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Vine Diseases Detection Trials in the Carpathian Region with Proximity Aerial Images

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***Abstract*— With the recent advances in the Agro 4.0 domain, the advanced inspection tools from the robotics domain in agriculture got into the focus. The automatic field inspection with autonomous robots started to get accepted by the farmers. However, one of the main challenges of the visual inspection is the geographical variety of the plants. In this work, we focus on the vineyard-specific inspection with low-altitude flying drones and we analyze the geographical correlation among the typical grape species in the Carpathian Basin using foundation machine learning models.**

I. INTRODUCTION

With the recent advances in the Agro 4.0 domain, the advanced inspection tools from the robotics domain in agriculture got into the focus and this is valid for the grape vineries too. Grape production has a long life history, as it serves as a base for several hundreds of years of traditional drinks and wine. Besides the traditional food category, it has also an important economic and cultural aspect, which brings into focus the more efficient precision agricultural setup as well. Therefore, today viticulture faces a traditional way from cultural perspectives and innovative aspects due to innovative technologies solutions. In the Carpathian basin, viticulture has different geographical distribution and characteristics, which requires a special approach in the precision agriculture context.

In this work, we investigate differences in viticultural characteristics in the Carpathian Basin with a focus on vine disease detection based on aerial close-range images. This is a crucial step in the precision viticulture context and can reduce up to 50% of the loss in production. However, the problem is far from trivial, especially if a wide variety of grapes is in focus, as this is the case in a larger geographical distribution. Advanced computer vision techniques are required to process the remote-acquired images in order to detect in an automatic manner the vine leaf diseases. These include pre-processing [1], segmentation [2] and detection with automatic navigation [3].

In the proposed setup we investigate the possibility of using a semi-automatic remote aerial survey according to Fig. 1:

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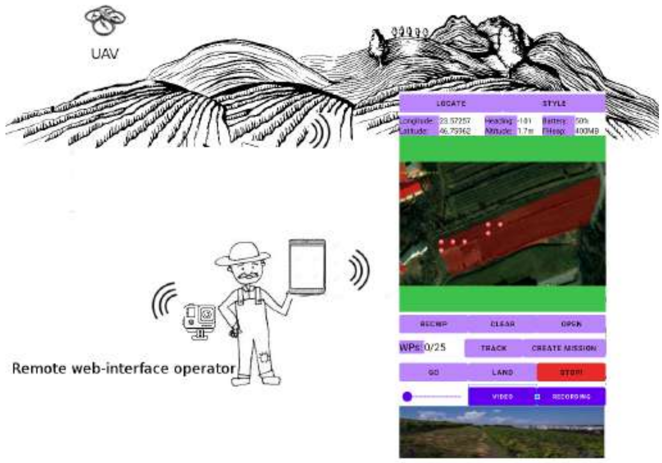

Fig. 1: Overview of the proposed vineyard monitoring method with remote drone and mobile interface

The main components of the architecture are the remote-operated semi-automatic drone flying at a low altitude for remote sensing of the vineyard; the operator or farmer performing the remote surveillance and the base station or dashboard for data evaluation.

In our experimental setup, we used a lightweight drone in order to avoid complex setup a drone permit requirements, however, with a 4K camera on board and remote image preview features. The latter allows real-time processing of images even on an embedded device, such as the Android-based remote receiver. The custom mobile base code as well as the vine disease detection (VDD) code are available at `http://rocon.utcluj.ro/~levente/?page_id=568`.

In section II we present shortly the geographically distributed grape species within the Carpathian Basin, while in section III we summarize the cross-domain evaluation results for different experiments made in this region. Finally, the paper concludes with the results and future work.

II. RELATED WORK

Vine disease detection (VDD) is an important component of precision viticulture, thus recently got into the focus. Proximal sensing of the vineyards is performed using conventional color cameras, as well as multispectral or hyperspectral variants. A short overview of the existing methods.

