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Deep learning models for plant disease detection and diagnosis

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ABSTRACT

In this paper, convolutional neural network models were developed to perform plant disease detection and diagnosis using simple leaves images of healthy and diseased plants, through deep learning methodologies. Training of the models was performed with the use of an open database of 87,848 images, containing 25 different plants in a set of 58 distinct classes of [plant, disease] combinations, including healthy plants. Several model architectures were trained, with the best performance reaching a 99.53% success rate in identifying the corresponding [plant, disease] combination (or healthy plant). The significantly high success rate makes the model a very useful advisory or early warning tool, and an approach that could be further expanded to support an integrated plant disease identification system to operate in real cultivation conditions.

1. Introduction

Plant disease diagnosis through optical observation of the symptoms on plant leaves, incorporates a significantly high degree of complexity. Due to this complexity and to the large number of cultivated plants and their existing phytopathological problems, even experienced agronomists and plant pathologists often fail to successfully diagnose specific diseases, and are consequently led to mistaken conclusions and treatments. The existence of an automated computational system for the detection and diagnosis of plant diseases, would offer a valuable assistance to the agronomist who is asked to perform such diagnoses through optical observation of leaves of infected plants (Mohanty et al., 2016; Yang and Guo, 2017). If the system was simple to use and easily accessible through a simple mobile application, it could also be a valuable tool for farmers in parts of the world lacking the appropriate infrastructure for the provision of agronomic and phytopathological advice. In addition, in the case of large-scale cultivations, the system could be combined with autonomous agricultural vehicles, to accurately and timely locate phytopathological problems throughout the cultivation field, using continuous image capturing. All these are, of course, valid under the condition that the system could achieve high levels of performance in detecting and diagnosing specific diseases in real-life conditions (i.e., in the cultivation field), and that it could be operated through an appropriate, easy-to-use, and user-friendly mobile application (a first step towards that direction has been made by Johannes et al. (2017) for the specific case of wheat plants).

With the development of computational systems in recent years, and in particular Graphical Processing Units (GPU) embedded processors, Machine Learning-related Artificial Intelligence applications have achieved exponential growth, leading to the development of novel methodologies and models, which now form a new category, that of Deep Learning (LeCun et al., 2015). Deep learning refers to the use of artificial neural network architectures that contain a quite large number of processing layers, as opposed to "swallower" architectures of more traditional neural network methodologies. The now computationally-feasible deep learning models have revolutionized sectors such as image recognition (LeCun et al., 1998; Dan et al., 2011), voice recognition (Hinton et al., 2012), and other similarly complex processes that deal with the analysis of large volumes of data (LeCun and Bengio, 1995), giving a huge boost to applications that use these processes, like, e.g., self-driving vehicles, machine translation and interpretation, etc. The introduction of these deep learning techniques into agriculture (e.g., Carranza-Rojas et al., 2017), and in particular in the field of plant disease diagnosis (Yang and Guo, 2017), has only begun to take place in the last couple of years, and to a rather limited extent.

The basic deep learning tool used in this work is Convolutional Neural Networks (CNNs) (LeCun et al., 1998). CNNs constitute one of the most powerful techniques for modeling complex processes and performing pattern recognition in applications with large amount of data, like the one of pattern recognition in images. Lee et al. (2015) presented a CNNs system for the automated recognition of plants, based on leaves images. Grinblat et al. (2016) developed a relatively simple, though powerful neural network for the successful identification of three different legume species based on the morphological patterns of leaves' veins. Mohanty et al. (2016) compared two well-known and established architectures of CNNs in the identification of 26 plant diseases, using an open database of leaves images of 14 different plants. Their results were very promising, with success rates in the automated

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Table 1a
Information and quantitative data of the database images.

