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Application of Convolutional Neural Network in Agriculture on the Example of Plant Disease Detection

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ABSTRACT

Artificial Intelligence (AI) technologies are used in various sectors of the national economy, particularly in agriculture. These technologies are used in various fields of agriculture: detection of plant diseases, classification and identification of weeds, crops identification and computation, water and soil management, weather (climate) forecasting, determination of animal behavior, etc. This paper reviews advanced Artificial Neural Network (ANN) techniques available to hyperspectral data processing, with a special emphasis on plant disease detection. It is proposed to apply the developed ANN model to the agriculture of the Republic of Armenia to make it more modern and efficient.

Introduction

The technological revolution of the recent decades has opened new opportunities for the entities engaged in agriculture to find better ways to treat, grow and produce foodstuff. Anyhow, there is also a growth in the pollution rate and therefore, in the possible pathways for plants intoxication. The poisoning causes various plant diseases. These are dangerous threats for nearly every farm type and the expected damage can be high especially for small ones. Obviously, from this perspective no growth in mass production or its quality can be envisaged. Fortunately, algorithmic methods, in the face of image processing algorithms, come to fill the mentioned gap enabling to identify possible deviations and to get sustainable outcomes (Sharada, et al., 2016, Hanson, et al.,2017). Another well-positioned approach has become very popular in recent years, which is related to image processing based on Convolutional Neural Networks.

Convolutional Neural Network (CNN) (Srdjan Sladojevic, 2016) is one of the main methods for image recognition (Mercelin Francis, 2019) and classification (Ciresan, et al., 2011, Krizhevsky, et al., 2012). Object detection and recognition sector is one of the areas where CNNs are widely used. CNN image classification model takes an input image, processes it and then classifies it per identified categories (e.g., dog, cat, tiger, lion). Computers perceive an input image as an array of pixels and the latter is related to the image sizes. Based on the image resolution, it will see (h = Height, w = Width, d = Dimension) matrix.

Materials and methods

It’s very hard to take a large-scale control on diseases and their prevention. Thus, very often farmers take a number of struggling measures against the plant diseases. One of the widely used practices is the application of toxic sprays over cropping areas. This method, though effective, implies high costs and environmental risk exposure. In this article, we present the ML-based method, which aims to utilize Convolutional Neural Networks for disease detection in plants.

Convolutional Neural Networks are the most widely used types of Artificial Neural Networks for image classification. Structural peculiarities make CNNs well suited for their use in pattern recognition algorithms and for image analysis. The main difference between CNNs and multilayered perceptrons is the availability of hidden convolutional layers. Like in an ordinary artificial neural network, a layer in this network can be also viewed as a transformation of input data. In case of CNN this transformation is a convolution operation. To make convolution possible, filters with finite numbers should be matched with each convolution layer. Each filter is a matrix of nxm size. In each transformation phase realized by the convolution layer, the filter slides over the input matrix and in every convolution span the product of the filter and the appropriate submatrix of the input matrix is calculated. As a result, the output matrix is generated. These filters can be viewed as model determinants. The deeper the net is the more complex the filters can be.

Plant Village Dataset (Saad Albawi, et al., 2017) has been chosen as a database for the study of the neural networks, which is available online for free. Pictures of this dataset were taken in the laboratory conditions and can provide up to 99.35 % accuracy. However, the image of the picture is quite different in case of taking it in real conditions. Moreover, in case of many problems, it is not possible to ensure high rate of accuracy.

Diagram 1 partially indicates the ratio of the number of plant diseases available in the database to the number of the corresponding pictures.

Not all diseases available in the mentioned database are found in the territory of the Republic of Armenia. However, taking into account the universality of the method, it is possible to use it in case of any visually observed disease: (Figure 1-6).

The raw dataset consists of colored, grayscale and segmented images. Colored images have been used as a data source for this experiment. Segmented images can be used as an alternative variant from the prospect of producing less noise. Each image has 256x256 pixel size. For in-depth study of neural networks, images should be represented as a three-dimensional array, even if the image is grayscale, additional dimension should be added for a single color channel. Also, cross-validation has been applied to data, where 80 % of the dataset was used for training and 20 % for testing purposes.

