An Image-Based Deep Learning Model for Cannabis Diseases, Nutrient Deficiencies and Pests Identification

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Abstract. In this work, a deep learning system for cannabis plants disease, nutrient deficiencies and pests identification is developed, based on image data processed by convolutional neural network models. Training of the models was performed using image data available on the Internet, while database development included data cleansing by expert agronomists, basic image editing, and data augmentation techniques commonly used in deep learning applications in order to expand the rather limited amount of available data. Three fungi diseases, two pests and three nutrient deficiencies were included in the identification system, together with healthy plants identification. The final model reached a performance of 90.79% in successfully identifying cannabis diseases (or healthy plants) in previously "unseen" plant images. The most difficult cannabis problems to be identified were powdery mildew and potassium deficiency. Results showed that transfer learning from existing models specialized in similar tasks to the one under development, is more successful than using transfer learning from more general models. Finally, even though the amount of training images in some of the considered problems was significantly small, no correlation between model performance and the size of the training dataset for each category was found.

Keywords: Cannabis · Convolutional Neural Networks · Disease detection · Disease diagnosis

1 Introduction

Cannabis sativa L. is an important herbaceous species originating from Central Asia [1]. Based on ecological constraints, cannabis evolved somewhere in temperate latitudes of the northern hemisphere. Eurasia is favored as its primary region of origin [2]. Although cannabis has been practiced for centuries [3, 4], it has recently seen a resurgence of interest because of its multi-purpose applications, delivering fibers, seeds and pharmaceuticals. As the interest of cannabis cultivation is growing, hempseed production has risen from 35,321 tn in 1990 and 68,430 tn in 2011, to 102,416 tn in

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2017 [5]. Hemp has been used for its strong fiber since ancient times. Currently the fiber is used for light weight papers, insulation material and biocomposites. Moreover, cannabis outer and inner stem tissues can be used to make bioplastics and concrete-like material, respectively [1]. Hemp seeds can be consumed raw or pressed into hemp seed oil, which has an excellent fatty acid profile. Both seeds and oil are used for human food and animal feed. The non-psychotropic Cannabinoid CBD is an interesting pharmaceutical and food supplement which is also derived from industrial hemp. The legalized cultivation and distribution of cannabis for medicinal and even, in specific cases, recreational purposes is increasing, thus the increased cultivation is likely to cause an increase in pathogens that can negatively affect the production and quality of the crop [6].

On-site and real-time plant disease detection constitutes a challenge for cannabis producers, as today the plant is grown in open-field and greenhouse cultivations in a very wide geographical distribution, and is highly susceptible to infections, making early detection of signs and symptoms crucial to the quality and quantity of final production. Plant disease diagnosis through optical observation of the symptoms on plant leaves, incorporates a significantly high degree of complexity. Due to this complexity, even experienced agronomists and plant pathologists often fail to successfully diagnose specific diseases, pests or abiotic stresses, and are consequently led to mistaken treatments. Smart farming [7] is important for tackling the challenges of agricultural production in terms of sustainability, food security and environmental impact [8]. The existence of an automated computational system for the detection and diagnosis of plant pest and diseases symptoms, would offer a valuable assistance to the agronomist [9–11].

In recent years, Artificial Intelligence (A.I.) applications that use Machine Learning methodologies, have achieved exponential growth, leading to the development of novel methodologies and models, which now form a new A.I. field, that of Deep Learning [12]. Deep learning provides high accuracy, outperforming existing commonly used image processing techniques [13], since it exploits artificial neural network architectures that contain a quite large number of processing layers, as opposed to “swallower” architectures of more traditional neural network methodologies. Mainly because of the recent advances in the development of Graphics Processing Units (GPU) embedded processors, deep learning models are now computationally feasible, and have revolutionized sectors such as image recognition [14, 15], voice recognition [16], and other similarly complex processes that deal with the analysis of large volumes of data [17].

