

Blackcurrant Plantations Monitoring Using Drones

Jānis Bičevskis, Reinis Odītis,

Ivo Odītis, Zane Bičevska

0000-0001-5298-9859, 0009-0003-5488-1608

0000-0003-2354-3780, 0000-0002-5252-7336

University of Latvia

Raina Blvd. 19, Riga, Latvia

Email: janis.bicevskis@lu.lv, ro17020@students.lu.lv,

ivo.oditis@lu.lv, zane.bicevska@lu.lv

Abstract—The work is dedicated to the study of drone use in horticulture, focusing on an example of blackcurrant cultivation. The research aims to use drones to monitor vegetation in plantations and to maintain the technological environment of plants, using traditional agrotechnical field care methods. The concept offers mapping and instance segmentation followed by multi-label classification operations, taking into account the specifics of blackcurrant plantations. The mapping operation creates blackcurrant plantation maps from images taken by drones at low altitudes. This ensures the acquisition of high-quality maps of large areas with the help of simple image photography cameras. Instance segmentation is intended for extracting singular leaf instances from mapped images, which are analyzed using classification methods to detect blackcurrant diseases, pest spread, nutrient and moisture deficiencies, and other plant vegetation-related parameters. Classification employs machine learning techniques and is specific to the cultivation of a particular plants – blackcurrants. The proposed technology, with appropriate adjustments, can also be applied to the vegetation monitoring of other horticultural plants.

I. INTRODUCTION

TODAY, drone manufacturing costs and production volumes have reached a level that allows their application in various fields, including precision agriculture. The scientific reviews available in the literature analyze the latest advances in drone technology used in precision farming. For example, [1] compiles 184 publications using Google Scholar and SCOPUS data, while [2] reviews 164 articles focusing on the application of AI methods in agriculture.

The authors of these studies unanimously conclude that drones can be used effectively to monitor plant vegetation, while agricultural operations should be carried out using ground-based equipment. During a flight, a drone can capture images of designated field areas and transmit them to computers 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 adopts a practical approach with the primary objective of developing a technology that integrates drones and artificial intelligence techniques to monitor plant vegetation. The system is designed to provide early warnings to farmers regarding plant diseases, pest infestations, nutrient

deficiencies, and other agronomic issues. A key contribution of this work is the development of a robust image analysis system capable of processing leaf images to reliably detect plant (particularly blackcurrant) diseases, thereby enhancing the system's applicability in real-world agricultural settings.

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 results obtained and presents the conclusions.

II. DRONE APPLICATION IN HORTICULTURE

To feed the rapidly growing global population, agricultural enterprises must produce more food without increasing the areas of cultivated land. 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 variety 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 the various scientific and technological challenges that are being addressed to achieve the goals of sustainable development, the use of new technologies and methodologies in agriculture has attracted the interest of the engineering research community ([3]). The objective is to develop technologies suitable for precision agriculture that improve the long-term profitability and efficiency of agricultural production ([4]).

A. General Overview of Drone Applications

According to [1] and [2], data from the Food and Agriculture Organization (FAO) indicate that global food production

must increase by 70% by 2050 to support 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 an increase in 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 problems, 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 ([5]), bibliometric analysis of drone use in agriculture ([6]), deep learning methods for controlled environment agriculture ([7]), robotic harvesting technologies (Mail et al., 2023), machine vision applications in agricultural robot navigation ([8]), AI in agriculture ([9]), Agriculture 4.0 ([10], [11]).

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 ([12], [13], [14]), monitoring sowing density and crop development ([15], [16]), weed and pest detection and classification ([17], [18], [19]) and yield prediction and maturity assessment ([20], [21], [22]).

In rare cases, drones can also be used for harvesting, precision fertilization ([23], [24], [25]), pesticide spraying ([26], [27], [28]) 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 ([29], [30], [31]).

B. 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, analyzing 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 detect and map the spread of pests and diseases 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.

III. APPLICATIONS OF MACHINE LEARNING IN PLANT DISEASE DIAGNOSIS

A. Overview and Summary of Existing Solutions

The authors have reviewed several solutions for diagnosing plant diseases using images of plant leaves. The works discussed in this subsection will not be described individually, but rather grouped according to the nature of the solutions reviewed, and common features will be highlighted to indicate current trends in addressing such problems.

