, temperature, atmospheric gases, weather conditions, and many other variables, often processed in cloud-based IT infrastructures for further analysis and forecasting (Dhanaraju et al., 2020), (Gagliardi et al., 2022), (Madushanki et al., 2019), (Bilotta et al., 2023).

2.2. Scope of drone applications

The use of artificial intelligence and cloud technology in drones has brought significant improvements to smart agriculture. These new technologies can capture high-resolution images, aerial maps, and thermal images, which can be utilized in various agricultural applications, including:

- Soil analysis: Drones can be used for soil sampling, analysing soil moisture levels, and assessing soil quality, helping farmers optimize fertilization and irrigation processes,
- Planting: Drones can be used for precise seed sowing and/or seedling planting, reducing labour and planting material costs,
- Crop spraying: Drones equipped with spraying systems can be used for the precise distribution of pesticides, herbicides, and fertilizers, minimizing environmental impact while saving time and financial resources,
- Irrigation management: Drones equipped with thermal sensors and infrared cameras can identify areas needing irrigation, helping to optimize water use and reduce waste,
- Yield mapping: Drones can generate yield maps, assisting farmers in optimizing crop management and increasing overall production,

- Livestock monitoring: Drones equipped with cameras can be used to monitor livestock health and behaviour, as well as track animal locations,
- Crop monitoring: Drones equipped with sensors and cameras can collect real-time data on crop health, growth, and yield, creating crop health maps,
- Field mapping: Drones can create high-resolution field maps, providing data on soil structure, topography, and plant populations, which can be used for informed decision-making regarding planting, fertilization, and other crop management practices,
- Pest and disease control: Drones can help to detect and map pest and disease spread in crops, helping farmers take timely action.

These drone applications have gained significant research attention over the past five years. Studies provide evidence of the potential of drones in agriculture. However, these results remain a future vision that is not yet accessible to practitioners. Implementing such technologies requires the involvement of highly qualified specialists and the establishment of modern infrastructure.

2.3. Drone usage for crop monitoring

Drones are increasingly being used for crop monitoring. The most monitored crops are:

- Cereals: Frequently monitored during growth stages for yield prediction and disease detection (Boursianis et al., 2022),
- Fruits and Vegetables: Crops such as grapes, citrus fruits, apples, tomatoes, and potatoes are monitored to detect pests, diseases, and assess yield,
- Oil Crops (soybeans, sunflowers): Vegetation monitoring, plant health assessment, and yield prediction,
- Specific crops (coffee, tea, cocoa, and tobacco) are primarily monitored for early detection of diseases or pest infestations, as well as yield optimization.

However, drone usage in crop monitoring faces several limitations, as outlined in studies by (Zou et al., 2021), (Shahi et al., 2023), and (di Gennaro et al., 2016). First, drones can cover only a limited area per flight, making large-scale farm monitoring challenging. Second, weather conditions, particularly wind and rain, can impact drone operability, limiting data collection in unfavourable conditions. Third, drone operation requires skilled personnel and specialized equipment, which can be costly and time-consuming to maintain. Additionally, regulations vary by country; for example, in Latvia, drones must remain within the certified operator's line of sight.

Other factors influencing drone efficiency include crop height, density, size, weather conditions, and sensor limitations. Despite these challenges, drone systems provide farmers with valuable insights and data to optimize crop management, improve productivity, and reduce pesticide and fertilizer usage.

2.4. Summary

The analysis of related works indicates that the application of drones in horticulture should begin with plant vegetation monitoring, while agricultural technological operations should remain reliant on ground-based traditional equipment. This is primarily due to the relatively low payload capacity of drones compared to conventional agricultural machinery.

3. Proposed solution of technology

This section presents the authors' proposed technology for monitoring blackcurrant vegetation using simple drones and artificial intelligence methods. The proposed solution is applied in a blackcurrant farming operation in Latvia.

