Optimize Agriculture using Artificial Intelligence

Detect Crop Disease with The Help of Convolutional Encoder Network

Lukas Walser
Data Science and Intelligent Analytics
FH Kufstein, Tirol, Austria
2010837042@stud.fh-kufstein.ac.at

ABSTRACT

Agriculture plays a significant role in the growth and development of the economy of any nation. But the emergences of crop-related diseases affect the productivity [1]. This has not only an impact on the economy itself, but also influences the security of food supply. Conventional methods of pest control are mostly controversial and no longer tolerable for the environment. To cope with these issues and to implement effective strategies to prevent the propagation of diseases, crop disease diagnosis with artificial methods is required.

...can be helpful

Where? In AI? In agricultu re?

Commonly used techniques are *k*-Means clustering, Convolutional Neural Network CNN, and image processing tasks. In this paper, a combination of Convolutional Neural Network and autoencoder is explained, which is referred as *Convolutional Encoder Network*, to identify crop disease using crop leaf images [1].

Keywords

Artificial Intelligence, Machine Learning, Deep Learning, Crop disease detection, Convolutional Encoder Network, PlantVillage dataset

1. INTRODUCTION

Artificial Intelligence AI is mainly used to describe the process of creating artificial human brains that are capable to recognize, learn, and process natural language [2]. It combines theoretical concepts with the development of computer systems, that need some human intelligence, like visual perception, speech recognition, decision-making, and language translation [3]. *Machine Learning ML* is the most popular and often used AI approach. Individuals, businesses, and government agency utilize such models to anticipate and learn from their data [4]. With a growing population and steady changing climate situation, recent challenges in the conventional agriculture emerged. Therefore, machine learnings models for the complexity the food industry are still evolved to counteract with problems like productivity shortages, or destruction of harvest through parasites, to ensure the security in nourishment in the future [6].

...artificial human brains capable of recognizing, learning, and processing natural language.

...which deal with the complexit y of the food industry...

Recognizing the harvest condition by using object recognition and deep learning models can be an important approach. The basic idea behind is simple – take an image of the leaves of a plant and detect disease with leaf pattern recognition and image classification [6].

2. CONVOLUTIONAL ENCODER NETWORK

2.1 Crop Disease Detection

Figure 1 demonstrates the basic idea of the crop disease detection. An image of the leaves of a plant is analyzed by a neural network, to separate the plants into specific classes (classification), based on their conditions like early blight, late blight, leaf mould or healthy.

Figure 1: Basic idea of the crop disease detection approach

2.2 Architecture

A *Convolutional Neural Network CNN* is defined as a deep learning network with multiple layers of neural connections as in Figure 2 is shown. The network is composed of convolutional, pooling layers, and fully connected layers [7].

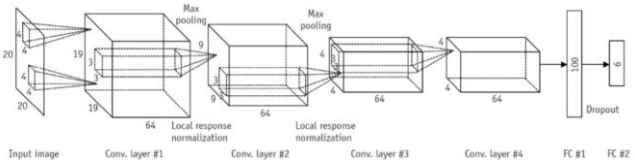

Figure 2: Architecture of a Convolutional Neural Network [7]

The main purpose of a convolutional layer is to detect edges, lines, and other visual elements like local patterns. The specialized filter operators, so-called convolutions, are learned by the system itself. This mathematical operation represents the multiplications of local neighbours from a specified pixel by a certain array of kernels [7].

A *Convolutional Encoder Network* is the combination of both CNN and the encoding part of autoencoders to obtain required features. An autoencoder is a special type of *Artificial Neural Network ANN*,

used for learning efficient encodings of data, which is not labeled (unsupervised learning). It combines basically two phases, first one is the encoding and second one the decoding part (not required) [1].

3. PROPOSED WORKFLOW & RESULTS

3.1 PlantVillage Dataset

For the main process of the encoding part, an image of the leaves is given as an input, to generate a high-dimensional feature vector to aggregate the attributes at multiple levels. For this, the *PlantVillage* dataset is used, which includes more than 50,000 images on healthy and infected leaves of crops [1].

The following figure illustrates the proposed workflow and single steps of the classification process. In the preprocessing, dimensions of the images are reduced, as well as making the sizes smaller [1].