The solutions include methods such as the use of convolutional neural networks, the application of transfer learning, the use of traditional classification methods, the application of segmentation, object detection, and data augmentation.

Convolutional neural networks dominate plant leaf image classification in the context of the reviewed studies. In most of the research reviewed by the authors, convolutional neural networks are either trained from scratch on specific plant data or used as part of transfer learning. For example, in the work by Khalid M. Hosny and co-authors titled “**Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern**” [32], several examples of convolutional neural network architectures - AlexNet, VGG16, and GoogLeNet - are analyzed. These are trained on the PlantVillage dataset [datasetPlantVillage] and enhanced with the use of local binary patterns to incorporate texture information. Another good example of convolutional neural network use is described in the work by Prabhjot Kaur and co-authors titled

“A novel hybrid CNN methodology for automated leaf disease detection and classification” [33], where a convolutional neural network (ResNet50) is combined with a support vector machine (replacing the fully connected layers of the convolutional neural network). An interesting application of convolutional neural networks is found in the publication by Rasika Gajendra Patil and Ajit More titled **“Grape Leaf Disease Diagnosis System Using Fused Deep Learning Features Based System”** [34], where the proposed method fuses the results obtained from the deep feature layers of two selected convolutional neural networks.

Similar to convolutional neural networks, transfer learning approaches are also commonly found in the reviewed solutions. They are widely used because they allow the utilization of pre-trained networks. An example is the study developed by Vinay Gautam and co-authors titled **A Transfer Learning-Based Artificial Intelligence Model for Leaf Disease Assessment** [35], where transfer learning is applied to models such as: AlexNet, VGG16, VGG19, InceptionV4, SqueezeNet, and Xception. The use of transfer learning is particularly important in situations where data collection is expensive or limited, such as in the case of rare diseases. A similar situation is observed in the study by Yan Guo, Jin Zhang, and co-authors titled **“Plant Disease Identification Based on Deep Learning Algorithm in Smart Farming”** [36], where the solution is based on pre-trained VGG16 and ResNet101 models. These models were fine-tuned for specific plant recognition using a dataset of 1000 images from the China Plant Image Bank.

Although deep learning models dominate the reviewed solutions, some of them still employ classical supervised learning methods. Techniques such as support vector machines, the k-nearest neighbors algorithm, and the random forest classifier are often used in combination with traditional feature extraction—such as histogram analysis, color moments, and shape descriptors [37],[38]. For example, in the previously mentioned work by Rasika Gajendra Patil and Ajit More [34], a convolutional neural network was initially applied to the dataset items, but the final classification was determined using a support vector machine classifier. Such methods are often easier to interpret and less demanding in terms of computational resources.

Similar to the use of convolutional neural networks and transfer learning, a commonly observed trend in solutions is the use of semantic or instance segmentation prior to classification in order to achieve better results. In the publication by Gangadevi Ganesan and Jayakumar Chinnappan titled **“Hybridization of ResNet with YOLO classifier for automated paddy leaf disease recognition: An optimized model”** [39], segmentation of diseased leaf regions was performed using K-means clustering. Similarly, in the publications by Muhammad Sharif and co-authors and by Vinay Gautam and co-authors [40], [35], semantic segmentation of the diseased regions was applied. This indicates that, in plant leaf disease diagnosis, it is valuable to use only the regions showing anomalies for classification, rather than the entire leaf instance. However, such an approach is effective only in solutions where the

processed dataset contains images in which each image depicts only a single leaf instance. In the solution described in the publication by Marcelo Vassallo-Barco and co-authors titled **“Automatic Detection of Nutritional Deficiencies In Coffee Tree Leaves Through Shape And Texture Descriptors”** [41], the Otsu thresholding method was used for instance segmentation, however, the publication does not specify the exact accuracy achieved by the proposed method, making it difficult to draw significant conclusions from this study. Instance segmentation is also found in the solution mentioned in the publication by F. Khan and co-authors titled **“A mobile-based system for maize plant leaf disease detection and classification using deep learning”** [37], where the YOLO model family is used. In this context, instance segmentation is applied to identify and classify leaf instances, including their masks, since the dataset images depict multiple leaves. This approach provides high data granularity and allows for the analysis of individual leaves.

