INTELLIGENT MONITORING OF THE PHYSIOLOGICAL STATE OF AGRICULTURAL PRODUCTS USING UAV

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The article discusses the technology for automated neural network monitoring of the vineyard's physiological condition. Images of leaves, obtained using an unmanned aerial vehicle (UAV), are the main indicator of the physiological vineyard's condition. The proposed solution is based on the integrated use of convolutional neural network method (CNN) and machine vision technologies. To determine the optimal neural network (NN) model, a variant analysis was carried out. In accordance with its results, the YOLOv7 model was chosen, which satisfies the introduced time limit and provides the required detection quality. The training of the YOLOv7 neural network was implemented in the Python environment using the PyTorch framework and the OpenCV computer vision library. The dataset consisting of 6320 images of grape leaves (including healthy and diseased ones) has been used for neural network training. The obtained results showed that the detection accuracy is at least 91%. Visualization of monitoring results has been carried out using heatmap, allowing to obtain information about vineyard physiological condition in dynamics. The proposed mathematical model allows to calculate the monitored vineyard's area made by one complex per day. The obtained results showed that effective monitoring area using one DJI Phantom 4 UAV per day is 2.5 hectares.

KEYWORDS

classification, CNN, machine vision, object tracking, physiological condition, risk monitoring, UAV, vineyard

1 INTRODUCTION

Mechatronic and robotic assistance systems are currently frequently used systems for facilitating human activity in several areas. These are mainly areas that are extremely laborious and require physical activity, areas that are dangerous for people and areas where there is a shortage of labor [Kuric 2011, Bozek 2012, Koniar 2014, Abramov 2015, Mascenik 2016, Peterka 2020, Klarak 2021, Liu 2021, Orchi 2021, Peng 2021, Fraiwan 2022, Lin 2022b, Pandian 2022, Huang 2023, Vagas 2023, Patiluna 2024].

In today's demanding and worsening climate conditions, growing agricultural crops is an extremely difficult task. There are a large number of risks and threats that cause huge losses in agricultural engineering. These are mainly unsuitable and deteriorated climatic conditions, lack of irrigation, animal and insect pests, diseases, molds, fungi and physiological damages and others. However, a serious problem is also the lack of workers who could carry out interventions and work activities in agriculture. Therefore, there are many research teams working on the applications of automation, robotics and digital-enabled manufacturing technology in agriculture.

The basic goal is to ensure a sufficient yield of agricultural crops with the support of innovative farming techniques. By applying these innovative technologies, it is also possible to achieve early detection of problem conditions and thus to decide on timely intervention in cultivation and thus to reduce losses with lower consumption of chemical substances in the cultivation process [Karpina 2016, Urban 2021, Kaur 2022, Oliveira 2024, Ortiz-Torres 2024, Zvezdina 2024].

This article is focused on the viticulture segment, which is extremely labor-intensive and errors that could occur in activities in this sector could mean huge losses in agricultural crop yields.

The main goal of introducing digital technologies in viticulture is to ensure high yields of high-quality table and technical grapes by minimizing and optimizing human labor [Sassu 2021, Egorov 2022]. In particular, these technologies make it possible to automate the processes of collecting and analyzing information on growing grapes, as well as controlling and optimizing the processes of cultivating and caring for grapevines through the implementation of effective monitoring technologies [Ammoniaci 2021, Tardaguila 2021].

The development and reduction in cost of UAV technologies have made it possible to increase effectiveness of local monitoring and control for agricultural cultivation purposes [Mahlein 2016, Tsouros 2019]. In agriculture, UAVs are used for various applications viz. remote monitoring [Navia 2016, Arroyo 2017, Di Gennaro 2016, Honrado 2017, Matese 2017a, Matese 2017b], biomass production monitoring [Matese 2018], weed spreading detection, disease detection [Di Gennaro 2017] and others. To achieve these goals, UAVs are equipped with specific devices such as video, multispectral or infrared cameras, and optionally, high-performance computing devices that allow resource-intensive calculations to be performed directly onboard, for example, neural network image processing. The use of UAV-mounted devices enables the automation of processes to determine the phytosanitary condition and biophysical characteristics of vine plantations based on photo and video data. Additionally, they are effectively utilized to calculate relative vegetation indices [Kerkech 2018, Matese 2018] (for example, NDVI, EVI, GNDVI, CVI, ExGR, GRVI, NDI, RGI and others) and for neural network detection of visual symptomatic reactions caused by various negative factors [Kerkech 2018, Tardif 2023].

Timely detection of grapes damage signs made by diseases is a very actively developing area of scientific research [Di Gennaro 2017, Albetis 2017] owing to the fact that timely detection will prevent the possible grapevine blight, increase the quantity and quality of products, and also localize disease foci. A large number of early methods for determining the physiological condition of grapes are based on the calculation of vegetation indices, biophysical parameters and extracting of spectral channels from hyperspectral images. However, they have a number of limitations [Kerkech 2018]. Partial overcoming of these limitations is possible through the analysis of visible symptomatic reactions which are manifested in the form of changes in color, shape and size of leaves.

