On-device Crop Disease Prediction: A realistic case for vineyards

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Abstract. Internet of Things (IoT) is one of the next big concepts to support societal changes and economic growth, with the help of Artificial Intelligence and edge computing. A whole new range of applications that leverage data and metadata from connected IoT devices provide novel human-centric services in areas such as smart agriculture. In this paper, we investigate the efficiency of executing ML-based crop disease prediction on a commercial drone device and demonstrate its potential in vineyards. We conduct inference of the trained models on several IoT and edge devices' processors and demonstrate the potential for real-time decision-making and therefore enabling targeted treatment for affected areas for optimizing crop protection strategies.

Keywords: IoT · Machine Learning · Crop disease prediction · Esca · Smart Agriculture.

1 Introduction

The Internet of Things (IoT) has gained great penetration in both business and everyday lives, with numerous distributed and highly diversified "things" sensing different aspects of their environment. Different combinations of devices, sensors and business scope across domains provide breeding grounds for numerous applications, leaving room for both inspiration and innovation. The connected things are continuously increasing in volume, and capabilities, collecting huge amounts of data. IDC predicted in 2020 that by 2025 there will be 55.7 B connected devices worldwide, 75% of which will be connected to an IoT platform [1]. Moreover, Gartner estimated in 2020 that 47% of organizations intend to increase investments in IoT [2]. The same survey reveals that IoT adoption is primarily driven by the Digital Twin and Artificial Intelligence (AI) technologies.

AI provides the intelligence to an IoT platform that enables translating raw information into useful forecasts and insights that allow triggering actions in business-specific defined workflows. Together, IoT and AI have revolutionized the perception of smartness in connected systems, providing insights to digital pioneers both in real time and in great detail.

The cloud computing revolution has democratized the development of use of technology, offering both business and end-users the illusion of unlimited resources availability and always-on experience of mobile and web services. Cloud computing has enabled the emergence of wide range of applications, supported by the Software-as-a-Service (SaaS), Platform-as-a-Service (PaaS) or Infrastructure-as-a-Service (IaaS) model, delivering complex functionality to the end user, without necessarily requiring powerful end devices.

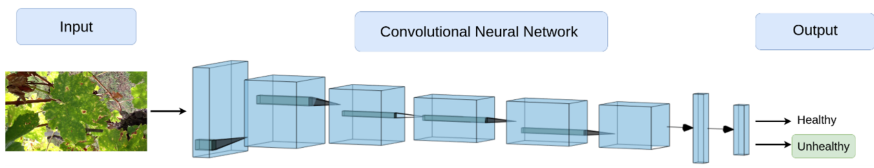

Fig. 1: Convolutional Neural Network model architecture.

Driven by these developments, the future of agriculture is undoubtedly digital, with smart agriculture and precision farming taking off, further supported by the rise of the latest technologies, which have great potential in enhancing the efficiency of irrigation, spraying and harvesting processes. However, the following challenges are still to be addressed for the Smart Agricultural use cases. First, on-device intelligence has already experienced implementations to run AI models directly on resource constrained devices. However, effective integration of intelligence closer to the field as an integral part of the IoT device to achieve data sovereignty has not yet been fully realized. Second, transparent IoT, edge and cloud communication is still missing in real implementations, although efforts are ongoing for coherent data communication and service delivery across these resources, both in the standardization part through the activities of ISO/IEC JTC 1 AG 8 and through research efforts [3–5].

In this paper, we investigate the efficiency of executing ML-based crop disease prediction on a commercial drone device and demonstrate its potential in vineyards. Crop diseases can be in many cases predicted or early detected using micro-climate measurements (mainly temperature and humidity at the air, the leaves and the soil), crop image processing and visual analytics [6, 7]. We experiment on crop diseases prediction, using deep learning (DL) which runs locally on the drone equipment, with images of the crop and the leaves captured from drone cameras. The rest of the paper is structured as follows. Section 2 presents both the case of Smart Agriculture in which Deep Learning (DL) for crop disease prediction is applied, as well as the experimental results. Section 3 draws conclusions over the obtained results.

2 AI-based Crop Disease Prediction

The case study refers to smart monitoring of vineyards with the help of Unmanned Aerial Vehicles (UAVs). Our study is focused on the detection of the Esca disease, which is a trunk disease of grapevines that concentrates worldwide concerns due to its increasing prevalence in most grapevine growing areas [8]. First symptoms of esca appear as dark red (for red cultivars) or yellow (on white cultivars) stripes on leaves, which eventually dry and become necrotic. Computer vision techniques have been proposed to detect the disease at an early stage [9, 10], while the authors in [11] combine Raman spectroscopy and chemometrics to detect Esca in asymptomatic grapevines. Our experiments suggest training of an ML crop disease prediction model at the edge and execution of it on the UAV.

2.1 Deep Learning for Crop Disease Prediction

The objective of our ML crop disease prediction model is image classification and thus we use Convolutional Neural Networks (CNNs). Our network consists of 5 Convolutional layers, each followed by a ReLU activation function and a MaxPooling operation, which can recognize successfully if the grapevine leaves are unhealthy, i.e., are affected by esca disease, or healthy. The architecture of our model is illustrated in Fig. 1. The classification model is trained on the Esca dataset [12], a publicly available dataset provided by the Department of Information Engineering, Polytechnic University of Marche, Ancona, Italy which contains 882 images of healthy grapevine leaves and 888 images of grapevine leaves affected by esca. Fig. 2 displays one random image per class of the dataset.

As the total number of images is not enough for training a ML model, following [12] we perform data augmentation and thus a large amount of images is acquired. Particularly, we perform the following augmentations: (a) Horizontal flip, (b) Vertical flip, (c) Rotation, (d) Width shifting, (e) Height shifting, (f) Zoom, (g) Blur and (h) Brightness.

