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Sustainable Smart Agriculture: Plant disease detection with deep learning techniques in cotton cultivation

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Abstract. To meet the needs of an ever-growing global population, the agricultural sector has the responsibility of increasing production, managing diseases and pests that attack crops, and implementing sustainable practices. Deep learning techniques used in sustainable smart agriculture have proven effective in this scientific field for their fast and reliable predictions and their contribution to accurate classifications, for reducing the reckless use of agrochemicals that impose a burden on crops. Early stage plant infestations detection is essential for rapid treatment achievement in order to reduce or eliminate its negative effects on the crops. In this work Convolutional Neural Networks (CNN) models were used, focused on the detection and recognition of pests and diseases. Specifically, using transfer learning from the pre-trained EfficientNet model, the model's accuracy and loss function were examined on a new data set with images of cotton plants from Greek crops, in order to identify healthy and aphid-infested plants.

Keywords: Convolutional Neural Networks, Plant Disease Detection, Smart Sustainable Agriculture

1. Introduction

One of the greatest challenges of the modern era is that approximately 50% of the world's agricultural output must be increased by 2050, in order to meet the needs of the growing population (FAO 2017). As a result of the growing demand for nutritious and safe food, more arable land and inputs such as water and energy will be required, but ecosystems and natural resources will also deteriorate (Berkum and Dengerink 2019). Among the major factors that affect food production are plant pests and diseases, which can significantly reduce the physical and economic productivity of crops. Taking appropriate management and control measures for pests and diseases is necessary in order to minimize production losses and ensure crop viability, emphasizing the importance of constant monitoring of crops along with rapid and accurate diagnosis (Abade et al. 2021). Dealing with plant pests and diseases has always been a major concern and threat to the agricultural sector (Arsenovic et al 2019; Toda and Okura 2019).

The purpose of this research is to propose a system that focuses on the detection and identification of pests and diseases in cotton cultivation with the help of CNN's architectural to create a mobile phone application to automate the process of identifying an infestation from downloading an image of an infected plant. Such a system can prove useful to farmers who will get real-time help in diagnosing their crop infestations. It can also provide data and access to information to the scientific community, government and companies regarding the spread of pests and diseases occurring in a crop at the regional level (Bhatia et al. 2019).

Sustainable Smart Agriculture/Farming

A smart approach to agriculture/farming is to use modern technologies in order to increase crop as well as maximizing resource efficiency and minimizing environmental impact (Tao et al 2021). Smart agriculture/ farming can deliver benefits to a wide range of factors, including agricultural productivity, environment impacts, food security, and sustainability (Kamilaris and Prenafeta -Boldu 2018). In a sustainable agriculture, farmers are able to make smarter decisions, preserving the natural environment without compromising the quality of future generations' essential needs (Dhanaraju et al. 2022).

2. Plant Disease and Pest detection via deep machine learning

In many cases, pests and diseases have become a global threat to some crops. The use of agrochemicals often has negative effects on cultivation, while at the same time it is a risk to human health (Panchal et al. 2021). Therefore, the main challenge of agriculture the accurate and timely diagnosis of pests and diseases that affect crops (Mohanty et al. 2016; Abade et al. 2021), in order to follow the appropriate treatment practices. Traditionally, crop pests and diseases have been identified by visually inspecting crops (Toda and Okura 2019). However, today, various technologies have been used to assist the identification process, including machine learning (ML). In the field of ML progress has led to the evolution of deep machine learning (Anjanadevi et al. 2020). Deep learning (DL) is a type of ML and Artificial Intelligence (AI) that mimics the way humans acquire certain types of knowledge (Brahimi et al. 2018). With the help of cutting-edge technologies, such as DL and cloud computing, real-time diagnosis and classification of the problem can be achieved. To improve the diagnosis recognition rate, many techniques using ML and pattern recognition have been studied, such as Artificial Neural Networks (Omrani et al 2014), Convolutional Neural Networks (Lu et al. 2017),Back Propagation Neural Networks, and other image processing methods (Arivazhagan and VinethLigi 2018).

