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# IDENTIFICATION OF CROP DISEASES USING DEEP LEARNING ALGORITHM

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## ABSTRACT

*In this paper we present an algorithm based on deep learning. The program allows the user to select in a graphical interface the type of plant for which it is desired to insert images for disease identification. To train and test models, we used our own data set with a relatively small number of images, and all images were captured in culture, and not in laboratory conditions. The algorithm is based on deep learning approach.*

KEYWORDS: plant disease identification, deep learning, computational fluid dynamics

## 1. Introduction

Plant diseases have by far a hard influence concerning food production in order to reduce or mitigate losses in production, consequently is of paramount importance that crop diseases are surveyed in a good manner to be detected and act accordingly to the current situation in real time. The nowadays recent large scale of use of deep learning algorithms dedicated to image processing applications in the domain of plant disease detection is providing a highly robust option to achieve extremely accurate results [1].

In general, traditional manual visual observation for disease diagnosis methods is inefficient and time-consuming, especially for small and medium-sized farms. With the modern advancement of computer vision and artificial intelligence algorithms, the plant disease detection protocol has become an integral part of crop health monitoring information collection, which substantially improves the efficiency of plant production [2].

Early identification and prevention of plant diseases are the important aspects of crop harvesting as they can effectively reduce any growth disturbances and thus minimize chemicals use. In this regard, the automatic detection of plant diseases using different machine learning (ML) algorithms has become an effective tool for modern agriculture. Various machine learning approaches such as neural network [3] and support vector machine (SVM) [4] have been used for plant and disease classification. However, such complex pre-processing images and method feature extraction step have lower performance and speed in real-time disease detection. Furthermore, one of the main drawbacks of traditional machine learning approaches is that they are not suitable for real-life discovery scenarios with complex non-uniform backgrounds. In this regard, recently, deep learning has made a significant breakthrough in the field of computer vision with various applications [5].

Artificial Vision (AV) together with Artificial Intelligence (AI), have developed techniques and methods for object recognition and classification with significant progress [7-9]. Deep learning algorithms allows trained data models to learn models using data with multiple levels of abstraction, achieving a high rate of precision in many domains such as object recognition and object detection. There are many basic deep learning models such as Deep Feed Forward, where data extracted from training process is propagated in only one direction in the network through several layers of neurons. There are several algorithms such as: Back-Propagation, Convolutional Neural Network, Recurrent Neural Network, including Long Short-Term Memory, Auto-Encoder, Deep Belief Network, and Deep Reinforcement Learning [8-11]. One particular very used category of feed forward network that may be very easy to be trained compared to fully connected networks is the one peculiar architecture named the convolutional neural network (CNN).

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## 2. Technique proposed

CNNs are considered by many scholars a highly powerful algorithm for modeling complex processes for image recognition in application where is required a fast data processing in real time. Many approaches are taken into account highly used architectures such as LeNet, AlexNet, VGGNet, GoogleNet, InceptionV3, ResNet, and DenseNet, allowing increase the recognition rate in plant disease identification. Despite the important highly precision provided by deep learning, several challenges are emerging to the real-life scenarios for the aim of recognition and identification of plant diseases. Several issues such as the genetic diversity of crops and diseases is affecting the results in case of real outdoor plant environment application. AlexNET is an object detection model that transforms the object detection task into a regression problem by generating bounding box coordinates and probabilities corresponding to each class.

In this paper we present an algorithm based on deep learning. The program allows the user to select in a graphical interface the type of plant for which it is desired to insert images for disease identification (Fig. 2).

According to our approach, during object detection, the input image is processed successively with 5 convolution and 2 pooling operations. The final layer is a fully connected layer with the confidence scores and conditional probabilities of the corresponding class for each target class (Fig. 1).

The classification problem also considers the position detection task. The purpose of the model is to identify a class of diseases. The algorithm is able to detect 17 classes of disease.

The image might be acquired by any means, using a phone camera, and any digital.