3.1. Informal description of solution

The technology is offered to blackcurrant growers for monitoring plantations using drones, enabling the detection of healthy blackcurrant plants, fungal diseases, and nutrient deficiencies. The system consists of three main stages:

- Mapping: Prepares maps of blackcurrant plantations with the required precision (scale), links them to GPS (Global Positioning System) coordinates, records drone flight routes, and specifies operations/photography to be performed during flights.
- Identification and segmentation: Uses trained neural networks to extract blackcurrant leaf clusters from the mapped images. Instance segmentation then identifies individual blackcurrant leaves, which are passed to the classification stage for further analysis.
- Classification: Uses trained neural networks to recognize healthy leaves, leaves affected by fungal diseases, and leaves indicating nutrient deficiencies.

As a result, the study provides a blackcurrant plantation analysis tool that gathers information on plantation conditions and visualizes it for growers, aiding decision-making regarding necessary interventions.

3.2. Mapping of horticultural areas

The area captured in drone images is usually significantly smaller than the cultivated field area in horticulture. This is determined by the technical parameters of the drone's camera and the scale of the captured images. As a result, field maps must be "stitched" together from individual drone images, which, when combined, form a complete field representation.

Figure 1. Example with combination of two images from neighbour fields that can’t be stitched together (images taken from height of 45 meters)

Additionally, stitching large image segments, as illustrated in Figure 1, can sometimes be of poor quality. The figure shows the merging of two images taken by a drone from a height of 45 meters, where visible discrepancies occur. These inconsistencies are caused by the technical limitations of image capture—differences in altitude and angles between images taken from different positions.

3.3. Selection and storage of image capturing routes

Since the horticultural field is created from several smaller images captured by the drone, additional actions need to be taken before capturing the image:

- marking the drone's starting point and determining the GPS coordinates;
- selecting the drone's flight route and image capture points so that, for example, using the *WebODM* (Web (a)), the images can be "stitched" together into field maps;
- the images must be captured efficiently, without interrupting the drone's flight;
- routes must be encoded and saved in .csv format for later use;
- the drone camera settings need to be adjusted to capture images with sufficient precision.

The route can be created using the *Mission Planner* program. It is necessary to create a route for the drone to fly and capture images that can later be stitched together. The overall image route is calculated based on the drone's flight altitude and camera parameters (e.g., the angle the camera captures) to ensure adequate overlap between images. As a result, a route will be obtained for the drone to follow, an example of which can be seen in the image prepared by the authors in Figure 2, which illustrates the mapping issues—low trees and uncovered areas.

The automatic flight is provided by the *Litchi* program. It is available both on the computer's website to create the route and on mobile phones to fly the route.

Figure 2. Routes where a drone could fly into a tree (image links) or not the entire area covered (image right)

3.4. Drone image processing

WebODM is used to merge drone flight images by detecting overlapping images using GPS coordinates, stitching them together, and correcting perspective distortions. This creates a cohesive aerial view for further analysis.

The image processing stage focuses on detecting and isolating individual blackcurrant leaf instances through instance segmentation and subsequent identification methods. Instance segmentation algorithms are applied to drone images to accurately separate each leaf from the background and other plant structures. Each leaf instance is identified separately, which enables detailed classification in the next stage. Segmentation and identification are crucial for preparing high-quality data for precision agriculture.

Trained AI models are used for segmentation and identification, fine-tuned specifically for blackcurrant leaf detection. Fine-tuning enhances the models' ability to recognize unique leaf structures and subtle variations, improving classification accuracy. This customization ensures high-precision results in identifying leaves and detecting plant health conditions. This pipeline enables an efficient and automated leaf classification system, supporting precision agriculture applications.

3.5. Identification

For the identification step, a training and validation dataset was created, consisting of 102 images (Figure 3). Each image was annotated using the open-source web-based annotation tool *CVAT* (WEB (b)) The dataset annotations were exported in YOLO (*You Only Look Once*) and COCO formats to support various deep learning frameworks.