In most practical cases disease monitoring is done by visual inspection using human labor [Liu 2021]. However, such an approach is time-consuming and constrains implementation of routine monitoring. More challenging way is to develop an evidence-based automated system of operational vineyard-scale monitoring of diseases and biorisks. At this time, the state-of-the-art CNN is believed to be the most effective approach to solve this scientific problem due to its wide-spread implementation in object detection problem [Wu 2020], face recognition [Herrmann 2016], action recognition [Chen 2018], weed detection [Bah 2018], plant disease identification [Saleem 2019], yield estimation [Yang 2019], and precise crop classification [Zhong 2020].

The primary goal of the present study is to develop the method, technique and algorithm for vineyard-scale detecting visible symptomatic reactions on grape leaves using CNN.

The main contributions of this article can be summarized as follows:

(1) Development of new techniques and methods based on data collection and processing procedures to be performed on separate hardware devices (UAV and PC). This approach allows the use of stationary GPU-based computing devices to perform demanding calculations.

(2) The YOLOv7 model provides a good balance of accuracy and computational efficiency for grape leaf detection with more than 90% mAP. This indicates that state-of-the-art deep learning methods can successfully detect foliage in a variety of field conditions. Using the Deep SORT algorithm for object tracking significantly reduced false alarms by avoiding re-counting leaves in overlapping frames. This step is critical to getting an accurate assessment of vine health over time.

(3) The ability to dynamically monitor the state of the vineyard during the growing season allows growers to respond promptly to biotic and abiotic stresses. In terms of scalability, the study found that a single UAV computer setup could effectively survey 2.5 hectares per day. This paves the way for adoption by small to medium-sized vineyards.

The remaining sections of this paper are organized as follows: Section 2 presents description of the test site, a basic algorithm of UAV-based monitoring, reasoning of an optimal CNN architecture, as well as characteristics of a test bench and procedure of the dataset creation. Section 3 is dedicated to variant analysis of CNN architectures to be used in UAV-based monitoring, NN training peculiarities and the results of UAV-based monitoring reinforced with CNN application. In section 4, discussion about obtained results is given in this paper part. Section 5 summarizes this work and also future research plans are also presented.

2 MATERIALS AND METHODS

2.1 Description of the site under study

Testing of the technology was carried out on the vineyard of the JSC "Agrofirma Chernomorets", which is situated in Crimea Republic, Bakhchisaraysky district, Uglovoye village (Fig. 1). The general view of the vineyard on which the video mate-rials were collected using UAV. Area of the plot is 72 ha, cultivar is black Pinot, planting date is 2007. Planting scheme is 3x3 (0.3) m, formation is one-sided cord, high stem, free-hanging shoot, rootstock is Berlandier x Riparia Caber-net 5BB. Non-covered, drip irrigation system.

Soil types in plots are ordinary black earth mycelar-carbonate foothills. The humus layer is 80 - 90 cm deep. The humus content of the upper layers is 2.9–3.6%. Total nitrogen content ranges from 0.21% to 0.3%. Hydrolyzable nitrogen content is 5 – 11 mg/100gr, which indicates the high availability of mobile nitrogen. The phosphorus content ranges between 0.07% and 0.16%. Mobile phosphorus content ranges from 0.5 to 6 mg/100 grams. The total potassium content in carbonate-rich chernozem ranges from 1.1% to 2.6%, and the mobile content ranges from 16 to 43 mg/100 grams. The absorption capacity in the upper horizons equals 32–39 mg-eq. The profile of micel-lar-carbonate chernozems was leached from water-soluble salts to a depth of 150–200 cm and more. Salinization at these depths is sulfate-calcium.

2.2 Description of the site under study

In order to achieve the goal, we suggest using technique based on application of an automated device for monitoring vineyards enhanced by NN method for detecting objects. Comprehensive analysis of implementation of a high-performance computing module for NN processing of video data showed that the most promising solutions are the following:

1. Allocation of high-performance computing module directly on board of the UAV. This variant allows to process the video stream from the UAV camera directly during the flight [Halawa 2017, Bokovoy 2019, Suzen 2020]. However, this variant negatively affects the weight and size characteristics and power consumption of the UAV. Also, this variant limits the flight speed due to the low processing speed of video stream frames. It is possible to increase the speed of flight and processing of the video stream by implementing a high-performance computing device based on programmable logic device (PLD), but this solution is rather expensive.

