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DETECTION OF VINEYARD DISEASES USING THE INTERNET OF THINGS TECHNOLOGY AND MACHINE LEARNING ALGORITHMS

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ABSTRACT. In recent years, the Internet of Things concept has rapidly spread in most fields because of the benefits it offers, motivating viticulturists to implement new technologies that increase crop production and quality, as well as streamline production costs. The study's purpose is to monitor, using Internet of Things technology, two methods of identifying vine-specific diseases, which can be determined by environmental conditions (temperature, humidity, rainfall) or by analyzing diseased leaves from the vine. The first method is associated with a field study that involves placing Internet of Things sensors inside crops to measure environmental and plant parameters, which are then sent and stored in the Cloud. Based on these parameters, a correlation is made with the values that determine the occurrence of a specific vine disease (powdery mildew, downy mildew, and grey rot). The second method involves the use of Unmanned Aerial Vehicle imaging to take images containing healthy and diseased leaves from different parts of the vine. To analyze these images, a web page has been developed integrating a machine learning algorithm that detects the leaf state from the drone image footage. After the analysis all the values are stored in a database and the results are displayed as graphs and charts that are visualized by the viticulturist so that he can take the necessary actions. This study is an important step in the implementation of Internet of Things technology in viticulture, helping to monitor the main environmental and plant parameters, as well as detecting the occurrence of diseases among the vine cultures.

Keywords: grapevine disease, environmental conditions, machine learning algorithm, IoT, viticulture

1. INTRODUCTION

Precision agriculture, in general, and precision viticulture, as a branch of the former, are of major economic importance in all grape-growing countries. Plants crops experience stress and diseases due to many factors: meteorological conditions, climatic changes that foster the occurrence of pests, the presence of bacteria, fungi and other pathogens, crop type (Ouhami et al., 2021; Wang et al., 2021). These factors induce

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several pathogenic plant changes which affect their physiological, morphological, and biochemical characteristics (Wang et al., 2021). The main concerns that arise are related to the stress and diseases prevention, forecasting and detection, to avoid the crop losses (Murugan et al., 2021). Even though these processes are very challenging (Rao et al., 2021, Zhang et al., 2018), the Internet of Things (IoT) and Artificial Intelligence together offer new possibilities to achieve the goals of stress and disease control, building different detection models, disease prediction mechanisms, analysis and assessment methods (Ouhami et al., 2021; Gupta et al., 2019). Some of the diseases that affect the plants are black measles, powdery mildew, black rot, Botrytis, bacterial spot (Militante et al., 2019; Chedea et al., 2021). Even though there are chemical treatments available to prevent or stop the spreading of such diseases, the use of pesticides increases the expenses associated with the crop maintenance and, most importantly, affects the soil, atmosphere, and final products (Sujatha et al., 2021).

Traditionally, human experts could identify diseases and pest occurrences through chemical techniques based on molecular plant leaves testing (Ouhami et al., 2021). There is also another method that involves observation and the analysis of the visual characteristics of the plants, but the accuracy of the process mainly depends on the knowledge and the experience of the observer (Wang et al., 2021). In the present, using IoT devices, data can be even real-time acquired, and, through the current communication technologies, images and video streams can be collected and sent to Cloud servers where more powerful computational resources are found and where intelligent decision support systems (IDSS) can be implemented (Zhang et al., 2018; Chedea et al., 2021). IDSS are based on image/data processing, computer vision, machine learning and artificial intelligence.

Concerning the image-based plant disease identification, one of the first stages resides in the image acquisition which can be either ground imaging, satellite imaging or aerial imaging (by using drones) (Wang et al., 2021). Ground imagining implies the use of smartphones and video cameras placed at ground level to acquire fruit and leaf images. This approach is very challenging as shadowing, brightness and background may affect the detection process. Nevertheless, it was proved that chemical and physiological plants features changes can be determined by multi- and hyperspectral images analysis (Wang et al., 2021; Förster et al., 2019).

Satellite imagery involves the use of hyperspectral, high spatial/high temporal resolution satellite images from different image satellites providers currently available or from commercial and non-commercial satellite images databases. The high-spatial resolution satellites has a resolution ranging between 0.5-30 m, while the high temporal resolution satellites have a very low spatial resolution (250 m, 500 m, 1000 m, depending on operating band) (Wang et al., 2021). Even though satellite imagery is characterized by a high spatial resolution, it is impossible to use it, though, for specific point-wise observations and for small, locally affected areas.