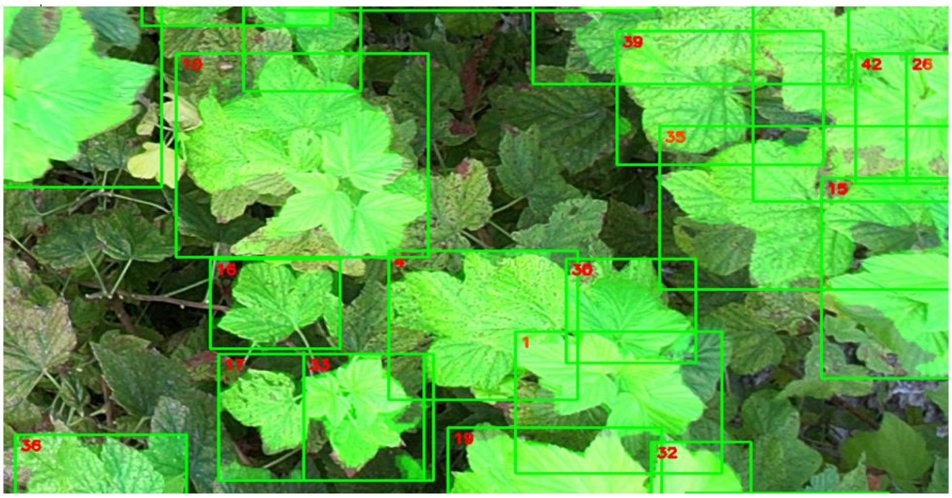

Figure 3. Leaf cluster marking in the field image

Several models were considered for analysing the images obtained in the identification step, focusing on accuracy, speed, and resource efficiency. The following models were selected for training: Faster R-CNN, ResNet50 FPN, Faster R-CNN X101-FPN, RetinaNet R101, YOLOv8x, YOLOv9e, and YOLOv10x. This model selection was based on proven performance in object detection and instance recognition across various datasets.

Faster R-CNN models (ResNet50 FPN, X101-FPN) are known for high precision, particularly in complex scenes. Feature Pyramid Network (FPN) enables the model to analyse objects at multiple scales effectively.

RetinaNet R101 was chosen for its effectiveness in handling imbalanced datasets. It uses focal loss, which improves the detection of less frequent classes by reducing the influence of dominant classes.

YOLO series models (YOLOv8x, YOLOv9e, YOLOv10x) have high-speed performance, making them ideal for real-time applications in resource-constrained environments while maintaining strong identification performance.

This diverse model combination allows for a comprehensive comparison of accuracy vs. performance trade-offs, ensuring the most optimal identification model is selected.

3.6. Instance segmentation

The segmentation step allows extracting blackcurrant leaves from the leaf clusters identified in the previous identification step. Instance segmentation is essential to achieving high accuracy by isolating each leaf as a separate object within the image. By precisely delineating each leaf instance, a higher level of granularity and detail is ensured in the subsequent classification process. This approach enables algorithms to analyse each leaf individually, thereby improving classification accuracy by accounting for subtle differences such as leaf shape, size, and potential disease symptoms. Instance segmentation plays a crucial role in ensuring high-quality data acquisition and precise result interpretation.

A dedicated instance segmentation dataset was created using images captured with a Nikon D3300 DSLR camera equipped with a 24.2 MP DX-format CMOS sensor. The images were taken in the same blackcurrant fields where automated drone missions were conducted. The dataset includes images of blackcurrant leaves from various angles to enhance diversity and improve model training by simulating different perspectives. A total of 87 annotated images were compiled, with annotations created using the same tool as the identification dataset—CVAT (Computer Vision Annotation Tool). The dataset contains a single object type: "blackcurrant leaf," with each object annotated using segmentation mask contour points.

Several popular segmentation models were considered, with an in-depth analysis of YOLO models (YOLOv5-seg, YOLOv7-seg, YOLOv8-seg, YOLOv9-seg), as referenced in (Oditis et al., 2025). Additionally, the SAM model family (SAM, SAM2) and Mask R-CNN were evaluated theoretically based on literature sources (Chegini, 2023).). Each model offers different approaches to instance segmentation, with unique advantages and limitations.

YOLO models, known for their speed and efficiency, making them ideal for real-time applications like video surveillance and robotics (Oditis et al., 2025). However, their accuracy in complex segmentation tasks may be lower compared to more sophisticated models.