Figure 1. Vineyard of JSC "Agrofirma Chernomorets"

2. Performing NN data analysis on a stationary high-performance computing device [Ampatzidis 2020, Aposporis 2020]. In this variant the UAV is used only for collecting video data and does not directly participate in data processing. This variant will significantly reduce the cost and speed up data collection. This is due to the fact that the UAV will not carry additional load.

The analysis of the variants described above showed that the second variant is optimal for automated vineyard-scale monitoring of physiological condition and potential biohazard. This is due to the fact that it is not required to solve this problem in real-time.

The general scheme of UAV-based monitoring is shown in Fig. 2. In accordance with the technology, the UAV must fly over each row of the vineyard at least three times in order to capture grape leaves from three different views: right side, left side, top. The video footage is transferred to a high-performance computing device with an installed program for automatic classification of diseased grape leaves.

The program automatically counts a number of diseased grape leaves in the frame. In accordance with the obtained values, visualization is performed in the form of a heat map, which is presented as a separate layer in GIS. On the map the color of each point corresponds to the number of diseased grape leaves counted by the NN and is linked to the coordinates where the UAV was shooting the corresponding frame. This procedure is necessary for synchronizing the video file and the log of the GPS tracker installed on the UAV.

2.3 Variant analysis of NN models

For the correct operation of the automated device, it is important to choose a NN architecture that will allow the most accurate detection of diseased grape leaves. To solve this problem, CNN was chosen as that architecture [O'Shea 2015].

This choice can be argued that the NN of this architecture demonstrates the highest efficiency of object recognition in images compared to alternative architectures [Russakovsky 2015, Gu 2018, Kuznetsov 2021, Kuznetsov 2022]. Currently, a large number of learning models based on CNN have been developed: YOLO, EfficientDet, ResNet, and many others [Jiang 2017, Pham 2020, Zheng 2020, Lin 2022a].

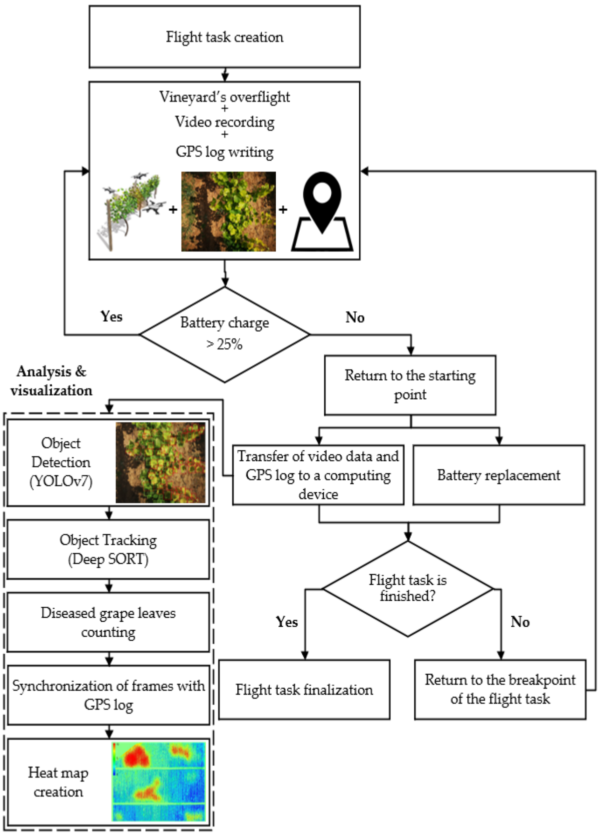


Figure 2. Process of monitoring vineyards using UAV and NN

We carried out a variant analysis, as a result of which the most popular NN models were analyzed for the speed and precision of diseased grape leaves detection. To assess the quality of the selected NN models and compare different algorithms, the following metrics (quality criteria) were used:

1. Complete Intersection over Union (CIoU) is a loss function that estimates the scale of the aspect ratio of a bounding box, taking into account the overlap area of the boxes, the distance between the center points, and the aspect ratio [41]:

$$loss_{CIoU} = 1 - IoU + \frac{l_1^2}{l_2^2} + \alpha v, \quad (1)$$

where l_1 is the Euclidean distance between the centers of the boxes of the detected and target objects; l_2 is the length of a diagonal of the detected box; α is a balancing factor (1); v is the coefficient of proportional consistency between the boxes of the detected and target objects (2).

$$\alpha = \frac{v}{(1-IOU)+v}, \quad (2)$$

$$v = \frac{4}{\pi^2}\left(arctan\frac{w^{gt}}{h^{gt}} - arctan\frac{w}{h}\right)^2, \quad (3)$$

where w^{gt} and h^{gt} are the width and height of the target box; w and h are the width and height of the detected object box.

2. Precision is a metric that reflects the proportion of objects correctly detected by the classifier [Ahmad 2020] and calculated by the equation:

$$P = \frac{TP}{TP+FP} \times 100\%, \quad (4)$$

where *TP* (True Positive) is the number of objects correctly detected by the classifier; *FP* (False Positive) is a classification error that characterizes the number of erroneously detected objects by the classifier.