The introduction of these deep learning techniques into agriculture and in particular in the field of plant disease diagnosis [10], has only begun to take place in the last couple of years. The basic deep learning tool used in the majority of works is that of Convolutional Neural Networks (CNNs) [14]. CNNs have been widely applied for solving problems in the agricultural domain, including plant species classification [18, 19], weed detection [19, 20], pest image classification [21] and plant disease detection and diagnosis [11].

For plant diseases identification in particular, CNNs has achieved great success [22] and helped to overcome challenges in automatic plant disease recognition [23]. Mohanty et al. in [9] 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 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. in [24] 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. Pawara et al. in [25] 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. Ferentinos in [11] developed a CNN model for the detection of plant diseases among 58 different [plant, disease] combinations, which included 25 different plant species. The identification model was trained with images captured in both experimental and real-cultivation setups, and an overall performance reaching a 99.53% success rate. Even more recently, several other advanced CNN models have been developed for diseases identification in specific plant species [26–28].

In this work, a CNN model specialized on the identification of specific problems in cannabis plants is developed. The model is trained with a variety of images of healthy and infected cannabis leaves, and it covers the most common cannabis cultivation problems, including diseases, pests and nutrient deficiencies. Section 2 of the paper investigates these most common problems, especially for greenhouse cannabis cultivation, and defines the corresponding focus of this work. In addition, it describes the deep learning model design methodology that was followed, the data collection and manipulation processes for the development of the necessary image database, and the techniques used for data augmentation and creation of the training and testing datasets for model training and validation, respectively. Section 3 analyzes the performance of the developed models, leading to the selection of the final identification model. Finally, Sect. 4 concludes the paper with some relevant conclusions and plans for future work.

2 Materials and Methods

2.1 Common Problems of Cannabis Cultivation

Diseases of cannabis plants are caused by organisms (e.g., fungi) or abiotic sources (e.g., nutrient deficiencies). Environmentally stressed plants become predisposed to diseases. Stress includes drought, insufficient light, untoward temperatures, or growing plants in monoculture. Disease prevalence shifts between greenhouse crops and outdoor crops. Serious and most common flower and leaf cannabis diseases at an indoor cultivation are nutritional diseases, pink rot, gray mold, powdery mildew, brown blight, and virus diseases [29]. The most significant fungi attack in cannabis is gray mold, caused by *Botrytis cinerea* which thrives in temperate regions with high humidity and cold to moderate temperatures. The two most common leaf spot diseases are yellow leaf spot caused by two *Septoria* species [30], and brown leaf spot caused by about eight *Phoma* and *Ascochyta* species. These diseases rarely kill plants but sharply reduce crop yields [31]. In [6], powdery mildew infection on cannabis plants was caused by *Golovinomyces cichoracearum*, whereas powdery mildew on cannabis was previously reported to be caused by *Leveillula taurica* and *Sphaerotheca macularis* [32]. In [33], a high frequency of detection by PCR (84%) of *Golovinomyces* species in cannabis samples was reported, indicating that one of the most prevalent disease reported to affect cannabis is powdery mildew. The most common abiotic diseases on cannabis crop are nutrient deficiencies [34]. Generally, deficiencies of mobile nutrients (N, P, K, Mg, B, Mb) begin in large leaves at the bottom of the plants. Shortages of less mobile nutrients (Mn, Zn, Ca, S, Fe, Cu) usually begin in young leaves near the top. Cannabis grows best in a nutrient-rich, well-drained, well-structured, high organic matter, silty loam soil. Fiber crops require high soil N, high K, then in descending order: Ca, P, Mg, and micronutrients. Seed crops, compared to fiber crops, extract less K and more P from the soil [35].

The most common flower and leaf pests in closed cultivations of cannabis plants are spider mites (*Tetranychus urticae*, *Aculops cannabicola*), aphids (*Phorodon cannabis*, *Myzus persicae*, *Aphis fabae*), whiteflies (*Trialeurodes vaporariorum*, *Bemisia* spp.), thrips, and leafhoppers, whereas slugs, rodents, and birds are pests of seedlings and seeds [36], rarely found in greenhouse cultivations. The most important non-insect pests are spider mites which suck plant sap and are the most destructive pests of greenhouse-grown cannabis. Outdoor crops may also become infested by mites in warm climates. Two species are causing the biggest crop damage: the two spotted spider mite (*T. urticae*) and the carmine spider mite (*T. cinnabarinus*). The hemp russet mite (*A. cannabicola*) is equally destructive, but less commonly encountered.