Additionally, it should be noted that the analyzed solutions also include image preprocessing methods and various data augmentation techniques. Given the frequent lack of data, different data augmentation methods are used - such as image rotation, zooming, cropping, and others. These methods help reduce the risk of overfitting and improve the generalization ability of the models.[36], [41]

B. Conclusions for the Selection of a Practical Solution

After analyzing and comparing various existing solutions, the author chose to apply convolutional neural networks (CNN) for leaf classification and instance segmentation to separate leaf instances prior to classification in the development of a practical solution. Since the previously mentioned work using YOLO models demonstrated high precision [37], the author selected the YOLO model family for the instance segmentation task and, based on the strong performance of ResNet models [34], chose ResNet models for the classification task. At the same time, it can be concluded that for each plant species, a specifically trained model must be developed because plants differ visually and various diseases may manifest differently. Therefore, the prototype of the study’s solution focuses on only one plant species - blackcurrants - on which the proposed solution is tested.

IV. 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.

A. Informal Description of Solution

The technology is offered to blackcurrant growers to monitor plantations using drones, allowing detection of healthy blackcurrant plants, fungal diseases, and nutritional deficiencies. The system consists of two main functions:

- Mapping: Prepares maps of blackcurrant plantations with the required precision (scale), links them to GPS (Global



Fig. 1. Blackcurrant plantation photo from 5 meters height (row spacing – 4 meters).

Positioning System) coordinates, records drone flight routes, and specifies operations/photography to be performed during flights.

- **Analyze and classification:** Uses trained neural networks to extract blackcurrant leaf clusters from the mapped images. The instance segmentation then identifies individual blackcurrant leaves, which are passed to the classification stage for further analysis. As a result, three types of leaves are identified: healthy leaves, leaves affected by fungal diseases, and leaves indicating nutrient deficiencies. As a result, the study provides a blackcurrant plantation analysis solution that gathers information on plantation conditions and visualizes it for growers, aiding decision-making on necessary interventions.

B. Mapping and Planning of Image Capturing Routes for of Horticultural Areas

The area captured by drones for image analysis is usually significantly smaller than the cultivated field area in horticulture. This is determined by the technical parameters of the drone camera and the scale of the captured images Fig. (1). To obtain complete information about the field, the authors took multiple photographs every 10 meters. Although the images do not fully cover the entire field (each image captures an area of approximately 8×5 meters), they still provide a sufficient overview of the field as a whole, which typically ranges in size from 2 to 20 hectares.

To obtain the necessary images, a drone flight route with a photography plan must be created for each monitored field. The route can be created using the Mission Planner program (web-03). The overall image route is calculated on the basis of the drone's flight altitude and camera parameters (e.g., the angle the camera captures). 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 Fig. 2.

The automatic flight is provided by the Litchi program. It is available on both the computer's website (web-04) to create the route and on mobile phones (web-05) to fly the route.

During the experiments, *Dji Mavic Air 2S* with a 4k camera was used. All pictures were taken from a height of 5m. To



Fig. 2. Drone mission plan: route and photography points

carry out the mission plan shown in Fig. 2 (which covered 2.5 hectares), approximately 15 minutes were required (time may be affected by wind speed), and one drone battery was used (i.e., the flight was continuous).

C. Image Analyzes and Classification

For the analysis of blackcurrant leaf images, the authors have chosen a solution that combines instance segmentation and multi-label classification. Instance segmentation ensures the separation of leaf instances from the background, while multi-label classification assigns each leaf instance to one or more of the predefined classes. For instance segmentation, the authors trained two models from the YOLO family — YOLOv8n-seg and YOLOv9c-seg. For multi-label classification, the authors trained three models from the ResNet family — ResNet-50, ResNet-101, and ResNet-152. Based on the training results, the authors selected one model for each task (instance segmentation, multi-label classification) and integrated the segmentation and classification models to form a unified solution for blackcurrant leaf analysis.