Unmanned Aerial Vehicle (UAV) imagery, instead, due to the mobility of UAV, can be exploited in such conditions where the crops are locally, incipiently affected. Another advantage resides in the lower costs and higher spatial resolution with

respect to satellite imagery, making it suitable for precise locations. Precision agriculture UAVs also use advanced multispectral cameras.

Several visual and non-visual approaches were proposed to detect grape leaves diseases. Further, the focus will be on artificial intelligence and machine learning algorithms for plant diseases detection.

Rao et al. (2021) proposed an algorithm to identify diseases associated with grapes and mango leaves. For grapes, they focused on black rot, black measles and leaf blight. The algorithm is based on the convolutional network (CNN) AlexNet. The images are acquired based on high-resolution camera, and pre-processing techniques are applied for distortion suppression. The images were trimmed to have a size of 256 x 256 pixels. The proposed model revised layers 23-25 of AlexNet model and it was trained based on Stochastic Gradient Descent Momentum algorithm. For grape leaves disease detection, the Precision, Recall, and F1 Score Accuracy were 0.9890, 0.9850, and 98.85% respectively.

Sanghavi et al. (2021) had a different approach and used environment parameters as air temperature, air humidity and rainfall amount to predict downy and powdery mildew. The algorithm is very simplistic, and it is based on parameter threshold.

Huang et al. (2020) proposed four modified deep learning models to detect and classify black measles, black rot, leaf blight and, with respect to the other approaches presented, a new disease phylloxera. They obtained an accuracy of 81.1% which is the smallest among the papers presented, but they used the largest image set among all approaches, 4311. They build a simple convolutional network model called Vanilla considered the basic model and they compared it with other three modified models: improved VGG16, improved MobileNet and, respectively, improved AlexNet with transfer learning.

Patil and Thorat (2016) used a sensor data-based approach, as in Sanghavi et al. (2021), but they employed relative humidity and leaf wetness duration to detect grape diseases. Even though they enumerate bacterial leaf spot, powdery mildew, downy mildew, anthracnose, rust and bacterial cancer, the proposed method does not discriminate between the six possible conditions. The authors compare the results obtained using a statistical approach (63.63% accuracy) with the results obtained using Hidden Markov Model (90.9% accuracy). Furthermore, urban farming can benefit from IoT (Marcu et al. 2020) and traceability using blockchain (Drăgulinescu et al., 2021).

2. STUDY AREA

The vineyard is located within the premises of BEIA, where the case study is implemented. The company is located in Bucharest, sector 4, in Campia Vlasiei, a subunit of Campia Romană. In order to specify a more precise location of the area where the measurements are carried out, we specify four cardinal points delimiting the vineyard area:

- 44.395598 north latitude and 26.102810 east longitude

- 44.394479 north latitude and 26.102688 east longitude
- 44.395596 north latitude and 20.102657 east longitude
- 44.395597 north latitude and 26.102717 east longitude

Fig. 1 shows both the Smart Agriculture Xtreme station, located inside the vineyard, and the soil and air monitoring sensors.

Fig. 1. Smart Agriculture Xtreme Station

3. METHODOLOGY

3.1. System Architecture

The architecture of the system used is illustrated in Fig. 2 and consists of an IoT-based smart viticulture platform designed to monitor, alert, and provide notifications to improve vine harvest.

The Vineyard level includes remote sensing and monitoring devices for collecting data on crop stages, crop yield estimation, soil nutrient content and crop disease detection. Among the sensing devices, soil and weather sensors, nutrient sensors and biosensors are used. Other remote monitoring methods include drone images. The hardware used employs solutions with various probes for monitoring environmental parameters and detecting vine diseases.

The Network layer comprises the network devices (communication modules, gateway) and provides communication over short or long distances between the detection devices and the higher levels of the platform. The communication technologies used in the project are Wi-Fi and 3G/4G. As these are very energy intensive, software routines are implemented at this level to make the transmission more efficient, also avoiding data loss. Sensor data are sent to the Meshlium gateway. The network protocol implemented to send the data to the upper layer (Cloud) is MQTT (Message Queuing Telemetry Transport), a simple protocol designed to limit resource consumption within an IoT platform.