Aphids also cause serious problems to cannabis. Some are specific feeders, such as the bhang aphid (*P. cannabis*) and hops aphid (*P. humuli*), while others are general feeders, such as the green peach aphid (*M. persicae*) and the black bean aphid (*A. fabae*). Aphids congregate on the underside of leaves and cause leaf wilting and yellowing, resulting sometimes in entire plant loss. Some aphids also infest flowering tops, which become hypertrophied or totally destroyed [36].

This work aims to detect and diagnose the most common diseases, pests and nutrient deficiencies of cannabis plants, focusing mainly on greenhouse cultivation. Thus, the problems shown in Table 1 were selected to be included in the initial deep learning model presented here.

2.2 Deep Learning Model Design

Artificial neural networks are mathematical models which are inspired by the network of neurons in the biological brain. Their main characteristic is the ability to be trained to perform a particular task using large amounts of data, through the process of supervised learning. During that process, neural networks "learn" to model some system with the use of specific data that contain matchings of inputs and outputs of the system to be modelled. CNNs [14] are an advanced form of traditional artificial neural networks, which have been evolved to focus mainly on applications with repeating patterns in different areas of the modeling space, as it happens, e.g., in image recognition applications. With the methodology used in their layering, CNNs manage to drastically

Table 1. Cannabis infections/problems identified by the proposed deep learning model.

Disease common name	Problem category	Involved organisms
Gray mold	Fungi	*Botrytis cinerea*
Powdery mildew	Fungi	*Golovinomyces* spp.
Yellow leaf spot	Fungi	*Septoria* spp.
Spider mites	Pests	*Tetranychus urticae, Aculops cannabicola*
Aphids	Pests	*P. cannabis, Myzus persicae, Aphis fabae*
Nitrogen deficiency	Nutrient deficiencies	N/A
Phosphorus deficiency	Nutrient deficiencies	N/A
Potassium deficiency	Nutrient deficiencies	N/A

reduce the required number of structural elements (number of artificial neurons) in comparison to traditional feedforward neural networks.

For image recognition in particular, several core architectures of CNNs have been developed [37–41]. Most specialized image recognition CNN models, usually use these core CNN architectures as a starting point for model development and training, rather than starting the model design and training from models with initially random weights. This is a process called transfer learning [42], which has proved to be extremely successful and resource-saving in a wide range of complicated tasks of visual imagery. Some specific applications may require special network architectures or large modifications of core architectures, but the majority of systems reach sufficient performance with the use of transfer learning from core CNN architectures.

Here, two transfer learning approaches were used and tested. In the first approach, CNN models were developed using transfer learning from three well known core CNN architectures that have been shown to work very well in the development of similar plant disease detection architectures [9, 11]: (a) AlexNet [37], (b) GoogLeNet [39], and (c) VGG16 [41]. These core models have been trained for object recognition in well-known, large image datasets, like Imagenet. In the second approach, a CNN model was developed using transfer learning from a very successful CNN model which is specialized in plant disease identification [11].

The plant disease identification model [11] that was used as a base model for the cannabis model developed in the second approach described before, was based on the VGG16 architecture [41]. An open database of 87,848 images was used for the development of that model, covering 25 different plants in a set of 58 distinct classes of [plant, disease] combinations, including healthy plants. The success rate of the model in identifying the correct [plant, disease] combination (or healthy plant) was 99.53%, making it probably one of the most powerful such models available, and surely the most widely applicable, as it not only included the largest variety of [plant, disease] combinations in the literature, but it also worked with images captured in both experimental and real cultivation setups. Thus, four different model design approaches were used in this work, resulting in four different CNN models, as presented in Table 2. Training was performed in MATLAB software package (by MathWorks®), using two NVIDIA® RTX2080 GPUs with the CUDA® parallel programming platform, in Linux environment (Ubuntu 18.04 LTS operating system).