1) Image Acquisition: The authors independently performed the acquisition of specific images used to train the models applied in the proposed solution. All the images used in the training, validation, and test datasets, as described in subsection IV-C3, were captured using a *Nikon D3300 DSLR* camera equipped with a 24.2 MP DX-format CMOS sensor. The images (sample image in Fig. 3) were taken from the same blackcurrant field, capturing photographs from various angles and under different lighting conditions to ensure dataset diversity. This diversity can enhance model training results and improve the robustness of the trained models in non-standard scenarios.

2) Image Annotation: Image annotation for instance segmentation and multi-class classification was performed using



Fig. 3. Image of blackcurrant leaves

various methods to support the formats required by the specific machine learning models.

For the instance segmentation datasets, each image was manually annotated by outlining the contour of each individual blackcurrant leaf instance. Annotation was performed using the open source image and video annotation tool *Computer Vision Annotation Tool (CVAT)*, developed by Intel. The annotations were then exported as point coordinates in the *YOLOv8 segmentation 1.0* format. This type of data annotation is time-consuming as images of blackcurrant bushes contain a large number of leaf instances that must be precisely annotated. Such accuracy is essential for the model to correctly detect and isolate leaves from the background and overlapping objects, which is critical for accurate instance segmentation. One of resulting images is available in Fig. 4)



Fig. 4. Instance segmentation annotation example

For multi-label classification, annotation was performed by isolating individual instances from blackcurrant leaf images using the *Adobe Photoshop* graphic editing software, creating images where each blackcurrant leaf instance was placed against a black background (sample Fig. 5). Each resulting image was then assigned a label indicating its correspondence

to one or more of the predefined blackcurrant health condition classes. The specific classification scheme — which includes the classes: healthy leaves (HL), leaves with nutrient deficiency (NDL), and leaves affected by *Mycosphaerella ribis* (MRL) — was developed in collaboration with an industry expert, based on an assessment of the blackcurrant field available to the author. A more detailed overview of the classes can be found in subsection IV-C3. All image labels were compiled into a structured file containing the image names and their corresponding class assignments.

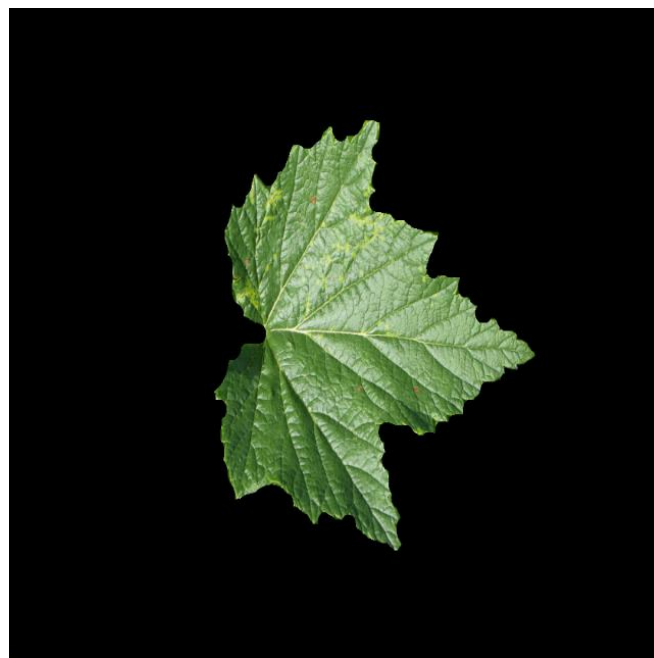


Fig. 5. Multi-label classification dataset example: leaf with nutrient deficiency

3) *Datasets overview*: This work utilizes two main datasets to support different stages of the proposed method: one for multi-label classification and another for instance segmentation. The multi-label classification dataset contains 287 images, each featuring a single blackcurrant leaf against a black background. These images are divided into training (229), validation (49), and test (49) subsets. Each leaf is labeled according to a classification scheme developed in collaboration with an industry expert, categorizing them as healthy leaves (HL), leaves with nutrient deficiency (NDL), or leaves affected by *Mycosphaerella ribis* (MRL). Since a single leaf may exhibit symptoms of multiple classes, a multi-label classification approach is used. The class distribution is provided in a Table I, showing that the total number of labeled instances exceeds the number of images due to overlapping class characteristics.