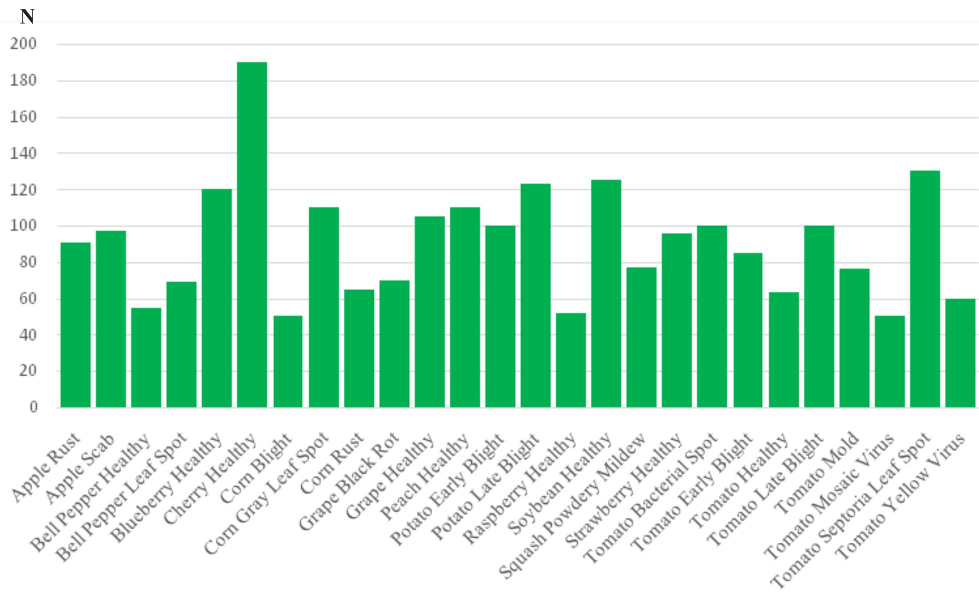


Diagram 1. Types of diseases and the number of the pictures (*Plant Village Dataset*).

Figure 1. Apple Black Rot, a picture in the dataset.

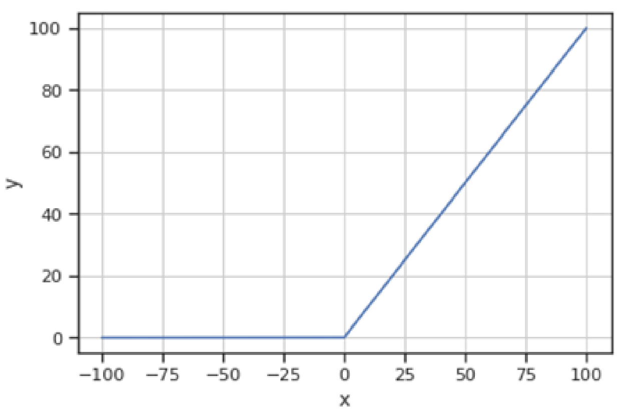
Figure 2. Apple Black Rot, a picture taken in real conditions.

Figure 3. Bell Pepper Bacterial Leaf Spot, a picture in the dataset.

Figure 4. Bell Pepper Bacterial Leaf Spot, a picture taken in real conditions.

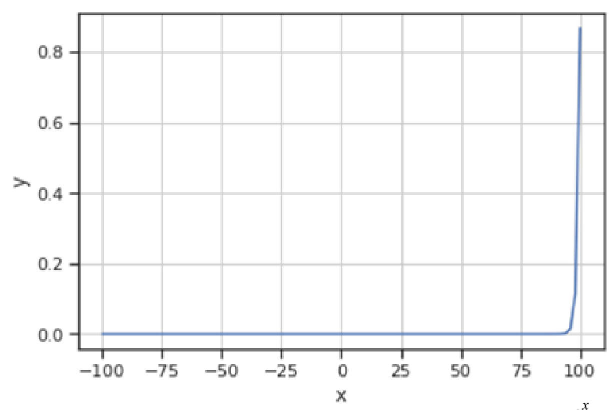
Figure 5. Corn Gray Leaf Spot, a picture in the dataset.

Figure 6. Corn Gray Leaf Spot, a picture taken in real conditions.



f(x)=max(0,x)

Diagram 2. ReLU Activation Function (*composed by the authors*).



$$f_n(x) = \frac{e^x}{\sum_j^n e^j}$$

Diagram 3. Softmax Function (*composed by the authors*).

Results and discussions

The model of the developed CNN has the following structure (Diagram 4). The network starts with the convolution layer, which consists of 32 filters each with 3x3 kernel. The ReLU (Rectified Linear Unit) has been chosen as an activation function (Diagram 2). Without ReLU or another kind of activation function, the network can be viewed as a sequential multiplication of matrices. ReLU has several advantages as an activation function. The ease of computation and scale invariance are among the most important privileges. Besides, ReLU is very suitable for those nets the weights of which have been randomly pre-estimated and at the start of study only part of the neurons are activated. So, the addition of the ReLU layer helps to add some non-linearity to the network. The max-pooling layer follows the activation function. Its objective is to decrease the number of random variables under observation and obtain some set of variables principal to the current problem. During matrix pooling, we should choose some nxm matrix and slide this over input data with some strides. On each step, this matrix will cover some nxm sub-matrix of input data and pool out maximum value from that. It should be noted, that max-pooling comes right after convolution and activation layers. So, on the whole the max-pooling function consists in the choice of the most activated parts from the output. Another common problem is overfitting. Due to overfitting the network starts to behave very well to the training data. As a result, it is unstable to any new, unexplored data and consequently fails in the testing phase. To avoid overfitting dropout technique has been applied. Dropout weakens some connections between two layers, so that network becomes unable to learn some features from the new input data, but on the other hand accuracy for the test data use improves. In case of currently developing network nearly 25 % of connections have been dropped after the max-pooling layer. The next two sets of convolutional and ReLU layers follow the max-pooling layers.

