Early detection of grapevine diseases using pre-trained Convolutional Neural Networks

Cristian Emmanuel Rios[1], César A. Estrebou[2], and Fernando Emmanuel Frati[1]

[1] Department of Basic and Technological Sciences,
National University of Chilecito, Chilecito, La Rioja, Argentina
crios@undec.edu.ar, fefrati@undec.edu.ar

[2] Computer Science Research Institute LIDI, School of Computer Science, National University of La Plata, La Plata, Buenos Aires, Argentina
cesarest@lidi.info.unlp.edu.ar

Abstract. This paper proposes to apply pre-trained Convolutional Neural Networks (CNN) for the early detection of two common grapevine diseases: peronospora and oídio. These diseases present similar symptoms and are of great viticultural importance. Our objective is to train a CNN using transfer learning techniques to accurately detect the presence of early symptoms of the diseases under study. To achieve that, we'll design a pipeline that starts with data acquisition in the field and finalizes with the early disease identification, including class definition, labeling, image preprocessing and training process of the CNN, employing edge computing-based service computing paradigm to overcome some inherent problems of traditional mobile cloud computing paradigm.

Keywords: Deep Learning · Convolutional Neural Networks · Object Detection · Edge Computing · Inclusive Inteligent Systems

1 Introduction and related work

Field-grown grapevines are considered one of the main crops of La Rioja. Peronospora and Oídio are two similar diseases that frequently attack this crop. Peronospora is a sporadic but severe disease that directly affects production, while Oídio mainly attacks the grapevine leaves. As both diseases decreasing the quantity and quality of the bunches, them must be controlled. On the other hand, consumer market trends are rapidly expanding towards organic agriculture.

Consequently, accurate and early detection and identification of these diseases would improve the grapevine farmer's opportunities to reach export markets, applying phytosanitary products used to control them in fewer quantities and at the appropriate crop stages.

Our main objective is, under an inclusive approach, to design an intelligent system for the early detection of grapevine diseases to carry out to farmers who (frequently) are prevented from access to technology by different factors. To achieve that, we will design a complete edge-to-cloud system [1] that could be used in real-time in the field, keeping data and computation close to the end user. We propose to leverage farmer smartphone capabilities (low latency, reduced power consumption, and location awareness) to sense, image capture, and run the software that implements the pre-trained CNN for detection. On the other hand, we will deploy private cloud infrastructure on the University servers to supply the power computing needed for the remanent system parts.

We pretend to achieve that employing CNNs techniques, taking advantage of the fact that pre-trained models provide highly discriminative information, despite being trained on scenarios and tasks completely different. There are significant examples of the application of CNNs for image classification in several fields:

Breast cancer detection using histopathology images and pre-trained deep learning models. This study, carried out on with digital histopathology images, evaluates three scenarios, starting from a classical machine learning scheme and logistic regression combined with principal component analysis. Then they include the use of pre-trained deep models and finally a deep model based on a convolutional neural network [2].

Recognition of necrotic lesions for the detection of the thrips plagues in peas using the deep learning model yolov4-tiny. This research proposes a fast and effective necrotic lesion detection system for the early detection of the thrips infestation in peas by implementing the yolov4-tiny deep learning method[3].

Tomato diseases and pests detection based on improved Yolo V3 Convolutional Neural Network. This study builds the dataset of tomato diseases and pests under the real natural environment, optimizes the feature layer of the Yolo V3 model by using an image pyramid to achieve multi-scale feature detection, improves the detection accuracy and speed of Yolo V3 model, and detects the location and category of diseases and pests of tomato accurately and quickly [4].

A new deep learning-based food recognition system for dietary assessment on an edge computing service infrastructure. CNN-based visual food recognition algorithms to achieve the best-in-class recognition accuracy, where edge computing was employed to overcome the system latency and low battery life of mobile devices. [5].

With this in mind, we propose to design a metodology that starts with data acquisition in the field and finalizes with the disease identification, including class definition, labeling, image preprocessing and CNN training process, using in its implementation, the Edge Computing paradigm.

2 Background

Peronospora is a disease that can penetrate the plant organs of the vine and develop inside the leaves, stems, and fruit, causing significant damage and consequences to the plant structure. Initially, it produces more or less circular, translucent, oily-looking spots on the leaves (Fig. 1.a).

Oídio, on the other hand, is a fungus that does not penetrate the plant organs but is found on the upper or lower side of the leaves. Initially, it produces spots similar to white or ashy powdery (Fig. 1.c). The nature of the spots they produce is one of the main differences between each disease. However, it is not easily distinguishable in such early stages. The differences between the two diseases become more evident as the signs progress. Fig. 1 b and Fig. 1 d show from left to right the progression of symptoms of peronospora and oídio in advanced stages, respectively [6].