3. Recall (completeness) is a metric that reflects the proportion of objects of the target class correctly detected by the classifier from all objects within images to be analyzed. In other words, this metric shows how well the NN algorithm finds expected objects [Yacouby 2020, Karrach 2020]:

$$R = \frac{TP}{TP+FN} \times 100\%, \quad (5)$$

where: *FN* (False Negative) is the classification error characterizing the number of objects erroneously not detected by the classifier.

4. Average Precision is a metric that calculates the average value of the precision for the Recall metric in the range from 0 to 1 [Pham 2020, Zheng 2020] and can be calculated as:

$$AP = \int_0^1 P(r)dr, \quad (6)$$

where $P(r)$ is the dependence function of Precision on Recall (completeness).

5. Mean Average Precision (average *AP*) is a metric that characterizes the average *AP* for each class [Wang 2019, Li 2020]:

$$mAP = \frac{1}{n}\sum_{i=1}^{n} AP_I, \quad (7)$$

6. *F*1 score is a metric characterizing the average harmonic value between Precision and Recall [Chicco 2020]:

$$F1 = 2 \times \frac{P \times R}{P+R}, \quad (8)$$

The above metric can be used for qualitative assessment of the effectiveness of detection made by NN algorithm. However, solving the proposed problem requires not only high-quality detection and classification procedures, but also their operational implementation. This is due to the fact that the period of NN processing of video footage captured during one UAV flight should not exceed the total time (t_{Dur}), taking into account the shooting, transmission of video data to the server and replacement of the battery for the next stage of UAV flight. Thus, one may evaluate the effectiveness of NN models taking into account the duration of NN processing (t_i) and the quality of the obtained results (evaluated using the F_i metric) by using equation:

$$S_i = \begin{cases} F1_i, under\ t_i < t_{Dur}, \\ 0, t_i \geq t_{Dur}; \end{cases}, \quad (9)$$

where S_i is the rating score of *i*-th model.

The duration of video file for model testing is 1800 seconds and has frame rate 25 fps and resolution 1080p. This duration is determined by the technical characteristics of the DJI Phantom 4 RTK UAV, which determine the autonomy of its operation. Testing was carried out on a hardware platform based on the NVIDIA GeForce RTX2080 GPU, Intel Core i5-8400 CPU, 16Gb RAM. Measuring the average total time spent on operations, including flying the DJI Phantom 4 UAV, copying the video file, replacing the battery, loading the next stage of the flight task, and performing operating procedures from the UAV, showed that t_{Dur} is about 3600 seconds. Thus, we consider NN models that process a test video file longer than this time to be unacceptable.

When comparing different NN models, it is necessary to adhere to the same training conditions. This was done by ensuring the best quality of training of various NN training models using the same dataset and computing device. After passing through all training epochs, the version of the model that demonstrates the best training quality parameters was selected.

2.4 *Object tracking*

To assess the vineyard-scale physiological condition, it is not enough to implement the Object Detection procedure. This is due to the fact that the detection of the same leaves will be carried out on several frames of the video sequence and will depend on external environmental factors and the UAV flight mode. Thus, the count of diseased leaves will not be correct. To solve this problem and, consequently, to improve the quality of monitoring, an object tracking method should be additionally applied (Object Tracking) [Dhillon 2020, Kapania 2020]. The integrated use of Object Detection and Object Tracking technologies allows to ignore already detected objects, which significantly reduces the number of repeated and false positives.

The Object Tracking technology is based on SORT (Simple Online and Realtime Tracking) or Deep SORT algorithms, which are used to track detected objects [Bozek 2020]. As part of the study, the Deep SORT algorithm is used, since it allows you to identify previously detected objects even after they have been lost from the frame for a long time. This feature of the Deep SORT algorithm is achieved through the use of two mathematical methods - the Mahalanobis distance [64] and the Kalman filter (4) [64]. The Mahalanobis distance is used to determine the similarities between known and un-known weights of objects detected by the NN. Kalman filter is often used to eliminate noise and emissions in previously defined weighting factors.

$$d(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_n - q_n)^2} = \sqrt{\sum_{k=1}^{n} (p_k - q_k)^2}, \quad (10)$$

where $d(p, q)$ is the distance between points p and q.

$$L = \lambda D_k + D_a(1 - \lambda), \quad (11)$$

where L is the distance from a certain object to the one calculated by the Kalman filter; λ is the regularization coefficient; D_k is the Mahalanobis distance; D_a is the distance by external similarity.