SAM (Segment Anything Model) family (SAM, SAM2) offers general-purpose segmentation, capable of segmenting any object with minimal input (e.g., a point or bounding box). It does not require task-specific training data, making it highly versatile. However, it lacks real-time processing speed.

Mask R-CNN is well-known for its high accuracy, especially in detecting overlapping and complex objects. Heavy computational requirements make it less suitable for real-time applications. Mask R-CNN is best suited for precision tasks like medical image analysis or autonomous driving.

A summarized model comparison is provided in Table 1. Based on the analysis, the YOLO model family was selected for instance segmentation, and further training will be conducted to determine the most optimal model for the task.

Although Mask R-CNN demonstrates higher accuracy, the specific requirements of the task call for instance segmentation of a single object type, prioritizing the solution's speed. This decision is based on the fact that a single field image covers approximately 260 sectors to be analysed, which require instance segmentation. Additionally, when surveying one hectare of field, about 7,500 images are obtained, meaning that instance segmentation must be performed on approximately 1.9 million sectors per hectare. These data strongly suggest the use of the YOLO solution for further analysis.

Table 1. Comparison of Instance Segmentation Models

Model	**Strengths**	**Weaknesses**	**Suitable Applications**	**Real-time Performance**
YOLO (YOLOv8-seg, YOLOv9-seg)	Fast, efficient for real-time tasks	Lower accuracy in complex segmentation tasks	Video surveillance, robotics	Excellent for real-time tasks
SAM (SAM, SAM2)	Universal object segmentation with minimal input	Lacks real-time processing speed	General segmentation tasks	Not suitable for real-time tasks
Mask R-CNN	High accuracy, especially for segmenting overlapping and complex objects	Resource-intensive, slow, not suitable for real-time tasks	Medical image analysis, autonomous driving	Low real-time performance but excellent accuracy

3.7. Classification

This chapter describes the blackcurrant leaf classification process and the conceptually chosen solutions. The classification process involves multi-class data classification, utilizing pre-trained models adapted to the specific dataset. These models are trained on pre-processed datasets to ensure accuracy and efficiency in blackcurrant leaf analysis. The use of artificial intelligence tools provides a generalized solution adaptable to various data types and classification criteria.

By analysing drone-acquired field images and evaluating blackcurrant bushes, three leaf classes were identified: “Healthy Leaf”, “Leaf with Nutrient Deficiency”, “Leaf with Fungal Disease”. It was also observed that some leaf instances exhibit characteristics of multiple classes, making multi-class classification necessary. In this chapter, the only object type under consideration is the blackcurrant leaf. This classification structure is sufficient to test the effectiveness of the selected approach. If needed, the set of classes can be expanded without altering the classification process, implementation, or planned solution. The class definitions were determined with input from a domain expert.

The training and validation dataset was collected from the same blackcurrant fields where automated drone missions were conducted. After image acquisition, data annotation was performed, where leaf instances were manually segmented and assigned to their respective classes. The dataset consists of:

- 118 images of leaves classified as "Healthy Leaf",
- 109 images of leaves classified as "Leaf with Nutrient Deficiency",
- 102 images of leaves classified as "Leaf with Fungal Disease",
- 57 images containing instances belonging to multiple classes.

(See Figure 4 for reference.)

Figure 4. Leaf examples: fungal disease, healthy leaf, leaf with nutrient deficiency

For the classification task, three families of artificial intelligence models popular for multi-class image classification were examined:

- ResNet, including ResNet50, ResNet101, and ResNet152;
- EfficientNet covering models from EfficientNet-B0 to EfficientNet-B7;
- VGGNet, including VGG16 and VGG19.

ResNet (Residual Network) architectures are designed to address issues in deep neural networks, such as the vanishing gradient problem. They use "skip" connections, allowing information to bypass certain layers, enabling the training of very deep networks without performance degradation, which is common in traditional deep networks .

EfficientNet is a highly efficient neural network architecture optimized for both accuracy and resource usage. It employs a compound scaling approach, simultaneously adjusting the network's width, depth, and resolution to enhance performance.