3. Convolutional Neural Networks (CNNs)

In recent years, CNNs have shown excellent results in many image classification tasks that have given researchers the opportunity to improve plant disease classification accuracy (Brahimi et al 2018). CNNs are a subset of ML approaches that have emerged as a versatile tool for assimilating large amounts of heterogeneous data and providing reliable predictions of complex and uncertain phenomena (Goodfellow et al 2016). There have been numerous examples of CNNs being applied successfully by different organizations in a variety of fields, using inputs such as audio, video, images, speech and natural language (Kamilaris and Prenafeta-Boldu 2018). With the help of architectural CNN, a system is proposed that focuses on the detection and identification of pests and diseases that attack a plant by simply capturing the image of the affected leaf or part of the plant (Bhatia et al 2019).

4. The case of cotton

Cotton (Gossypium sp.) is considered one of the leading agricultural crops. It has been cultivated for more than 6,000 years as a source of fiber (WPR 2022), with ever-increasing demand and production. It is considered as an international trade crop that plays a decisive role for the economy of the countries in which it is grown (Chi et al. 2021). It is among the top 10 agricultural products in global trade and is cultivated in more than 100 countries, occupying 2.5% of the world's arable land (Nunes Alves et al. 2020).

The most important concern in cotton cultivation throughout the growing season is the control of weeds, pests and diseases, factors that cause serious economic losses each year, either in the form of reduced yield or reduced fiber quality. Pest control of cotton is highly dependent on the use of agrochemicals. Therefore, their early and accurate identification would offer a substantial benefit for the further sustainable management of the crop (Nunes Alves et al. 2020). Regarding the cotton pests, as it is referred in the literature, about 1326 insect species are hosted in the crop (Rajendran et al. 2018). The green bollworm (*Helicoverpaarmigera*), aphids (*Aphis gossypii*), the lynx (*Lyguspratensis L.)* and the spider mites (*Tetranychusurticae*), are some of the main pests of cotton (Chi et al. 2021).

5. Related Work

Regarding the classification and identification of cotton pests and diseases from field images using deep ML few results have been reported in the world literature. It is most commonly used for identification of leaf diseases, identification of plants, and crop yield estimation (Kamilaris and Prenafeta-Boldu 2018a; Nunes Alves et al 2020). For instance, Mikail and Baran (2021) used artificial neural networks and support vector machine AI methods to predict cotton production. Udawant and Srinath (2019) used CNN to classify the diseased part of cotton plant images with a high accuracy rate to differentiate between healthy and diseased cotton plant (Udawant and Srinath 2019). As part of a transfer learning methodology (2020), Nunes Alves et al. (2020) proposed a classification system for cotton pests (primary and secondary), obtaining initial weights from ImageNet and using the proposed insect image dataset, in which original images as well as augmented images were used to train the networks (Nunes Alves et al 2020). Kalpana1 et al. (2020) conducted a research on the automatic recognition of cotton plant diseases using CNN to diagnose bacterial infection using images taken from the field (Kalpana1et al. 2020). Caldeira et al. (2021) presented the results of a successful use of DL to identify cotton leaf infestations, showing that it can indeed help diagnose crop pests and diseases.

6. Methodology

7.1 Used Tools

Several tools were used in this research. The programming used the Python 3.8.5 language. To run the application, the Tensorflow library (CPU version) was used. TensorFlow is an open source neural network library of Google, developed by the GoogleBrain team for many uses. Essentially, TensorFlow removes the need to build a neural network from the beginning.

This study also used Keras, an open-source neural network library written in Python that can run on Theano, TensorFlow, or CNTK. Convolutional networks, recurrent networks, and their combinations are supported, as well as their individual use. In order to solve low-level calculations, it uses the Backend library. As a high-level API wrapper, the backend library can run on TensorFlow, CNTK, or Theano. This library is responsible for creating and editing the model used. As an additional layer of complexity, matplotlib.pyplot was used to make matplotlib behave like MATLAB. Each pyplot function makes some change to a figure, e.g. creates an image, creates a plot area on an image, draws some lines on a plot area, etc.

Furthermore, the weights of the model from EfficientNet were used. In EfficientNet, a complex coefficient is used to uniformly scale depth, width, and resolution dimensions. The network is optimized to achieve maximum accuracy, but is also penalized if the network is too computationally heavy. It is also penalized for slow inference time when the network takes too long to make predictions. This basic model has been scaled up to have the EfficientNets family. In this work, it has been chosen the EfficientNetB0, the architecture of which is shown in Figure 1.