The Cloud tier comprises the database involved in storing the time series data that will be used by the Application tier. It also includes the gateway that handles the analysis of images sent by drones. In addition, Machine Learning techniques are used in this layer so that the Application layer can predict the occurrence or presence of a disease.

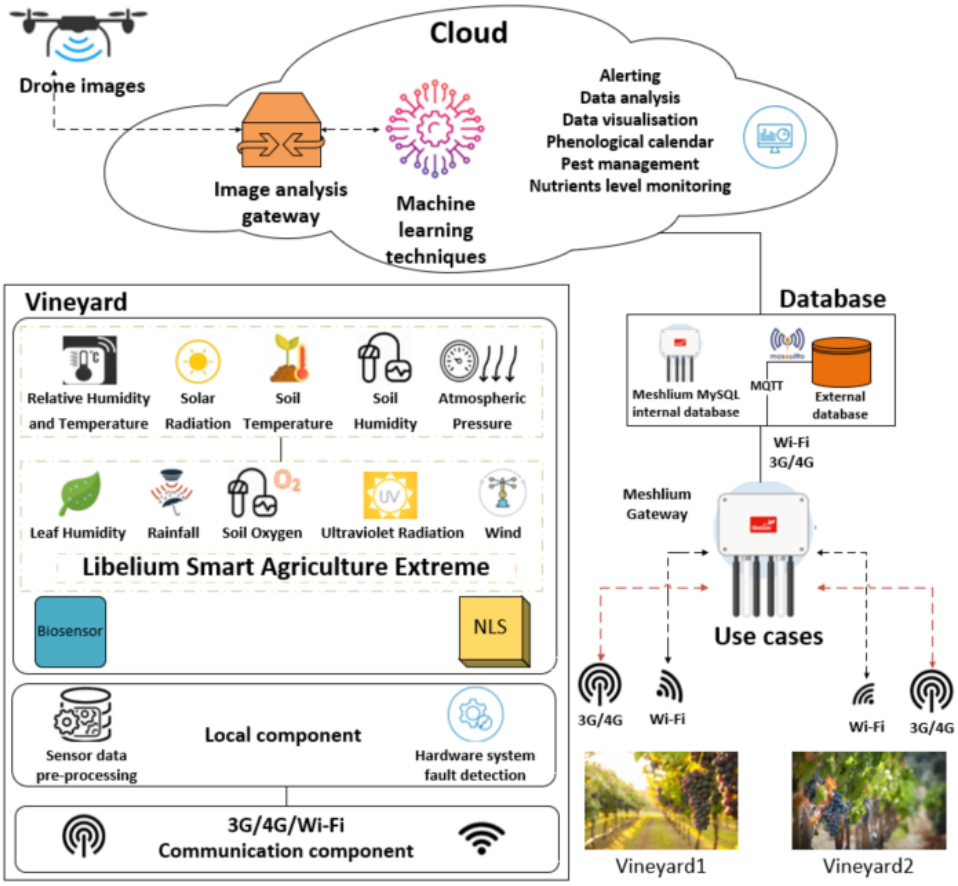


Fig. 2. System architecture

The Application layer is designed to support the platform with a powerful dashboard that supports decision-making, visualization and analysis of data based on maps, notifications and alerts. The platform therefore monitors weather conditions and manages risks associated with plant diseases. The platform is not about providing large amounts of data, but about generating and delivering versatile, useful and user-friendly information.

3.2. Disease Detection

The study aims to detect diseases that can occur in grapevines using two methods. The first method relies on the parameters collected from sensors to make predictions about the occurrence of a disease, while the second method uses machine learning techniques to analyze the images captured by the drone and provides information about the vine leaf conditions.

The prediction realized within the first method focuses on analyzing sensor data to predict the occurrence of three types of grapevine diseases: downy mildew, powdery mildew, and grey rot.

Downy mildew is a fungal disease that occurs in early autumn when temperatures start to drop. This disease is characterized by bright green spots and a moldy coating on the leaves, which affects photosynthesis. Once the vine is affected by this disease, it is difficult to treat, as it can spread to the berries, causing them to dry out and shrivel. Moist conditions, temperatures in the range 14.9°C - 20.3°C and rainfall in the range 184 mm - 727 mm are required for infection to occur (Romanazzi et al., 2016).