VGGNet is a classical deep neural network for image classification, known for its simple and structured architecture. It primarily relies on convolutional layers with 3x3 filters. However, this design results in high computational complexity and memory requirements, making it slower compared to more modern architectures (Simonyan, 2015).

For the classification process, the ResNet family was selected, with ResNet50, ResNet100, and ResNet512 models considered during training. This choice was based on ResNet's high accuracy and performance, which surpass those of the VGGNet models. From the comparison in Table 2, it is evident that ResNet effectively mitigates the gradient vanishing problem, allowing the training of deeper networks without performance loss.

While EfficientNet is highly efficient in resource utilization, ResNet provides an optimal balance between accuracy and speed, which is crucial for blackcurrant leaf classification, where high reliability and processing speed are required. These advantages make ResNet the most suitable model family for successfully executing the given task.

Table 2. Comparison of Classification Model Families

Model family	**Strengths**	**Weaknesses**	**Application areas**	**Efficiency / Resource usage**
ResNet	Solves the gradient vanishing problem in deep networks using "skip" connections	Deeper architecture may be challenging to train with small data	Image classification, data analysis, computer vision	Efficient in training deep networks without performance loss
EfficientNet	Optimizes both accuracy and resource usage through proportional scaling	Higher complexity in the optimization process	Mobile applications, AI solutions	High efficiency, low resource requirements
VGGNet	Simple architecture, clear and intuitive	High computational complexity, slower compared to modern models	Image classification, computer vision, early research applications	Low efficiency and high memory requirements
Mask R-CNN	High accuracy, especially in segmenting overlapping and complex objects	Resource-intensive, slow, not suitable for real-time tasks	Medical image analysis, autonomous driving	Low real-time performance, but excellent accuracy

3.8. Summary

The proposed technology utilizes several artificial intelligence methods for a specific application – monitoring the vegetation of blackcurrants. The selected methods proved to be sufficiently effective for this particular application.

4. Fields history

For every farm, it is beneficial to maintain a field record journal that logs all activities within a specific agricultural area, including completed horticultural operations, the use of crop materials, and plant protection products. Several information systems already exist to support such functionalities.

This study, however, focuses on collecting field images, offering a different perspective on historical data—both visually and through insights derived from image analysis. The goal of our research is to develop a solution that allows for visual tracking of field changes over time while also providing timely detection of plant health issues identified through image analysis.

4.1. Field surveying process

To ensure field history tracking:

- identify the surveyed fields (this information is used to plan drone flight and photography routes),
- conduct field surveys using drones to capture images and link them to specific geolocations,
- analyse the images to identify plant health issues,
- visualize the extracted information on a map for better interpretation and decision-making.

This type of solution is designed for horticulturists. Their main interest is tracking long-term changes in fields, especially in crop cultivation involving perennial plants such as blackcurrants. In such cases, even historical images taken from the same vantage point can provide valuable insights into field conditions, moisture levels, pest infestations, disease development, and more.

Although the functionalities may seem simple, this type of solution comes with certain technical challenges. First, to obtain images suitable for whole-field analysis, several hundred photos per hectare must be captured, making the imaging process time-consuming and requiring multiple drone flights. Second, storing historical images can be space-intensive, considering that blackcurrant plantations typically cover between 2 to 20 hectares. Third, analysing such a vast number of images is time-consuming, as it involves identifying and classifying thousands of leaves.

To address these technical challenges, it is important to recognize that a complete photographic record of the entire field is not necessary to assess the condition of blackcurrant plantations. A similar approach is used in soil fertility assessment, where sampling is conducted systematically at predetermined intervals—for example, every 20 meters. In this case, evaluating one hectare would require only 36 images, significantly reducing storage and analysis demands. This approach would still provide sufficiently representative information about the field's condition and the spread of potential issues.

4.2. Field browser functions

The field browser provides the following key functions:

- Field survey planning – defining field boundaries, preferably using the territorial division applied by the Rural Support Service.