2.5 *Dataset creation*

In order to solve the problem, it is advisable to use photos of grape leaves as initial data when forming a dataset. The labeled dataset allows to train NN in order to recognize and classify objects of interest within images with prefixed values. In light of the automated monitoring, it is recommended to use UAV video recording, it is also advisable to use storyboarded video materials of flying around the vineyard rows as a data set for training a NN. At the same time, practice of video filming has shown that when creating a dataset, it is necessary to take into account features associated with the actual operation of the UAV:

1. When flying in rows, it is necessary that video recording of grape plants should be carried out by an unmanned aerial vehicle camera at a distance of one to two meters at a camera installation angle of 90° to 105° in the horizontal plane.
2. When flying an unmanned aerial vehicle directly over a row, video recording of grape plants should be carried out at a height of no more than three meters at an angle of 90° to 100° in the vertical plane.
3. When recording video, the automatic exposure function must be turned off in the UAV camera. This procedure is necessary to preserve the details in the light and dark areas of the image under different lighting conditions. Video recording of grape plants should be carried out on a clear day with a wind speed of no more than 4 m/s.

Training NN on the generated dataset requires its preliminary preparation, called markup, or image annotation. This process allows to attach metadata to each dataset image that carries information about the properties of objects (class names, object location on the image, etc.). The main complexity of this procedure is inevitable manual marking of all objects in the images. An expert need to highlight the objects of interest on image. The correctness of object recognition by the NN will significantly depend on the quality of the annotation. In view of this, it is necessary to fully select all objects of interest on the photo. If necessary, objects are periodically omitted or incorrectly selected, the NN will not be able to identify all the patterns required or will identify them incorrectly. During pro-cessing, the NN will independently find patterns in the intensity of pixel color channels, their alternation, etc.

Labeling (annotation) of images of grape leaves was carried out using the LabelImg tool (https://github.com/tzutalin/labelImg).

The YOLOv7 NN was trained in the Python environment using the PyTorch 1.13.1 framework and the OpenCV 4.7.0.72 computer vision library. The following parameters were used to train the NN model: number of epochs was 150, batch-size was 7, input image size 640×640, optimizer - stochastic gradient descent (SGD). Training was performed using the CUDA 11.6 hardware-software architecture of parallel computing and cuDNN 8.9.1 library for training NN.

2.6 *Test Bench*

To test the technology in the vineyard, a DJI Phantom 4 quadcopter UAV was used. This UAV has an average flight duration of 30 minutes. It is equipped with a video camera mounted on a gyrostabilized suspension. Camera specifications: sensor – 1/2.3'' CMOS, 12.4 × 106 effective pixels; lens - FOV 94° 20 mm (35 mm format equivalent) f/2.8. In the experiment, the video recording mode (FHD 1920 × 1080, 24 fps) was used.

The test bench was equipped with a high-performance computing device based on the NVIDIA GeForce RTX2080 GPU, Intel Core i5-8400 CPU, 16Gb RAM has been used. To implement an interactive map, a developed GPS tracker was attached to the UAV. The block diagram of the GPS tracker is shown in Fig. 3.

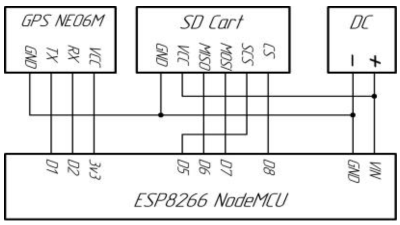


Figure 3. Structural diagram of a GPS tracker

ESP8266 is used as the main microcontroller. To obtain geospatial information, the measuring module has a GPS receiver based on the NEO-6M-0-001 chip based on the Ublox NEO-6M STM chip. This module is a stand-alone GPS device with a high-performance u-blox 6 positioning processor. To communicate with the microcon-troller, a UART (TTL) interface is used with a supported baud rate from 4800 to 230400 baud, 9600 baud by default. The log with geotags is recorded on a microSD memory card. For this, a specialized microSD card module is used, which is connected to the microcontroller via the SPI interface.

3 RESULTS

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

3.1 *Dataset*

Up to 6320 photos of grape leaves (including healthy and diseased ones) were used to form training, test and validation datasets in proportion of 75%, 20% and 5% correspondingly. Examples of photos from the training dataset are shown in Fig. 4.

Figure 4. Photos from the training sample

3.2 *Variant analysis*

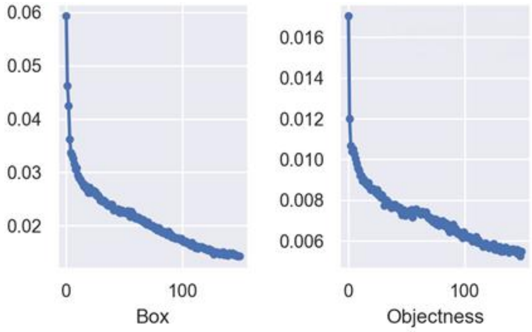
The results of the variant analysis are presented in Table 1. They showed that the YOLOv7 algorithm is the most optimal for the detection and classification of diseased grape leaves.