Table 2. Basic features of the four CNN models developed for cannabis disease identification.

Model name	Base model for transfer learning	Base model reference
CANCNN1	AlexNet	[37]
CANCNN2	GoogLeNet	[39]
CANCNN3	VGG16	[41]
CANCNN4	58 [plant, disease] classes id. model	[11]

2.3 Data Collection and Manipulation

This work concerns the identification of 8 different problematic situations of cannabis plants, as well as healthy plants, comprising a set of 9 different classes. As mentioned in Sect. 2, five classes concerned corresponding plant diseases and infections, common for cannabis plants (gray mold, powdery mildew, yellow leaf spot, spider mites, and aphids), and three classes concerned nutrient deficiencies (nitrogen, phosphorus, and potassium). Images of healthy and diseased cannabis plants of various stages of the infections were collected from the Internet, using relevant keywords. The initially collected images were then filtered by expert agronomists to assure that they indeed belonged to their designated category. For training and testing of the developed CNN models, images of leaves of cannabis plants were used (single or multiple leaves). Thus, after data cleansing and some image manipulation involving extracting specific parts of entire images to form separate images of leaves, the number of images for each of the 9 classes (c0 – c8) were those shown in Table 3.

Table 3. Information and quantitative data of the collected cannabis leaves images.

Class	Problem name	No. of images	% of total images
c0	N/A (healthy plants)	102	20.4%
c1	Gray mold	57	11.4%
c2	Powdery mildew	69	13.8%
c3	Yellow leaf spot	19	3.8%
c4	Spider mites	59	11.8%
c5	Aphids	18	3.6%
c6	Nitrogen deficiency	72	14.4%
c7	Phosphorus deficiency	60	12.0%
c8	Potassium deficiency	44	8.8%
	TOTAL	500	100.0%

Figure 1 shows an example of each of the 9 classes. Images in the compiled database include photographs shot in both experimental conditions (e.g., on a table with uniform background) and real cultivation conditions. The database comprised of a total of 500 images, with the richest class (class c0 – healthy plants) containing 20.4% of them and the poorest class (class c5 – Aphids) containing 3.6% of them. It is obvious that there is a quite uneven distribution of images between the 9 classes (Table 3), which is something definitely not ideal for training a robust neural network model. However, the influence of dataset sizes in the performance of the final model is investigated and the corresponding results are presented in Sect. 3 below.

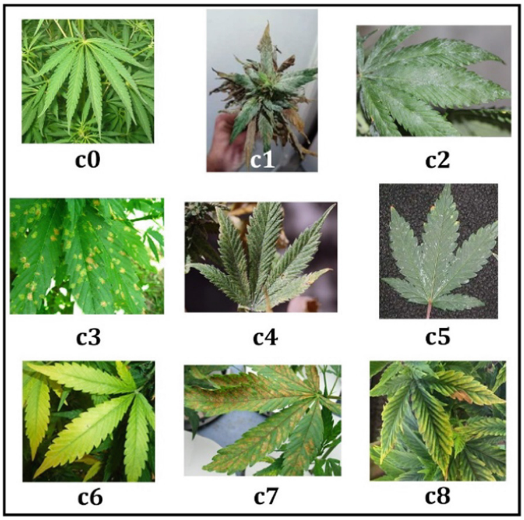

Fig. 1. Sample leaf images of the 9 classes in the database. c0: Healthy, c1: Gray mold, c2: Powdery mildew, c3: Yellow leaf spot, c4: Spider mites, c5: Aphids, c6: Nitrogen deficiency, c7: Phosphorus deficiency, c8: Potassium deficiency. (Color figure online)

No additional image editing was performed at the stage of developing the training/testing database. The alternative of using grayscale versions of the images for training was not considered, as previous works (e.g., [9]) have indicated that this approach does not improve the final classification performance of deep learning models in similar applications. The same holds for segmentation of the leaves from the background of the images, thus this additional step in the process was also not considered [11].