- Drone flight planning – setting flight routes and photography points, including altitude and camera parameter configuration.
- Automated drone flight execution – performing flights autonomously and saving captured images.
- Image analysis – conducting segmentation, identification, and classification using a pre-trained neural network.
- Blackcurrant plantation condition monitoring – allowing selection of a specific field for evaluation, enables to view images in different resolutions and timeframes (field images can be viewed on different dates, switching between them changes the displayed field area and resolution).

A sample result of the field browser operation is shown in Figure 5. A map of a 5-hectare blackcurrant plantation was created using a drone, with a portion of the area undergoing in-depth analysis—including segmentation, identification, and classification. This analysis provides an overview of the plantation's condition, revealing healthy leaves – 97.4%, fungal disease presence – 1.7%, nutrient deficiency detected – 1.0% of the surveyed area. This assessment of the plantation's condition provides valuable insights for the agronomist, enabling informed decisions on necessary crop management actions.

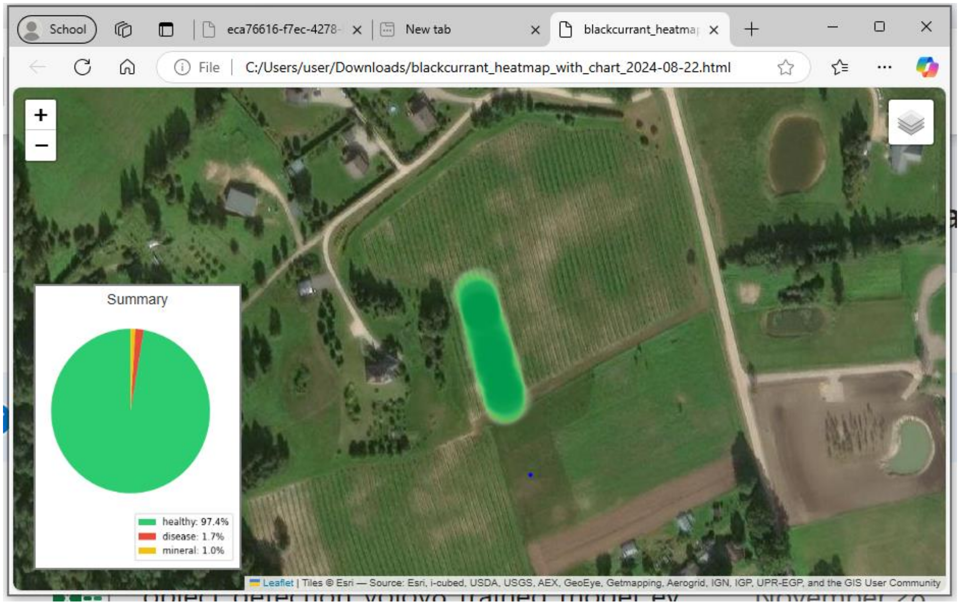

Figure 5. Blackcurrant Field Condition (Nutrient Deficiency: 1.0%, Fungal Disease: 1.7%, Healthy Leaves: 97.4%).

5. Discussion

The study results demonstrate new technologies for monitoring blackcurrant vegetation. Instead of traditional visual assessments by horticulturists, an automated system is proposed, offering several advantages: precise crop evaluation using AI methods, applicability to large blackcurrant plantations, economic efficiency, and ease of implementation.

However, these achievements should be considered a first step toward precision agriculture in blackcurrant cultivation, requiring further development. The proposed approach relies on blackcurrant leaf analysis, which means it can only detect diseases affecting leaves, while issues affecting roots and stems—such as blackcurrant clearwing moth (*Synanthedon tipuliformis*) and blackcurrant bud mite (*Eriophyes ribis*)—remain undetected.

Similarly, yield prediction requires an alternative approach, possibly analysing entire blackcurrant bushes rather than just leaves. Pest infestations can also only be partially identified through leaf analysis.

Nevertheless, other blackcurrant cultivation challenges, such as crown rust, can be identified using similar methods by analysing different plant parts, segmenting them in images, and classifying them based on the specific problem being addressed.