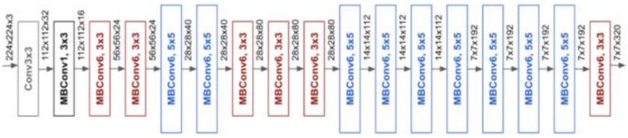

Figure 1. Architecture of the basic EfficientNetB0 model (Source: Montalbo and Alon 2021)

As figure 1 reveals, the base model EfficientNetB0 is the input point that receives an input image with dimension 224x224x3. Multilayer convolutional (Conv) layers are used to extract features from all layers of the model. The kernel receptive field used is 3x3kernel, and MBConv (mobile inverse congestion convolution) is applied at each layer. It does 18 convolutions and starts with 4 layers of 3X3, then goes to 5X5, another 3 layers of 3X3, 7 with 5X5 and ends up with a 3X3 and produces 7X7X320 filters in total. EfficientNetB0 is selected because it combines depth, breadth, and resolution, allowing for scalable yet precise model development. Compared to other deep machine learning, EfficientNetB0 scales each dimension using a fixed set of scaling factors. This approach outperformed other state-of-the-art models trained on ImageNet data (Montalbo and Alon 2021).

To visualize the results, TensorBoard, which is a tool that represents the learning process of each model and other parameters that the user can choose, was used.

7.2 Training

A total of 160 photos were used during training for each of the classes (aphids, healthy); 130 were used for training the model and 30 for verification.

7. Results

The size of images reshaped for EfficientNetB0 model input layer requirements (224, 224, 3) and the output layer of the model consist of two classes. The total parameters of the model were 4,052,133 but only 2,562 were trainable. The model was adjusted for the first 5 epochs using the pre-trained weights and for the last 5 epochs changed the weights of the model using information of the new input images.

Figure 2. Classification Accuracy Chart

According to Figure 2, the training accuracy started with value 0.7 and after 10 epochs (5 pre-trained and 5 new training epochs) got the value of 0.88. The validation accuracy for the testing data was equal to 0.85.
In terms of how well the model was trained, the training error of the model as epochs 1 to 10 progresses, as it is revealed from the plot, decreases from 0.6 to 0.31 at the 9th epoch, and then starts to increase. As a result of this, training must stop since for the totality of the data it makes no sense to continue the training. In validation the results were also very satisfactory at 0.35 at the 8th epoch.

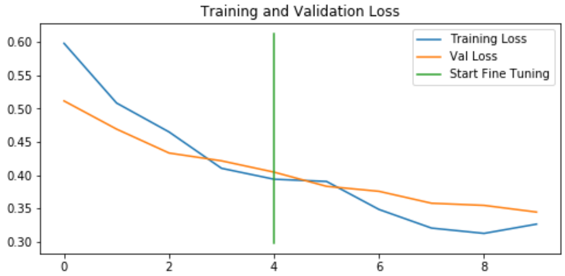

Figure 3. Training and Classification Error Plot

Figure 4presents an unknown image that was used as a test data input. The image was categorized by the model as “aphids" resulting that the plant is affected by aphids, with a probability of 0.80. However, despite the leaves of the plant not being captured at a very close distance, the model accurately identified the plant as an affected one.

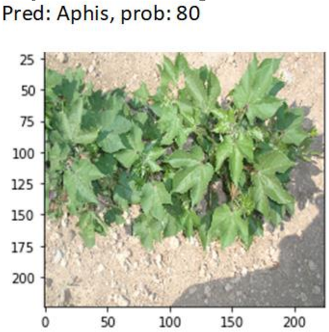

Figure 4. Correct classification of an unknown image

8. Conclusions

In the present research, the problem of classification was investigated using images of plants taken in the field. After an extensive literature review, EfficientNetB0 was selected as the model, which further improves the performance of the model and makes the model converge faster and less prone to fluctuations. EfficientNet can implement transfer learning (transfer its knowledge to our own data) and then be trained with new weights. The central conclusion of this research is that for the real data of healthy and aphid-infested cotton plants, the training results were 88% and the validation was 85%. It is therefore a very good technique that can be used more widely to predict more pests and diseases with the necessary training to implement a mobile application to facilitate farmers in identifying infestations in the field.

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