Powdery mildew is one of the most difficult diseases to treat, as it can survive inside the branches over winter. This disease affects both the berries and the leaf, coating them with a fine fungus, preventing photosynthesis. Conditions favorable to the occurrence of the disease are temperatures above 10°C, high air humidity and low rainfall during the growing season.

Gray rot mainly affects the berries, but the effects can also be seen on the leaves as dull green spots that turn brown and necrotic. In conditions of high relative humidity, the affected parts are covered by the gray spore of the fungus. The temperature favorable for disease development varies between 14.2°C - 21.6°C, and the rainfall range is narrower, 181 mm - 561 mm (Thorat, 2018).

The main sensors from which data are collected for disease prediction are:

- air humidity
- precipitation
- atmospheric pressure
- soil temperature
- soil humidity
- air temperature

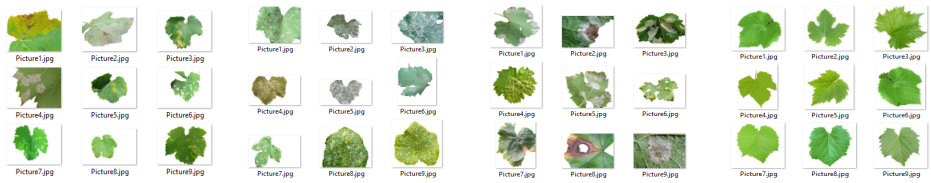
The software for analyzing the parameters monitored in the vineyard is designed to alert the vine grower if an environment ideal for the development of vine diseases (downy mildew, powdery mildew and grey rot) is detected. In this way, the wine grower can prevent the appearance or spread of the disease by treating the vine immediately.

The second method focuses on the detection of vine diseases using ML algorithms to analyze the images captured by the drone. Prediction will be made based on the diseases described above (downy mildew, powdery mildew and grey rot).

To make the disease detection software it is necessary to train a neural network used to determine the health status of the plant.

A first step is to create databases for each disease analyzed, including a database for healthy leaves (Fig. 3), so that when we want to analyze images from the drone the software is able to show us the percentage match of those images with the databases created.

The images from the drone will be processed and then introduced into the analysis algorithm. The acquired image from the drone is used as input to the image processing system. Fig. 4 outlines the steps followed in image analysis.



downy mildew powdery mildew gray rot healthy

Fig. 3. Part of the analyzed dataset

For the study to be complete a web page with a user-friendly interface has been developed (Fig. 5) so that any user/grower can upload images, run the disease detection algorithm and see the prediction result. The web page runs locally for the time being, so that it cannot be accessed from external sources.

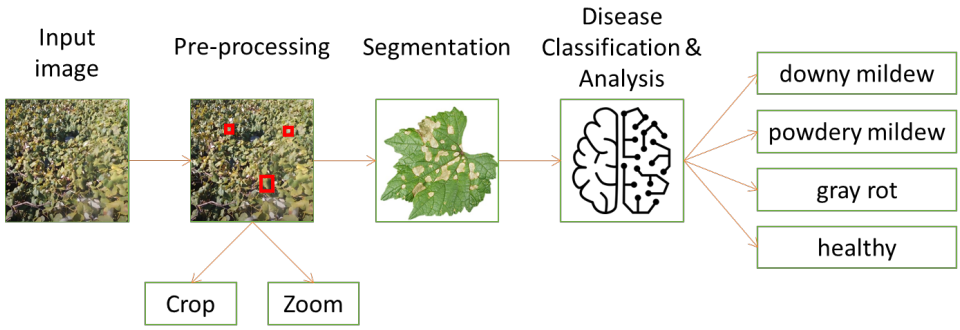


Fig. 4. Image processing diagram

Fig. 5. User interface

Depending on the plot from which the images have been taken and analyzed, it can be decided where specific treatments for each disease should be carried out.

4. RESULTS

The following experimental results have been extracted from the monitoring of vine culture. The monitoring was carried out over a vineyard season starting in June 2021 and ending in October 2021 (Fig. 6 - 9). This selected period of five months is the time when the grapes are approaching maturity until they are harvested. It is also during this period that the grapes are more susceptible to diseases.