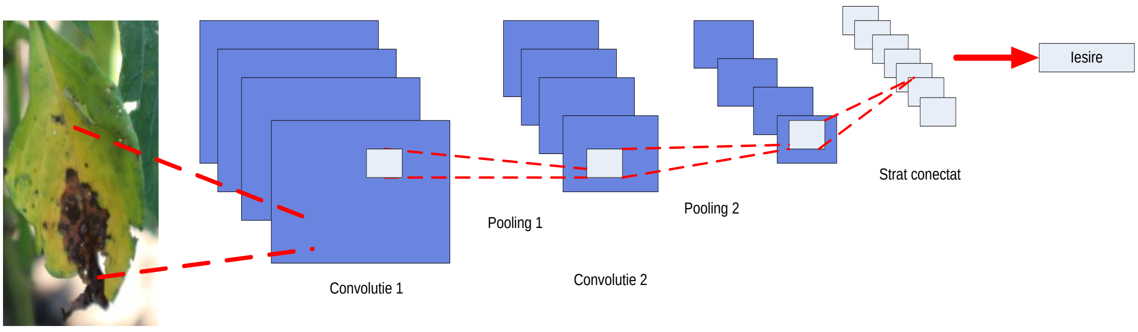


***Fig. 1.*** *Deep learning algorithm architecture*

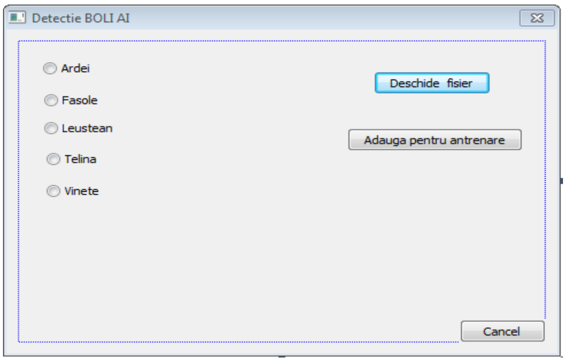


***Fig. 2.*** *Program interface*

The developed model must solve both the classification problem - displaying the class of diseases - and the problem of positioning the object in the image to confirm to the user that the operation is successful (Fig. 5).

There are specific diseases that impose special challenges, especially those that present very small surfaces with a geometry that can easily be confused with the chromatic structure of the leaves (Fig. 3). To train the neural network, we used sets of our own images taken from culture. Unlike several approaches of other groups of researchers, who used training sets with backgrounds from the laboratory, the algorithm uses images from its own culture for training, where the background is a natural one. This allows more

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training data to be entered and allows the platform to have the option to enter new training data.

The size of the images for training the neural network is 120 x 120 pixels. The number of images is in range of 80-200 images varying on each disease. In addition, for each data set, 20% more training images from the original set were generated by augmentation (rotation and dimming). The platform allows a new image entered by the user to be used for learning.

This was done to increase the training set and eliminate identification errors related to the positioning of the plant relative to the camera.

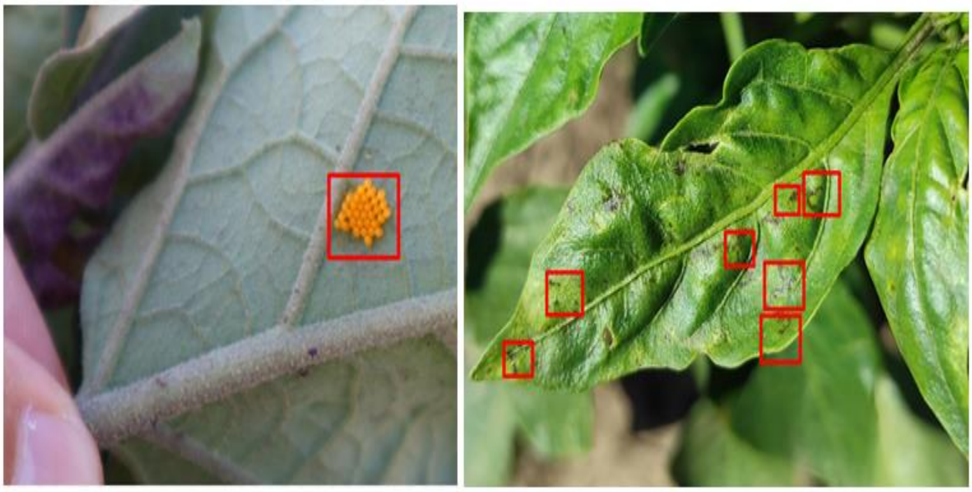

***Fig. 3.*** *Identification of disease*

For testing, 50 images were used for each of the diseases indicated in this program testing platform. The precision detection is shown in Table 2.