Class	Plant common name	Plant scientific name	Disease common name	Disease scientific name	Images (number)	Laboratory conditions (%)	Field conditions (%)
c_0	Apple	Malus domestica	–	–	1835	89.7	10.3
c_1	Apple	Malus domestica	Apple scab	Venturia inaequalis	630	100.0	0.0
c_2	Apple	Malus domestica	Cedar apple rust	Gymnosporangium juniperi-virginianae	276	100.0	0.0
c_3	Apple	Malus domestica	Black rot	Botryosphaeria obtusa	712	87.2	12.8
c_4	Banana	Musa paradisiaca	–	–	1643	0.0	100.0
c_5	Banana	Musa paradisiaca	Black sigatoka	Mycosphaerella fijensis	240	0.0	100.0
c_6	Banana	Musa paradisiaca	Banana speckle	Mycosphaerella musae	3284	0.0	100.0
c_7	Blueberry	Vaccinium spp.	–	–	1735	86.7	13.3
c_8	Cabbage	Brassica oleracea	–	–	420	0.0	100.0
c_9	Cabbage	Brassica oleracea	Black rot	Xanthomonas campestris	64	0.0	100.0
c_10	Cantaloupe	Cucumis melo	–	–	1055	0.0	100.0
c_11	Cassava (manioc)	Manihot esculenta	Brown leaf spot	Cercosporidium henningsii	43	100.0	0.0
c_12	Cassava (manioc)	Manihot esculenta	Cassava green spider mite	Mononychellus tanajoa & progresivus	892	100.0	0.0
c_13	Celery	Apium graveolens	Early blight, Cercospora	Cercospora apii	1204	0.0	100.0
c_14	Cherry (& sour)	Prunus spp.	–	–	854	100.0	0.0
c_15	Cherry (& sour)	Prunus spp.	Powdery mildew	Podosphaera spp.	1052	100.0	0.0
c_16	Corn (maize)	Zea mays	–	–	4450	26.1	73.9
c_17	Corn (maize)	Zea mays	Cercospora leaf spot	Cercospora zeae-maydis	1457	35.2	64.8
c_18	Corn (maize)	Zea mays	Common rust	Puccinia sorghi	1614	73.9	26.1
c_19	Corn (maize)	Zea mays	Northern Leaf Blight	Exserohilum turcicum	985	100.0	0.0
c_20	Cucumber	Cucumis sativus	–	–	267	0.0	100.0
c_21	Cucumber	Cucumis sativus	Downy mildew	Pseudoperonospora cubensis	1318	0.0	100.0
c_22	Eggplant	Solanum melongena	–	–	515	0.0	100.0
c_23	Gourd	Langenaria spp.	Downy mildew	Pseudoperonospora cubensis	114	0.0	100.0
c_24	Grape	Vitis vinifera	–	–	613	69.0	31.0
c_25	Grape	Vitis vinifera	Black rot	Guignardia bidwellii	1180	100.0	0.0
c_26	Grape	Vitis vinifera	Esca (Black measles)	Phaeomoniella chlamydospora	1384	100.0	0.0
c_27	Grape	Vitis vinifera	Leaf blight	Pseudocercospora vitis	1076	100.0	0.0
c_28	Onion	Allium cepa	–	–	154	0.0	100.0
c_29	Orange	Citrus sinensis	Huanglongbing	Candidatus Liberibacter	5507	100.0	0.0

identification up to 99.35%. However, a main drawback was that the entire photographic material included solely images in experimental (laboratory) setups, not in real conditions in the cultivation field. Sladojevic et al. (2016) developed a similar methodology for plant disease detection through leaves images using a similar amount of data available on the Internet, which included a smaller number of diseases (13) and different plants (5). Success rates of their models were between 91% and 98%, depending on the testing data. More recently, Pawara et al. (2017) compared the performance of some conventional pattern recognition techniques with that of CNN models, in plants identification, using three different databases of (a rather limited number of) images of either entire plants and fruits, or plant leaves, concluding that CNNs drastically outperform conventional methods. Finally, Fuentes et al. (2017) developed CNN models for the detection of 9 different tomato diseases and pests, with satisfactory performance.

In this work, specific CNN architectures were trained and assessed, to form an automated plant disease detection and diagnosis system, based on simple images of leaves of healthy and diseased plants. The available dataset contained images captured in both experimental (laboratory) setups and real cultivation conditions in the field. The proposed deep learning approach may find more general solutions than shallow approaches, which learn with less data but are specific to few crops (e.g., Pantazi et al., 2016). The next section presents the basic principles of the tested models, the datasets used for training and testing, and the experimentations that were designed for the investigation of the factors that affect the performance and robustness of the developed system. Section 3 presents the results of the application of the proposed models for plant disease detection and diagnosis, while the paper closes with some concluding remarks and directions for future research towards the evolution and enhancement of the developed system.

2. Materials and methods

2.1. Convolutional neural network models

Artificial neural networks are mathematical models that mimic the general principles of brain function with their neurons and synapses that interconnect them. Their main characteristic is their ability to be trained through the process of supervised learning. During that process, neural networks are "trained" to model some system with the use of existing data that contain specific matchings of inputs and outputs of the system to be modelled. CNNs (LeCun et al., 1998) are an evolution of traditional artificial neural networks, focused mainly on applications with repeating patterns in different areas of the modeling space, especially image recognition. Their main characteristic is that, with the methodology used in their layering, they drastically reduce the required number of structural elements (number of artificial neurons) in comparison to traditional feedforward neural networks. For image recognition applications, several baseline architectures of CNNs have been developed, which have been successfully applied to complicated tasks of visual imagery.

The five basic CNN architectures that were tested in the problem investigated in this work concerning the identification of plant diseases from images of their leaves, were the following: (i) AlexNet (Krizhevsky et al., 2012), (ii) AlexNetOWTBn (Krizhevsky, 2014), (iii) GoogLeNet (Szegedy et al., 2015), (iv) Overfeat (Sermanet et al., 2013), and (v) VGG (Simonyan and Zisserman, 2014). These models and their training and testing processes, were implemented using Torch7[1] machine learning computational framework, which uses the LuaJIT[2]

[1] http://torch.ch
[2] http://www.lua.org