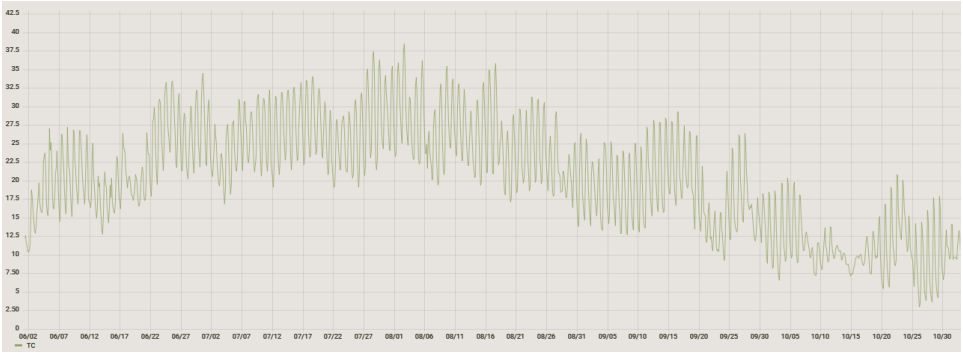


Fig. 6. Air temperature

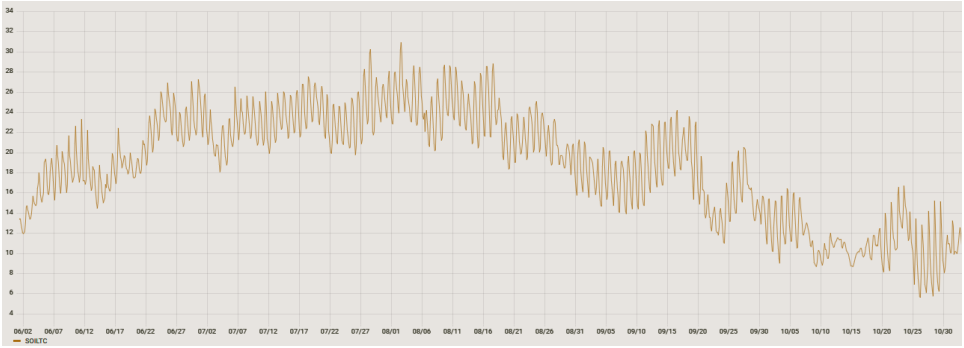


Fig. 7. Soil temperature

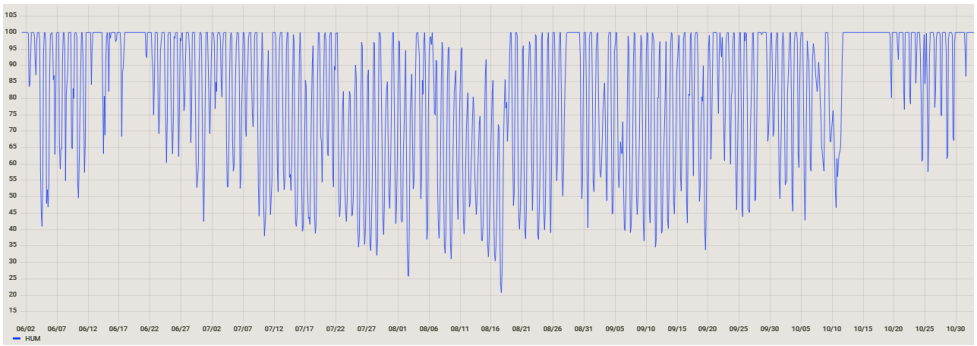


Fig. 8. Air humidity

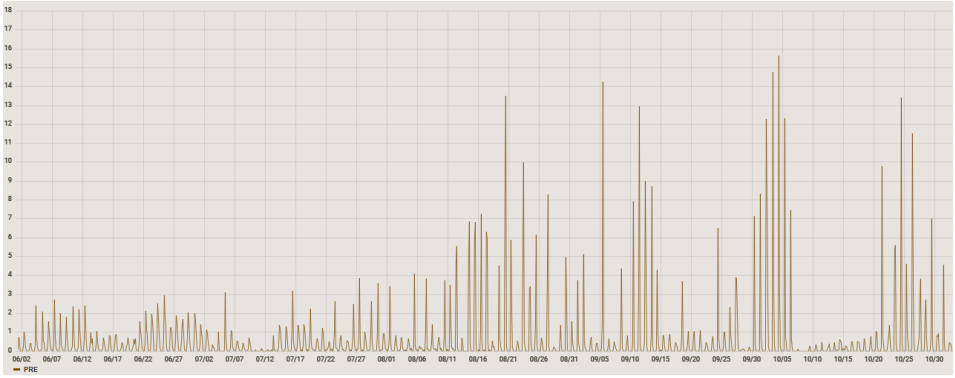


Fig. 9. Rainfall

After analyzing the graphs, the following information was extracted for each month so that changes in the weather can be observed and how they might cause a disease to appear on the vine. Several filters were applied to these data, such as minimum, maximum and average values for each month. In the case of rainfall, the values were summed to determine the total amount of rainfall accumulated each month. The report on relevant parameters for disease detection is shown in Table 1.

Table 1. Statistics on relevant parameters for disease detection

Parameter	Month	Min	Max	Average
Soil Temperature [°C]	June	9.7	32.0	20.9
	July	15.9	32.3	23.6
	August	18.9	32.3	24.4
	September	12.1	28.9	20.2
	October	6.9	24.2	14.9
Air Temperature [°C]	June	8.2	35.9	22.5
	July	14.4	38.9	26.3
	August	18.3	39.7	27.2
	September	11.6	38.7	23.1
	October	3.9	31.2	15.6
Air humidity [%]	June	36.0	100	68.0
	July	30.0	100	65.0
	August	21.0	100	60.5
	September	35.0	100	67.5
	October	40.0	100	70.0
		Sum		
Rainfall [mm]	June	41.3		
	July	20.1		
	August	32.2		
	September	34.3		
	October	33.4		

The drone images are processed so that only the region of interest is analyzed, with the focus on the plant leaf. Fig. 10 shows an example of each category of leaves analyzed, chosen from the test set.

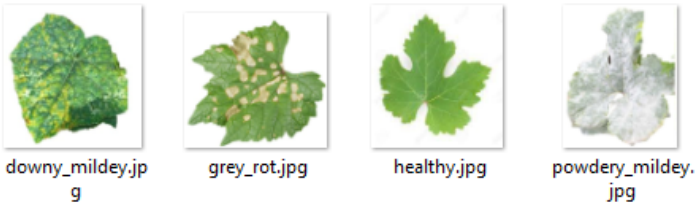


Fig. 10. Selected images from the dataset

Analysis results can be checked both on the server and in the web platform. Following the analysis, the detection percentage of a certain disease on the examined leaves is displayed. In Fig. 11 you can see the results for the images previously selected from the test set.

Fig. 11. ***Prediction percentage for selected images***