That said, the resulting number of images is 23010, of which 11544 are unhealthy and the other 11466 are healthy grapevine leaves. In addition, we split the images randomly into 13806 train, 5752 test and 3452 validation images. Table 1 shows the number of images per class for each of the train, validation and test phase of the model.

Table 1: Number of images per class for each phase of the model.

Num. Images					
Train Images		**Validation Images**		**Test Images**	
Unhealthy	***healthy***	***Unhealthy***	***healthy***	***Unhealthy***	***healthy***
6926	6880	1732	1720	2886	2866

Metrics.The metrics used for performance evaluation for our classification model are the *Accuracy*, *Recall*, *Precision* and $F1 - Score$. These metrics are derived from the following four categories:

- **True Positive (TP):** refers to a correct prediction of the positive class.
- **False Positive (FP):** refers to an incorrect prediction of the positive class.
- **True Negative (TN):** refers to a correct prediction of the negative class.
- **False Negative (FN):** refers to an incorrect prediction of the negative class.

That said, having 2 classes in our classification problem, we can now define the above metrics as:

- **Accuracy**. Number of samples correctly identified as either truly positive or truly negative out of the total number of samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

- **Precision**. Number of samples correctly identified as positive out of the total samples identified as positive.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

- **Recall**. Number of samples correctly identified as positive out of the total actual positives.

$$Recall = \frac{TP}{(TP + FN)} \tag{3}$$

- **F1-Score**. The harmonic average of the precision and recall, it measures the effectiveness of identification when just as much importance is given to recall as to precision.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

2.2 Experimental Results

Our classification model is trained for 5 epochs in both NVIDIA RTX A4500 and NVIDIA GeForce GTX TITAN X independently, and achieves 94.94% accuracy and 94.93% precision, recall and f1-score. The training and the validation loss curves during training are shown in Fig. 3. We can observe that our model is able to learn our binary classification problem within a short period of time as both of our training and validation losses are decreased sharply. Table 2 shows

(a) Healthy grapevine leaves. (b) Grapevine leaves affected by esca disease.

Fig. 2: Samples from esca dataset [12].

a summary of the evaluation metrics for our model's training procedure. As expected, the training results in both NVIDIA RTX A4500 and NVIDIA GeForce GTX TITAN X GPU are identical as the ML model architectures are the same and the weight initialization of the models was performed with a specific seed number. Table 2 shows the training and test duration of the ML model with respect to the GPUs. NVIDIA RTX A4500 performs the best as it has a larger memory with a size of 20GB in contrast to NVIDIA GeForce GTX TITAN X that has 12GB memory.

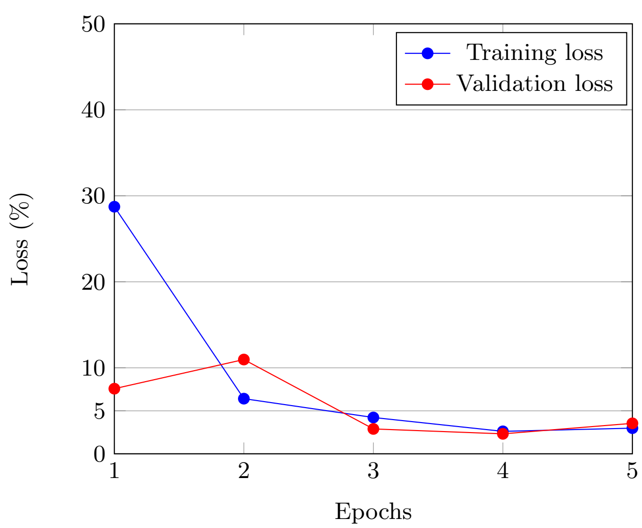

Fig. 3: Training and Validation loss during the training procedure.

Table 2: Evaluation metrics for crop disease prediction model.

Model Performance (%)				
Crop disease	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Prediction	94.94	94.03	94.03	94.03

2.3 Inference Results

The above trained model is tested on 4 different devices, namely Nvidia Jetson Xavier NX 16GB, Nvidia Jetson Nano 4GB, NVIDIA RTX A4500 and NVIDIA GeForce GTX TITAN X. We perform inference of the model in each device and we measure the inference time across these devices, i.e., the time the model needs to process a single image with its trained weights and classify the image. The results are shown in Table 3. As expected, the least inference time was observed in NVIDIA RTX A4500 with a value of 0.038 seconds. However, it is worth mentioning that NVIDIA Jetson Xavier NX 16GB performs better than the other devices with inference time of 0.1878 seconds outperforming even the NVIDIA GeForce GTX TITAN X GPU with a high difference of approximately 0.19 seconds, i.e., half of the time, emphasizing that way its powerful performance.

Table 3: Inference time of the ML model across all devices.

Device	**Nvidia Jetson Nano 4GB**	**Nvidia Jetson NX 16GB**	**Nvidia GeForce GTX TITAN X**	**Nvidia RTX A4500**
Inference Time (s)	0.4224	0.1878	0.2972	0.0380

3 Conclusion

In this paper, we aim to address the problem of crop disease prediction using deep learning techniques. Particularly, we trained a CNN image classifier to classify grapevine leaves as either healthy or unhealthy, i.e., affected by esca disease. Our model's performance evaluation shows the effectiveness of employing a deep learning classification network for this task, achieving high accuracy in distinguishing between healthy and diseased leaves. We conducted inference of the trained models on several IoT and edge devices' processors and measured the respective times indicating the potential for real-time decision-making. The results validate that our model can support real-time esca disease prediction on the drone, thus enabling targeted treatment for affected areas for optimizing crop protection strategies.

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