Traditional methods rely on feature level matching for disease patches, such as in the work of [4] which relies on geometric features. A popular approach is to focus on a single image level-based disease detection with a transfer learning approach for VDD. One of the most common variants to do this is based on the ResNet [5] architecture.

Another approach focusing on laboratory condition leaf images with variable leaf sizes is solved by using convolutional neural networks such as the originally proposed in the work of [6] and later on adapted in the work of [7].

For the VDD problem, there are several approaches based on the use of specific color spaces such as HSV or advanced image segmentation steps such as in the work [8].

The foundation models such as *Faster R-CNN* [9] or *VGG16* [10] are used also for VDD even with close proximity drone images, however, a preliminary segmentation step is used to perform the VDD.

Although several methods tackle VDD such as the work of [11] based on semantic segmentation or the work of [12] using depth cameras or the use of infrared cameras suggested in [13] and remote aerial sensing [14], the need for close-proximity remote sensing solutions is still a priority in the researcher community.

More relevant is also the transfer learning capability across the geographical regions, which is missing from the state-of-the-art. We explicitly tackle this problem in our current work, focusing on the VDD across different geographical regions within the Carpathian Basin.

III. Geographical vine distribution

In this work, we focused on the Carpathian Basin as a geographical region to perform VDD experiments with more than 20 different locations. A short list of the measurement locations is presented in Fig. 2

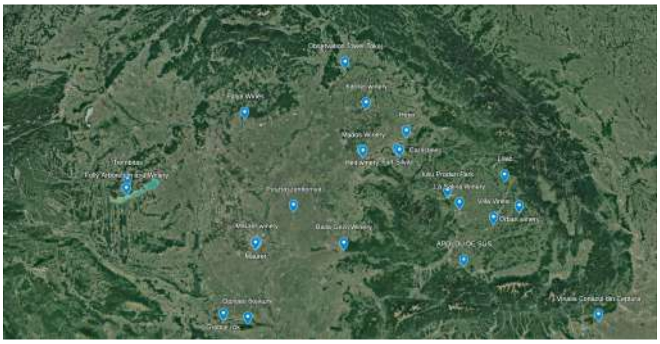

Fig. 2: Geographical distribution of the training data set

In the following subsection, we briefly present the main historically used viticultural regions and the most common types of grapes produced in these areas.

A. Main viticultural regions

The Carpathian basin is a large basin situated in south-east Central Europe and is surrounded by the Carpathian Mountains to the north and east, the Alps to the west, the Dinaric Mountains and Šumadija Mountains to the south. There are several important wine regions in this basin, a good overview of them can be found in [15].

The most famous wine region is **Tokaj-Hegyalja** in Hungary, and there are around 900 hectares of land that belong to Slovakia. The microclimate is determined by the sunny, southfacing volcanic slopes and the proximity of Bodrog and Tisza rivers, and is conducive to the proliferation of Botrytis. This fungus, which causes noble rot and the subsequent desiccation of the grapes (aszú), needs just the right combination of cool, humid mornings and warm afternoons. Furmint, Hárslevelű (Lindenblättriger), Sárgamuskotály (Yellow Muscat), Kabar, Kövérszőlő and Zéta are the only grape varieties officially permitted for use in this region.

Eger wine region is located in Hungary on the southern slopes of the Bükk and Mátra Mountains, where the soil is a mixture of clay, loess, and tuffeau. In this region, the spring comes relatively late and the climate is of a dry nature. The red wine grapes grown here include Merlot, Cabernet Sauvignon, Kékfrankos (Blaufränkisch), Kékoportó (Blauer Portugieser), and Pinot Noir. The white wine grapes grown here include Chardonnay, Hárslevelű (Lindenblättriger), Olaszrizling (Welschriesling), Leányka (Weiße Mädchentraube), and Szürkebarát (Pinot Gris).