The instance segmentation dataset comprises 87 images, split into 71 for training and 16 for validation. Each image includes only blackcurrant leaves, and each leaf has been manually annotated with precise contours. This detailed annotation process is resource-intensive but essential, as it enables the

TABLE I
DISTRIBUTION OF CLASS OCCURRENCES ACROSS TRAINING, VALIDATION,
AND TEST SETS

Class	Training (229 images)	Validation (49 images)	Test (49 images)
HL	92	21	19
NDL	85	19	16
MRL	80	14	18
Total Labels	257	54	53

segmentation model to accurately detect and isolate individual leaves from complex backgrounds.

4) *Model training overview*: For the instance segmentation training process, the following models were used: YOLOv8n-seg and YOLOv9c-seg [42]. These were trained using the open-source Ultralytics package in Python [43], which provides an efficient workflow for YOLO models, including automated hyperparameter configuration such as learning rate adjustment based on gradient changes, default use of the Adam optimizer, and automatic batch size selection based on available GPU memory — set to 8 in this case. Each model was trained with three different image resolutions: 256x256, 512x512, and 1024x1024. This approach allowed the author to evaluate model behavior across varying resolutions and assess the impact of image size on instance segmentation accuracy. Based on the training loss analysis, 70 epochs were chosen for the final training.

For the multiclass classification training process, the following models were used: ResNet-50, ResNet-101, and ResNet-152. These models were implemented using the PyTorch machine learning library in Python and initialized with default pretrained weights to leverage feature representations learned from large-scale datasets. The final fully connected layer of each ResNet model was replaced to enable prediction of three target classes, making them suitable for the classification of disease instances on blackcurrant leaves. Input images were resized to 256x256 pixels and transformed into tensors for model processing. The models were trained using the BCE-WithLogitsLoss loss function, combining Sigmoid activation with binary cross-entropy for numerical stability in multiclass tasks. The Adam optimizer was chosen for its ability to dynamically adjust learning rates and incorporate momentum. To identify optimal hyperparameters, a grid search was conducted over the number of epochs, learning rate, and batch size for each ResNet variant. The best-performing configurations were: 70 epochs, a learning rate of 0.0001, and batch sizes of 16 (ResNet-50 and ResNet-152) or 8 (ResNet-101).

5) *Model training results*: The training results of the instance segmentation models YOLOv8n-seg and YOLOv9c-seg are summarized in Tables II and III, showing their performance across different image resolutions (256x256, 512x512, 1024x1024). Both box (B) and mask (M) performance metrics were evaluated, including mAP50, mAP50-95, and precision (Pre), which together assess the models' ability to localize and delineate object instances at the pixel level. The results indicate that YOLOv9c-seg consistently outperformed YOLOv8n-

seg.

across all tested resolutions and metrics. The highest performance was observed at the highest resolution (1024x1024), where YOLOv9c-seg achieved mAP50 values of 0.72130 for boxes and 0.69930 for masks. Additionally, an increase in input image resolution correlates with improved model performance for both architectures, emphasizing the significance of higher resolution imagery in enhancing segmentation precision. This is particularly important within the context of this study, where precise delineation of blackcurrant leaf instances from the background is essential for subsequent classification tasks. Nonetheless, the results are not without limitations, likely attributable to the relatively small size of the training dataset employed.

TABLE II
YOLOv8N INSTANCE SEGMENTATION RESULTS

Model	YOLOv8n-seg		
Image size	256x256	512x512	1024x1024
mAP50 (B)	0.59164	0.65656	0.67211
mAP50-95 (B)	0.38272	0.49653	0.52423
Pre (B)	0.67455	0.73628	0.74736
mAP50 (M)	0.58450	0.65931	0.66956
mAP50-95 (M)	0.34303	0.47840	0.51023
Pre (M)	0.74249	0.76106	0.75789

TABLE III
YOLOv9C-SEG INSTANCE SEGMENTATION RESULTS

Model	YOLOv9c-seg		
Image size	256x256	512x512	1024x1024
mAP50 (B)	0.64149	0.68866	0.72130
mAP50-95 (B)	0.46194	0.54670	0.68643
Pre (B)	0.74662	0.87470	0.88182
mAP50 (M)	0.65124	0.69849	0.69930
mAP50-95 (M)	0.47340	0.51147	0.53121
Pre (M)	0.72102	0.79023	0.81230