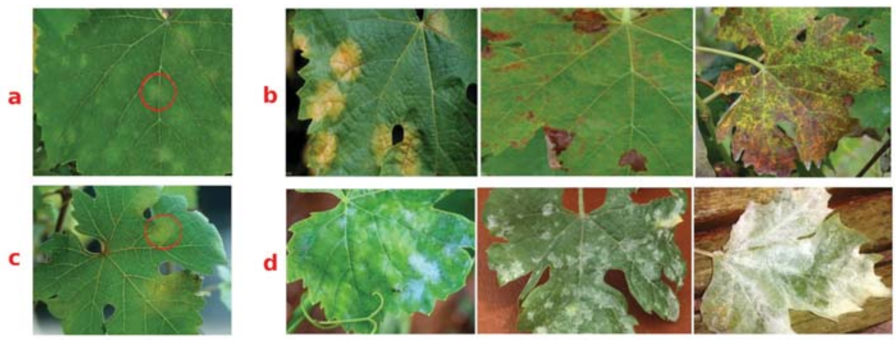

Fig. 1. a) Early symptom of peronospora, b) evolution of peronospora symptoms (from left to right), c) early symptom of oídio d) evolution of oídio symptoms (from left to right).

On the other hand, a new factor to be taken into account in agriculture is organic production, which is regulated in Argentina by Law 25.127 [7], required by an ever more demanding export market. To comply with this law, the farmer must avoid using synthetic fertilizers, pesticides, or genetic manipulation. It also promotes disease control biological methods and minimizes air, soil, and water pollution. Given the above, early detection of these diseases can impact significatly at the grapevine grower.

3 Proposal

Our proposal consist of the next stages:

Field data collection. The leaf of the plant is the plant organ that shows early symptoms of both Oídio and Peronospora. For this reason, we will work with images of leaves in their natural state and different light conditions using a mobile device connected to the Internet to facilitate rapid diagnosis. Images may have a complex background, but the leaf will take up most of the area. Although this could complicate the process of image analysis and, later, the training of the neural network, it is essential to make a diagnosis in the field as quickly as possible.

Class definition. Considering that it is more difficult to distinguish between Oídio and Peronospora in the early stages, experts who can recognize the evolution of symptoms in both diseases must supervise the composition of the image set. So, as we propose to use pre-trained CNN models, we will need to define classes for training. For each disease, we suggest classifying it in the early stages and advanced stages. Table 1 describes the characteristics that the subset of images belonging to each class should have.

Table 1. Description of classes

Nro	Name	Features
1	Early peronospora	Presence of more or less circular spots of a few centimeters, translucent and with the appearance of "oil stains".
2	Advanced peronospora	Presence of chlorotic spots that can reach several centimeters in diameter, visible on both sides of the leaf, with whitish efflorescence lesions on the underside. In adult leaves, the manifestation of mosaic lesions and/or necrosis.
3	Early oídio	Presence of more or less circular spots of a few centimeters, similar to white or ashy powder. Sometimes at the beginning of the attack, they appear as small oily spots on the upper side of the leaves, together with brownish dots.
4	Advanced oídio	Leaves appear twisted or curled, covered with dust on the upper and lower sides, and accompanied by necrosis.

Image labeling. Applying a label to all or part of an image to indicate the class to which it belongs is a necessary step in supervised learning. An expert in plant disease identification should carry out this process. The labeling method depends on the general approach chosen for image analysis. For example, if we want to classify them, we could move each image to different labeled folders or to integrate labels in the image metadata. Instead, if we want to detect objects, we should outline the region of interest (ROI) in the image, sketching the coordinates of the target object. Often, the ROI shape is rectangular but can fit more precisely to the target object.

Image preprocessing. The images must fit the size of the CNN input layer. If not, we need to resize them first. Colors are relevant in this case study (Oídio tends to be grayish white, while Peronospora tends to be oil stain-like shades). Therefore, we will not do a grayscale conversion. We will have to normalize the dataset to maintain fairness across all images and ensure they contribute equally to the loss function. So, we must scale all images to an equal range of [0,1]. Finally, we will use data augmentation to increase the diversity of the dataset without having to collect new images. This process consists of performing transformations on the existing image files (flipping, rotating, and changing brightness) that do not alter the identification of the diseases [8].

CNN transfer learning training. To find the best model for the case study, we propose to study the effect of model complexity on classification accuracy for four CNN models: AlexNet[9], GoogLeNet[10], ResNet[11], and YOLO[12].

4 Preliminary conclusions

The detailed analysis of fungal diseases for the case study allowed us to delimit temporally and spatially the evolution of Oídio and Peronospora on grapevine leaves. The review of related works shows us that pre-trained models could be efficient solutions for the early detection of the described symptoms. We proposed a methodology for data acquisition, training image classification, labeling, and preprocessing techniques for the case study that will result in the design of the edge-to-cloud computing architecture according to the requirements of early detection in the vineyard.

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