In the Hungarian **Balaton** wine region the climate is moderated by Lake Balaton, and the soil is mainly volcanic (basalt). This region is home to the unique white grape Kéknyelű, and also produces Szürkebarát (Pinot Gris), Muskotály (Muscat), Hárslevelű (Lindenblättriger), Furmint, Olaszrizling (Welschriesling), Tramini (Gewürztraminer) and Chardonnay.

In the Hungarian **Észak-Dunántúl** wine region the continental climate is moderated by the river Danube. White wine grapes grown on its limestone-based soil include Chardonnay, Sauvignon Blanc, Rajnai rizling (Rhein Riesling), Tramini (Gewürztraminer), Olaszrizling (Welschriesling), and Leányka (Weiße Mädchentraube).

Duna wine region is located in the center of Hungary between the rivers Danube and Tisza. The land here is flat with mostly sandy soils. The climate is arid and hot. The red wine grapes grown here include Kékfrankos (Blaufränkisch), Zweigelt, and Kadarka. The white wine grapes grown here include Rajnai rizling (Rhein Riesling), Chardonnay, Olaszrizling (Welschriesling), and the spicy Cserszegi fűszeres.

Pannon wine region lies west of the Hungarian Great Plain. The vineyards are mostly on mineral-rich loess and terra rossa soils. In Szekszárd sub-region the climate is temperate continental with mild winters and warm summers, while Villány sub-region, close to the Croatian border, has a Mediterranean mesoclimate with hot and sunny summers. The red wine grapes grown in this region include Kékfrankos (Blaufränkisch), Cabernet Sauvignon, Merlot, Kadarka, and Pinot Noir. The white wine grapes grown here include Chardonnay, Olaszrizling (Welschriesling), and Tramini (Gewürztraminer).

Burgenland wine region is located in Austria, and there are approximately 1800 hectares that belong to **Sopron** wine region in Hungary. The climate of this region is strongly influenced by its proximity to the Lake Neusiedl, and is more temperate than the rest of the Carpathian Basin, with cooler summers and wetter winters. The soil is a mixture of gravel, sand, chalk, and limestone. This is predominantly a red wine-producing area, the main red variety is Blaufränkisch.

Little Carpathians wine region in western Slovakia has a continental climate, and the soil is a mixture of clay and sand. **Južnoslovenská** wine region is located in southern Slovakia, where the warm continental climate is moderated by the river Danube. The vineyards are planted on loess uplands. **Nitra** wine region is located in the central southwest of Slovakia. The region has a hot and very dry lowland climate. **Stredoslovenská** wine region is an area in the south of central Slovakia, where the climate is mild and dry. **Východoslovenská** wine region in the south of eastern Slovakia has warm, continental climate. Soils in this area are mainly of volcanic origin. Most of the grape varieties grown in these regions are used for white wines such as Veltlínske zelené (Grüner Veltliner), Rizling vlašský (Welschriesling) and Müller-Thurgau, while several varieties are used for red wines such as Frankovka modrá (Blaufränkisch), and Svätovavrinecké (St. Laurent).

Transylvania wine region, with sub-regions Aiud, Alba Iulia, Sebeş-Apold, Lechinţa, and Târnave) is Romania's coolest region, which is particularly well known for its range of white wine grapes, such as Feteascǎ Regalǎ, Chardonnay, Pinot Gris and Sauvignon Blanc.

Eastern Continental wine region of Croatia extends along the Drava River toward the Danube River. This region has hot summers and cold winters. The most notable wines coming from this region are made using white grapes including Graševina (Welschriesling), Gewürztraminer, Pinot Blanc and Chardonnay. The red wine grapes grown here include Frankovka (Blaufränkisch).

The Serbian **Fruška Gora** wine region is nestled between the Danube and Sava rivers, and there are around 300 hectares that belong to **Ilok** region in Croatia. The most notable white grape varieties include Smederevka, Tamjanika, Riesling, Chardonnay and Traminac (Gewürztraminer). Red grape varieties for this region include Prokupac, Frankovka (Blaufränkisch), Cabernet Sauvignon, Merlot and Slankamenka.