Table 1. Results of Variant Analysis of NN Models

Model name	mAP %	P %	R %	F1 %	t s	S
YOLOv7	96	95	99	97	3330	97
EfficientDet -D2	86	88	89	89	3150	89
EfficientDet -D1	86	73	89	80	2250	80
YOLOv5	85	72	87	79	3555	79
MobileNetv2_140	91	55	91	69	1980	69
EfficientDet -D0	87	53	88	66	2025	66
EfficientDet -D7	94	99	96	97	16065	0
ConvNeXT_basw_in22k	90	73	92	82	15030	0
RegNety_008	95	62	98	76	6525	0
ResNetv2 152x2 bitm in21k	93	61	91	73	4770	0
ViT_large_r50_s32_224	82	67	81	73	16200	0
YOLOv3	97	57	95	71	4950	0
DenseNet-161	80	60	83	70	7110	0
BAT_ResNext26ts	84	58	87	70	7650	0
Gluon_Xception65	85	55	83	66	11250	0
SPNASNet_100	79	53	82	65	5400	0

3.3 *NN Training*

Fig. 5 shows charts illustrating the training quality of the NN model depending on epochs. In this experiment of training diseased grape leaves using the YOLOv7, the mAP_curve, PR_curve, P_curve, R_curve etc. metrics were used during the model training process. It is noticeable that the metrics describing the average value of mAP go into saturation. It indicates that the NN has successfully trained on the prepared dataset.



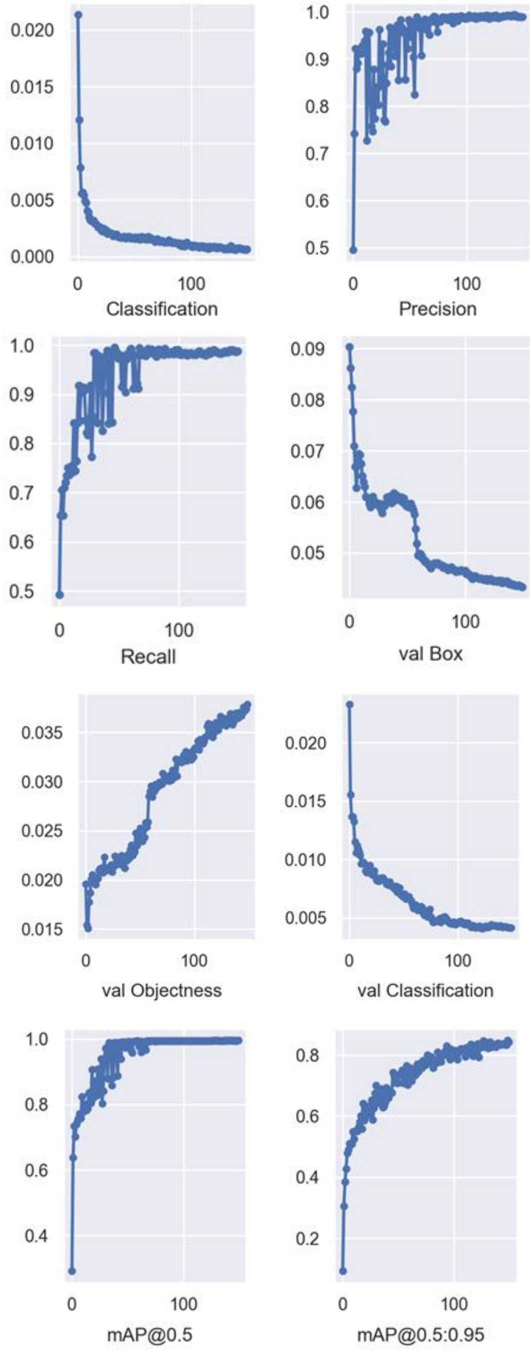


Figure 5. Charts of metrics dependence on NN training epochs

3.4 *Detection results using heatmap*

The next step after the successful training and testing of the NN was practical use for the detection and classification of diseased grape leaves. The trained and tested NN was already capable for detecting typical diseases of the vineyard (Fig. 6), however, for greater clarity and ease of interpretation of the results, we decided to create an inter-active map of the vineyard.

An interactive map allows one to display the detection results in the form of points on the map (geotags) with a photo and a number of detected disease foci, which may help the vineyard staff to locate the problem area. Also, displaying a photo with a detected problem will allow one to eliminate possible false positives at an early-stage triggering. If necessary, the final file with geotags can be loaded into the navigator to plot the route to the problem area.

In the process of implementing the procedure for NN processing of video materials, a log is formed containing the frame time and the number of diseased leaves detected by the NN. Visualization of vineyard-scale physiological condition is made in the form of a heat map (Fig. 7), the input data for which are synchronized logs of NN processing and a GPS tracker (with combined timestamps).