5.1. Additional applications of the method

A diligent horticulturist monitors not only the spread of blackcurrant diseases but also frost damage, flowering progress, yield ripening time and volume predictions, and other vegetation-related events. Although these aspects were not the primary focus of this study, they could be addressed by modifying the proposed method—for example, by segmenting and classifying flower buds and berry clusters accordingly.

Beyond plant vegetation monitoring, the method can also be applied to optimizing agricultural operations. By identifying disease-affected field areas, maintenance tasks such as targeted spraying can be carried out only in infected regions. This would lead to significant savings in materials and labour resources.

A promising direction for further development is integrating the method into dynamic robotic management. By transferring real-time data from the blackcurrant plant analysis module to an agricultural operations execution robot, it would be possible to perform precise interventions only where necessary, further increasing efficiency and sustainability.

5.2. Limitations of the method’s application

When analysing the benefits of the proposed method, it is also important to highlight its limitations.

One key limitation is the lack of precision in determining nutrient deficiencies. While the method can detect a deficiency, it cannot specify which particular nutrient—potassium, phosphorus, or nitrogen—is lacking. Currently, this type of analysis is performed using soil and plant agrochemical testing, which involves manually collecting soil and leaf samples. This process requires significant labor resources.

A more advanced approach involves spectral analysis of plants, which can provide more precise nutrient deficiency diagnostics. However, this requires more complex imaging cameras and advanced processing methods, which are not yet widely available due to high costs and a lack of specialists.

Additionally, leaves are just one indicator of plant health, but they do not reveal all potential issues. For example, pest infestations, such as the blackcurrant clearwing moth, which primarily affects the stems rather than the leaves, cannot be detected using this method. Furthermore, yield estimation—a crucial aspect from an economic perspective—

is not covered by this approach. Addressing these gaps requires further research and development in this field.

6. Conclusions

Key conclusions of the conducted research and its application results:

1. Integration of Drones and AI is Effective for Precision Agriculture. The proposed system successfully integrates drone-based imaging with artificial intelligence methods to monitor blackcurrant plantations. This approach enables accurate, large-scale assessment of plant health conditions while reducing the need for manual inspection.
2. Modular Architecture Ensures Flexibility and Scalability. The system's modular structure—mapping, identification and segmentation, and classification—allows for flexibility in adapting the pipeline to different crops or environmental conditions. Each module can be fine-tuned or replaced independently to improve performance.
3. Mapping functions can be implemented using standard solutions available in commercial drone systems or through adapting open-source solutions for blackcurrant cultivation. Identification and segmentation solutions must be developed individually in collaboration with industry experts—in this project’s case, blackcurrant growers. This includes training a neural network for leaf recognition and transmitting the identified leaf information for classification. The classification task involves training a neural network to recognize specific characteristics of blackcurrant leaves, which is the project's final goal and of interest to horticulturists.
4. YOLO Models Balance Speed and Accuracy for High-Volume Analysis. While models like Mask R-CNN offer higher segmentation accuracy, the YOLO model family was selected for its superior processing speed, making it more suitable for handling the large volume of images required in agricultural drone surveys.
5. ResNet Models Provide Robust Classification Capabilities. The ResNet family of models proved optimal for classifying blackcurrant leaves due to their ability to train deep networks efficiently. Their balance of accuracy and computational efficiency makes them suitable for real-world deployment in agricultural settings.
6. System Supports Informed Decision-Making for Growers. By providing detailed visualizations and health assessments of blackcurrant plantations, the system aids growers in making timely decisions regarding interventions such as fertilization or disease management.
7. Field-Validated Data Collection Enhances Reliability. The use of annotated datasets created from real blackcurrant fields ensures that the models are trained and validated with realistic, domain-specific data, improving the accuracy and practical applicability of the system.
8. Potential for Wider Application. Although developed specifically for blackcurrants, the solution demonstrates potential for adaptation to other types of crops and agricultural monitoring tasks, supporting broader applications in precision horticulture.

Following the identification of fungal diseases and nutrient deficiencies, potential future applications include yield prediction, pest detection, and identification of other plant diseases. A key challenge remains improving the speed of image analysis, as computational demands may exceed the capabilities of simple and inexpensive hardware.

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