B. VDD pipeline

For the VDD we used the semi-automatic RoboFlow labeling tool. The pipeline includes the data acquisition from a low-cost drone, the loading in the RoboFlow tool, the annotation, preprocessing and augmentation. The processing pipeline is shown in Fig 3 with the necessary processing steps included for this process such as data acquisition, preprocessing, annotation, model generation, semi-automatic labelling and model update with the final model generation and deployment on real embedded devices.

Aerial data acquisitions were carried out in three wine regions of the Carpathian Basin using remotely piloted quadcopters. All flights were performed under moderate weather conditions (light wind and no rain) by manual piloting at low altitudes (max. 6m above ground level). At a vine parcel near *Hrhov* (**Východoslovenská** wine region, Slovakia), a DJI Phantom 3 Professional drone was employed. For recording the dataset in a vineyard at *Ilok* (**Fruška Gora** wine region, Croatia) and *Diosig* (**Transylvania** wine region, Romania), we used a much smaller and lighter quadcopter, DJI Mini 3 with 12 MP integrated camera. At *Diosig*, a DJI P4 Multispectral drone was also employed. Table I contains some characteristics of these UAVs and the technical specifications of the integrated cameras. In all three cases, the video recordings and images were captured in the maximum resolution as possible.

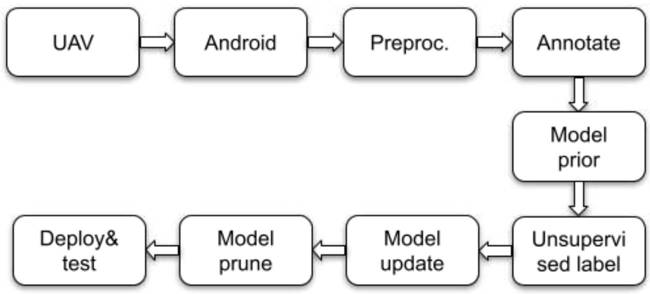

Fig. 3: The processing pipeline

The well-known Yolo version 7 was used with pre-trained weights from the COCO dataset for the training. Further on, with different models trained in different geographical regions, we compared them against our base model from Transilvania, which had the most pictures and with vertical time data collection, too. In the following section, we present the results of the geographically distributed VDD on our large-scale dataset.

As a training goal, our objective is to increase the *Intersection over Union (IoU)* between the ground truth mask and the predicted mask, Equation (1), therefore the loss is $1 - IoU$:

$$IoU = \frac{\mathbf{X}_{GT} \cdot \mathbf{X}_{pred}}{\sum_{i,j} (\mathbf{X}_{GT}^{ij} + \mathbf{X}_{pred}^{ij} - \mathbf{X}_{GT}^{ij} * \mathbf{X}_{pred}^{ij})} \quad (1)$$

where $\mathbf{X}_{GT}$ and $\mathbf{X}_{pred}$ are the ground truth and the prediction masks respectively. This type of loss expresses both the model capability to find necessary parts with VDD and the location accuracy for the detection bounding boxes for these regions.

IV. Geographical VDD transfer learning

In our work, we focus on the semiautomatic annotation tool RoboFlow [19] with an enhanced Yolo version [20]. The base version of our model contains more than 10,000 annotated images, with more than 30,000 labels containing manually annotated and validated vine leaves with abnormalities. An example of annotated leaves is shown in Fig. 4.