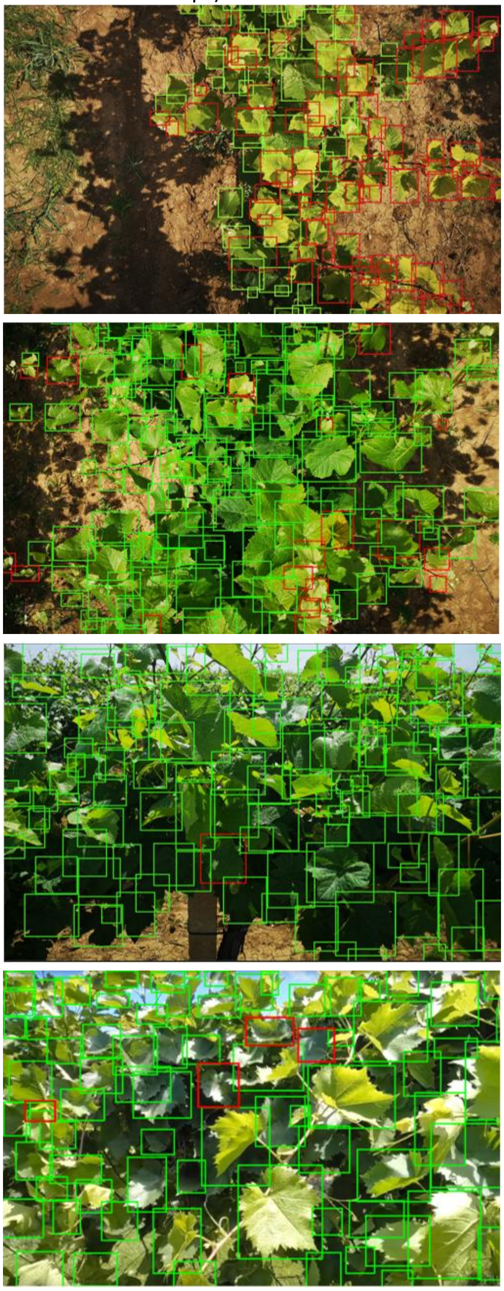
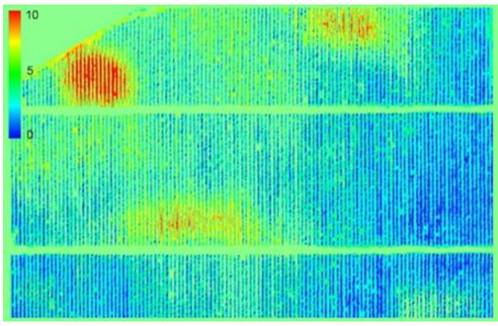


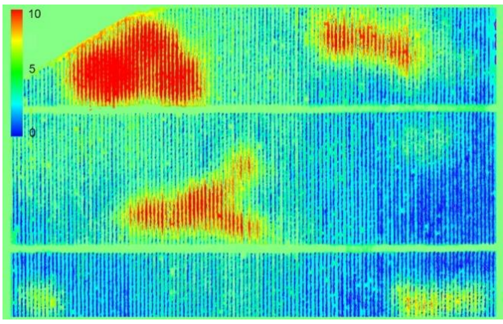
Figure 6. Results of detection of diseased grape leaves

The interactive map allows service personnel to quickly obtain information about physiological condition not only in static, but also in dynamic mode. The presence of problem areas in the studied part of the vineyard is visualized by means of different colors of markers in accordance with the number of detected diseased leaves. The red areas on the interactive map indicate that the NN algorithm determined the proportion of diseased leaves to be more than 10%.

The heatmap on Fig. 7 was derived after launching the flight mission of UAV-based monitoring reinforced by CNN for the vineyard of the JSC "Agrofirma Chernmrets" (Crimea) in June and July, 2023, respectively (A and B). Calculations showed that when using computing equipment based on the RTX2080 GPU and the DJI Phantom 4 UAV, the effective monitored vineyard area per day is 2.5 hectares.