***Table 2.***

| Pepper | Precision[%] | Beans | Precision[%] |
|---|---|---|---|
| Myzus persicae | 80 | Tetranicus urticae | 98 |
| Fusaium oxisporum | 99 | Colletotrichum lindemuthianum | 98 |
| Xanthomonas vesicatorie | 99 | Xanthomonas campestris | 99 |
| Alternaria tenuis | 98 | | |
| Tabacco mosaic virus in pepper | 93 | | |
| Alfalfa mosaic virus in pepper | 92 | | |
| Lovage | Precision[%] | Celery | Precision[%] |
| Euleia heraclei | 99 | Cercospora apii | 89 |
| Septoria apiicola | 93 | Septoria petroselini | 79 |
| Eggplants | Precision[%] | | |
| Leptinotarsa decemlineata-adult | 86 | | |
| Leptinotarsa decemlineata- larve | 87 | | |
| Leptinotarsa decemlineata- egg | 85 | | |

It is important to note that although CNN architectures are powerful in classification, segmentation, and object detection tasks, they require a large amount of data to be trained.


***Fig. 4.*** *Reduced size disease*

The platform allows a new image entered by the user to be used for learning. This usually requires large amounts of data, but this can be mitigated using methods such as filters associated with multiple disease classes. Identifying diseases with a point-like appearance, from a colour point of view resembling the leaf is a particular challenge. However, the algorithm allows recognition with a good detection rate (Fig. 4).

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***Fig. 5.*** *Detection of disease location*

## 3. Conclusions

There are various approaches to solve the problem of disease identification with the help of artificial intelligence algorithms. However, there is still no effective solution.

The team developed an intelligent platform capable of identifying 17 classes of diseases using images of plants with healthy and diseased leaves. To train and test models, we used our own data set with a relatively small number of images, and all images were captured in culture, and not in laboratory conditions. This presents multiple advantages and shows the robustness of the identification algorithm. After splitting the dataset into training images and testing images we achieved the best accuracy rate of 99% and it took 400 iterations to train the network with images.

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## References

**[1]. Akhtar A., Khanum A., Khan S. A., Shaukat A.**, *Automated Plant Disease Analysis: Performance comparison of machine learning techniques*, (In) Eleventh International Conference on Frontiers of Information Technology, IEEE, p. 60-65, 2013.

**[2]. Amara J., Bouaziz B., Algergawy A.**, *A deep learnin gbased approach for banana leaf diseases classification*, (In) Proceedings of Datenbanksysteme für Business, Technologie und Web (BTW 2017) – Workshop Bonn: Gesellschaft für Informatik, 2017.

**[3]. Arivazhagan S., Shebia R. N., Ananthi S., Varthini S. V.**, *Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features*, Agricultural Engineering International: CIGR Journal 15, 2013.

[4]. Arivazhagan S., Ligi S. V., *Mango Leaf Diseases Identification Using Convolutional Neural Network*, International Journal of Pure and Applied Mathematics, 2018.

**[5]. Atila M., Uar M., Akyol K., Uar E.**, *Plant leaf disease classification using efficientnet deep learning model*, Ecol Inform. 2021.

**[6]. Sabrol H., Kumar S.**, *Recent studies of image and soft computing techniques for plant disease recognition and classification*, Int J Comput Appl., 2015.

**[7]. Yalcin H., Razavi S.**, *Plant classification using convolutional neural networks*, In: 2016 5th international conference on agro-geoinformatics (agro-geoinformatics), New York: IEEE, 2016.

**[8]. Fuentes A., Lee J., Lee Y., Yoon S., Park D. S.**, *Anomaly detection of plant diseases and insects using convolutional neural networks*, In: ELSEVIER conference ISEM 2017-The International Society for Ecological Modelling Global Conference, 2017.

**[9]. Hasan M. J., Mahbub S., Alom M. S., Nasim M. A.**, *Rice disease identification and classification by integrating support vector machine with deep convolutional neural network*, In: 2019 1st International conference on advances in science, engineering and robotics technology (ICASERT), 2019.

**[10]. Thenmozhi K., Reddy U. S.**, *Crop pest classification based on deep convolutional neural network and transfer learning*, Comput Electron Agric., 2019.

**[11]. Fang T., Chen P., Zhang J., Wang B.**, *Crop leaf disease grade identification based on an improved convolutional neural network*, J Electron Imaging, 2020.