The semiautomatic labeling is available after annotating a few thousand images, from which the trained model can

	DJI Phantom 3 Professional	DJI Mini 3	DJI P4 Multispectral
Weight (battery and propellers included)	1280 g	248 g	1487 g
Max. Horizontal Speed	16 m/s	16 m/s	16 m/s
Camera Sensor	1/2.3" CMOS	1/1.3" CMOS	Six 1/2.9" CMOS (1 RGB and 5 monochrome)
Lens	FOV 94°f=2.8	FOV 82.1°f=1.7	FOV 62.7°f=2.2
RGB sensor ISO Range	100-1600, 100-3200 (video)	100-3200	200-800
Electronic Shutter Speed	8 – 1/8000 s	2 – 1/8000 s	1/100 – 1/20000 s, 1/100 – 1/10000 s (multispectral)
Image Max. Size	4000 × 3000 pixels	4000 × 3000 pixels	1600 × 1300 pixels

TABLE I: Main technical specifications of the employed UAVs [16], [17], [18]

Fig. 4: Annotation example with infected leaves

be used for label suggestion. However, this still needs to be revised by a human specialist. After performing these validations, we cross-validated the base model from the Transylvanian region against other datasets from the Carpathian Basin for VDD.

A. Results

In our first trials, we investigated the cross-domain relationship between the base region and the one from **Fruška Gora**, more specifically *Ilok*. The results of the validation in terms of training loss, mAp and precision are shown in Fig. 5:

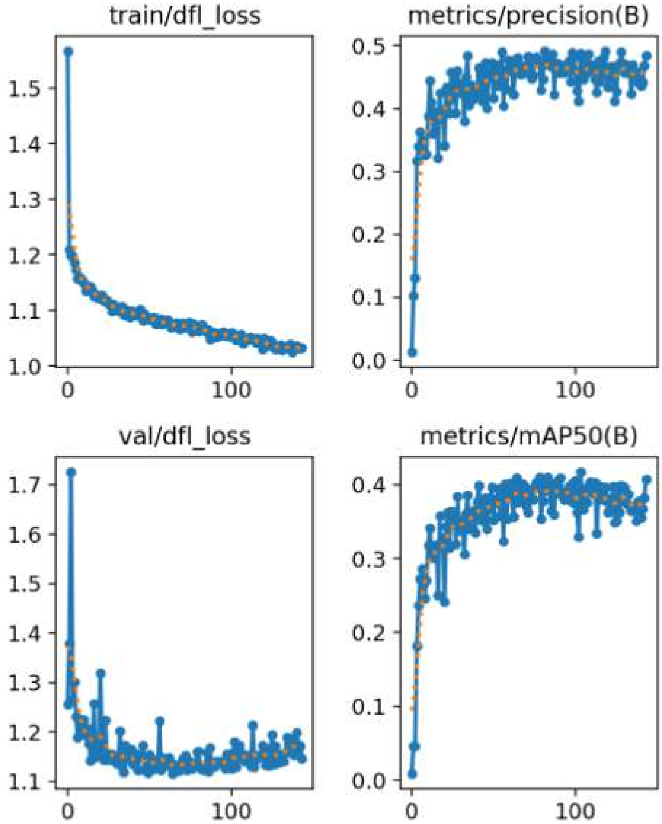

Fig. 5: The training results for Ilok

In the next trial, we investigated the geographical domain correlation for VDD from the **Východoslovenská** region more specifically from *Hrhov*. The results are shown in Fig. 6

Finally, the closest region for the base model was tested at *Diosig* showing the best correlation with the Transylvanian regional dataset, the evaluation metrics being shown in Fig. 7, on which the precision has a quality jump at the middle can be interpreted as the model is receiving geographically correlated information from a close regional viticultural dataset.

A further investigation point would be the ability of the early-stage models to predict and generate the label for the early-stage models with the semi-unsupervised labeling for the final model fine-tuning. Already existing commercial tools such as *RoboFlow* have similar features included in their products, which can be useful in this context.