2.4 Training/Testing Datasets and Data Augmentation

The 500 images database was divided into two datasets, the training set, and the testing set, by randomly splitting the images so that 85% of them formed the training set, and 15% formed the testing set. Thus, 424 images were used for training the CNN models and the rest 76 images were kept for testing the performance of the models in classifying new, previously "unseen" images. In order to increase the rather limited size of the training data, several data augmentation techniques were also used and their influence in increasing the training performance of the models was investigated. These techniques included random rotations of images within ±10 to $\pm45°$, and random image translations in both x and y dimensions. Finally, all images were resized to fit the necessary input dimensions of each tested architecture (227 $\times$ 227 pixels for AlexNet, and 224 $\times$ 224 for GoogLeNet, VVG16 and the [plant, disease] identification model of [11]).

3 Results

All four CNN models presented in Sect. 2.2 (Table 2) were trained using several different values for the training parameters concerning learning rate, batch size, momentum, etc. Also, all models were trained using either the original training data or the augmented training data, for comparison. Their performance on the testing dataset is shown in Table 4.

Table 4. Performance (correct classification rate) of different CNN models on the testing dataset.

Model	Trained on original data	Trained on augmented data
CANCNN1	81.58%	85.53%
CANCNN2	80.26%	86.84%
CANCNN3	82.89%	88.16%
CANCNN4	84.21%	90.79%

From the results presented in Table 4 it is clear that data augmentation played a crucial role in the development of models with high performance, and that CANCNN4 model, which was based on transfer learning from the plant/disease identification model presented in [11] outperformed the other three models which were based on more general network architectures. The performance of the final model achieved a 90.79% success rate on the testing dataset. Two versions of this specific model reached that success rate, with slightly different success rate distributions among the 9 classes under consideration. These distributions are presented in Table 5, and shown graphically in Fig. 2. The first version of the model (CANCNN4a) had a rather low performance in the case of class c8 (Potassium deficiency), thus the second version of the model (CANCNN4b) was selected as the final model of this work, which resulted in more uniform performance distribution among all 9 classes. Both versions had an overall performance rate of 90.79%, with their only difference being the batch size during training (64 for the first version and 32 for the second version). The results showed that the most difficult cannabis problems to be identified correctly were powdery mildew and potassium deficiency. Finally, these distribution results, when considered together with the number of available images for each category (Table 3), show that there is no actual correlation between model performance and the size of the training dataset for each category (Fig. 3).

Table 5. Success rates (%) for each class category (and overall performance) of the two versions of the best model architecture (CANCNN4).

Class	Category	CANCNN4a	CANCNN4b
c0	Healthy	100.00	100.00
c1	Gray mold	88.89	88.89
c2	Powdery mildew	80.00	70.00
c3	Yellow leaf spot	100.00	100.00
c4	Spider mites	100.00	100.00
c5	Aphids	100.00	100.00
c6	Nitrogen deficiency	100.00	100.00
c7	Phosphorus deficiency	88.89	88.89
c8	Potassium deficiency	57.14	71.43
	Overall	90.79	90.79