A



B

Figure 7. Interactive heatmap of the vineyard-scale physiological condition obtained with a time interval of one month A – in June 2023; B – in July 2023

4 DISCUSSION

The study demonstrates how UAVs enhanced with CNN can be used to monitor the physiological condition of vineyards. The proposed approach builds on existing technologies that diagnose grapevine diseases from leaf images using CNNs [Li 2020, Peng 2021, Fraiwan 2022, Kaur 2022, Lin 2022b]. Most existing methods for detecting grape diseases using CNNs focus on analyzing images of individual leaves without the use of automated imaging techniques [Orchi 2021, Lin 2022b, Pandian 2022, Huang 2023, Sharma 2023]. In other words, the initial data for disease classification are presented as images of individual grape leaves. The limitations of the proposed methods restrict the possibility of effective monitoring of entire vineyards. Additionally, to implement these methods, mainly lightweight CNN models (MobileNet, ShuffleNet, YOLO-tiny, etc.) are utilized. The use of lightweight versions of CNN models is necessitated by the performance limitations of mobile computing devices. To overcome the constraints of the aforementioned methods, a new approach is required [Kuric 2011]. It must efficiently detect and count leaves captured under different conditions and minimize the chance of re-counting previously detected leaves. The solution to these challenges necessitates much more computationally intensive processes. In the present study we demonstrated a new technique and methods based on data collection and processing procedures to be performed on separate hardware devices (UAV and PC). This approach enables the utilization of stationary GPU-based computing devices to perform intensive computations.

Competitive distinction of the proposed approach is that it can evaluate not only individual leaves, but the whole vineyard. This approach is less accurate in determining the disease of specific vines, because the resolution of individual leaves on the analyzed image is lower, and not all leaves are in the frame, so some diseased leaves may be missed. However, this approach allows tracking the disease spread dynamics and detecting disease outbreaks early.

Additionally, several key findings can be highlighted from this work. First, the YOLOv7 model was shown to provide a good balance of accuracy and computational efficiency for grape leaf detection, with over 90% mAP. This indicates that state-of-the-art deep learning methods can successfully detect foliage under variable field conditions. Second, the use of the Deep SORT algorithm for object tracking significantly reduced false positives by avoiding re-counting of leaves in overlapping frames. This step is critical for getting an accurate assessment of vineyard health over time.

The interactive heatmap visualization tool provides a user-friendly format to view results and identify problem areas that require attention. The capability to monitor a vineyard status dynamically over a growing season enables growers to respond promptly to biotic and abiotic stresses. In terms of scalability, the study found that a single UAV-computer setup could effectively survey 2.5 hectares per day. This paves the way for adoption by small to mid-sized vineyards.

Some limitations should be noted. The image dataset, while substantial at over 6000 images, was collected from a single vineyard. Expanding the diversity of grape varietals and diseases would help improve model robustness. Data augmentation techniques could also be utilized to increase the number and variability of training images. In addition, optimizing flight patterns and image acquisition parameters could potentially increase the survey area covered per UAV sortie.

5 CONCLUSIONS

The developed technology of automated vineyard physiological condition monitoring based on UAV and object detection algorithm YOLOv7 aimed to ensure high yields of high-quality table and technical grapes by minimizing and optimizing human labor. As an indicator of the physiological state, images of grape leaves obtained with the help of UAVs were used. For automated classification of leaves, it is proposed to use deep learning CNN. The results of testing the precision detection of diseased leaves by a trained NN showed that the mAP value is less than 91%, which is sufficient to identify problem areas. Visualization of the vineyard-scale physiological condition is made in the form of a heatmap. The proposed technology makes it possible to use stationary GPU-based computing devices to perform resource-intensive calculations and shows rather good results in diseased leaves detection even in hard shooting conditions: variable lighting, complex background, partial overlap of leaves. The integrated use of Object Detection and Object Tracking technologies allows to ignore already detected objects, which significantly reduces the number of repeated and false positives.

Overall, this work demonstrates proof-of-concept for an intelligent UAV-enabled system to monitor vineyard health. The capacity to detect foliar abnormalities in a rapid, comprehensive and automated manner would be a valuable precision viticulture tool.

Future research could explore incorporating multispectral or thermal imagery to complement visual disease detection. The system could also be extended to estimate additional physiological parameters, such as crop yield. This study provides a foundation to build upon with deep learning and robotics technologies in agriculture [Hortobagyi 2021].

Implementation of the technology into the production process of agro-industrial enterprises will effectively detect and promptly eliminate diseases in the early stages, which will positively affect the yield of products, as well as reduce the possible financial risks of the enterprise. Also, the proposed solution is the basis for creating a decision support system to protect grapes from diseases and assessing biotic risks in vineyards. Monitoring biotic risks will allow winegrowers to prevent the spread of pests and diseases, thereby improving the sustainability and resilience of vineyards.

There are many areas where mechatronic assistants and artificial intelligence techniques can be used. These are industrial areas and engineering designs, but also in the area of common products such as household items, medical devices, work tools, equipment for sports and other areas [Ostertag 2014, Virgala 2014, Pivarciova 2016, Qazizada 2016, Wojke 2017, Saga 2019, Bozek 2020, Kelemen 2021, Kelemenova 2021a,b, Kuric 2021 & 2022, Li 2021, Suder 2021, Zelnik 2021, Lestach 2022, Mikova 2022, Ruzarovsky 2022, Vagas 2022 & 2024, Bratan 2023, Sharma 2023, Romancik 2024].

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