V. CONCLUSIONS

In this work, we focused on automatic vine disease detection using close proximity remote sensing images from a low-cost aerial drone. The main focus was on the creation of a valid geographically distributed dataset and the detection of diseases in different viticultural regions in the Carpathian Basin. The results suggest a good correlation among the different geographical regions for transfer learning, which allows us to conclude that certain generic common features are present in the different diseases affecting the vineyards in this geographical region.

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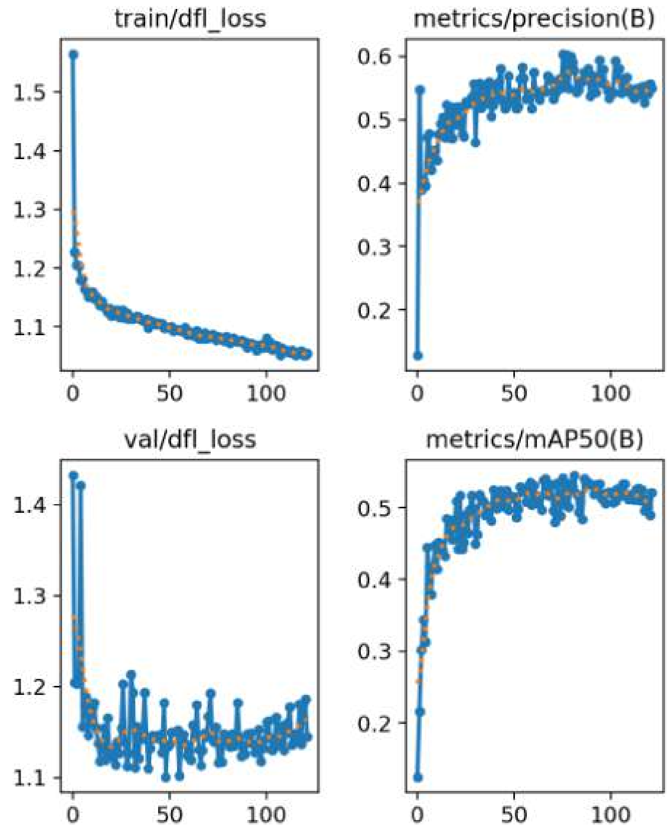

Fig. 6: The training results for Hrhov

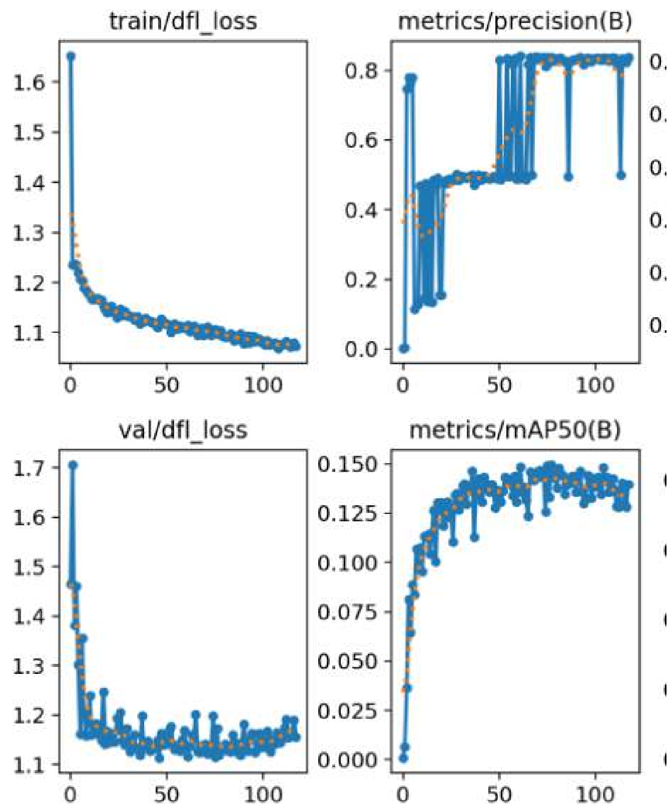

Fig. 7: The training results for Diosig

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