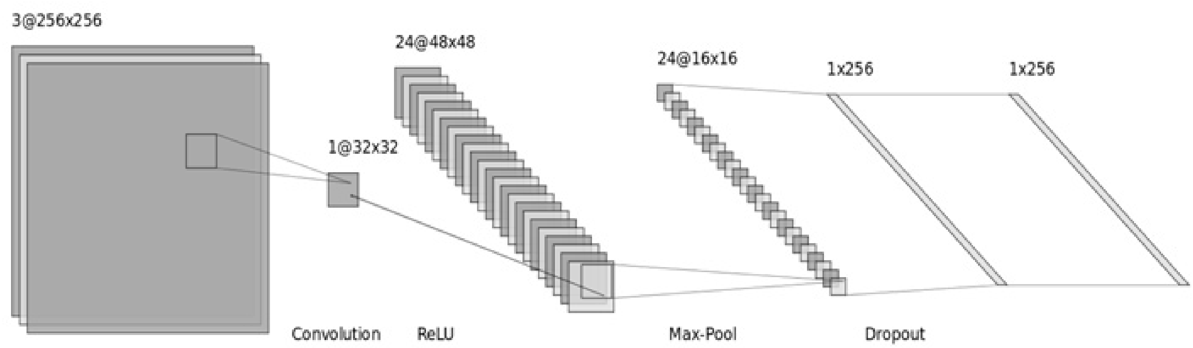


Diagram 4. Illustration of the first part of the network (*composed by the authors*).

Diagram 5. Training and Validation accuracy (*composed by the authors*).

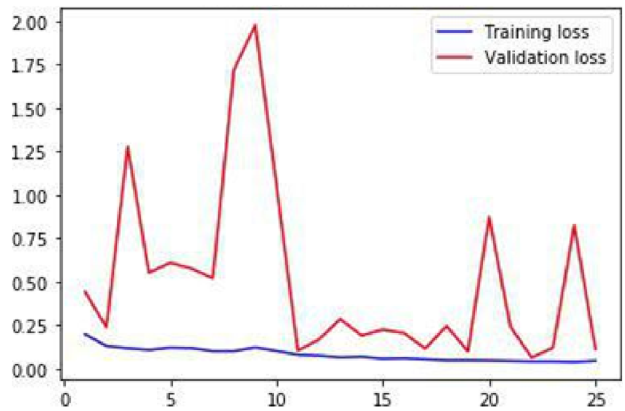


Diagram 6. Training and Validation loss (*composed by the authors*).

For the final part of the network, one more set of fully connected layer with respective activation layer was applied. Softmax function was used as the last layer (Diagram 3). Its main objective is to make probabilistic interpretations on the network outputs.

There is also a problem related to model optimization. Keras Adam (Diederik Kingma, 2015, Sashank, et al., 2018) optimizer was used as an optimization algorithm. Basically, it is another approach based on Stochastic Gradient Descent or SGD.

The results achieved throughout training and validation procedures are introduced in diagrams 5, 6. They also illustrate accuracies achieved during the training and validation phases. As it is known, the whole training and testing process consists of 25 phases. The best accuracy achieved in the training process was detected in the 23rd phase which is equal to about 97 %. It is clear that the introduction of such an outcome in the agricultural sector is practically rather beneficial. Diagram 6 shows loss function results during the training and validation phases.

Finally, it should be mentioned that 96.77 % accuracy was achieved during the testing phase, using the network described above.

Conclusion

Based on the aforementioned study results it can be concluded that Machine Learning models such as Artificial Neural Networks and their variations (CNNs) can have a great impact on the current state of agriculture. In this article a special attention was paid to the mechanisms for disease detection in the plants leaves. Upon the investigations it can be inferred that it is possible to detect the infected leaves of the plants with high accuracy even in fluctuating light conditions (Zeiler, 2014). In case of the availability of appropriate equipmet this method can be used to automate the solution of some agricultural problems.

However, it should be noted that the described method has limited applicability. One of the limitations consists in the fact that this method is not applicable to the plants infected at their initial development stage. In this case, it is impossible to solve the problems related to visual symptoms, as they are actually missing at this stage. Thus, whether the plant is infected or not is possible to find out only in laboratory conditions. Another restriction is related to the fact that the diseased plant may lack visual disease symptoms at all, or they may appear at the stage of the disease, when it can be only retarded, but not treated.

The practical application of the mentioned mechanisms can be considered as the further development of the current work. It is recommended to implement investigations and researches on the plants diseases in the territory of Armenia. Appropriate database should be reserved throughout the mentioned investigations. The described methods can be applied to these data to get accurately designed models. There are various tools which enable to serialize the designed Machine Learning/Deep Learning models for their further use. With such rich toolkits it's possible to develop either cloud-based or client-based mobile application to ease the process of plant protection and to find diseases in the early stage of plant development.

In the result of accomplished research and engineering works on the applications of the created models for artificial neural networks we recommend to use this model in the agriculture of the Republic of Armenia. In this way, it will be possible to invest modern and robust technologies into agriculture. Under such circumstances it is possible to ensure high qualitative and quantitative indices for agricultural products.

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