Table IV summarizes the training performance of three ResNet architectures (ResNet-50, ResNet-101, and ResNet-152) on a multi-label classification task. Among the evaluated models, *ResNet-152* achieved the highest overall performance, with accuracy, sensitivity, specificity, and precision reaching 94.0%, 96.7%, 98.8%, and 98.2% respectively. *ResNet-101* also demonstrated strong results, attaining 93.1% accuracy and 96.5% precision, while *ResNet-50* showed slightly lower accuracy (89.6%) but competitive sensitivity and precision,

and even outperformed *ResNet-101* in specificity. The results suggest that increasing model complexity yields diminishing returns, as the simpler *ResNet-50* architecture delivered satisfactory performance. The similar metric values across architectures imply that dataset characteristics, such as size and class distribution, may exert greater influence on model efficacy than network depth. Consequently, *ResNet-50* offers a favorable balance between accuracy and computational efficiency, making it a practical choice for this classification task.

TABLE IV
MULTI-LABEL CLASSIFICATION RESULTS TABLE

Model	ResNet-50	ResNet-101	ResNet-152
Acc (%)	89.6	93.1	94.0
Sen (%)	91.3	94.8	96.7
Spe (%)	98.2	98.1	98.8
Pre (%)	91.3	96.5	98.2
Epochs	70	70	70
Batch size	16	8	16
Lr	0.0001	0.0001	0.0001

Summarizing the instance segmentation and multilabel classification model training results, the authors selected YOLOv9c-seg for instance segmentation and ResNet-50 for multilabel classification as the final practical solution.

V. HISTORY OF FIELDS

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.

However, this study 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 visual tracking of field changes over time while also providing timely detection of plant health issues identified through image analysis.

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,
- analyze the images to identify plant health issues,
- visualize the extracted information on a map for better interpretation and decision-making.

The results of the image analysis conducted on a single day are presented in Fig. 6. As shown, within the selected location, 6.51% of the identified leaves were classified as diseased, 0.38% exhibited signs of nutrient deficiency, and 93.10% were determined to be healthy.

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



Fig. 6. Blackcurrant field condition analysis result

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. Even if the captured images do not cover the entire field area, their number is sufficiently large, and storing historical images can be space-intensive, considering that blackcurrant plantations typically cover between 2 to 20 hectares. Moreover, analyzing such a vast number of images is time-consuming as it involves identifying and classifying thousands of leaves.

The problem can be partially solved by increasing the decreasing of the image capture grid, e.g., from 10 to 20 meters. A similar approach is used in the evaluation of soil fertility, where the sampling is carried out systematically at predetermined intervals. In this case of 20 meters, 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.

VI. 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 plant 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 analyzing 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 analyzing different plant parts, segmenting them in images, and classifying them based on the specific problem being addressed.

A. 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 labor 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.

B. Limitations of the Method's Application

When analyzing 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 diagnosis of nutrient deficiency. However, this requires more complex imaging cameras.

In addition, leaves are only one indicator of plant health, but they do not reveal all potential problems. 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.

VII. CONCLUSIONS

Key conclusions of the conducted research and its application results:

- 1) Blackcurrant plantation monitoring is recommended to be carried out in two stages: (1) field mapping – capturing plantation field images with the required precision; (2) image instance segmentation and multi-label

classification – an instance segmentation model extracts individual leaf instances from the mapped images, and a multi-label classification model employs a trained neural network to identify fungal diseases and nutrient deficiencies by assigning one or more class labels to each leaf.

- 2) Mapping functions can be implemented using standard solutions available in commercial drone systems or by adapting open source solutions for blackcurrant cultivation. Segmentation solutions must be developed individually in collaboration with industry experts, in the case of this project, 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 final goal of the project and is of interest to horticulturists.
- 3) The final result consists of blackcurrant field images that visually distinguish between healthy areas, fungal disease-affected zones, and nutrient-deficient regions. The field history application provides horticulturists with an intuitive tool to monitor blackcurrant crop development over time
- 4) Scientific literature and practical experience confirm that drone-based plant condition monitoring is effective. Collected crop image datasets have significant potential for machine learning applications.

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

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