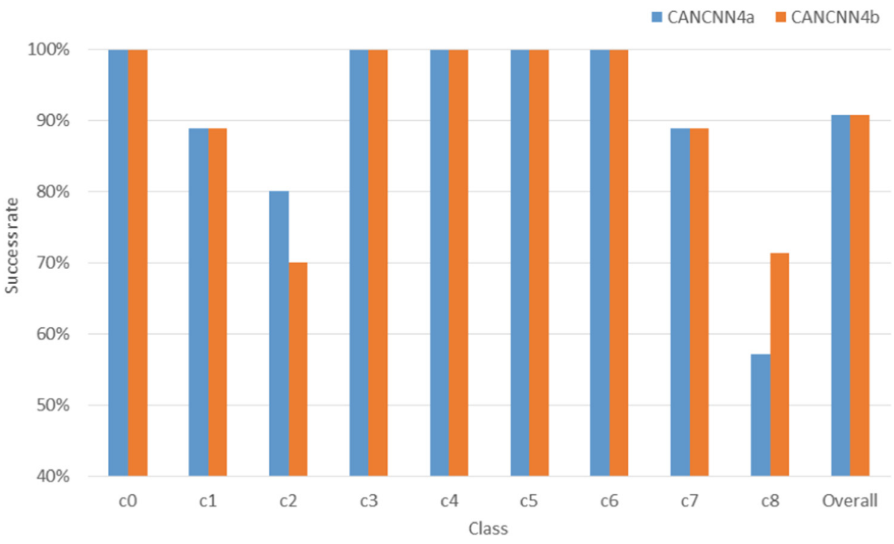

Fig. 2. Success rates distribution over each class category (and overall performance) of the two versions of the best model architecture (CANCNN4).

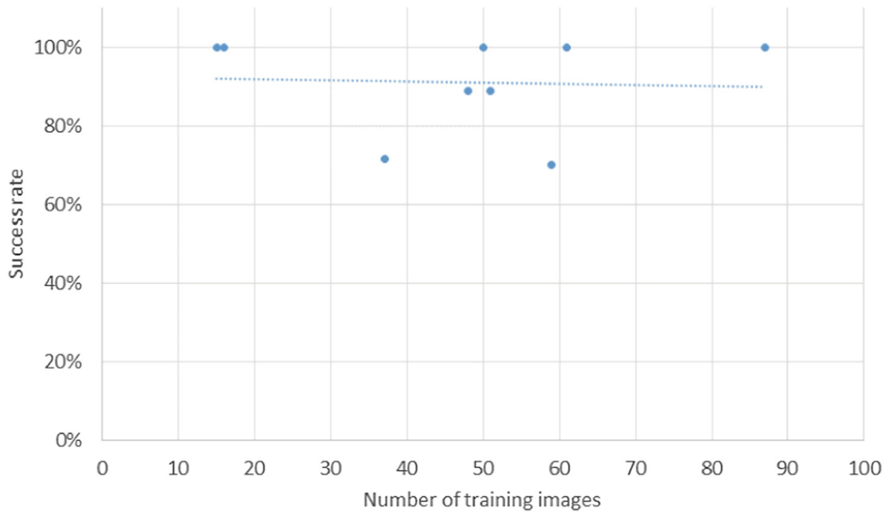

Fig. 3. Success rate per class of final model in relation to corresponding training data size of each class.

4 Conclusions

This work presents the development of specialized deep learning models, based on convolutional neural networks, for the identification of cannabis infections, concerning diseases, pests and nutrient deficiencies. Training of the models was performed using image data available on the Internet, while database development included data cleansing by expert agronomists, image editing to produce separate leaves images from photographs of multiple plants, and data augmentation techniques commonly used in deep learning applications in order to expand the rather limited amount of available data.

Four different CNN model approaches were investigated, concerning transfer learning from three well-known image classification CNN architectures and from one previously developed model for general plant disease identification, which included 28 different plant species (but no cannabis plants). The comparison results between the four approaches made clear that transfer learning from existing models specialized in similar tasks to the one under development, is more successful than using transfer learning from more general models. The performance of the final model, which reached a rate of 90.79% in correctly classifying testing images in either one of the 8 considered infections or as healthy, showed that the most difficult cannabis problems to be identified were powdery mildew and potassium deficiency. Even though the amount of training images in some of the considered problems was significantly small, no correlation between model performance and the size of the training dataset for each category was found, thus highlighting the power of CNNs and transfer learning in this specific task.

However, in order to develop a more robust disease identification system for cannabis, which would work in real cultivation conditions, much more training data need to be collected. As a future work, such data will be created in greenhouse cannabis cultivation conditions, and the model will be also further expanded to include more diseases and other common cannabis plants problems.

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