Table 2 presents a comparison between the two methods employed in the paper.

Table 2. ***Comparison between Method I and Method II***

Method	Data sources	Classification methods	Advantages	Disadvantages
I	Air temperature and humidity, soil temperature, rainfall	Statistical	More suitable for real-time applications. Can support time-series based prediction mechanisms.	Local data, cannot cover a high area with certain sensors (underground sensors, for example)
II	Grape Leaves Images	Machine Learning, Deep Learning	High coverage through the exploitation of UAV mobility. Global coverage through satellite imaging. Higher detection probability due to physiological characteristics observed on the leaves.	Data rate limitations. Image resolution choice challenges. Resource-consuming computing. Lightning, illumination changes

5. CONCLUSION

Following the experiments and tests carried out, it can be said that the study achieved its objective of detecting the state of the vineyard through the environmental parameters monitored and the images from the drone. The parameters monitored using IoT technology are stored in Cloud in order to later perform analysis on them in terms of the values that facilitate disease occurrence. The algorithm used for disease prediction from the drone images is based on a neural network trained for each disease (mange, wilt and gray rot), but also for healthy leaves. Both approaches have shown significant results, with the first contributing to the disease prevention and the second to its detection. This field study is indeed a real help for winegrowers as it can contribute to the development of an effective strategy to solve problems that may occur in specific areas of the vineyard. This can help prevent grape infection, increase crop yield and quality, and make production costs more efficient. As future work we envision analyzing the vine growing season 2022 in Romania.

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