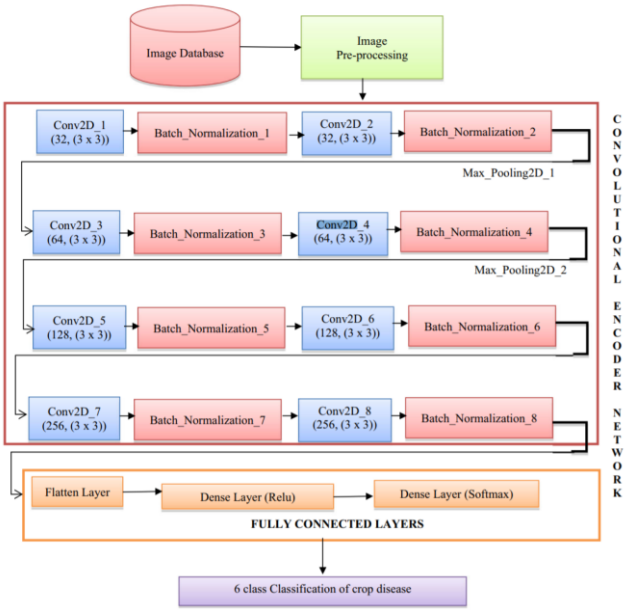

Figure 3: Proposed workflow of crop disease detection [1]

The images itself are randomly selected and processed with Python. The figure above shows an example of the images in the database. After using the encoding network, the images are classified in six different classes, like in Figure 5 is shown [1].

...4 below...

like shown in Figure 5

Figure 4: Randomly selected images of database [1]

Class	Disease	Crop
0	Early blight	Potato
1	Late blight	Potato
2	Leaf mould	Tomato
3	Yellow leaf curl virus	Tomato
4	Rust	Maize
5	Healthy	All (potato, tomato, maize)

Figure 5: Different classes of health status [1]

The single health status of the plants Potato, Tomato and Maize are Leaf mould, Yellow leaf curl virus, Rust and Healthy. The results of the precision computation for 100 epochs using a 3 x 3 filter of randomly selected images can look like in the following figure [1].

Class	Precision	Recall	F1-score	Support
Class 0	0.88	0.90	0.89	51
Class 1	0.86	0.88	0.87	50
Class 2	0.90	0.94	0.92	50
Class 3	0.94	0.90	0.92	50
Class 4	1.00	0.98	0.99	50
Class 5	0.86	0.84	0.85	50
Avg./total	0.91	0.91	0.91	301

Figure 6: Precision computation results [1]

4. CONCLUSION

Using Computer Vision and deep learning models can be efficient and trustworthy in the prediction of crop leaf diseases. Though, the research field is still young and there will be upcoming challenges, detecting crop leaf diseases with Artificial Intelligence can improve conventional agriculture in the future.

A Convolutional Encoder Network is the combination of both CNN and autoencoders. It is used to obtain required attributes from data, which is not labelled and consists of multiple different layers like convolutions, pooling layers, and fully connected layers.

With the PlantVillage dataset, more than 50,000 images on healthy and infected leaves of crops are available for testing and predicting.

5. REFERENCES

[1] A. Khamparia, G. Saini, D. Gupta, A. Khanna, S. Tiwari, V. H. C. de Albuquerque4, Seasonal Crops Disease Prediction and Classification Using Deep Convolutional Encoder network, 2018 Circuits, Systems, and Signal Processing, doi:10.1007/s00034-019-01041-0

[2] R.T. Adek M. Ula A Survey on The Accuracy of Machine Learning Techniques for Intrusion and Anomaly Detection on Public Data Sets 2020 International Conference on Data Science, Artificial Intelligence, and Business Analytics (DATABIA) 2020 19 27 doi:10.1109/DATABIA50434.2020.9190436

[3] T. R. N and R. Gupta, ''A Survey on Machine Learning Approaches and Its Techniques," 2020 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), 2020, pp. 1-6, doi:10.1109/ SCEECS48394.2020.190.

[4] G.G. Patil R.K. Banyal, Techniques of Deep Learning for Image Recognition 2019 IEEE 5th International Conference for Convergence in Technology (I2CT) 2019 1 5 10.1109/I2CT45611.2019.9033628

[5] R. Khan, M. Abbas, R. Anjum, F. Waheed, S. Ahmed, F. Bangash, Evaluating Machine Learning Techniques on Human Activity Recognition Using Accelerometer Data, International Conference on UK-China Emerging Technologies (UCET) 2020 (2020) 1–6, doi:10.1109/ UCET51115.2020.9205376

[6] R. Khan, S 2018, A Guide to Convolutional Neural Networks for Computer Vision (San Francisco), pp 53-4

[7] Ting, Fung Fung, T. Yen Jun, Sim, Kok Swee, 2018. Convolutional Neural Network Improvement for Breast Cancer Classification. Expert Systems with Applications, doi: 10.1016/j.eswa.2018.11.008